MOUNTAIN-PLAINS CONSORTIUM

MPC 15-301 | X. Qin, Z. He, and H. Samra

Improving Rural Emergency Medical Services (EMS) through Transportation System Enhancements Phase II

A University Transportation Center sponsored by the U.S. Department of Transportation serving the Mountain-Plains Region. Consortium members:

Colorado State University
North Dakota State University
South Dakota State University
University of Colorado Denver
University of Denver
University of Utah
Utah State University
University of Wyoming

Improving Rural Emergency Medical Services (EMS) through Transportation System Enhancements Phase II

Xiao Qin, Ph.D., PE
Associate Professor

Zhaoxiang He
Graduate Research Assistant

Department of Civil and Environmental Engineering
University of Wisconsin-Milwaukee

Haifa Samra, Ph.D.
Associate Professor
Nursing, School of Health Sciences
University of South Dakota
Sioux Falls, SD

December 2015

Acknowledgements

This work was sponsored by the Mountain Plain Consortium (MPC) at North Dakota State University. The authors would like to thank South Dakota Emergency Medical Services (EMS) for providing the EMS data.

Disclaimer

EXECUTIVE SUMMARY

Providing acute medical care outside of the hospital, Emergency Medical Services (EMS) is crucial in rural environments where hospitals are not close by and are difficult to access. Establishing EMS performance measures is critical in improving a rural community's access to these services and eliminating systemic inequalities; however, an absence of quantitative performance analysis leads to challenges in developing attainable objectives and service metrics. Hence, the main objectives in this study are as follows:

1) to establish more specific, data-driven, and rural EMS performance-based measures
2) to increase the utilization of rural EMS resources through station planning and location optimization
3) to identify key variables contributing to response time, specifically, en route time

This study used the National EMS Information System (NEMSIS) South Dakota data to exemplify two approaches to establishing data-driven performance measures for each rural EMS provider. The measures—timely service and service coverage—are both dependent on mobility and the accessibility of the transportation network in which a suggested 8-minute response time zone is calculated for every provider. Service coverage is measured by the coverage ratio, which is the number of emergency calls within the 8-minute zone over the total number of emergency calls responded. Timely service is gauged by the percentage of emergency calls that were actually responded to in less than 8 minutes within the 8-minute zone. The results of performance measures help to identify the specific areas for improvements and needed resource and training.

If the service provided by the current EMS provider is not sufficient, the stations can either be relocated or augmented to increase the service coverage and quality. Maximizing ambulance coverage area and minimizing en route time are two different goals for strategically locating EMS stations. Maximizing ambulance coverage can be treated as the maximal covering location problem (MCLP) that maximizes the demand served within a specified time or distance for a given number of stations. Minimizing en route time is the location set covering problem (LSCP) that aims to minimize the number of facilities when all demands are met. The two objectives influence each other in such a way that reducing the average en route time for uncovered demand areas may decrease the total coverage ratio. The balance can be achieved through optimizing a bi-objective covering location model that considers not only the coverage rate but also the en route time equity. Case studies were performed for Todd County, a less populous county with relatively high demand, and Minnehaha County, a populous county with moderate demand to demonstrate the varying optimal solutions under different constraints.

The factors contributing to en route time were thoroughly reviewed and 13 key variables were identified, including six variables that are specific to 911 calls (e.g., case type, response, mode, location type) and seven variables that characterize the service provider (e.g., professional/volunteer, unit hour utilization, road connectivity). Among several regression models developed and evaluated, the Geographically Weighted Regression (GWR) model was found to produce the best statistical goodness-of-fit and provide additional insights into the particular spatial patterns of coefficient estimates that can be used to explore the influence of unobserved heterogeneity among EMS providers.

Several directions for future research were recommended. Linking EMS data with patient's outcome is of strong interest because there is no direct evidence to prove that a shorter total EMS response time leads to a less severe consequence. A lack of quality data can be a main factor affecting analysis results, performance measures, and goal setting. Actionable strategies to improve EMS data quality are in great and urgent need. Lastly, although the GWR model has substantially improved the prediction accuracy, its overall goodness-of-fit is still low. Other spatial models such as spatial filtering may be more effective in accounting for spatial heterogeneity.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

CODES	Crash Outcomes Data Evaluation System
EMS	Emergency Medical Service
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
GIS	Geographic Information System
GWR	Geographically Weighted Regression
ITS	Intelligent Transportation System
LISA	local indicator of spatial association
MLR	Multiple Linear regression
NEMSIS	National EMS Information System
NFPA	National fire Protection Association
NHTSA	National Highway Traffic Safety Administration
SDDOT	South Dakota Department of Transportation
VMT	Vehicle Mile Traveled

LIST OF FIGURES

LIST OF TABLES

1. BACKGROUND

Almost 40,000 people die on the nation's highways each year, and about 70% of those fatalities happen on rural roads. Fatalities from motor vehicle crashes that occur in rural areas have been a major consideration when evaluating rural highway safety. The NHTSA found that the number of fatalities from rural vehicle crashes in the U.S. in 2010 was 17,915, compared with 14,530 from urban vehicle crashes [1]. According to 2010 highway statistics, 66% of the VMT on public roads took place in urban areas (1,982,400 VMT in millions), and 34% (984,148 VMT in millions) occurred in rural areas [2]. The results show that twice the number of vehicle crash fatalities occur in rural areas than urban areas (1.82 vs. 0.73 fatalities per 100 VMT in millions) given the same amount of VMT.

When a crash results in traumatic injury, the victim’s chances of survival depend significantly on the amount of time it takes to receive emergency care and the level of expertise of those providing the care. Rural EMS is a system that includes personnel, vehicles, equipment, and facilities delivering medical care to those who need immediate care but are too far from a hospital. EMS is considered a vital expansion of emergency room services [3], as it provides prehospital care from the time a 911 call is placed until the patient can be transferred to a hospital. EMS has long been considered one of the four cornerstones of a successful transportation safety management system, or the “Four Es”: EMS, engineering, education, and enforcement [4]. These systems are charged with covering substantially larger areas than their urban counterparts, yet they are underfunded and understaffed.

The rural transportation network connects local residents to employment, health care, social activities, and business opportunities; thus, a functional and reliable rural transportation system is critical to the economic growth, public health, traffic safety, and social welfare of rural communities. Long travel distances are common in South Dakota [5], a prominent rural state, as the population is sparsely distributed. The task of delivering people, goods, and services becomes more difficult as distances increase, especially for time-sensitive services such as EMS. According to the NHTSA, “Delay in delivering emergency medical services is one of the factors contributing to the disproportionately high fatality rate for rural crash victims” [6]. According to a survey of rural experts, access to EMS has been considered a top ranking rural health concern [7].

An EMS system was built in South Dakota in 1972 as a result of a trend in the development of local EMS in the U.S [8]. The system includes more than 100 ambulance services and four helicopter services. The service in South Dakota is regulated by the Department of Public Safety, but there is no requirement that a community or county have an ambulance service; there is also no documented plan for the provision of EMS in South Dakota. According to a recently conducted case study by Becknell, there has been no sustaining state or federal funding for these services, meaning the local communities are left responsible for the maintenance of these services [9]. A decline in volunteerism, an aging population, and increasing demands have added to the issue for small communities struggling to survive [9].

Improved EMS will have direct impacts on the traffic safety and public health of rural communities. EMS can be enhanced by a better planned, designed, and operated roadway network that connects hospitals with communities in need. In order to provide safe, timely, and quality services, it is necessary to obtain a realistic estimate of the medical demand and the capacity of current transportation infrastructure pertaining to the services. The gaps between service providers, patients, and the transportation network connecting the two, need to be identified and closed to better support EMS.

Phase I of this project was to conduct a needs assessment for rural EMS in South Dakota and to identify issues with respect to delivering quality services to its residents. Three major objectives included: 1) assess the EMS service needs from the rural communities, 2) evaluate the efficacy of rural EMS in support of swift and safe EMS operations, and 3) identify existing issues with the SD EMS providers or first responders in relation to road conditions and traffic controls.

In Phase I, EMS data were reviewed from both spatial and temporal perspectives. Spatial analysis was focused on the visual presentation of EMS demand and service performance on a county level. Spatial clusters were identified for areas sharing similar properties and performance using local indicators for spatial autocorrelation (LISA). Temporal analysis was performed to break down the service demand and performance patterns by month of year, day of week, and time of day. Descriptive statistics and a two-tailed t test were applied for describing and comparing variables of interest: several time- and distance-dependent variables such as response time, en route time, on-scene time, and transporting time, as well as the distance to and from the incident scene. Noticeable differences were found for area type, location, and the use of light and sirens.

Three main objectives were developed for Phase II:

1) Establish more specific, data-driven, and rural EMS performance-based measures
2) Increase the utilization of rural EMS resources through station planning and location optimization
3) Identify key variables contributing to the time intervals during an EMS process

It is anticipated that using state-of-the-art methodologies to analyze EMS "big data" can reveal new patterns for service demand, disclose the relationships between service performance and contributing factors, and assist in developing evaluation metrics and informing decision-making.

2. LITERATURE REVIEW

EMS has been extensively researched due to increasing awareness of the vital importance it plays in public health. In order to provide an overview of current EMS practices and studies, this literature review includes facts and statistics for rural EMS, available EMS data, and related EMS research.

2.1 Facts and Statistics of Rural EMS

This section provides facts and statistics on the status, practices, issues, and needs of current rural EMS. The NCHRP 500 report "Volume 15: A Guide for Enhancing Rural Emergency Medical Services" served as a guideline for enhancing rural EMS. The report identified possible issues related to rural EMS and suggested strategies and methods to enhance service performance [101010]. Four main objectives for enhancing EMS in rural areas were proposed: "integrate services to enhance emergency medical capabilities, provide or improve management and decision-making tools, provide better education opportunities for rural EMS, and reduce time from injury to appropriate definitive care." The four objectives yielded 24 strategies. Due to varying levels of sophistication and development among EMS agencies in rural areas across the country, state EMS directors, local system managers, policy makers, and state and local highway agencies should determine which objectives and strategies are most appropriate for their site based on their existing services and resources.

This NCHRP report is instrumental to understanding the issues, gaps, and needs in service, as well as providing an objective evaluation of EMS activities and guiding effective interventions in rural areas. "Provide or improve management and decision-making tools" and "reduce time from injury to appropriate definite care" are the two objectives that are most relevant to our study. In particular, one strategy under the second objective is, "Identify, provide, and mandate efficient and effective methods for collection of necessary EMS data." This is of vital importance, as data issues can be a major obstacle in evaluating EMS [11], which has been found elsewhere, as well as in Phase I of this study.
The disparities are widespread among rural EMS providers, including geographic barriers, lack of professional, paraprofessional, and financial resources, aging or inadequate equipment, absence of specialized EMS care and local medical facilities, the sporadic nature of rural crashes, and a workforce that is predominately composed of volunteers [3]. These disparities contribute to the service differentials between urban and rural EMS that can be measured through a number of indices.

As a result of the disparities rural EMS systems face, the response times in rural areas are longer than in urban areas. In 2004, NHTSA reported that the national average for overall EMS response time (time from notification to definitive care) for fatal crashes is 36 minutes in urban areas and 53 minutes in rural areas [12]. More than 36% of fatal crashes that occurred in rural areas had response times that exceeded 60 minutes, while only 10% of fatal crashes in urban areas exceeded 60 minutes. The 2011 report statistics were even worse: the national average for EMS response time for fatal crashes was 37.22 minutes in urban areas and 54.49 minutes in rural areas [13]. Table 2.1 provides a comparison of South Dakota and national statistics. South Dakota performed slightly better (3.13 minutes or 9% shorter) in urban areas. Overall response time for fatal crashes in urban areas was shorter in South Dakota when compared with the national average, but was similar or slightly longer than the national average with regard to crashes in rural areas. Specifically, the notification time in rural South Dakota was 2 minutes (32.4%) shorter than the national average, but the en route time to the crash scene was 2 minutes (16.1%) longer than the national average.

Table 2.1 Average EMS Response Times for Fatal Crashes

	Urban (minutes)		Rural (minutes)	
	SD[1]	National Average[2]	SD[3]	National Average[4]
Time of crash to EMS notification	5.00	3.47	4.71	6.17
EMS notification to EMS arrival at the crash scene	6.40	7.19	14.49	12.39
EMS Arrival at Crash Scene to Hospital Arrival	26.18	27.39	40.07	38.65
Time of Crash to Hospital Arrival	34.09	37.22	54.57	54.49

1: Based on 15 fatal crashes
2: Based on 13,578 fatal crashes
3: Based on 86 fatal crashes
4: Based on 16,053 fatal crashes
*Source: NHTSA Traffic Safety Facts 2011

The NCHRP report, "Synthesis 451: Emergency Medical Services Response to Moto Vehicle Crashes in Rural Areas," focuses on traffic crashes and explores EMS responses to rural crashes from both the EMS provider and the transportation system staff perspectives [14]. The report presents the current state of practices for a broad cross-section of EMS system characteristics, identifies factors that affect the timely provision of effective medical care in rural areas, and examines broader issues such as personnel, data records, and interactions with other agencies. Information was organized in the following categories:

- Dispatch, including crash detection and reporting, road condition reporting, dispatching functions, and communication systems
- Trauma care, including equipment and preparation, on-scene and transport issues, air medical transport, telemedicine, tribal EMS, and care protocols and procedures
- EMS management, including staff recruiting, retentions and training, interagency cooperation and coordination, and planning and innovation
- Data inclusion with retrospective and real-time data linkages and data metrics

2.2 EMS Data

Data on EMS demand and certain time-related variables such as responding and transporting time are critical to analyzing EMS performance. EMS systems are not organized under the same structure; some are under the control of the fire department, some are controlled by the municipality or county, some are private or hospital-run, and others are a combination. EMS stations also range from urban to rural/remote, volunteer to paid, municipal to private, air and ground, and large to very small. These differences create challenges for the capture of statewide data. A number of innovative developments in recent years, such as the National EMS Information System (NEMSIS) and Crash Outcome Data Evaluation System (CODES) platforms, have attempted to solve the issue of EMS system data capture [15,16]. NEMSIS is the national repository that will potentially be used to store EMS data from every state. CODES provides a system to link EMS data to patient outcome data. When the scope is limited to fatal crashes, the Fatality Analysis Reporting System (FARS) can be considered as another dataset to analyze EMS performance [17]. Data from FARS are more complete and specific than NEMSIS data because they include information on the crash, vehicles, and persons involved, meaning an outcome analysis (e.g. logistic analysis) can be performed [18].

Although 75% of EMS survey respondents in the NCHRP report indicated that data were collected about crash details, responses, and injury severity, only three indicated any linkage to hospital records and just one linked to driver's license data [14]. Almost no cost or compensation data are linked to response or crash records. A study of the existing efforts to collect real-time patient data and link that information to the emergency room preparation and impact on patient outcomes would be valuable.

Frameworks such as the NEMESIS database exist for linking records between different data sets. Efforts to link data to other data sets have proven only partially successful, as unique identifiers that can help to relate records between different sources do not exist. Statistical matching techniques have been attempted but are only partially able to match records. Idaho has implemented a program to collect crash scene and patient data during the response and transmit them to hospital staff. The approach allows for a direct connection between data collected at the scene and patient outcome data, as the information is made a part of the patient care record [14]. A study conducted by Newgard resulted in a satisfactory linkage rate between NEMSIS data and hospital data using probabilistic linkage [19].

2.3 EMS Research

A literature review was performed mainly from the transportation perspective, not from a medical standpoint. Research with regard to service demand, service performance, and transportation safety are the three areas of interest and are explored below.

Service demand contains current demand evaluation and future demand prediction. Demand can be evaluated using 911 call volume or 911 call volume per capita, respectively. 911 calls are aggregated by geographical unit, such as by county or EMS station [20]. The temporal aspect is also considered so that call demand can be summarized by time of day, day of week, and month of year. Statistical methods can be used to predict service demand for the entire area for one year [21]. 911 call forecasting models have been developed to support dynamic ambulance deployment for resource optimization, as the number of calls can be precisely estimated by time and by location[22]. Channouf developed time-series models to predict daily and hourly call volumes to EMS in a major city in Canada [22]. Various socioeconomic, demographic, and other characteristics in the defined area often served as predictor variables to forecast call demand [21]. Different models were introduced to avoid model issues of previous studies, such as autocorrelation and multicollinearity [23, 24].

Service Performance includes but is not limited to service performance measures, dispatch of EMS vehicles, allocation of service facilities, ITS technologies, and transport policies and protocols. In future sections, this report will discuss several studies with regard to service performance [13], and will also explore comprehensive methodologies used for the allocation of service facilities.

A variety of measures were proposed to evaluate service performance, such as time- or distance-related variables, outcome-based variables, and other indexes. NHTSA developed 35 EMS performance measures for the local system, which include a time-based variable (Mean Emergency Patient Response Interval) and an outcome-based variable (EMS Cardiac Arrest Survival Rate) to Emergency Department Discharge. The local system could choose either variable depending on the site's unique characteristics [13]. Researchers from Europe developed 14 indicators to measure road safety performance associated with trauma management. The indicators include, "availability of EMS stations; availability and composition of EMS medical staff; availability of and composition of EMS transportation units; characteristics of the EMS response time; and availability of trauma beds in permanent medical facilities" [25].

Among all performance measures, response time is considered a major performance index to evaluate EMS performance [26]. Although patient outcome depends on many factors such as severity of injury and preexisting conditions, the time required for an EMS unit to arrive at the scene (response time) and the time required for a patient to receive definitive care (Overall response time) play a significant role in the survival rate. The Centers for Disease Control and Prevention reports a 25% reduction in mortality risk when trauma victims receive definitive care at a level I trauma center [27]. Crashes in rural areas usually occur far away from level I trauma centers, and timely transportation to those centers depends on the availability of swift EMS. The explicit relationship between clinically significant improvements in patient outcome and a reduction in time between EMS and definitive care has not been fully established, but the general consensus is that the shorter the amount of time to definitive care, the better the patient outcome. Therefore, it is crucial to bring critical patients to definitive care immediately, specifically within 60 minutes (the golden hour or golden time) of a traumatic injury being sustained.

Benchmarks exist for response time and other time-related variables, but none of them have proven to be accurate [28]. A response time of 8 minutes has been considered a criterion, especially for life-strengthening cases, but no scientific research shows the correctness of this number [28]. NFPA 1710 states, “Advanced life support response time: Eight minutes (480 seconds) or less for the arrival of an advance life support unit at an emergency medical incident, where the service is provided by the fire department” [29]. In the NFPA report, response time refers to en route time. Considering that en route time is spent during transport, which connects more closely with the road network, the 8-minute benchmark for en route time was selected as the major performance measure for this study.

A few studies have focused on improving service performance by reducing response time. Do used a quantile regression analysis to identify factors related to response time by dividing factors into patient-level and system-level [30]. Do found that patient factors had little influence on response time. Rather, he found that the addition of each call in the last hour increased response time [30]. Meng used a mixed logistic model to explore the uncertainty of accident notification time and response time and predict the risk of death in work zones [31]. In these studies, GIS has been widely used to analyze response time associated with the road network [32].

3. METHODOLOGY

This study utilizes several methodologies, including a point pattern analysis (K function and cross K function), a genetic algorithm process for solving the maximal covering location problem (MCLP), and linear regression and geographically weighted regression models.

3.1 Point Pattern Analysis

A point pattern analysis was conducted to assess if 911 calls cluster together. If the call concentration existed, the cluster analysis technique was employed to identify where possible clusters occur; next, a visual assessment, or co-location pattern, helped identify whether the clusters existed across multiple stations.

3.1.1 K function

Ripley's K function is a spatial statistical method used to analyze whether the points appear to be clustered, dispersed, or randomly distributed in a point pattern analysis area [33]. It denotes the expected number of points that would fall into a circle of radius r around a randomly selected point. The null hypothesis is that all points are randomly distributed and the corresponding K function is πr^2. The K function and corresponding L function are shown below:

$$\mathrm{K}(\mathrm{r}) = \lambda^{-1}\mathrm{E}\begin{pmatrix} \textit{number of extra points within distance r} \\ \textit{of a randomly chosen point} \end{pmatrix} \tag{1}$$

$$L(r) = \sqrt{\mathrm{K}(\mathrm{r})/\pi} \tag{2}$$

Where,
λ = Density (number per unit area) of points;
E ( ) = expected value;
K(r) = K function;
L(r) = L function;

If L(r) – r >0, which means the K function is larger than πr^2, the points show a clustered pattern. If L(r) – r <0, then the points show a dispersed pattern. The expected value can be plotted with upper and lower 5% bounds, which indicates a 95% confidence interval using the Monte Carlo simulation. If the L(r) –r is above the upper bounds, the pattern can be treated as significantly clustered. If the L(r) –r is below the lower bounds, the pattern can be treated as significantly dispersed. If the L(r) –r is within the bounds, the points can be treated as randomly distributed.

3.1.2 Cross K function

When the objects belong to two kinds of points, such as 911 calls and EMS stations, the co-location pattern should be investigated. "Co-location pattern" is an ecological term indicating which kind of spatial features frequently locate together [34]. A co-location pattern can be detected and measured using spatial statistics such as the Ripley's Cross-K function [34]. Khan et al. used a network-constrained cross K-function to analyze the relationship between ice-related crashes and bridges, finding that ice-related crashes clustered around the bridges [35].

The cross K function is used to analyze the co-location patterns between two kinds of points; for example, with A $(a_1, a_2, \ldots, a_i)$ and B $(b_1, b_2, \ldots, b_j)$, the cross-K function measures whether the two kinds of points are clustered, dispersed, or randomly distributed [33]. The null hypothesis is that all of the points in A are randomly distributed following a binomial point process, regardless of location of B. The cross K function and corresponding L function are shown below:

$$K^{ba}(r) = \lambda_a^{-1} E\begin{pmatrix} number\, of\ Points\, A\, within\, distance\, r \\ of\ a\ point\, b_i\, in\, B \end{pmatrix} \tag{3}$$

$$L^{ba}(r) = \sqrt{K^{ba}(r)/\pi} \tag{4}$$

Where,

λ_a = Density (number per unit area) of points A;
E ( ) = expected value of A following binomial point process for each point in B;
K^{ba}(r) = K function of A relative to B, for the binomial point process;
L^{ba}(r) = L function of A relative to B, for the binomial point process;

Similar to the K function, the expected value can be plotted with upper and lower 5% bounds, which indicates a 95% confidence interval using the Monte Carlo simulation. If the L(r) –r is above the upper bounds, the pattern can be treated as significantly clustered. If the L(r) –r is below the lower bounds, the pattern can be treated as significantly dispersed. If the L(r) –r is within the bounds, the points can be treated as randomly distributed.

3.2 Genetic Algorithm Process

The genetic algorithm adapts Darwin's natural evolution theory to the optimization algorithm. It has been used to solve different problems including facility location. Similar to natural evolution, the essence of the algorithm is to improve the offspring using reproduction mechanisms (crossover and mutation) and to keep those with higher fitness functions. The algorithm is a bottom-up approach, which starts with a set of solutions and results in one optimal solution.

The steps for the genetic algorithm are shown in Figure 3.1 [36].

Step 1: Create the initial population for the solutions (G set of individuals)
G set of initial solutions will be created to activate the process.
Step 2: Evaluate the fitness function of each individual in the population
The fitness function for each solution will be calculated. A higher fitness function value indicates being closer to the optimal solution. The solution with the highest value is the optimal one.
Step 3: Repeat (generate offspring)

Offspring will be generated by following four steps: selection of parent from individuals in population, performing genetic operators (cross-over and mutation) to generate new individuals, adding new individuals into the population, and removing individuals with low fitness function. These steps will be repeated until termination criteria are satisfied.

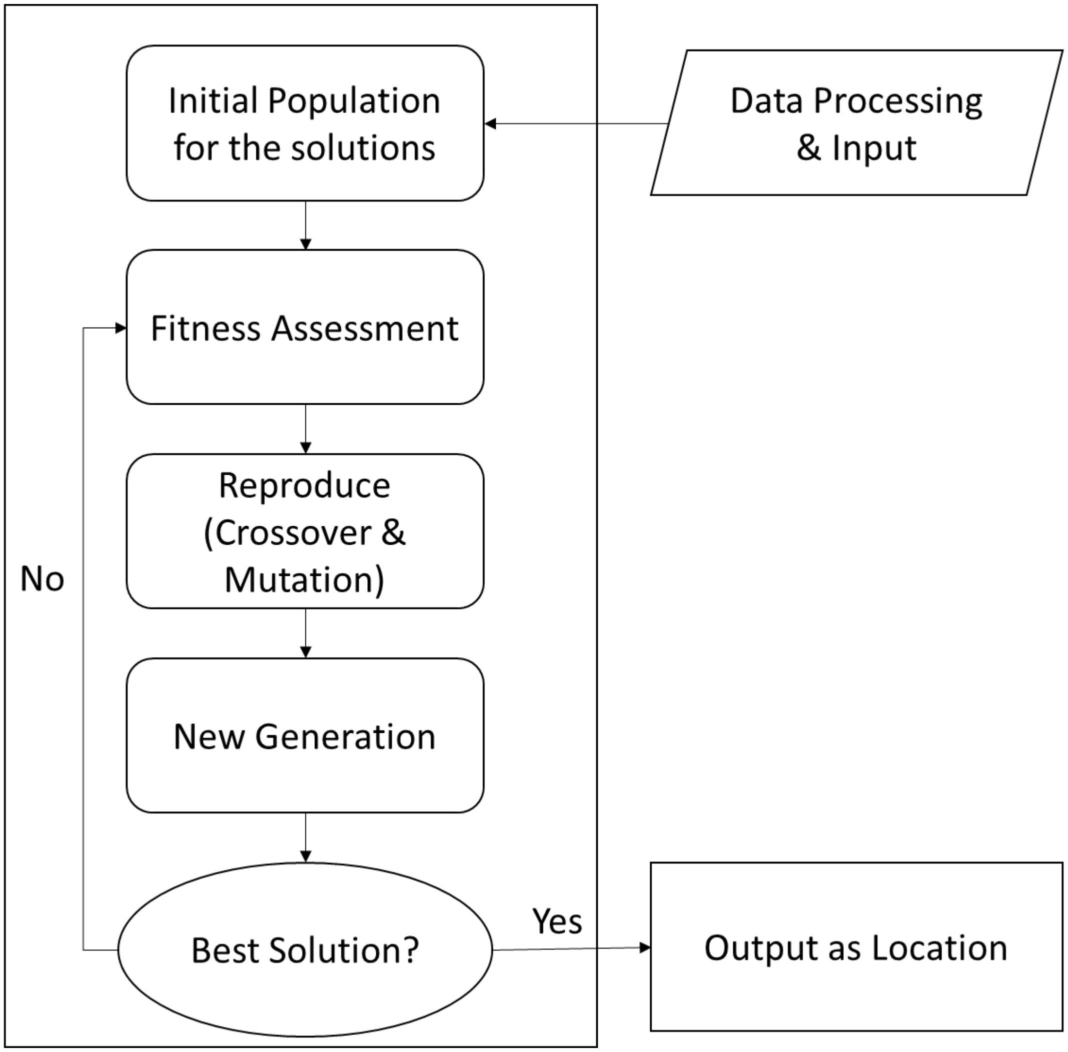


Figure 3.1 Flow Chart for Genetic Algorithm

3.3 Regression Models

3.3.1 Multiple Linear Regression Model

The linear regression model (MLR) is the simplest regression model for identifying a statistically significant relationship [5]. The time-related performance variable is treated as the dependent variable, and all other variables are treated as independent variables. The assumption for this model is that the residuals are independent, normally distributed, have a mean of zero, and have constant variance. The equation is written as:

$$y = \beta_0 + \sum_{k=1}^{p} \beta_k x_k + \varepsilon \tag{5}$$

where y, x_k, ε indicates the dependent variable, kth independent variable, and the normal error, respectively; and coefficients β_k are the global parameters.

3.3.2 Geographically Weighted Regression

MLR may not be appropriate for use with spatial data due to its limitation in capturing spatial heterogeneity [5]. The influence of the independent variable may vary across space, or some variables may have larger impacts on certain locations and smaller impacts on others. Thus, varying parameters, as opposed to fixed parameters, may be more appropriate for describing this phenomenon. The Geographically Weighted Regression (GWR) should be used as an alternative to handling spatial heterogeneity [5].

Zhao used the GWR model to estimate annual average daily traffic, and found that the GWR model performed better than the GLM model [37]. Du used the GWR model to capture the relationship between transport accessibility and land value [38], and Li used the Geographically Weighted Poisson Regression for county-level crash modeling in California [39].

GWR uses local instead of global parameters to estimate different relationships between dependent and independent variables for each geographic location. The GWR model can be written as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{k,i} + \varepsilon_i \tag{6}$$

where y_i, $x_{k,i}$, ε_i indicate dependent variable, kth independent variable and the normal error at location i, respectively; (u_i, v_i) is the coordinate of the ith location; and coefficients $\beta_k(u_i, v_i)$ are the local parameters at the location[5]. Based on the concept of GWR models, the local parameters $\beta_k(u_i, v_i)$ (*k:* 0, 1,…, *p*) are estimated for each location i; thus *n*(P+1)* parameters are estimated for *n* observations The parameters for each location are estimated as follows:

$$\beta_k(u_i, v_i) = \left(X^T W(u_i, v_i) X\right)^{-1} X^T W(u_i, v_i) Y \tag{7}$$

where $W(u_i, v_i)$ is the n*n spatial weight matrix, which can be expressed as follows:

$$W(u_i, v_i) = \begin{bmatrix} w_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{in} \end{bmatrix} \tag{8}$$

Where w_{ij} denotes the weight given to each location j in the model for location i [5].

The local parameters for each location in the GWR model can be estimated based on observations from nearby locations. The parameters at one location are affected more by observations close to that location, as opposed to observations made farther away. The influence factor around i is called weighting function w_{ij}. Two commonly used weighting functions, Gaussian and bi-square, are listed below:

Gaussian: $$w_{ij} = e^{-\frac{d_{ij}^2}{h^2}} \tag{9}$$

Bi-square: $$w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h_i}\right)^2\right)^2 & if \rightarrow d_{ij} < h_i \\ 0 \rightarrow otherwise \end{cases} \tag{10}$$

Where d_{ij} is the distance from location i to location j, h and h_i are the bandwidth for these two functions [5].

Bandwidth for the Gaussian function is constant, which means the magnitude of the function is the same for each location [5]. Bandwidth for the bi-square function h_i is defined as the nth nearest neighbor from location i, and can vary among locations [5]. Bi-square's magnitude has the ability to vary according to the density of data; thus, this adaptive function is often used when data are not distributed randomly or evenly. The Corrected Akaike Information Criterion (AICc) is often used to select the optimal bandwidth and the best model. The model with the lowest AICc is the best performer [5].

When comparing different models using goodness-of-fit, R square and AICc are treated as the most commonly used tools:

$$AICc = D(h) + 2K(h) + 2\frac{K(h)(K(h)+1)}{p - K(h) - 1} \tag{11}$$

Where, D ( ) is the deviance of parameters; K ( ) is the effective number of parameters; h is the bandwidth and p is the number of points.

4. ANALYSIS AND DISCUSSION

After the Phase I assessment of the needs of rural EMS systems, researchers decided this study should focus on the following: a geospatial analysis of EMS station locations, optimization of EMS locations, and a regression analysis of EMS service performance. Geospatial analysis uses en route travel time to study the spatial aspect of EMS stations. Two performance indices were developed for each EMS station. EMS station locations can be recommended based on the results of optimization in order to achieve the shortest en route time. Several regression models have been developed and evaluated; the best regression model is used to identify statistically significant determinants to the travel time.

Three-year EMS data (2011-2013) was available. Phase II used the EMS ambulance dataset used in Phase I, as well as EMS station data and roadway data. EMS station data were provided on the South Dakota Emergency Medical Services web site, which includes the name, location, and professional status of the EMS station, as well as the number of ambulances. The EMS station data vary by year. In 2011, 2012, and 2013, there were 113, 125, and 109 EMS ambulance stations, respectively. The data were not aggregated for analysis, as the EMS stations vary by year; therefore, the analysis in Phase II was based on the 36,198 emergency calls that occurred in the latest year, 2013.

SDDOT provided roadway data that include both interstate highways and local roads. Speed limit information in this dataset can be used to perform a network-based analysis. The en route travel speed, if available in the EMS dataset, was used in place for the posted speed limit. The blank speed limit for road segments without posted speed limit was set as 35 mph.

4.1 Geospatial Analysis of EMS Stations

The geospatial analysis aims to evaluate EMS station locations at the state level from the spatial perspective, and also to provide two performance indices at the station level.

4.1.1 911 Call Clusters

The most straightforward method of evaluating the preparedness for an EMS location is to observe whether it overlaps with or is close to the concentration of 911 calls. The geospatial statistics were used to examine whether there were any 911 call clusters and, if so, where the clusters exist. The K function was used to measure the global pattern of clusters, and the Getis Ord G* was used to identify clusters at the local level.

The point patterns of all 911 calls were examined with the K function in the statistical software R. Figure 4.1 shows that the observed curve is located far above the 5% upper bound of the theoretical curve; this is a strong indication that the clustering pattern is statistically significant at the 95% confidence interval. The corresponding distance r for the summit of the curve suggests that the 911 calls display the strongest clustering pattern 3.5 miles away from the global view or the state level.

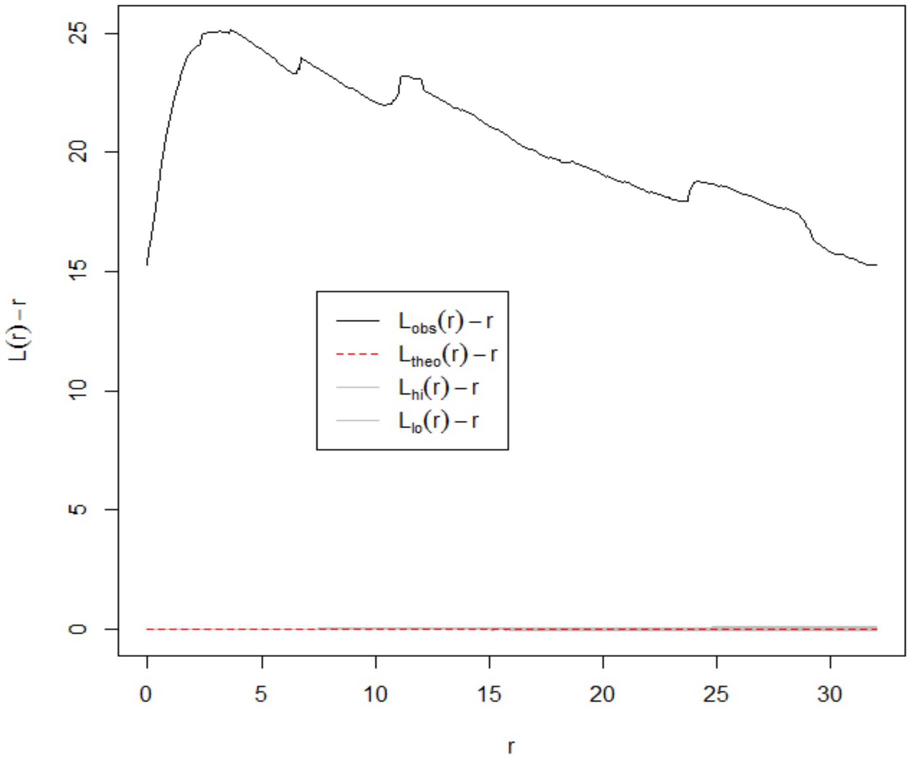


Figure 4.1 K Function expressed as L(r)-r for all 911 calls

Next, the Getis Ord G* analysis was used to identify the location of each cluster. First, the map was divided into grid cells using the "Create Fishnet" tool under the data management toolbox in the ArcGIS software package. The K function informed the choice to use a 5-by-5-mile cell size; on a global level, this size contains the most points clustered. Figure 4.3 shows the input for the grid-creating process in ArcGIS.

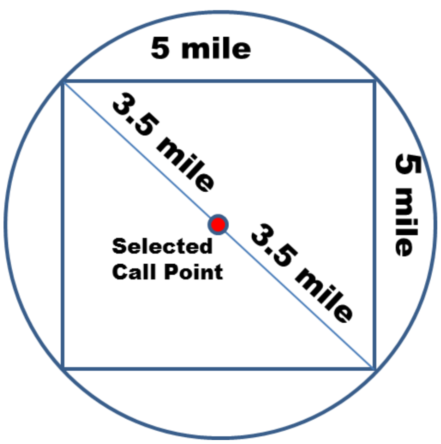


Figure 4.2 Identifying the Cell Size for Getis Ord G* Analysis

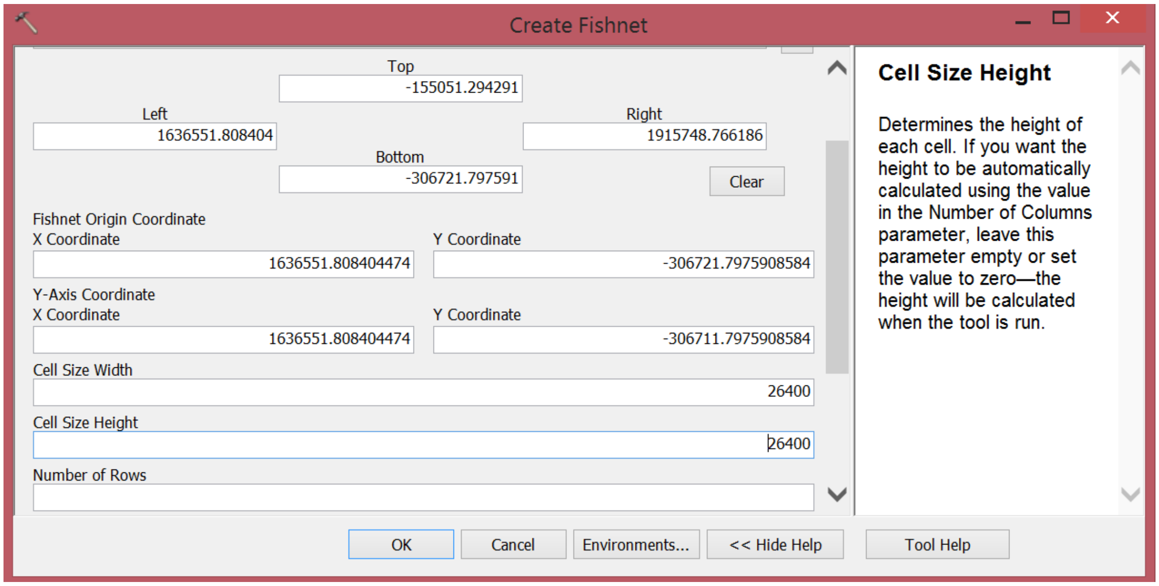


Figure 4.3 Screenshot of "Create Fishnet" Tool in ArcGIS

The number of 911 calls was counted in each cell, and the cell attribute is the number of calls. The Getis Ord G* analysis was performed on the calls per cell. Figure 4.4 shows the identified clusters where the light color (yellow) areas are clustered calls at the 90% confidence interval (G*=1.65). From the map, most EMS stations were visually observed to be located in the center of the cluster, which indicates the current EMS stations are positioned properly within the distance proximity of 911 calls.

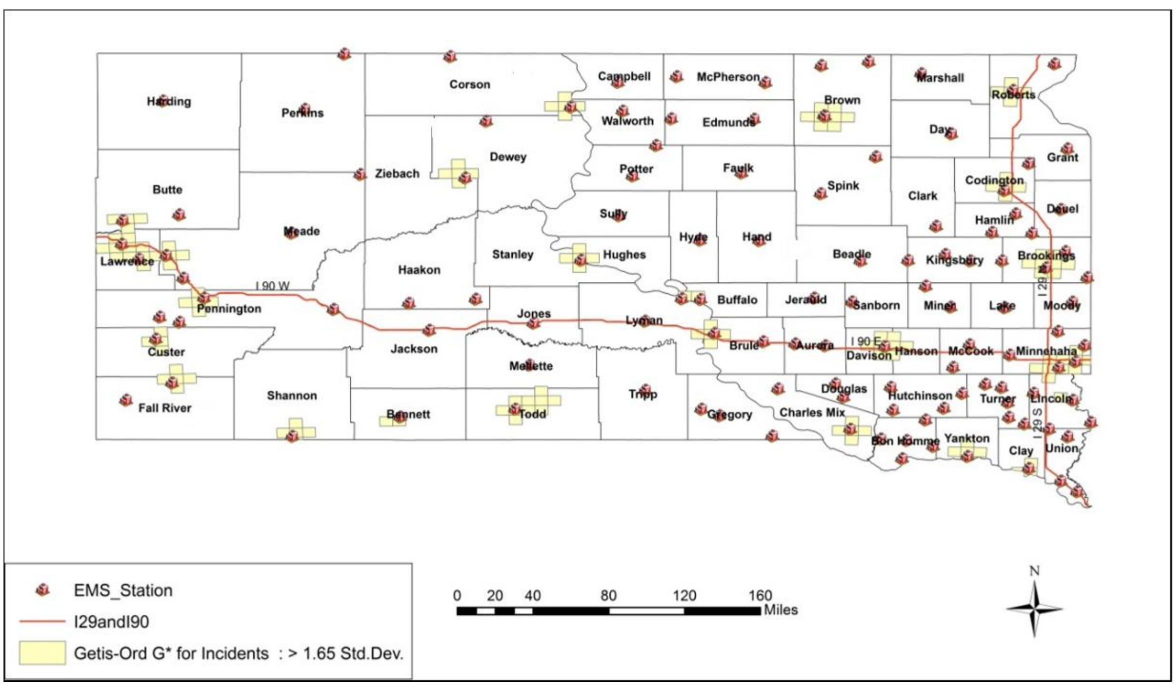


Figure 4.4 Clustering Analysis Using Getis-Ord G*

4.1.2 Co-location Analysis of EMS Stations and 911 Call Locations

The approval of the visual assessment can be further supported by the cross-K function. Figure 4.5 shows the results of the cross-K function, in which the observed curve is located above the 5% upper bound of the theoretical curve when the distance r is shorter than 25 miles. The finding concludes there is a strong colocation pattern between incidents located within 25 miles of an EMS station. When the distance is larger than 25 miles, however, the spatial association between the EMS station and 911 calls is weak. Since Figure shows that most concentrations of 911 calls are within 25 miles of an EMS station, the current EMS stations seem to be positioned according to where the majority of 911 calls occur.

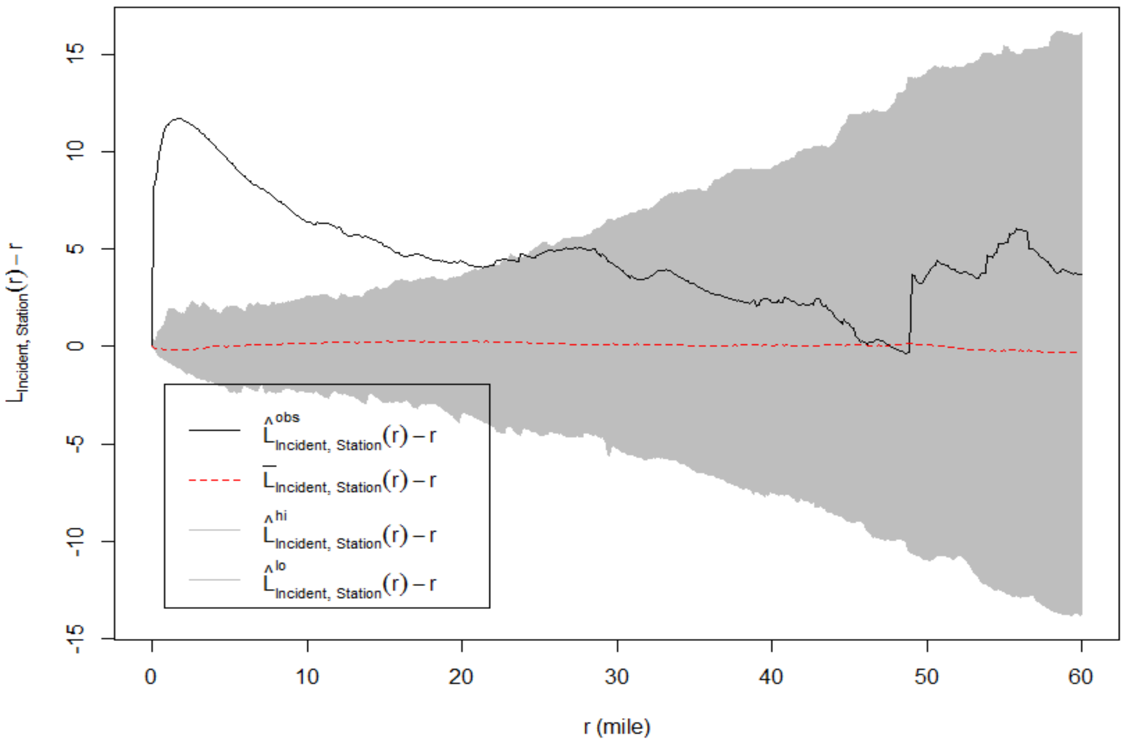


Figure 4.5 Cross K Function and L Function for Incident Location and EMS Station

4.1.3 EMS Station Spatial Coverage

The quantitative assessment provides the measure of service coverage area for each EMS station, or the square miles that can be served by EMS within an acceptable time interval. According to literature review, this study used en route time with an 8-minute benchmark [29]. Coverage area was generated using the road network and network analyst toolbox in ArcGIS. Figure 4.6 shows that only a small portion of the state was covered by EMS within the 8-minute travel time. Several counties like Shannon County, for example, have a sparsely distributed population and thus have more points uncovered than covered by EMS. This observation prompted the realization that optimization of EMS locations should be based on en route time. More details on optimization of EMS locations are included in Section 4.2.

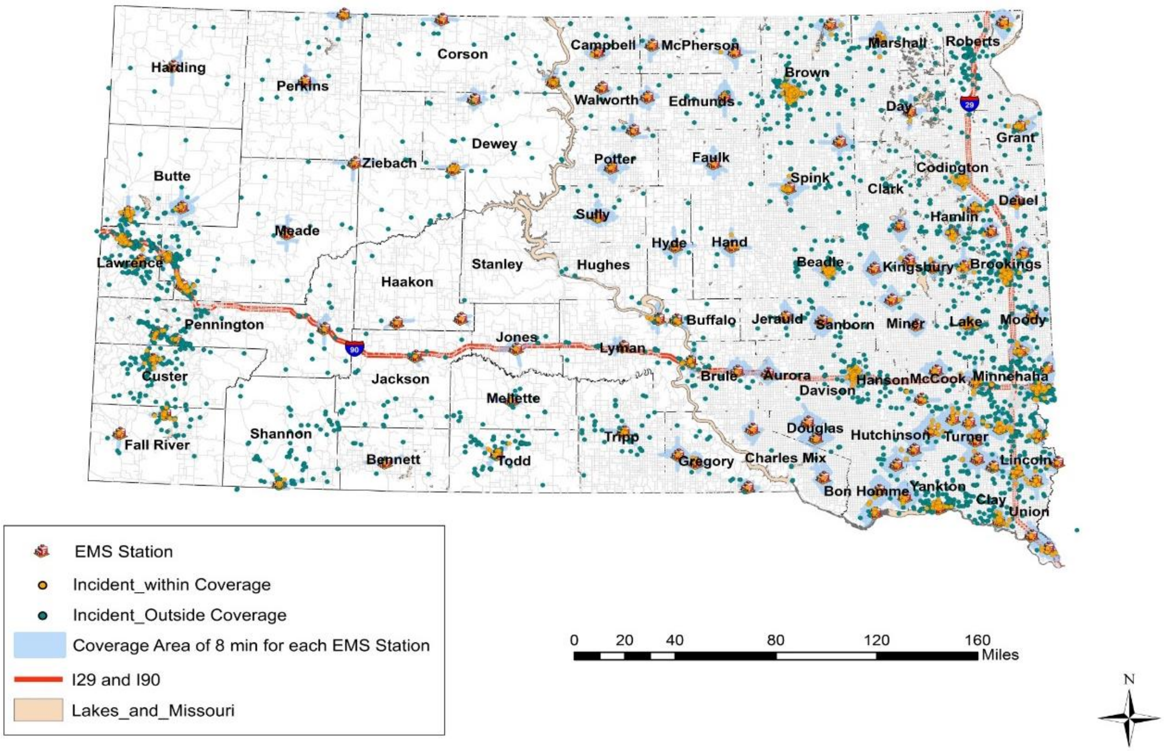


Figure 4.6 EMS Coverage Map in 2013

Coverage ratio, or the number of 911 calls that took place within the 8-minute coverage area for all EMS stations over the total call volume, was calculated as 60% based on the 2013 EMS data. The relatively low coverage ratio is most likely due to sparsely distributed demand, which is not uncommon in rural areas.

4.1.4 Performance Indexes for EMS Stations

Performance index I represents the service coverage ratio, and performance index II represents service swiftness for each EMS station. Equations 12 and 13 and Figure 4.7, Illustration of Two Performance Indexes, show both indexes.

$$Performance\ Index\ I\ =\ B / A \tag{12}$$

This index indicates the number of call cases within the 8-minute coverage over the number of total calls responded to by an EMS station.

$$Performance\ Index\ II = C / B \tag{13}$$

This index indicates the percentage of the cases with the actual ER time no more than 8 minutes within the 8-minute coverage for each station.

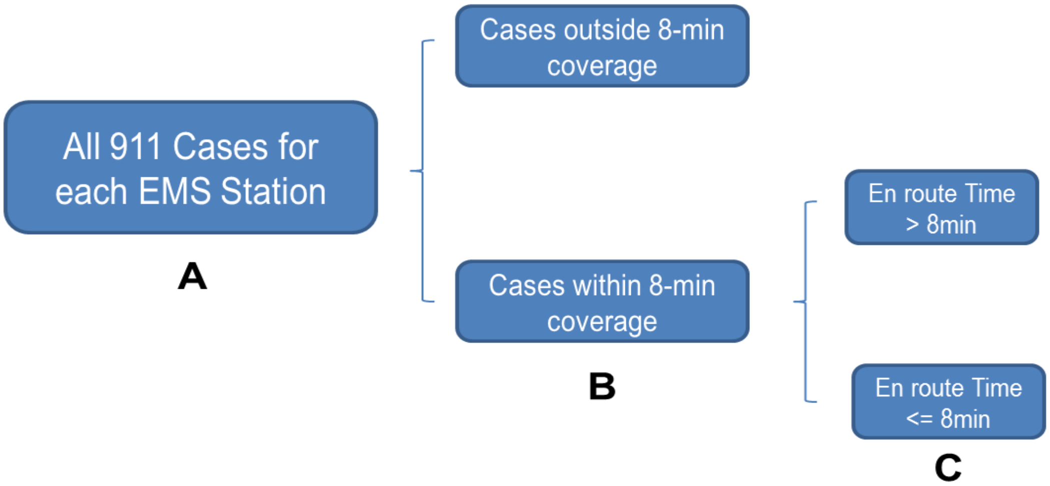
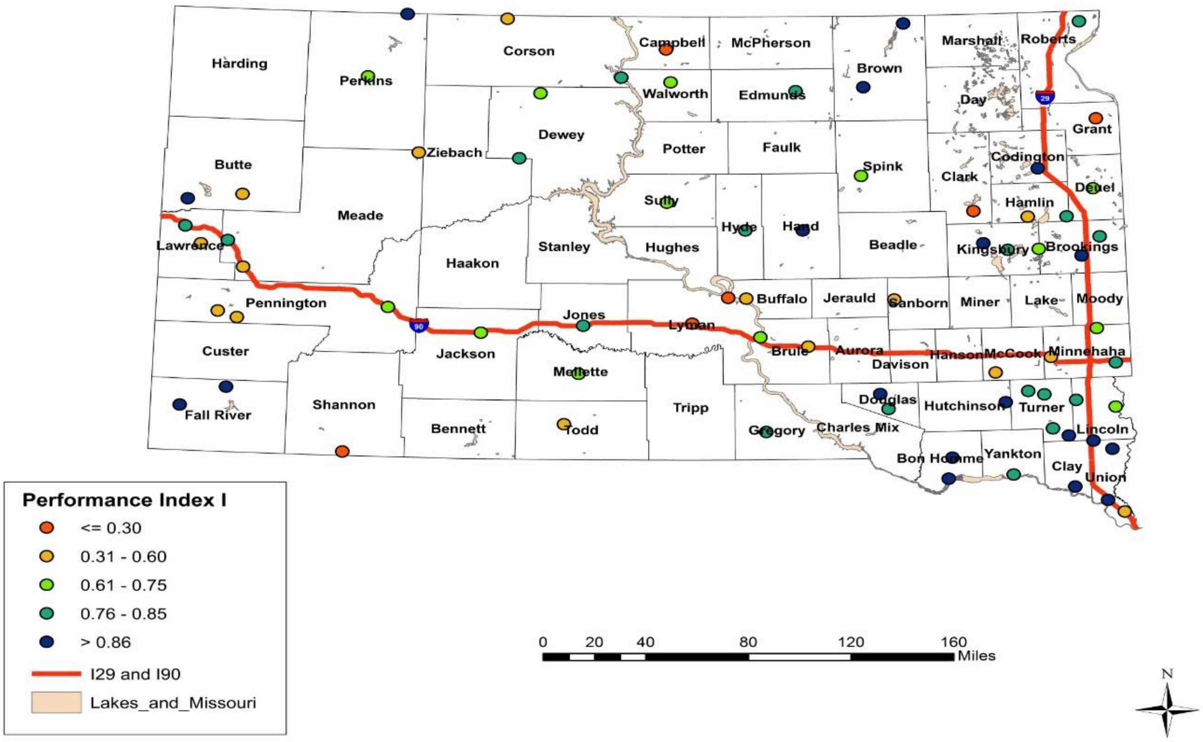


Figure 4.7 Illustration of Two Performance Indexes

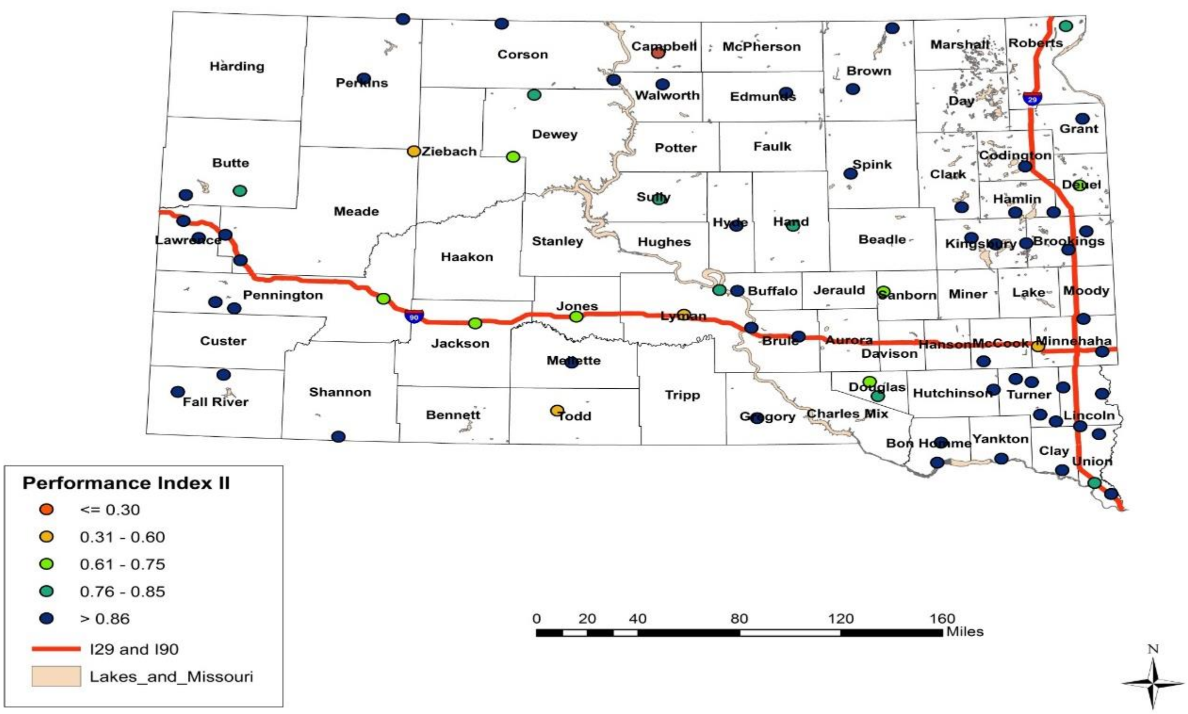
Figure 4.8 offers an in-depth look at the EMS station performance based on the performance indexes. Among 13,041 cases with complete information, only EMS stations with more than 10 cases in the cleaned dataset were analyzed and included in the map. Figure 4.8(a) shows that about half the stations have a Performance Index I of 0.75 or higher. The index values were randomly distributed across the state without obvious patterns. Figure 4.8(b) shows that almost three-quarters of the stations have a Performance Index II of 0.85 or higher, which means most of the stations responded within 8 minutes of their presumed 8-minute coverage areas. Stations with a high performance index concentrated around the two interstate highways (I-29 and I-90), as these areas have a higher population density.

One caveat for this network-based analysis is that the 8-minute travel time coverage area is calculated by the estimated travel speed. The travel speed for some highway segments was unknown, and was thus set to be the average en route speed of 35 mph.

Because travel distance is the main factor affecting the en route time, optimizing EMS station locations to improve service coverage (Performance Index I) is the best way to improve service performance. It is likely that other factors aside from distance contribute to the variation of en route time. A regression analysis can identify the statistically significant factors related to en route time (e.g., weather, roadway conditions, urgency of the incident), and therefore help find a solution to improving Performance Index II. The following two sections discuss the optimization and regression analyses.



(a) Performance Index I



(b) Performance Index II

Figure 4.8 Performance Index for each EMS station

4.2 Optimization of EMS Locations

Maximizing ambulance coverage area and minimizing en route time are two basic methods of optimizing EMS station locations. The former is treated as the maximal covering location problem (MCLP), in which ambulances are located at existing stations on the network to maximize the demand that can be served in a specified time or distance [40]. The latter, the location set covering problem (LSCP), aims to minimize the number of facilities when all demand points are covered [40]. The LSCP includes p-center and p-median problems, where the *p*-median problem minimizes demand-weighted travel distance and the *p*-center problem minimizes the maximum distance between demand zones and their nearest ambulance station [40].

In this study, the coverage area with the size of 8-minute travel distance was used. Coverage rate, or the ratio of 911 calls covered to the total 911 calls, was used to evaluate the EMS facility location both for the entire state and for each station. To be consistent with these criteria, the MCLP model was used. Several papers consider the ambulance location problem as a multiple-objective function. Daskin et al. condensed various covering models with objectives such as multiple, excess, backup, and expected into one multi-objective model, allowing them to balance between the number of facilities and the extra coverage [41]. Although MCLP can maximize the service coverage, other aspects should be considered when working with rural areas. Rural communities have less access to EMS stations due to dispersed population and farther distance from EMS stations. Patient survivability rates are directly related to response time [42], so it is necessary to minimize the average distance from an uncovered zone to the closest station. This is actually a transformation of p-median problems considering only uncovered demand zones. Considering this objective as the service equity problem, the bi-objective problem was formulated. The MCLP model was selected to achieve the first objective of maximizing the coverage rate. The bi-objective model considering service equity will be proposed in the methodology section. Metaheuristic was considered as the most effective solution to the proposed optimization problem. Several metaheuristic solutions, including the genetic algorithm, simulated annealing, ant colony optimization, and tabu search are suitable for the location optimization problem; but the genetic algorithm has been proven the most popular and effective solution [43]. Thus, the genetic algorithm was selected to solve the proposed model.

4.2.1 Optimization Targets

The purpose of optimizing EMS station locations is to increase the 8-minute coverage areas in rural areas. It is also necessary to consider service equity for demand areas that are under-covered or uncovered. Hence, the two objectives are as follows:

1) Objective 1 (Coverage Ratio): maximize the number of calls covered by Z1
2) Objective 2 (Service Equity): minimize average en route time for uncovered demand Z2

Two targets were identified for the optimization process: target one includes only the first objective, and target two combines both objectives in an attempt to maximize the coverage rate as well as minimize the average en route time for uncovered demand points.

4.2.2 Methodologies

The findings from the rural EMS needs assessment informed the decision to not apply the high demand and busy situation effects to EMS stations in South Dakota; the original covering location model, regardless of the busyness effect, was considered. Two models were developed to optimize the EMS station location in accordance with the first and second targets, respectively:

1. A single-objective covering location model, which considers only the coverage ratio (maximize the expected number of calls that were responded to in a pre-specified time/distance frame over the total number of calls)
2. A bi-objective covering location model, which considers not only the coverage rate but also the equity (minimize the average en route time between uncovered calls and their closest available stations)

The optimization formulation is explained below. Let Z1 and Z2 represent the two objectives. Let the first constraint be the definition of y_i, which is a binary outcome (i.e., y_i equals one if node *i* is covered by one or more available facilities, and zero otherwise) and the second constraint to be the total number of available facilities.

Target 1: Objective 1 Max $\mathbf{Z1} = \dfrac{\sum_{i\in I} D_i y_i}{\sum_{i\in I} D_i}$ (14)

Target 2: Objective 1 and 2 Max $\mathbf{Z1} = \dfrac{\sum_{i\in I} D_i y_i}{\sum_{i\in I} D_i}$ (15)

and Min $\mathbf{Z2} = \dfrac{\sum_{i\in I} D_i (1-y_i)\min(t_{ij})}{\sum_{i\in I} D_i (1-y_i)}$ (16)

Subject to:

$$y_i \le \sum_{j\in N_i} x_j \quad i \in I \tag{17}$$

$$\sum_{j\in J} x_j = p \tag{18}$$

$$x_j \in \{0,1\} \quad j \in J$$

$$y_i \in \{0,1\} \quad i \in I$$

Where:

i , I The index and set of demand points,

j , J The index and set of candidate facility locations,

D_i 911 demand at point *i*,

t_{ij} The shortest en route time from demand point *i* to facility at point *j*,

T The time standard within which coverage is expected (T =8),

N_i $\{j \mid t_{ij} \le T\}$ the point *j* that are within a time of *T* to point *i*,

p The number of facilities to be built,

x_j A binary variable that equals one when a facility is built at point *j* and zero otherwise, and

y_i A binary variable that equals one if node *i* is covered by one or more facilities and zero otherwise.

The genetic algorithm in the R software was used to solve both models. To solve the first model, solutions were obtained after converting equations to the r codes. The responding fitness function was the same as the first objective, which is: $F_1 = \mathbf{Z1} = \frac{\sum_{i \in I} D_i y_i}{\sum_{i \in I} D_i}$ (19)

The second model, a multiple-objective optimization problem, adopted the multi-criteria evaluation techniques [44]. One of the techniques, the weighted sum method, converts multiple objectives (fitness functions) into a single objective (fitness function) by adding all weights for each objective (functions). Experts should determine whether weights represent the priority of each objective. If there is no special preference, equal weight is chosen for the fitness function. In this study, equal weight was chosen for both objectives, namely $w_1 = w_2 = 0.5$. As the genetic algorithm tries to maximize the fitness function, the corresponding fitness function of the second (minimization) objective should be the inverse, which is:

$$F_2 = \frac{1}{\mathbf{Z2}} = \frac{\sum_{i \in I} D_i (1 - y_i)}{\sum_{i \in I} D_i (1 - y_i) \min(t_{ij})} \tag{20}$$

When combining the two fitness functions into one, each function should be normalized due to the differing measurement scales. The combined fitness function is:

$$F_3 = w_1 \times \frac{F_1 - F_{1\min}}{F_{1\max} - F_{1\min}} + w_2 \times \frac{F_2 - F_{2\min}}{F_{2\max} - F_{2\min}} \tag{21}$$

In order to maximize the combined fitness function, four values are needed: $F_{1\max}$, $F_{1\min}$, $F_{2\max}$ and $F_{2\min}$. The four values can be obtained by using the genetic algorithm to identify solutions that maximize fitness functions F_1, $\frac{1}{F_1}$, F_2 and $\frac{1}{F_2}$ separately.

4.2.3 Case Study

The case study area can be a city, a county, or an entire state. One city may be suitable for studies on populous urban areas, but not for a rural state. EMS demand for one city in South Dakota is too low to be optimized, but the entire state is too large because large disparities such as service protocol, resources, and budget exist for different parts of the state; therefore, a county-level analysis was performed. Todd County and Minnehaha County were chosen for this study because one represents a low-populated area and the other represent a relatively high-populated area. Among the areas with low-population density, Todd County had one of the highest EMS demands and a longer-than-average en route time, yet only one EMS station location. Among the areas with high population density, Minnehaha County has multiple EMS stations and a shorter-than-average en route time.

According to the “National EMS Assessment,” about 40% of EMS agencies are fire departments [45]. An EMS can be stationed at a hospital, a police department, an independent government agency, or a nonprofit or for-profit corporation. Candidate EMS stations can be any of three types: 1) existing EMS station(s); 2) a fire station, hospital, or police station; 3) a randomly selected location. The randomly selected locations were based mainly on the demand zone and road network to cover more ground. It is better to select locations after discussing them with county EMS officials. Because optimization is a time-consuming process, the total number of candidate EMS stations was set to be five and 10 for Todd County and Minnehaha County, respectively.

Data used for optimizing candidate EMS station locations in the candidate counties were prepared using ArcGIS. The “Create Fishnet” tool was first used to create grid cells as demand zone. A one-by-one-mile cell was chosen to accurately reflect the location of each 911 call. After the grids were generated, 911 calls were aggregated by each grid cell and the number of calls in each cell was set as the cell attribute. The central coordinates for each demand zone were then identified, and the cost matrices (specifically, the time matrix) from the candidate stations to the central points were calculated using the network analyst toolbox in ArcGIS. The optimization process uses the time matrix and call volume in each demand zone to obtain the solution for the selected number of facilities.

In this analysis, all 911 calls within the selected counties were included in the analysis, regardless of whether or not they were actually responded to by the associated EMS stations.

Case Study 1: Todd County

Figure 4.9 shows candidate stations and demand zones in Todd County. The existing station was referred to as Station 1, and it was based on the fire station. The candidate station locations were selected as: 1) the existing station (Station 1); 2) a hospital location (Station 2); and 3) a randomly selected location (Station 3, Station 4, Station 5). For the purpose of illustration, the randomly selected locations were based on intersections close to the obvious incident clusters.

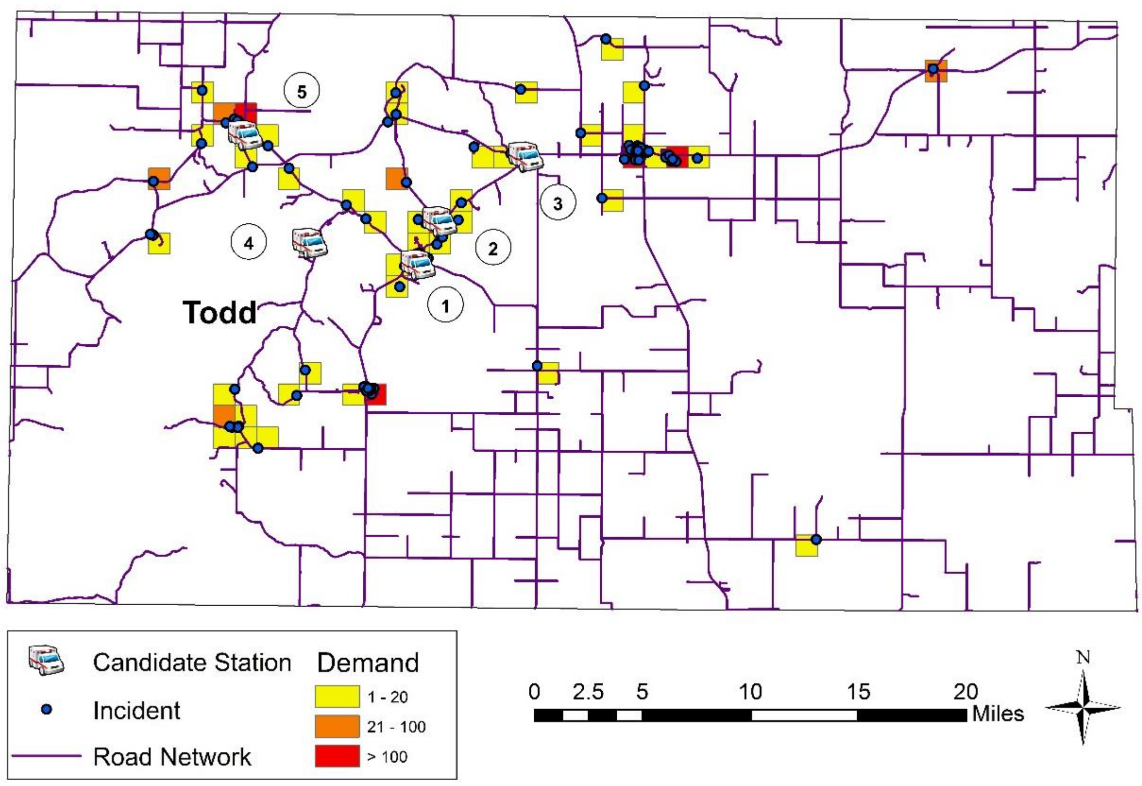


Figure 4.9 Todd County with Candidate Stations and Demand Zones

Due to street network discontinuities in the GIS shapefile, some values in the time matrix cannot be generated using the ArcGIS tool, as shown in Figure 4.10. The messy lines indicate the expected time from candidate stations to the central point of each demand zone. Among 4,374 calls recorded in Todd County in 2013, 149 were lost after generating the time matrix. More than 99% of the calls remained, supporting the validity of the results for this case study.

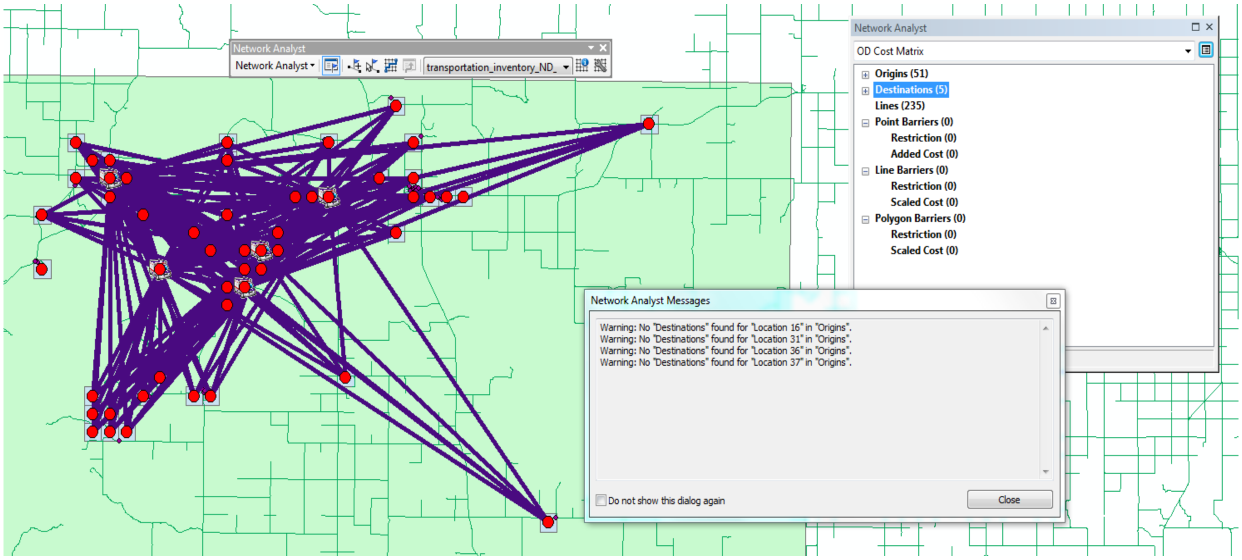


Figure 4.10 Screenshot of Generating Time Matrix in ArcGIS (Todd County)

a) Optimal Solutions

The genetic algorithm in the R software was used to generate the optimal solutions for the single objective and multiple objectives individually. Due to the limited source and moderate demand in Todd County, the number of facilities to be located was set as 1, 2, and 3 (p=1, 2, 3), respectively.
Figure 4.11 shows the basic configuration for the genetic algorithm in the R software, which was set based on common practice.

Population size = 20
Number of generations = 2000
Elitism = 1
Crossover probability = 0.8
Mutation probability = 0.05

Figure 4.11 Basic Configuration for Genetic Algorithm in R

Before performing the multi-objective optimization, F_{1max}, F_{1min}, F_{2max} and F_{2min} were calculated using the single objective optimization. The results were shown below.

$F_{1\max} =$ 0.7103 when j=5;

$F_{1\min} =$ 0.0568 when j=1;

$F_{2\max} =$ 0.0453 when j=3;

$F_{2\min} =$ 0.0116 when j=1.

The combined fitness function was

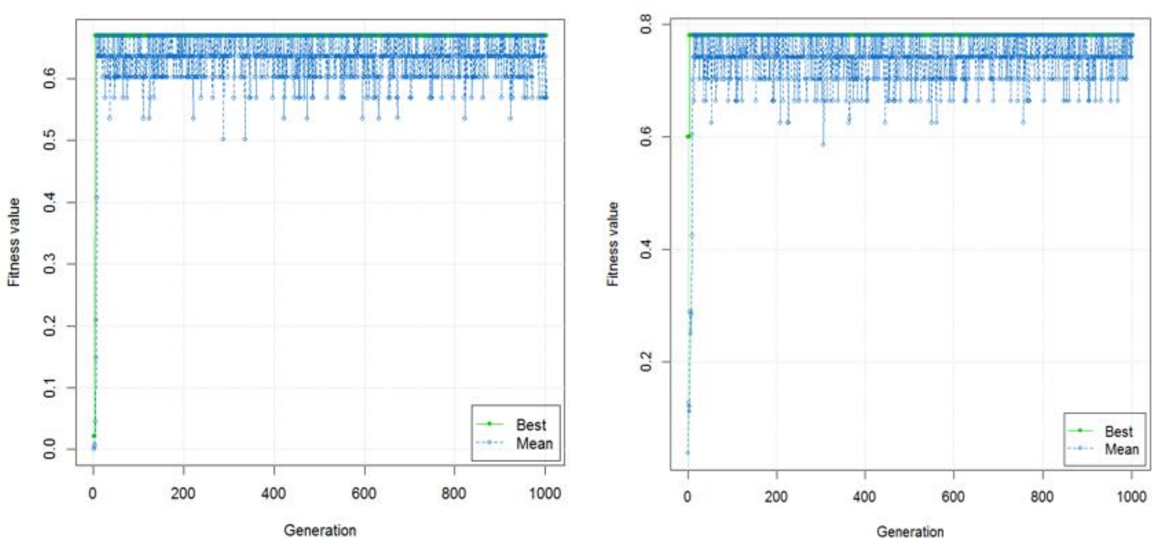
$$F_3 = 0.5 \times \frac{F_1 - 0.0568}{0.7103 - 0.0568} + 0.5 \times \frac{F_2 - 0.0116}{0.0453 - 0.0116} = 0.7651 \times F_1 + 14.8368 \times F_2 - 0.0449$$

The optimization process for multiple objectives was conducted using the combined fitness function. The optimal locations by the number of facilities were shown in Table 4.1. When there is only one EMS station, the optimal solutions for both single and multiple objectives are the same as those for the existing station (Station 1); this indicates that the current station is located in the best possible location. When two EMS stations are allowed, Station 5 remains in both target areas because only Station 5 can cover zones with high demand in the northwestern area. Station 3 increases the coverage ratio because it can cover the high-demand areas in the northeastern direction; thus, it was chosen for the coverage objective. Station 1 was selected for multiple objectives because it can shorten the en route time to zones in the southwestern area and therefore shorten the average en route time for uncovered zones; however, it also decreases the coverage ratio. When three EMS stations can be built, Station 1 and Station 5 appear in both target categories, and the explanation for Station 3 and Station 2 are the same as two station scenarios.

Table 4.1 Optimal Solutions for Todd County

Optimized Location		**Number of Facilities**		
		1	2	3
Target	**Single Objective**	1	3,5	1,3,5
	Multiple Objectives	1	1,5	1,2,5

Fitness function by generation (p=1) for single objective and multiple objectives is shown in Figure 4.12. The best value of the fitness function (the green curve) reaches its peak and remains stable after several generations. When the best value of the fitness function does not remain stable within the chosen 2,000 generations, the number of generations should be increased until a constant value is observed. During this analysis, the best fitness function values remained steady within 2,000 generations, which suggests that the basic settings were appropriate. Figure shows that the best fitness value is just below 0.7 for single objective and just below 0.8 for multiple objectives.



(a) Single Objective **(b) Multiple Objective**

Figure 4.12 Figure Fitness Function by Generation (p=1)

b) Single Objective vs. Multiple Objectives

Figure 4.13 shows the fitness function trend for different numbers of facilities (p). Both fitness functions increase as p increases, and keep almost constant after p=2 ($F_1 \approx 0.7$ and $F_3 \approx 0.8$); this suggests that p=2 may be a good choice if increases for both coverage ratio and equity are expected.

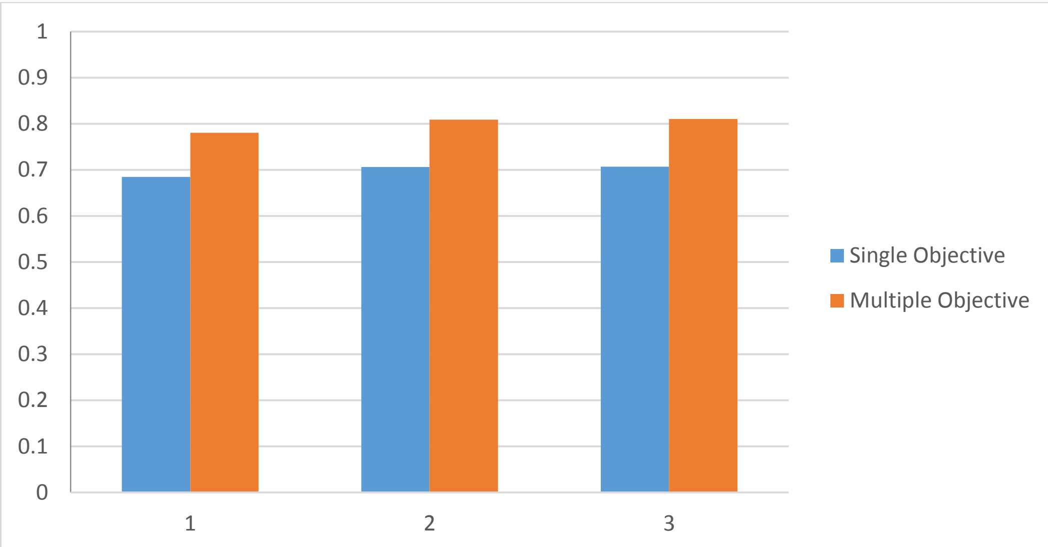


Figure 4.13 Fitness Function Value Under Optimized Station Location

Figure 4.14 shows the effect of the added equity objective on the coverage ratio for different numbers of facilities compared with the single coverage objective. When p=1, there is no effect on the first objective (coverage ratio) for the added equity objective. A negative effect was observed for p =2 and 3 (-1.61 and -1.30, which is -2.28% and -1.84% in percentage), and the effect shows a decline trend.

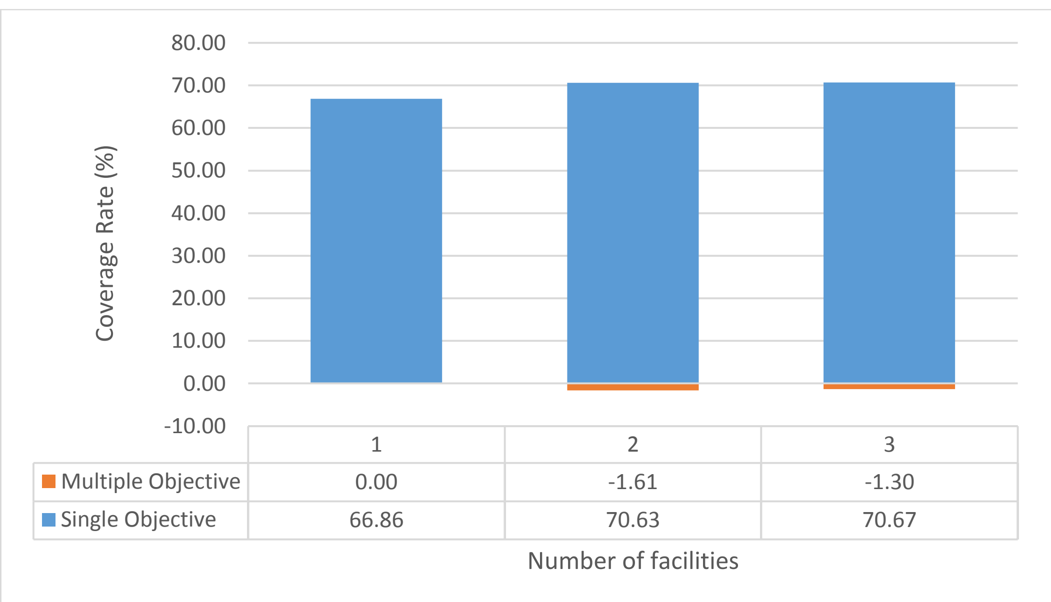


Figure 4.14 Coverage Ratio under Optimized Station Location

By contrast, Figure 4.15 shows the effect of the equity objective on the average en route time (uncovered zones) for the different numbers of facilities compared with the single coverage objective. When p increases from two to three, the negative effect of the equity objective on average en route time decreases (5.02 to 1.90, which is 9.92% to 3.99% in percentage). The reduction is more considerable than that of the coverage ratio (9.92% to 3.99% vs 2.28% to 1.84%), indicating that the slightly reduced equity objective in the coverage ratio exchanges for a sharply decreased en route time for uncovered zones. If both an expected coverage ratio and an expected average en route time (uncovered zones) are provided, the number of facilities can be determined.

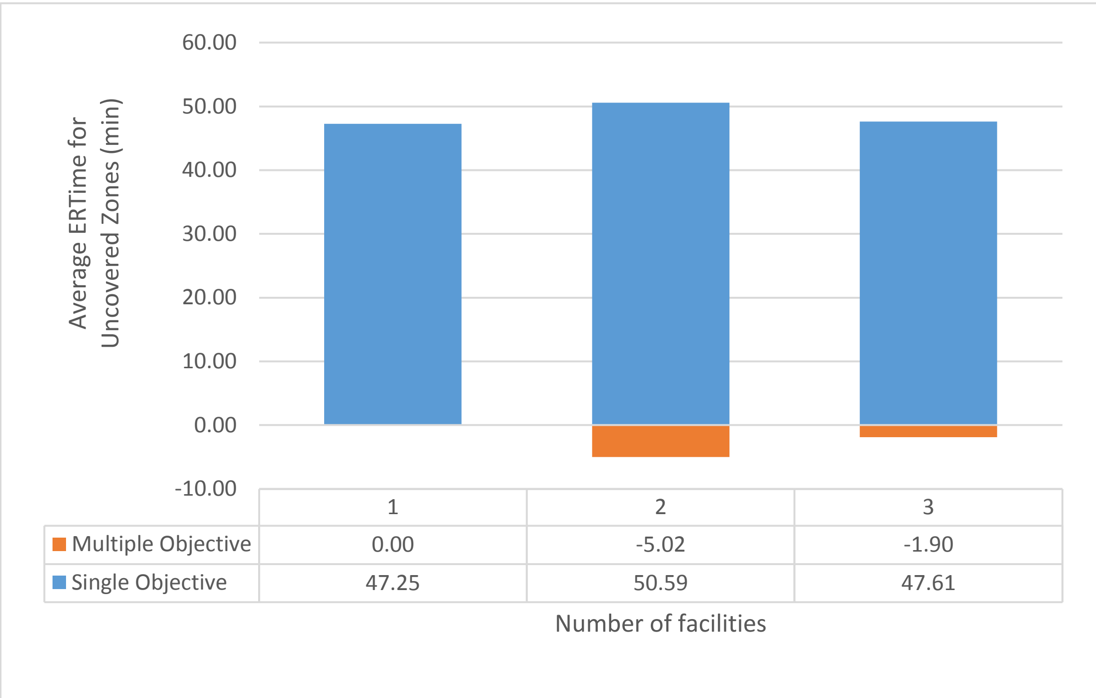


Figure 4.15 Average ERTime for Uncovered Zones Under Optimized Station Location

Case Study 2: Minnehaha County

Candidate stations and demand zones in Minnehaha County are shown in Figure 4.16. The existing stations, all of which were based on fire stations, were labeled from Station 1 to Station 4. The candidate station locations were selected as: 1) the existing stations (Station 1, Station 2, Station 3, and Station 4); 2) hospital locations (Station 5, Station 6, and Station 7), a police station (Station 8); and 3) randomly selected locations (Station 9 and Station 10). The randomly selected locations were chosen the same way as those in Todd County. When generating time matrix, more than 99% of the calls remained, supporting the validity of the results for this case study.

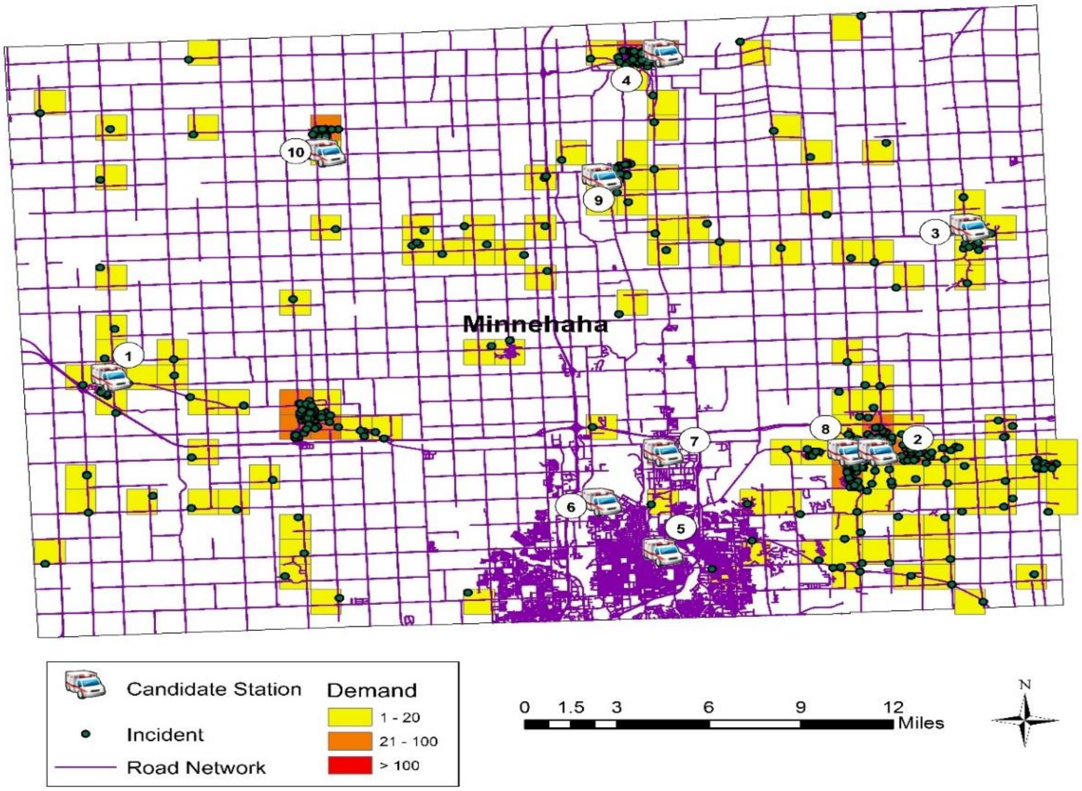


Figure 4.16 Minnehaha County with Candidate Stations and Demand Zones

a) Optimal Solutions

The genetic algorithm in the R software was used to generate the optimal solutions for a single objective and multiple objectives individually. Due to the limited source and moderate demand in Minnehaha County, the number of facilities to be located was set as 4, 5, 6, and 7 (p=4, 5, 6, 7), respectively. The genetic algorithm in the R software was set based on common practice. Before performing the multi-objective optimization, F_{1max}, F_{1min}, F_{2max}, and F_{2min} were calculated using the single objective optimization, and the results were shown below:

$F_{1\max} = 0.8466$, when j=10;

$F_{1\min} = 0.0081$, when j=1;

$F_{2\max} = 0.0927$, when j=10;

$F_{2\min} = 0.0314$, when j=1.

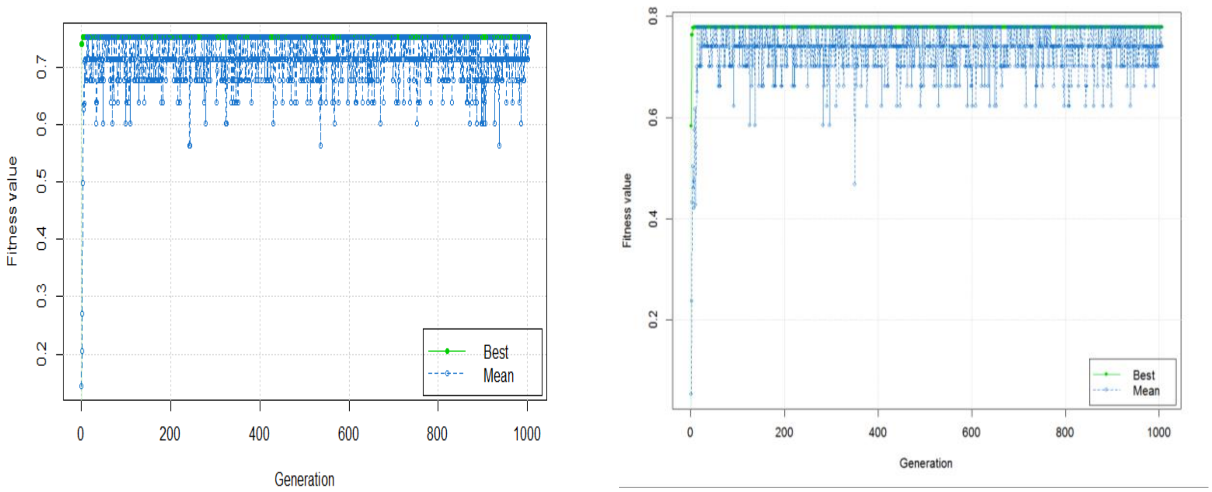
The combined fitness function was

$$F_3 = 0.5 \times \frac{F_1 - 0.0081}{0.8466 - 0.0081} + 0.5 \times \frac{F_2 - 0.0314}{0.0927 - 0.0314} = 0.5963 \times F_1 + 8.1566 \times F_2 - 0.2609$$

Table 4.2 shows the results of the optimization process for multiple objectives, which was conducted using the combined fitness function. The fitness functions by generation (p=4) for a single objective and multiple objectives are shown in Figure 4.17.

Table 4.2 Optimal Solutions for Minnehaha County

Optimized Location		Number of Facilities			
		4	5	6	7
Target	**Single Objective**	4,6,8,10	3,5,6,8,10	2,4,6,8,9,10	1,2,5,6,8,9,10
	Multiple Objectives	5,6,7,8	1,5,6,7,8	1,2,5,6,8,10	1,2,3,5,6,8,10



(a) Single Objective **(b) Multiple Objective**

Figure 4.17 Figure Fitness Function by Generation (p=4)

b) Single Objective vs. Multiple Objectives

Figure 4.18 shows the fitness function trend for the different numbers of facilities (p). Both fitness functions increase as p increases.

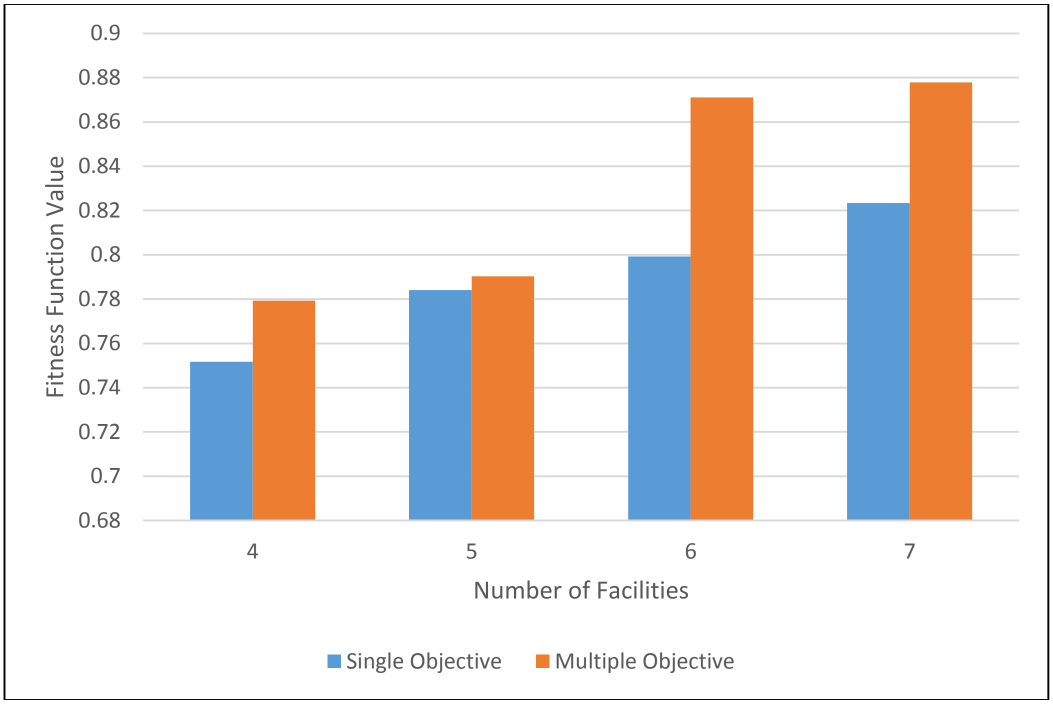


Figure 4.18 Fitness Function Value Under Optimized Station Location

Figure 4.19 shows the effect of the added equity objective on coverage rate for different numbers of facilities compared with the single coverage objective. The added equity objective had a negative effect on the coverage rate; when p=4, the coverage rate was decreased by 10.90. When p increases from 4 to 5, the negative effect decreases significantly (10.90 to 0.88, or 14.50% to 1.12%), but when p increases from 5 to 7, the negative effect increases gradually (0.88 to 1.51 to 3.83, or 1.12% to 1.89% to 4.65%).

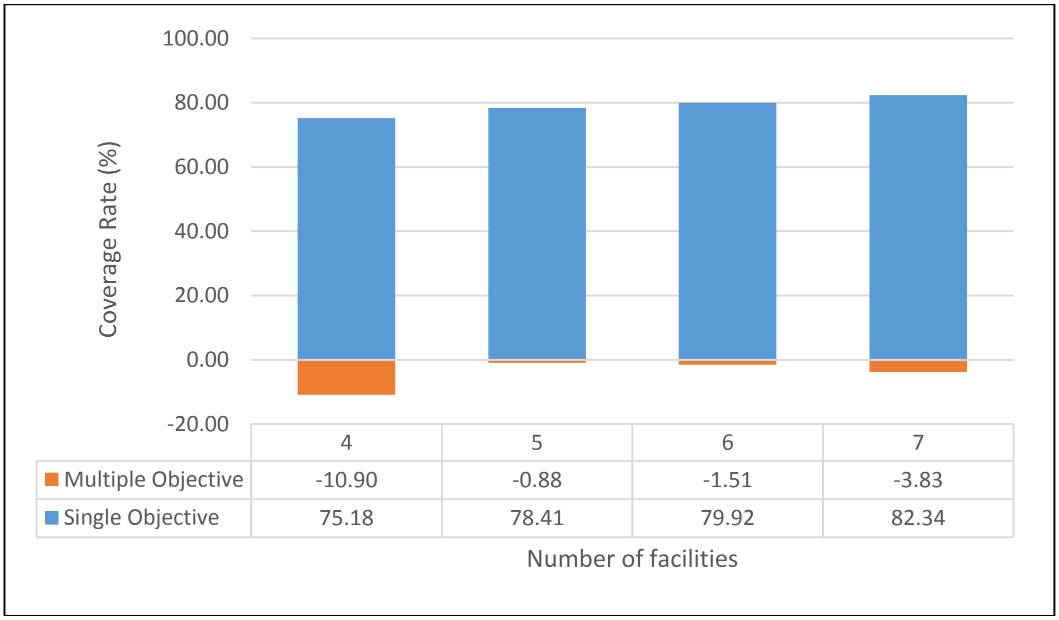


Figure 4.19 Coverage Rate Under Optimized Station Location

By contrast, Figure 4.20 shows the effect of the added equity objective on average en route time (uncovered zones) for different numbers of facilities when compared with the single coverage objective. An obvious negative effect was observed when p= 4 (-0.48, or 3.72%), and the negative effect is close to zero when p varies from 5 to 7. Figure 4.21 and Figure 4.22 show that when p becomes large enough, the added equity objective reduces the coverage rate in exchange for a very slight decrease on average en route time for uncovered zones (more than 1% vs zero).

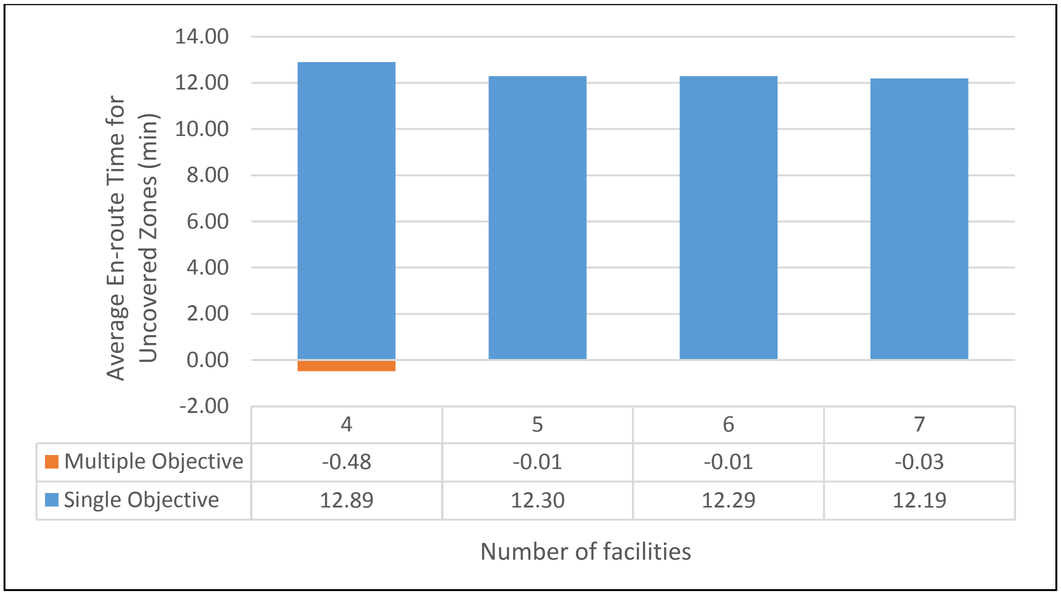


Figure 4.20 Average ERTime for Uncovered Zones Under Optimized Station Location

c) Current Station Location vs. Optimized Location

Table 4.3 shows the coverage ratio and average en route time for uncovered zones between the current station locations and optimized locations based on the current number of locations. Such comparison is unavailable for Todd County because its optimized location is the same as the current location. The table shows significant improvements with regard to both coverage objective and equity objective, which suggests that current station locations are neither qualified nor located in the most effective places. The comparison between the single-objective and multi-objective solutions shows that the added equity objective reduces the coverage rate from 75.18% to 64.28% in exchange for a very slight decrease (i.e., 0.47 minutes) in average en route time for uncovered zones.

Table 4.3 Current Station Location Vs Optimized Location

	Coverage Rate (%)	ERTime for Uncovered Zones (min)	Facilities
Existing	43.39	21.20	1,2,3,4
Single Objective	75.18	12.89	4,6,8,10
Multiple Objectives	64.28	12.42	5,6,7,8

4.2.4 Conclusions

The strategies for optimizing EMS station locations have been explored for two selected counties: Todd County (high demand and few stations) and Minnehaha County (moderate demand and multiple stations). Single objective (coverage ratio) and multiple objectives (coverage ratio and service equity) were evaluated for different numbers of facilities. The optimal solutions were obtained using the genetic algorithm in the R software. A comparison of optimal and existing locations was conducted.
In general, the added equity objective has a negative effect on the coverage ratio, but it reduces the average en route time for uncovered demand zones. The effect on coverage ratio and on equity decreases with the number of facilities. Further analysis of the optimal EMS locations for Minnehaha County reveals that stations are located closer to demand cluster centers when targeting a single objective, and they are located between clusters and zones far away from them when targeting multiple objectives.
The added equity objective had a very limited impact on the coverage ratio, but it significantly reduced en route time for the uncovered areas in Todd County. The situation was reversed for Minnehaha County, where the added equity objective decreased the coverage rate significantly in exchange for a slightly reduced en route time for the uncovered demand zones. The variation may be due to the counties' different proportions of demand and supply; Todd County has high demand but few facilities, while Minnehaha County has more facilities but a moderate demand.

4.3 Regression Analysis

Although most stations had a high Performance Index II (percentage of the cases with the actual ER Time no more than 8 minutes within the 8-minute coverage for each station), some had a value of less than 0.6, meaning more than 40% of the cases within the 8-minute coverage area had an en route time of more than 8 minutes. A regression analysis identified the statistically significant explanatory variables for en route time using the 911 calls within the coverage area to explore the underlying causes of longer en route time.

4.3.1 Scope of Regression Analysis

The analysis focused only on cases within the 8-minute coverage area for each station. The relevant information included the accurate location coordinates of 911 calls and en route time. Location coordinate information was retrieved from "Google Maps API." Geocoding accuracy (shown in Table 4.4) is provided for each point generated by this application. Data used for the regression analysis included only the points with an accuracy level of "ROOFTOP," the highest accuracy level mapped by Google Map API.

Table 4.4 Geocoding Accuracy Level for Google Map API

Accuracy	Definition	Count for 2013
APPROXIMATE	Location information that are characterized as approximate	52.03%
GEOMETRIC_CENTER	Geometric centers of a location such as a polyline or polygon	10.14%
RANGE_INTERPOLATED	An approximation interpolated between two precise points	24.81%
ROOFTOP	Location information accurate down to street address precision	13.02%

Although only 13% of the total 911 calls have the accurate location information, the total number is still sufficient for any statistical analysis. After verifying the 911 calls and their receiving agencies, 1,586 cases with their 18 corresponding EMS stations were processed for the regression analysis. The distribution of these 911 calls and EMS stations is mapped in Figure 4.21.

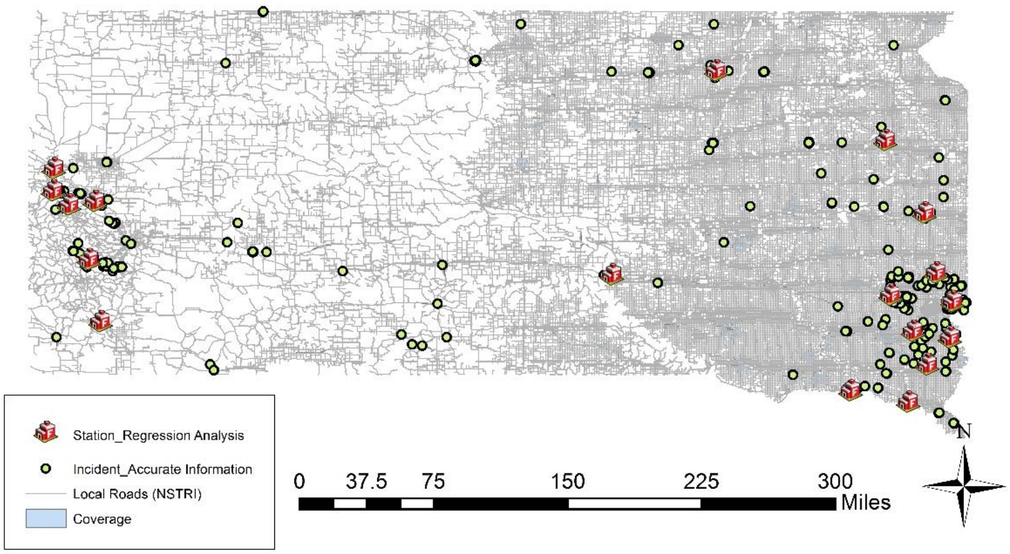


Figure 4.21 911 Cases with Corresponding EMS Stations For Regression Analysis

4.3.2 Variable Preparation

The en route time can be affected by a number of factors, including the call's level of urgency, the EMS station features, weather, highway and traffic conditions, etc. An independent variable can be categorized as either a case-specific variable or a station-specific variable. Each 911 call record has more than 50 attributes, some of which are useful for evaluating the service performance while others are not. Hence, data reduction is necessary to help screen the most relevant attributes before fitting the data with a regression model.

After a careful review of all EMS attributes, the caller's complaint, light and siren usage, dispatch time, and location type were considered as the case-specific input variables. The caller's complaint may be a significant factor affecting en route time. The shortest en route time was associated with patients who suffered past strokes, had breathing problems, or were suffering from cardiac arrest. A new variable called "case type" was created to represent the severity of a 911 case. The light and siren attribute refers to whether the ambulance driver turned on the light and siren when responding to an individual case. The service needs assessment shows that the use of light and siren is highly associated with travel speed, and can also be considered a surrogate measure for urgency. Dispatch time includes the time of day and day of week for each dispatch. Month of year for each dispatch was reclassified as either a winter month (November to April) or non-winter month, a surrogate variable for the weather data. The location type notes whether the incident is in a public area.

An EMS station can be staffed with professional emergency medical technicians or volunteers, and all stations are equipped with a different number of personnel, vehicles, and medical equipment. The location of an EMS station and the streets and highways in its proximity affect the response time; hence, accessibility, mobility, staff, vehicles, and workload are treated as station-specific input variables. Road density and connectivity are accessibility indicators, and average speed is a mobility indicator. The connectivity index can be calculated by dividing the number of links by the number of nodes [46]. Both roadway accessibility and mobility indexes were calculated with ArcGIS using the 8-minute travel distance buffer for the corresponding EMS station. Station workload, which shows whether or not an EMS station is busy, can affect EMS performance to some extent. Two types of workload variables were introduced: annual call volume and unit hour utilization (UHU) [47]. Annual call volume is the same with the service demand. UHU indicates the amount of time one ambulance unit is occupied over the total amount of time (365* 24 hours=8,760 hours a year). As a common practice, a UHU between 35% and 45% is most efficient. EMS stations with a UHU below 35% are considered not busy [47]. The equation is shown below:

$$UHU = \frac{D \times TotalTime}{n \times 8760} \tag{22}$$

Where,
D is the yearly demand for each station,
TotalTime is the average total time in the hour for each station and,
n is the number of ambulances for each station.

Other socioeconomic variables such as population and area type were not considered because they are highly correlated with the service demand variables. Each variable is described in Table 4.5. The accessibility and mobility indicator for each station are formulated from Equation 23 to 25:

Road Density = *Sum* (*length*) / *Covered Area* (23)

Road Connectivity = (# *of links*) / (# *of nodes*) (24)

Road Speed = *Sum* (*Speed* * *Length*) / *Sum* (*length*) (25)

Roadway length and number of links and nodes can be measured from the South Dakota highway links and nodes map in ArcGIS by clipping an 8-minute polygon for each EMS station.

Table 4.5 Variable Description

		Category	Variable	Description
Dependent Variable		Time	ERTime	En-route time
Independent Variable	**Case-Specific**	Case Type	Case Type	Severity (1) or not (0)
		Light &Siren	Response Mode	Light/Siren on (1) or not (0)
		Dispatch Time	Time of Day	If the vehicle was dispatched in the day (1) or night (0)
			Day of Week	If the vehicle was dispatched in the weekday (1) or weekend (0)
			Month of Year	If the vehicle was dispatched in the snow season (1: Nov. - Apr.) or Non-snow season (0: May - Oct.)
		Location Type	Location	If the incident is in the public area (1) or not (0)
	Station-Specific	Accessibility	Road Density	Sum(Road Length)/Covered Area
			Road Connectivity	# of Links/ # of Intersections
		Mobility	Road Speed	Sum(Link Length * Link Speed)/Sum(Link Length)
		Staff	Professional	If the staff in the EMS station are professional (1)
		Vehicle	Vehicle	# of Vehicles in the EMS Station
		Workload	EMS Demand	911 Call Volume
			UHU	Unit Hour Unitization

Figure 4.22 shows an example of a clipped area for an EMS station. The list of EMS stations and variables is presented in Table 4.6.

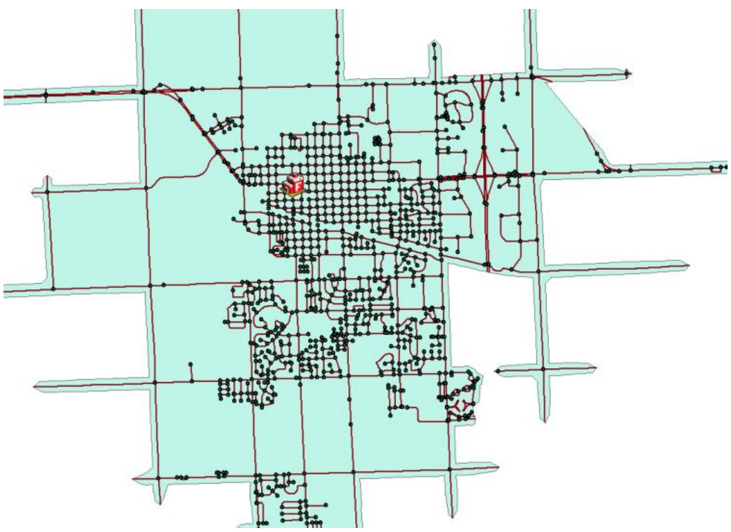


Figure 4.22 Calculation of Accessibility and Mobility

Table 4.6 Calculation of Accessibility and Mobility

Station	Sum(length)	Sum(Speed*Length)	# of links	# of nodes	Covered Area	Road Density	Road Connectivity	Average Speed
1	153.91	4454.76	2018	1371	37.08	4.15	1.47	28.94
6	38.20	1322.42	454	290	33.82	1.13	1.57	34.61
10	94.39	3051.27	1467	1079	25.87	3.65	1.36	32.33
12	18.81	537.40	624	504	8.33	2.26	1.24	28.57
15	27.55	955.54	444	304	17.05	1.62	1.46	34.68
21	52.69	1783.70	735	565	15.29	3.45	1.30	33.85
25	41.84	1453.66	474	316	26.35	1.59	1.50	34.75
45	6.04	216.08	106	98	1.73	3.50	1.08	35.75
46	22.78	762.54	559	442	5.28	4.31	1.26	33.47
49	26.17	917.78	393	249	19.25	1.36	1.58	35.08
62	5.62	169.46	254	227	2.74	2.05	1.12	30.18
63	19.55	676.69	490	340	34.59	0.57	1.44	34.61
72	49.96	1714.25	759	564	24.35	2.05	1.35	34.31
77	18.63	626.89	494	391	4.08	4.56	1.26	33.65
94	65.18	2169.29	832	645	8.30	7.85	1.29	33.28
97	52.33	1687.70	754	584	6.83	7.66	1.29	32.25
105	102.50	3254.64	1790	1256	20.38	5.03	1.43	31.75
109	212.66	7319.07	1096	787	10.54	20.18	1.39	34.42

Table 4.7 shows the descriptive statistics of variables. The percentages for “1” or “0” are quite substantial for some binary variables such as Case Type, Day of Week, and Professional, which indicates that the data may not represent the characteristics for these variables due to the disproportionate data distribution.

Table 4.7 Descriptive Statistics of Dependent and Independent Variables

Variable	**Mean**	**Min**	**Max**	**S.D.**
ERTime (min)	3.67	1.00	25.00	2.39
Case Type		0	(12.67%)1	
Response Mode		0	(27.80%)1	
Time of Day		0	(56.05%)1	
Day of Week		0	(71.69%)1	
Month of Year		0	(55.73%)1	
Location		0	(21.12%)1	
Road Density	6.05	0.57	20.18	6.19
Road Connectivity	1.39	1.08	1.58	0.09
Road Speed	32.48	28.57	35.75	2.34
Professional		0	(72.57%)1	
Vehicle	4.77	1.00	7.00	1.88
EMS Demand	1104.85	133.00	2115.00	685.89
UHU	0.02	0.00	0.04	0.01

4.3.3 Model Comparison and Selection

In total, there were six case-specific variables and seven station-specific variables. A correlation analysis was performed for all independent variables. Table 4.8 shows that a correlation exists in the following four pairs: Professional and Vehicle, Professional and Demand, Vehicle and Demand, and Demand and UHU.

Table 4.8 Correlation Matrix

	Professional	**Vehicle**	**Demand**	**UHU**
Professional	1.00			
Vehicle	0.81	1.00		
Demand	0.65	0.50	1.00	
UHU	-0.02	-0.25	0.61	1.00

Two models were developed in order to avoid the correlation effect; one model included the Profession and UHU variables, and the other included the Vehicle and UHU variables.

Model 1: Case Type + Lights & Siren + Time of Day + Day of Week +Month of Year+ Location + Road Density + Road Connectivity + Speed + **Professional +UHU**

Model 2: Case Type + Lights & Siren + Time of Day + Day of Week +Month of Year+ Location + Road Density + Road Connectivity + Speed +**Vehicle +UHU**

MLR and GWR were applied to both models. The choice of weight function is of vital importance for the GWR model; hence, both the Gaussian and bi-square functions were evaluated for the weight function. The Gaussian function is not appropriate for unevenly distributed data because it provides a fixed bandwidth that may lead to a different number of calibrated data points associated with each station. Due to the unevenly distributed data in this case, an adaptive function was used to ensure the local models were calibrated on the same amount of data points. Thus, six models were developed: Model 1_MLR, Model 1_Gaussian, Model 1_Bi Square, Model 2_MLR, Model 2_Gaussian, and Model 2_Bi Square. AICc or R^2 was calculated to select the model with the best goodness-of-fit. GWR 4.0, a statistical software package specially developed for GWR, was used to develop the GWR models [48].

According to the results in Table 4.9, the GWR model with the bi-square function performs better than with the Gaussian function (i.e., lower AICc and larger R^2). Also, GWR models were better than MLR models overall. Model 1_Bi Square has a slightly lower AICc than Model 2_Bi Square. While comparing Model 1 with Model 2, it was found that it is better to include Professional and UHU variables, as the calculation of UHU is associated with Vehicle. Model 1 was recommended as the best model as it showed visible improvements after using a GWR in which R^2 changes from 0.05 to 0.22.

Table 4.9 Model Comparison

	Goodness-of-fit (GOF)	
	AICc	**R^2**
Model 1_MLR	7204.64	0.05
Model 1_Gaussian	7021.98	0.17
Model 1_Bi Square	*6967.42*	*0.22*
Model 2_GLM	7191.99	0.06
Model 2_Gaussian	7065.12	0.15
Model 2_Bi Square	6972.26	0.22

4.3.4 Coefficent Estimates of Multiple Linear Regression

Table 4.10 shows the coefficient estimates for MLR. Case Type, Time of Day, Day of Week, and Month of Year were not statistically significant. A disproportionate data distribution might contribute to the insignificance of Case Type and Day of Week. The positive sign for Response Mode indicates that when the light and siren were on, the ERTime increased. The negative sign for Location indicates that incidents happening in a public areas had a reduced ERTime. When road accessibility (Road Density and Road connectivity) increased, ERTime decreased. Also, road speed played a positive effect on ERTime. The coefficient for Professional may not be accurate as most cases (72%) were responded to by a station staffed with professionals. UHU, an indicator for station workload, had a positive effect on ERTime.

Table 4.10 Coefficient Estimates for MLR

Parameters	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	1.31	1.82	0.72	0.472055	
Case Type	0.13	0.18	0.70	0.487287	
Response Mode	0.57	0.14	3.94	8.43E-05	***
Time of Day	-0.02	0.12	-0.15	0.882641	
Day of Week	0.06	0.13	0.46	0.648899	
Month of Year	0.06	0.12	0.55	0.58421	
Location	-0.30	0.14	-2.07	0.038452	*
Road Density	-0.03	0.01	-2.77	0.005706	**
Road Connectivity	-2.33	0.68	-3.41	0.000663	***
Road Speed	0.13	0.05	2.60	0.009352	**
Professional	0.54	0.17	3.25	0.001168	**
UHU	43.86	9.18	4.78	1.96E-06	***

Significant Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.3.5 Geographically Weighted Regression

GWR modeling is more appropriate than MLR modeling because it can improve the prediction accuracy and efficiency when spatial correlation exists in the data. The spatial cluster pattern of residuals can be tested by Moran's I statistics. In Table 4.11, the Moran's I results suggest significant spatial autocorrelation in the data. After applying GWR, spatial autocorrelation no longer existed in the model residual. This exercise proves that GWR is a more proper method to account for spatial autocorrelation in the EMS data.

Table 4.11 Moran's I Test on Residuals

Global Moran's I Summary	MLR	GWR
Moran's I Index	0.05311	-0.00293
z-score:	21.90237	-0.93640
p-value:	<0.00001	0.34907

Moreover, a GWR ANOVA test in Table 4.12 shows that the GWR model is a significant improvement over the global model (large F value).

Table 4.12 GWR ANOVA Table

Source	SS	DF	MS	F
Global Residuals	8580.122	1574		
GWR Improvement	1499.441	38.809	38.636	
GWR Residuals	7080.681	1535.191	4.612	8.376809

A geographical variability test of local coefficients was performed using a model comparison to test whether coefficients vary across the space. When testing the geographical variability of the kth coefficient, a comparison is carried out between the fitted GWR model and a switched model, which is identical to the fitted GWR except that the kth coefficient is a fixed value. If the original GWR model performs better than the switched model, the kth coefficient varies over the space.
Results are shown in Table 4.13. The "DIFF of Criterion" denotes the difference of criterion (AICc) between the original GWR and the switched models; if the difference is positive (usually bigger than two), the corresponding variable can be treated as a global variable. For example, Time of Day and Month of Year are identified as global variables.

Table 4.13 Geographical Variability Tests of Local Coefficients

Variable	F	DOF for F test		DIFF of Criterion
Intercept	75.81	0.40	1541.55	-30.05
Case Type	5.74	3.61	1541.55	-13.56
Response Mode	0.90	3.46	1541.55	4.13
Time of Day	1.27	3.74	1541.55	3.02
Day of Week	1.82	3.76	1541.55	0.92
Month of Year	0.71	3.68	1541.55	5.11
Location	3.53	3.21	1541.55	-4.81
Road Density	1.41	1.05	1541.55	0.71
Road Connectivity	429.93	0.97	1541.55	-375.98
Road Speed	9.59	0.16	1541.55	-1.25
Professional	26.07	0.87	1541.55	-21.20
UHU	3.04	0.97	1541.55	-0.98

4.3.6 Mixed Geographically Weighted Regression

Unlike GWR, a Mixed GWR is a local model in which all independent variables are initially set as local variables. After an iterative process, some independent variables became global variables and some remained local. An iterative golden section search of the AICc function revealed that the 367 nearest neighbors yielded the optimal AICc score, and hence, the 367 nearest neighbors were considered as the bandwidth. A mixed GWR was performed using GWR 4.0, and bi square adaptive weight function was selected to maintain consistency with previous GWR settings. Table 4.14 shows the global coefficient estimates, none of which are statistically significant.

Table 4.14 Global Coefficient Estimates

Variable	Estimate	Std. Error	t value
Intercept	3.82	2.84	1.34
Time of Day	0.07	0.11	0.64
Day of Week	0.07	0.12	0.58
Month of Year	0.05	0.11	0.42
Road Density	-0.09	0.06	-1.55

Table 4.15 shows the local coefficient estimates, which are categorized as minimum, lower quartile, median, upper quartile, and maximum. The sign of the estimated parameters varies over space for all local variables except for Response Mode. The range between minimum value and maximum value were large when compared with the parameter estimate value.

Table 4.15 Local Coefficient Estimates

Variable	Min	Lower Quartile	Median	Upper Quartile	Max
Case Type	-1.84	-0.48	0.02	0.57	1.02
Response Mode	0.03	0.42	0.66	0.86	1.18
Location	-1.35	-0.83	-0.61	0.31	0.52
Road Connectivity	-77.28	-0.97	1.00	13.46	27.97
Road Speed	-1.31	-0.52	-0.02	0.04	1.42
Professional	-0.80	0.52	0.87	1.17	24.07
UHU	-294.52	-142.71	11.08	88.82	2890

Here, UHU is chosen as the example to illustrate how GWR results should be applied. Figure 4.23 and Figure 4.24 show the parameter estimate map for UHU and the local t value map for UHU, respectively. An overall pattern was identified from the parameter estimate map. The effect of UHU ranges from -294.52 to 2890, which is much higher than the estimated value of 42.86 generated by the MLR. Figure 4.23 shows that a strong negative effect exists mainly in the southeastern part of the state. When observing the t value map in Figure 4.24, most of these points are insignificant, which reveals that a variable that is significant at a global level may not be significant at a local level. All of the variables have been reviewed using both the parameter estimate map and the local t value map (shown in Appendix).

GWR's strength is in its ability to offer an in-depth view of the effects and statistical significance of each variable. A variable may be statistically significant at some stations, but not at others, and some variables may have a consistent performance across the space while others do not. Inconsistent results may be due to unobserved confounding factors that can be further studied in future research. Table 4.16 shows each station and its corresponding significant variables that affect service performance. The Local R^2 provides the estimate of the percentage that en route time can be explained by the corresponding variable.

GWR outperformed MLR in Model Comparison and Selection in terms of statistical goodness-of-fit. An inspection of the statistically significant variables produced by each regression model can shed additional insights into the influence of these factors on en route time. Response Mode, Location, Highway Density, Connectivity, Speed, Professional, and UHU are statistically significant variables for MLR. A positive Response Mode coefficient indicates that en route time increases when the light and siren are on; the increase may be caused by traffic delays. A negative sign for Location indicates that incidents happening in public areas correspond to a reduced en route time. En route time decreases when road accessibility (Highway Density and Highway Connectivity) increases. Workload UHU has a positive effect on en route time; however, Speed and Professional have a positive effect on en route time, which is counterintuitive.

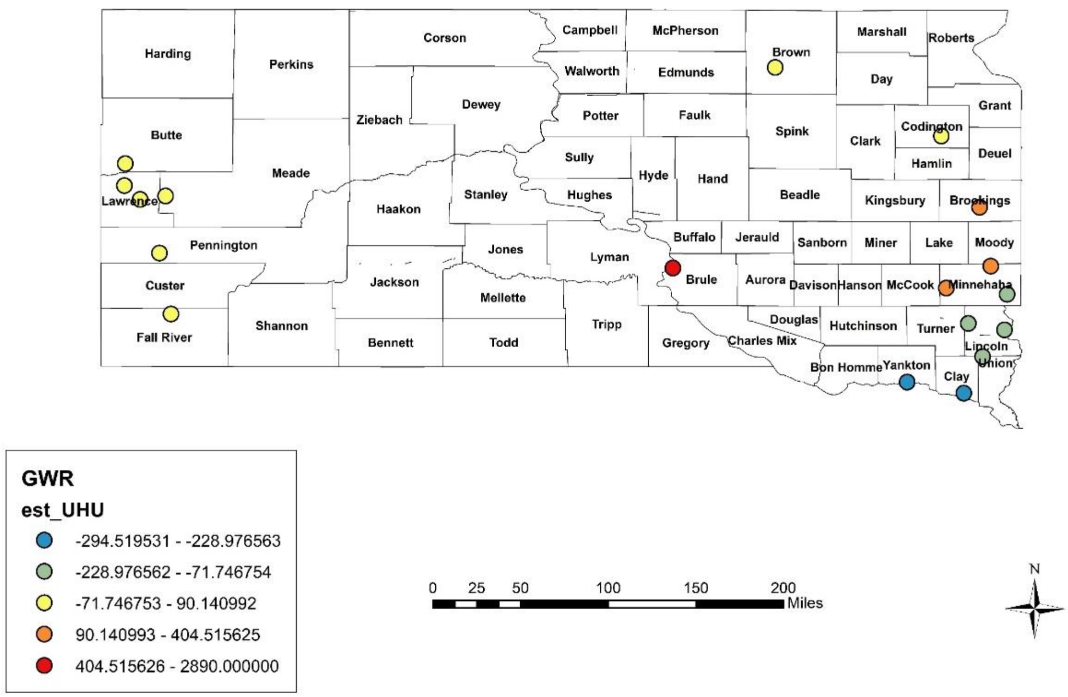


Figure 4.23 Parameter Estimate Map for UHU

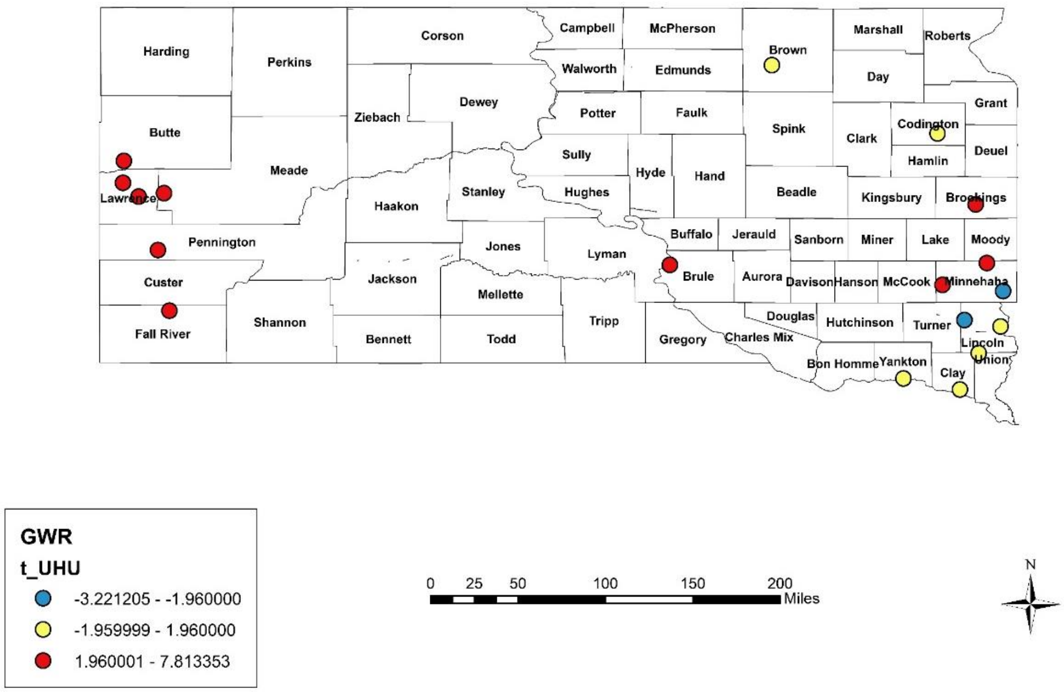


Figure 4.24 Local t value Map for UHU

In GWR, the Highway Density variable is not statistically significant, but the Case Type variable is; more importantly, the statistical significance of all seven variables varies across stations. The local significance shows a negative sign for western stations and a positive sign for eastern stations. The negative effect meets the expectation of urgent and severe cases corresponding to a shorter en route time, but the positive effect can be the result of other unknown local factors that require further investigation.
Response Mode is locally significant for all western stations; this result is consistent with MLR results, meaning increased en route time is associated with light and siren situations. The Location variable is locally significant for some eastern stations with a negative sign, suggesting that incidents happening in public areas are associated with shorter en route times.

A negative effect is observed for MLR with regard to Highway Density and Highway Connectivity; however, for GWR, Highway Density is insignificant while Highway Connectivity is positive for some stations and negative for others. MLR results with regard to Speed are perplexing, as a higher speed is associated with longer en route time. GWR results show that a higher speed can shorten en route time. Similarly, UHU is positive for MLR and it varies for GWR. The disparities among stations in terms of coefficient estimates suggest a need to review more detailed information before attempting to reach any definitive conclusions, especially for the stations with questionable performance. Considering the significant factors – model performance and spatial autocorrelation – in the EMS dataset, the GWR model is considered more revealing and more appropriate for evaluating EMS station service performance.

4.3.7 Summary

A regression analysis was performed on en route time using 911 cases within each EMS station's 8-minute coverage area. A careful review of all possible factors related to en route time was conducted, and 13 variables (six case-specific variables and seven station-specific) were prepared. Models were compared using R^2 and AICc, and the GWR model was selected as the best performer. Moran's I test identified that a spatial autocorrelation existed in the residuals for MLR. On the other hand, GWR accounts for spatial heterogeneity, and its model residual was free of the spatial autocorrelation. A statistical test further revealed that the spatial variability did not apply to some variables. Lastly, a mixed GWR was applied for the data because it included both global parameters and local parameters for different variables, taking the spatial variability into account. Statistically significant factors affecting the ERTime were observed, and parameters for different EMS stations were estimated to provide a guide for local agencies looking to reduce en route time

Table 4.16 Significant Contributing Factors Affecting En Route Time for Each Station

EMS Station	Case Type	Response Mode	Location	Highway Connectivity	Speed	Professional	UHU	Local R^2
Aberdeen Ambulance Service	N/A	N/A	-0.83	N/A	N/A	N/A	N/A	0.02
Watertown Fire Dept. & Ambulance Service	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.07
Brookings Ambulance Service	N/A	N/A	N/A	27.97	-1.31	0.93	219.14	0.03
Dell Rapids Community Ambulance Service	N/A	N/A	-0.64	-8.75	0.19	2.33	404.52	0.21
Humboldt Fire& Ambulance Service	-1.84	N/A	N/A	19.78	-0.98	5.26	262.27	0.30
Med Star Paramedic Ambulance	N/A	N/A	-1.35	N/A	N/A	N/A	-142.71	0.13
Lennox Area Ambulance	-0.99	N/A	-0.84	27.75	-1.12	3.07	-134.28	0.35
Inwood Ambulance Service	N/A	N/A	-0.92	N/A	N/A	1.40	N/A	0.26
Beresford Community Ambulance Service	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.17
Yankton County EMS	N/A	0.86	N/A	N/A	N/A	N/A	N/A	0.07
Clay County Ambulance Service	N/A	0.83	-0.61	N/A	N/A	1.17	N/A	0.18
Missouri Valley Ambulance Service	N/A	N/A	N/A	-77.28	1.42	24.07	2890.00	0.35
Butte County Ambulance Service	1.02	1.15	N/A	N/A	N/A	0.87	88.47	0.20
Spearfish Emergency Ambulance Service	1.00	1.16	N/A	N/A	N/A	0.87	88.71	0.20
Lead - Deadwood Regional Hospital Ambulance	1.00	1.16	N/A	N/A	N/A	0.87	88.86	0.20
Sturgis Fire Dept.	1.00	1.16	N/A	N/A	N/A	0.87	88.82	0.20
Hill City Ambulance Service	0.97	1.17	N/A	N/A	N/A	0.87	89.47	0.20
Hot Springs Volunteer Ambulance Service	0.94	1.18	N/A	N/A	N/A	0.86	90.14	0.20

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study established data-driven performance metrics for EMS by accomplishing three tasks: geospatial analysis, optimization of EMS station locations, and EMS service performance analysis and evaluation. The data used in this study include EMS ambulance data, station data, and highway network information. Although three-year EMS data (2011-2013) were collected and analyzed, results are based on the 2013 EMS data for brevity and consistency.

Geospatial statistics (such as Getis Ord G*) helped discover the clustering of 911 calls. Many EMS stations are located within the proximity of 911 call clusters. The spatial association of 911 calls and EMS stations was confirmed visually and by the Ripley's cross-K function. This finding should not be a surprise because both 911 calls and EMS stations are more likely to be in populous areas; however, the co-location of the 911 calls and EMS stations does not always guarantee a timely and swift service. To evaluate the positioning and service quality of each EMS station, two performance indexes were developed: Performance Index I measured the 8-minute coverage ratio of each EMS station, and Performance Index II provided the percentage of the cases with an actual ERTime within 8 minutes and the total percentage of cases within the 8-minute coverage area. A well-positioned station with well-trained staff should be able to respond to more 911 calls within 8-minutes and/or should have a higher percentage of successes if a 911 call is located within the estimated 8-minute coverage area.

If the service provided by the current EMS stations is not sufficient, the stations can either be relocated or augmented to increase the service coverage and quality. All stations should be strategically located to maximize their coverage. The options for optimizing EMS station location were explored, and two counties were selected: Todd County (high demand with few stations) and Minnehaha County (moderate demand with multiple stations). Two targets were set up for increasing coverage ratio and service quality. Optimal solutions were obtained by running the genetic algorithm in the R software. Extensive comparisons have been performed between optimal locations and existing locations under different scenarios (i.e., relocating or adding more service stations). With the help of accurate information, the optimization tool can help the EMS agencies to strategically plan new stations or relocate existing stations to provide better services with limited resources.

A regression analysis was performed on en route time based on the 911 calls within the 8-minute coverage area for each EMS station. In previous analyses, a total of 13 input variables were identified, including six case-specific and seven station-specific variables. Models with different assumptions and combinations of variables were developed and compared. The results show that GWR significantly increased the model performance compared with MLR. The statistical test also revealed that the GWR model outperformed the MLR model. The comparison showed that some variables may be spatially invariant. Consequently, a mixed GWR was applied, and coefficient estimates of significant variables were obtained for each station. The mixed GWR model not only identifies statistically significant factors that accelerate or delay the EMS service at the station level, but it provides a more accurate prediction of en route time.

5.2 Recommendations for Future Work

Several recommendations for future research were uncovered in this study. Linking EMS data with patient's outcome is of strong interest because there is no direct evidence to prove that a shorter total EMS response time leads to a less severe consequence. However, such a valuable evaluation cannot be performed with the EMS information at its current capacity and accuracy but can be linked to the hospital data, which is difficult to obtain. Thus, the availability of perfectly matched hospital data is essential for the patient outcome analysis associated with an EMS response.

A lack of quality data can be a main factor affecting analysis results. Rural states like South Dakota have a very low annual EMS call volume, making it difficult for researchers to recognize meaningful trends in the data. A small dataset can be further deteriorated by missing or low-quality data. For example, the 2013 dataset had 36,198 emergency calls, yet valid information was provided for only 13,041 (36%) of the responses. Hence, it is strongly recommended to improve the EMS data quality in future data collection. More advanced methodologies should be developed to minimize the impact of poor or missing data.

Lastly, although the GWR model has substantially improved the model prediction accuracy, its overall goodness-of-fit is quite low. Without other supporting information to explain the parameter estimates, the location-dependent estimates of the significant parameters are less enlightening. Researchers should explore other models, such as spatial filtering, that may account for spatial heterogeneity.

REFERENCES

1. Administration, N.H.T.S., *Traffic Safety Facts 2010: A compilation of motor vehicle crash data from the Fatality Analysis Reporting System and the General Estimates System. DOT HS 811 659.* US Department of Transportation, NHTSA, Washington DC, 2012.

2. FHWA. *Highway Statistics 2010*. Highway Statistics Series 2014 [cited 2015 February 10]; Available from: http://www.fhwa.dot.gov/policyinformation/statistics/2010/.

3. Rawlinson, C. and P. Crews, "Access to quality health services in rural areas emergency medical services: a literature review." *Rural Healthy People*, 2010, 2003. 1: p. 77-82.

4. FHWA. *Highway Safety Improvement Plan* 2011 [cited 2013 November 5]; Available from: http://safety.fhwa.dot.gov/hsip/resources/fhwasa1102/flyr3_in.cfm.

5. Fotheringham, A.S., C. Brunsdon, and M. Charlton, *Geographically weighted regression*. 2003: John Wiley & Sons, Limited.

6. NHTSA, *Promoting Safe Passage into the 21 Century*. 1998, SDDOT.

7. Gamm, L., et al., "Rural healthy people 2010: Identifying rural health priorities and models for practice." *The Journal of Rural Health*, 2002. 18(1): p. 9-14.

8. Team, N.T.A., *State of South Dakota, A Reassessment of Emergency Medical Service.* 2002.

9. John Becknell, A.R., *The Future of Rural Ambulance Services in South Dakota: A Case Study of the Jones County Ambulance* 2013.

10. Plan, A.S.H.S., *Volume 15: A Guide for Enhancing Rural Emergency Medical Services.* 2005.

11. Knott, A., *Access to emergency medical services in rural areas: The supporting role of state EMS agencies*. 2002: Rural Health Research Center.

12. NHTSA, *Traffic Safety Facts 2011: A Compilation of Motor Vehicle Crash Data from the Fatality Analysis Reporting System and the General Estimates System*. 2004, USDOT.

13. Facts, T.S., *A Compilation of Motor Vehicle Crash Data From The Fatality Analysis Reporting System and the General Estimates System (Washington, DC: US Department of Transportation, National Highway Traffic Safety Administration, 2013), 146-147 [online]* http://www-nrd*. nhtsa. dot. gov.* Pubs/811754AR. pdf, 2011.

14. Minge, E.D., *Emergency Medical Services Response to Motor Vehicle Crashes in Rural Areas*. 2013.

15. Dawson, D.E., *National emergency medical services information system (NEMSIS).* Prehospital Emergency Care, 2006. 10(3): p. 314-316.

16. Clark, D., *Practical introduction to record linkage for injury research.* Injury Prevention, 2004. 10(3): p. 186-191.

17. NHTSA, *Fatality analysis reporting system*. 2008.

18. ESRI, *GIS for fire station location and response protocol* 2007.

19. Newgard, C.D., et al., "Developing a statewide emergency medical services database linked to hospital outcomes: a feasibility study." *Prehospital Emergency Care*, 2011. 15(3): p. 303-319.

20. Rogers, D.B., *Determing A True Response Time And Methods That Could Improve Response Times For The Centerville-Osterville-Marstons Mills (Ma) Department Of Fire-Rescue & Emergency Services.* 2005.

21. Setzler, H., C. Saydam, and S. Park, "EMS call volume predictions: A comparative study." *Computers & Operations Research*, 2009. 36(6): p. 1843-1851.

22. Channouf, N., et al., "The application of forecasting techniques to modeling emergency medical system calls in Calgary, Alberta." *Health Care Management Science*, 2007. 10(1): p. 25-45.

23. Baker, J. and K. Fitzpatrick, "Determination of an optimal forecast model for ambulance demand using goal programming." *Journal of the Operational Research Society*, 1986: p. 1047-1059.

24. Denton, J.W., "How good are neural networks for causal forecasting?" *The Journal of Business Forecasting*, 1995. 14(2): p. 17.

25. Gitelman, V., K. Auerbach, and E. Doveh, "Development of road safety performance indicators for trauma management in Europe." *Accident Analysis & Prevention*, 2013. 60: p. 412-423.

26. Al-Shaqsi, S.Z.K., "Response time as a sole performance indicator in EMS: Pitfalls and solutions." *Open Access Emergency Medicine*, 2010. 2: p. 1-6.

27. Prevention, C.f.D.C.a., *Motor Vehicle Safety*. Injury and Violence Prevention, 2013.

28. Peleg, K. and J.S. Pliskin, "A geographic information system simulation model of EMS: reducing ambulance response time." *The American Journal of Emergency Medicine*, 2004. 22(3): p. 164-170.

29. Association, N.F.P., *NFPA 1500 (2007): Standard on Fire Department Occupational Safety and Health Program*. 1992: National Fire Protection Association.

30. Do, Y.K., et al., "A quantile regression analysis of ambulance response time." *Prehospital Emergency Care*, 2013. 17(2): p. 170-176.

31. Meng, Q. and J. Weng, "Uncertainty analysis of accident notification time and emergency medical service response time in work zone traffic accidents." *Traffic Injury Prevention*, 2013. 14(2): p. 150-158.

32. Patel, A.B., et al., "A validation of ground ambulance pre-hospital times modeled using geographic information systems." *International Journal of Health Geographics*, 2012. 11(1): p. 42.

33. Ripley, B.D., *Spatial statistics*. Vol. 575. 2005: John Wiley & Sons.

34. Shekhar, S. and Y. Huang, *Discovering spatial co-location patterns: A summary of results*, in *Advances in Spatial and Temporal Databases*. 2001, Springer. p. 236-256.

35. Khan, G., et al., "Application and integration of lattice data analysis, network K-functions, and geographic information system software to study ice-related crashes." *Transportation Research Record: Journal of the Transportation Research Board*, 2009(2136): p. 67-76.

36. Sivaraj, R. and T. Ravichandran, "A review of selection methods in genetic algorithm." *International Journal of Engineering Science and Technology*, 2011. 3(5).

37. Zhao, F. and N. Park, "Using geographically weighted regression models to estimate annual average daily traffic." *Transportation Research Record: Journal of the Transportation Research Board*, 2004(1879): p. 99-107.

38. Du, H. and C. Mulley, "Relationship between transport accessibility and land value: Local model approach with geographically weighted regression." *Transportation Research Record: Journal of the Transportation Research Board*, 2006(1977): p. 197-205.

39. Li, Z., et al., "Using geographically weighted Poisson regression for county-level crash modeling in California." *Safety Science*, 2013. 58: p. 89-97.

40. De Smith, M.J., M.F. Goodchild, and P. Longley, *Geospatial analysis: a comprehensive guide to principles, techniques and software tools*. 2007: Troubador Publishing Ltd.

41. Daskin, M.S., K. Hogan, and C. ReVelle, "Integration of multiple, excess, backup, and expected covering models." *Environment and Planning B*, 1988. 15(1): p. 15-35.

42. Chanta, S., M.E. Mayorga, and L.A. McLay, "Improving emergency service in rural areas: a bi-objective covering location model for EMS systems." *Annals of Operations Research*, 2014. 221(1): p. 133-159.

43. Sivanandam, S. and S. Deepa, *Introduction to genetic algorithms*. 2007: Springer Science & Business Media.

44. Grabaum, R. and B.C. Meyer, "Multicriteria optimization of landscapes using GIS-based functional assessments." *Landscape and Urban Planning*, 1998. 43(1): p. 21-34.

45. Mears, G., et al., *National EMS Assessment.* Washington, DC, Federal Interagency Committee on Emergency Medical Services, US Department of Transportation, National Highway Traffic Safety Administration, DOT HS, 2011.

46. Litman, T., *Evaluating accessibility for transportation planning.* 2008.

47. TriData, *ASSESSMENT OF FIRE DEPARTMENT RESOURCE LOCATIONS, STAFFING, and FACILITIES*. 2007, a Division of System Planning Corporation.

48. Nakaya, T., *GWR4 User Manual* 2014, GWR 4 Development Team