

**Evaluation of Spatial Accessibility to Ohio Trauma Centers Using a GIS-based Gravity
Model**

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Abstract

Traumatic injury is one of the leading causes of death in all age groups. Ensuring adequate and effective access to trauma centers is key to improving the quality of care for injured patients.

This study evaluates the spatial accessibility of Ohio trauma centers and identifies potentially underserved Ohio counties. A gravity based accessibility model using Geographic Information System (GIS) was adapted to incorporate US census data, trauma center location data, and trauma center utilization data to quantify accessibility to trauma centers at both the zip code and county levels. An underserved index was developed to identify the location and clustering pattern of underserved regions within the state. Findings of this study can be used to evaluate regionalized trauma care and provide evidence for trauma care system improvements in Ohio.

1. Background

Regionalized trauma care is considered the best approach for matching patient needs with the available resources and provider expertise to achieve optimal patient outcomes (1-4). As of 2013, the state of Ohio had 178 hospitals with emergency departments, 48 of these were verified trauma centers by the American College of Surgeons Committee on Trauma (ACS-COT). However, the 2013 ACS-COT review for Ohio reported on a likely misdistribution of trauma centers in Ohio and recommended “conducting an assessment of the current trauma system to guide data-driven decisions regarding the location and level of new trauma center designations” (5). The Report further stated that the current Ohio Emergency Medical Services (EMS) triage guidelines do not “account for geographic proximity or facility designation levels.”

Geographic proximity problems have been assessed using spatial accessibility models which take into account the locations of both the demand (e.g. population in the region) and the supply (e.g. trauma centers) (6). There are two types of popularly adopted accessibility models. One is based on the concept of catchment area, while the other is based on a gravity model of demand and supply. A catchment area is defined as the extended area from a service center (e.g. trauma center). The catchment area-based accessibility model divides the entire region into binary zones: accessible (within the catchment area) and inaccessible (outside the catchment area). Studies found that catchment areas, Euclidean distance, and drive-time distance could all be effective in defining the catchment area of a service center (7-9).

However, the catchment area-based method of evaluating accessibility has limitations. First, its binary classification of the region is sometimes too idealistic and insufficiently granular

especially for large geographic regions such as states. In addition, it does not consider a distance decay effect but treats each location within the catchment area as having equal opportunities of access. Furthermore, the definition of the catchment area varies between applications and, consequently, the results are often difficult to compare across studies. Alternatively, the gravity-based accessibility model can be used to overcome these limitations. A gravity model evaluates accessibility on a more granular scale for all locations in the region by incorporating both spatial and aspatial factors into the modeling process (10, 11). The gravity model has been shown to be a reliable measure of calculating spatial access, whether potential or realized (6).

Research efforts have been made in assessing accessibility to health care locations including network-based catchment area analysis (12, 13) and gravity based modeling (10, 14). Although largely effective, many of these methods have not yet differentiated or incorporated levels of service (e.g. trauma center levels) as model parameters, which may be important for weighing preferences and service quality assessment (15). Furthermore, previous models have focused more on potential access and left revealed access and its relationship to potential access largely unaddressed. To our best knowledge, geospatial accessibility to trauma centers has not been formally studied at the state level in Ohio.

The first objective of this study was to explore how both levels of service and realized access (such as trauma center utilization data) can be incorporated into a GIS-based gravity model to conduct an assessment of spatial access to trauma center care in Ohio. The second objective is to identify underserved areas in terms of access to trauma care in Ohio.

2. Data Source

2.1 Trauma center data

Two data sources were used in our analysis of trauma center accessibility. The first data were the general information about the 47 trauma centers in Ohio and the 86 trauma centers in five bordering states (Indiana, Kentucky, Michigan, Pennsylvania and West Virginia) including trauma center classification (Level I, II, and III), street address, and trauma center discharge counts. Trauma centers are verified by the American College of Surgeons a standard set of criteria, with Level I centers providing the highest level of care followed by Level II and III centers. There are no Level IV and V trauma centers in Ohio, but some neighboring states have those designations (5). Since we were focused on Ohio, only Level I, II, and III were included. In 2013 and 2014, there were 14 Level I, 12 Level II, and 21 Level III trauma centers in Ohio. In five bordering states, there were 37 Level I, 41 Level II, and 8 Level III trauma centers.

The second data source we used was the trauma center utilization information represented by 2013 Ohio hospital inpatient discharge data, which included the zip code and county information of the patients for each of the trauma centers that provided the service. Using discharge data from each trauma center, total discharge counts can be aggregated based on patient's residence zip code and county.

2.2 Census data and geographic data

Our study also used U.S. census datasets. These population datasets are freely available from the U.S. census website for all census levels including census blocks. Because the hospital discharge data were at the zip code level, we needed to produce estimates of the population for each zip code by aggregating the population on the census block level.

3. Study Method

A series of analyses were carried out in sequential steps using GIS. These steps included geocoding, estimating the zip code population, building the gravity model, mapping accessibilities, and identifying underserved areas.

3.1 Geocoding trauma center locations

Locations of all Level I, II, III trauma centers in both Ohio and five bordering states were geocoded with geographic coordinates using ArcGIS software, a popular geographic information system software application. ArcGIS was also used to carry out the modeling, mapping, and analysis described in the following sections. A GIS layer including all point representations of trauma center locations was created.

3.2 Estimating population by zip code

Zip code is not a standard census area, so we had to produce zip code level estimates of the population prior to building the gravity model at that level. A zip code could consist of multiple census blocks, either fully or partially enclosed. For each pair of overlapping block and zip code (Figure 1), the population of the overlapped area was estimated based on the total population of the block and the percentage of the overlapped area. A geometric point was used to represent the overlapped area (the dot shown in Figure 1). As a block area is relatively small compared to a zip code, we assumed the population is evenly distributed within the block segment A. The total population of zip code i is therefore calculated as:

$$p_i^Z = \sum_{k=1}^n p_k^B \quad (1)$$

where p_i^Z , the population of zip code i , is the sum of the population p_k^B of each block k (or partial block k within the zip code); n is the total number of block (segments) within the zip code.

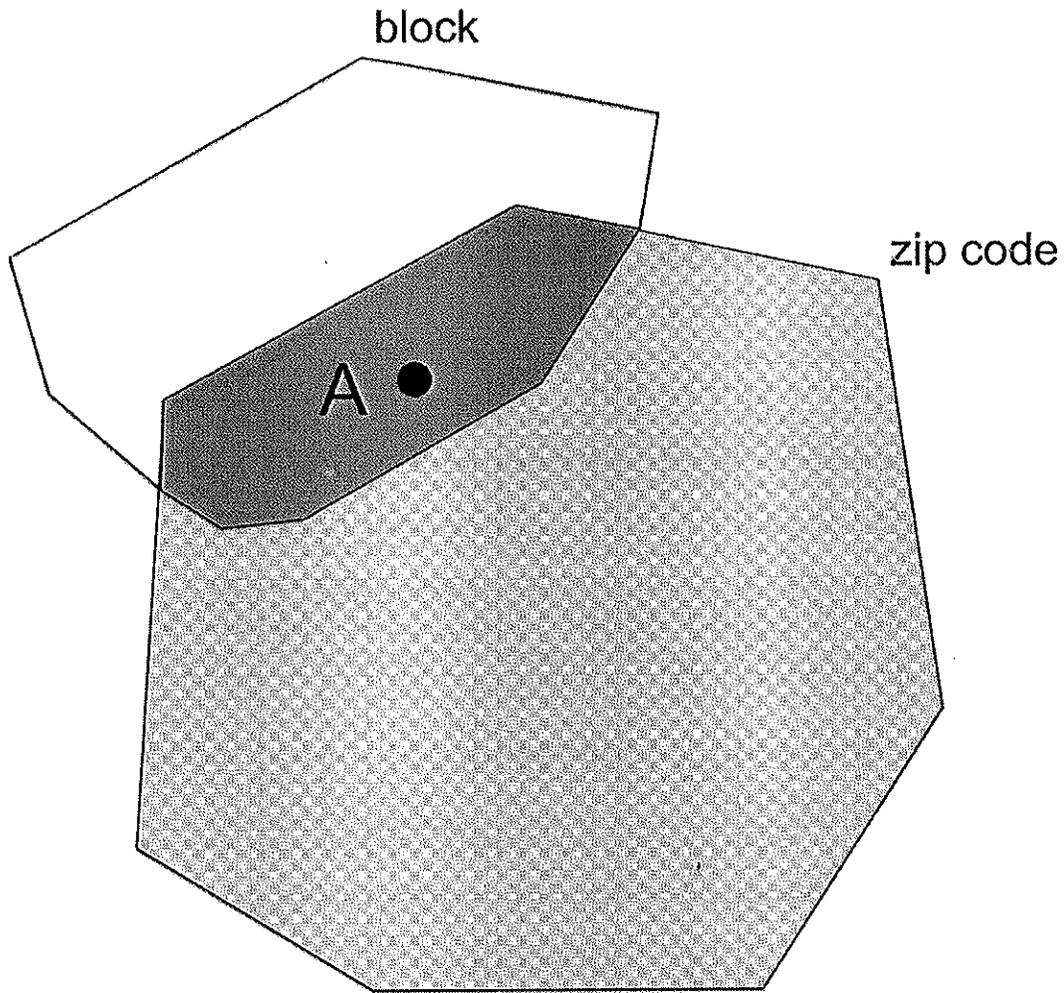


Figure 1. Population mapping from block to zip code

Distance calculation for the gravity model in our study was based on point-based locations. When producing a point representation of a zip code area, the geometric centroid is often not accurate. Population-weighted centroids (pwc) have been used previously to more accurately estimate point locations of areal units (16, 17). Based on point locations of blocks, we estimated the total population of the zip code using the pwc calculation. In Figure 2, each dot represents a block location. The population-weighted centroids of a zip code were calculated as:

$$x_c = \frac{\sum_{i=1}^n p_i x_i}{\sum_{i=1}^n p_i} \quad y_c = \frac{\sum_{i=1}^n p_i y_i}{\sum_{i=1}^n p_i} \quad (2)$$

where x_c and y_c are the x and y coordinates of a zip code area. x_i and y_i are the x and y coordinates of the i-th block centroid within the zip code; p_i is the population at the i-th census block within the zip code.

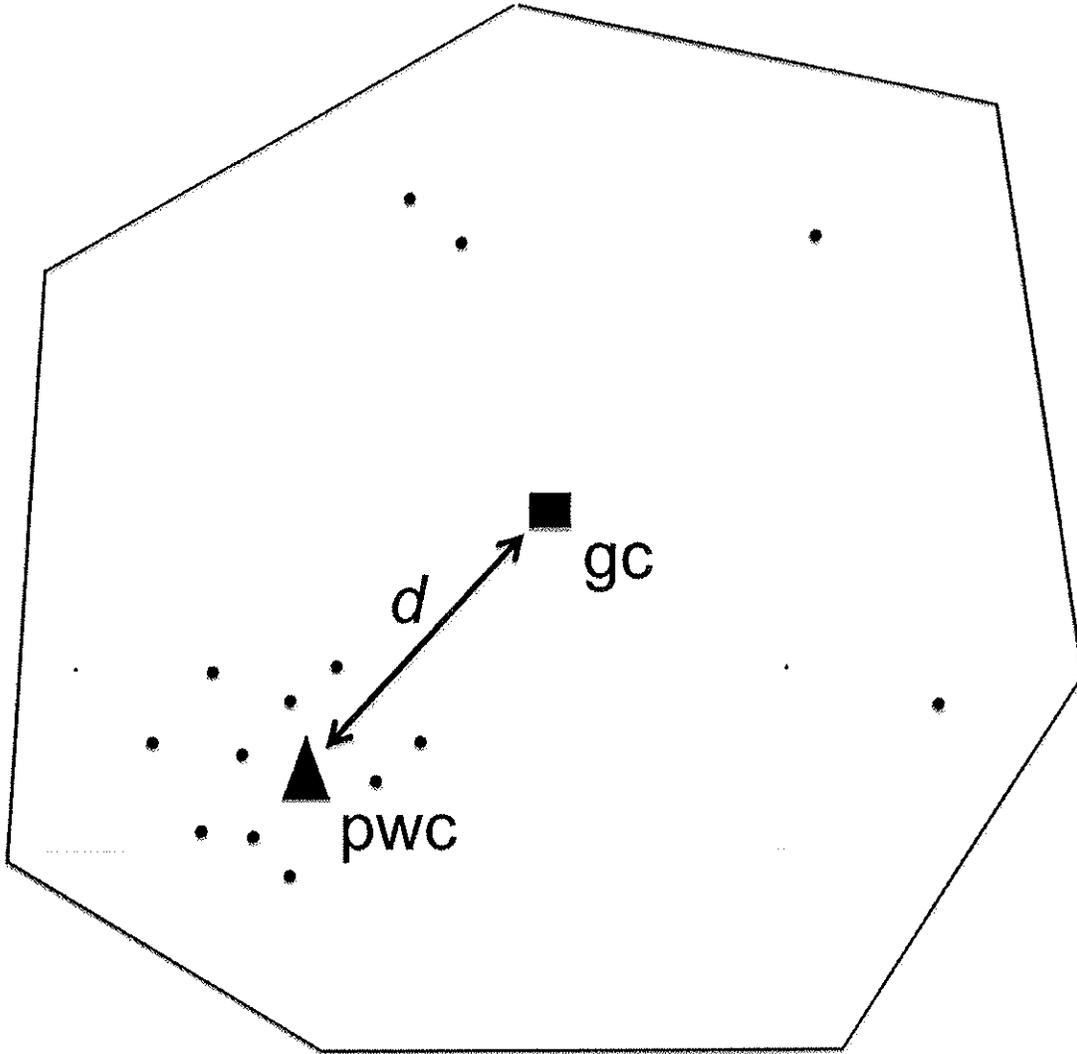


Figure 2. Geometric centroid (gc) vs population weighted centroid (pwc)

3.3 The gravity-based accessibility model

The gravity model was first introduced by Lowe in 1996 (11). The model is based on Newton's Law of Gravitation which postulates that the attraction of object A to object B is proportional to

the mass of object A and inversely proportional to the distance between them. In our study, both supply and demand were modeled using a gravity analogy. The general assumption is that the geospatial accessibility of a trauma center increases with the increase of its supply capacity and decreases with its distance to the demand location. Similarly, more demand from the vicinity of the trauma center could lead to decreased accessibility for each location in the vicinity.

We used d_{ij}^β to represent a distance decay component between trauma center location j to demand location i . The travel friction coefficient is represented by β . A higher β suggests a quicker decay of accessibility given the increase of distance. Previous research has investigated the sensitivity of β and its relationship with driving time and found that driving time from 20 to 60 minutes with 5 minute increments can be represented by setting β from 2.2 to 0.6 with -0.2 increments (14). In our study, we used 0.6 as the β value to estimate the one-hour driving time. We used U_{ij} to denote the potential supply from trauma center location j to demand location i and calculated this index as:

$$U_{ij} = \frac{k_j S_j}{d_{ij}^\beta} \quad (3)$$

S_j is the total supply capacity at trauma center location j . Previously, the total number of physicians and the total number of beds were the most commonly used proxies for supply capacity. However, in our case these, or similar, variables, were not available. Therefore, we set $S_j = 1$, for all trauma centers to reflect our inability to consider the difference between their service capacity in terms of total number of physicians and total number of beds.

S_j was weighted by the service level parameter k_j and divided by distance decay component d_{ij}^β . The service level parameter, k_j , was set to be 4, 2 and 1 respectively for Level I, II and III trauma centers to quantify the service levels. In this case, the quality of service as indicated by service levels was accounted for by a linear function $k_j = 2^{n-1}$, n was the level of the trauma center.

We further used V_j to denote the total potential demand to trauma center location j and calculated it as:

$$V_j = \sum_{i=1}^m \frac{k_i D_i}{d_{ij}^\beta} \quad (4)$$

The total number of population locations (zip code areas) was m , and V_j was the sum of the total demand D_i weighted by k_i and distance decay component d_{ij}^β . The weight of the demand at location, k_i with i suggesting the level or the intensity of the demand. In our study we set k_i to be 1 for all demand locations. One could set a different k_i relating to different levels of demand (e.g. population at different risk levels).

Based on U_{ij} and V_j , the final gravity model in our study was calculated as:

$$A_i^Z = \sum_{j=1}^n \frac{U_{ij}}{V_j} \quad (5)$$

where A_i^Z was the final accessibility score of the zip code i with a larger value indicating better accessibility, and n was the total number of trauma center locations. The accessibility of any particular zip code was the sum of its potential access to all trauma centers.

Our gravity model was implemented at the zip code level of population location but we also mapped our results to counties for interpretation purposes. Policy makers may be more familiar with a county as a target unit rather than a zip code. It is also beneficial to be able to map accessibility results between different geographic levels to integrate different kinds of demographic data available at different geographic levels into the analysis. Real data such as hospital discharge can then be used to conduct sensitivity analyses for a gravity model when mapping results between different geographic levels is possible.

To project accessibility index results from zip code level to county level, we followed an approach similar to the process of mapping block population to the zip code level as discussed previously. However, instead of using the sum of accessibility on the zip code level, a population-weighted average was used to calculate the accessibility index of each county as follows:

$$A_i^C = \frac{\sum_{j=1}^n p_{ij} A_{ij}^Z}{\sum_{j=1}^n p_{ij}} \quad (6)$$

where A_i^C was the accessibility of county i , and A_{ij}^Z was the accessibility of zip code j in county i ; p_{ij} was the population of zip code j in county i , and n was the total number of zip codes within county i . The accessibility of the county i was calculated as the population weighted average of the accessibility of all zip codes (or zip code fragments) that were completely within that county. If a zip code was cut off by a county boundary, a similar area-weighted accessibility equation was applied to estimate the accessibility of the part of zip code that was within the county boundary.

Previously, gravity models have been employed both in their classic form (14) and with modifications of travel time function (11). In both cases, the gravity model was applied at a single geographic level. Here, we made two modifications. First, we introduced the weight parameter to model trauma center levels, which was an important attraction factor. This is not available in the classic gravity model, which only considers service capacity as the only attraction factor. Assigned weights (4, 2, 1) differentiate Level I, II, and III trauma centers with higher weights indicating higher service levels (18).

The second modification allowed for mapping between different geographic levels. Our model was first built on a smaller geographic scale (zip code level) and then results were mapped to a larger scale (county level) for interpretation. The modified gravity model considered both spatial factors (distance or equivalently 60 minute driving time) and aspatial factors (the trauma center service level and the demand). We dropped the supply capacity variable because we did not have service capacity data for hospitals outside of Ohio.

To implement the gravity model on two geographic levels, in ArcGIS we first calculated the accessibility index at the zip code level based on Equations (1-5). Then, a sequence of spatial join and field calculations operations were applied to map zip code level accessibility results to the county level based on Equation (6). For supply locations (trauma center locations), the service weight parameter k_j was set to be 4, 2 and 1 respectively for Level I, II and III trauma centers. For demand locations (zip code locations), total population of each zip code was used as D_i . The distance between demand location and supply location was calculated based on

Euclidian distance and travel friction coefficient β was set to be 0.6, representing the 60 minutes of travel time (14).

3.4 Data classification and symbolization

Accessibility results are visualized in ArcGIS for spatial pattern interpretation. Two steps are involved: data classification and class symbolization. Data classification decides the grouping of accessibility results. There are several methods for classifying real-valued data in GIS. One of these is the natural breaks (Jens) method. This method maximizes the variance between groups and minimizes the variance within each group (19). We applied this method in ArcGIS to classify the accessibility index into three classes high, medium, and low corresponding to areas of high access, good access and low access, respectively. Accessibility was rendered using the graduated colors on a grey scale color ramp with darker color indicating better access.

Aggregated results at the county level also used the same classification scheme.

3.5 Identify and rank underserved counties

In our study, underserved counties were defined as those with high discharge and low accessibility. An underserve index should be positively correlated with discharge volume and negatively associated with the accessibility. Thus, we defined underserve index U_i^c for county i using the following equation:

$$U_i^c = \frac{d_i}{p_i A_i^c} \quad (7)$$

where d_i was the total hospital trauma patient discharge volume for county i ; p_i was the total population of county i , and A_i^c was the accessibility index for county i .

Since the accessibility index was calculated as a population ratio, the scale effect of the population amount was removed from the model. Therefore, county level hospital trauma patient discharge data were normalized by the total population of each county as accomplished by Equation (7).

One of the limitations of a gravity model is that it only calculates potentials and its relationship to the reality usually is unknown. Hospital trauma patient discharge data are a type of commonly available reality data that can be used as a measure of revealed access (compared to potential access based on the gravity model). As shown here by leveraging both accessibility results and reality data in the underserved index, we have overcome this limitation of the gravity model.

In our study, the underserved index of all counties was also classified using the ArcGIS natural breaks method. Three classes of underserved area were identified: highly underserved, underserved and served corresponding to high, medium and low underserved index respectively. In addition, we scaled the underserved index score based on a range of 1 to 100 with the maximum value being 100. Finally, we ranked and identified the top 10 underserved and served counties.

4. Results

Figure 3 shows that the potential access to Ohio trauma centers at the zip code level was unevenly distributed. High access zip codes clustered around urban centers where a concentration of high-level trauma center was located. We also observed that a large number of zip codes had relatively low access compared to a small number of high access zip codes.

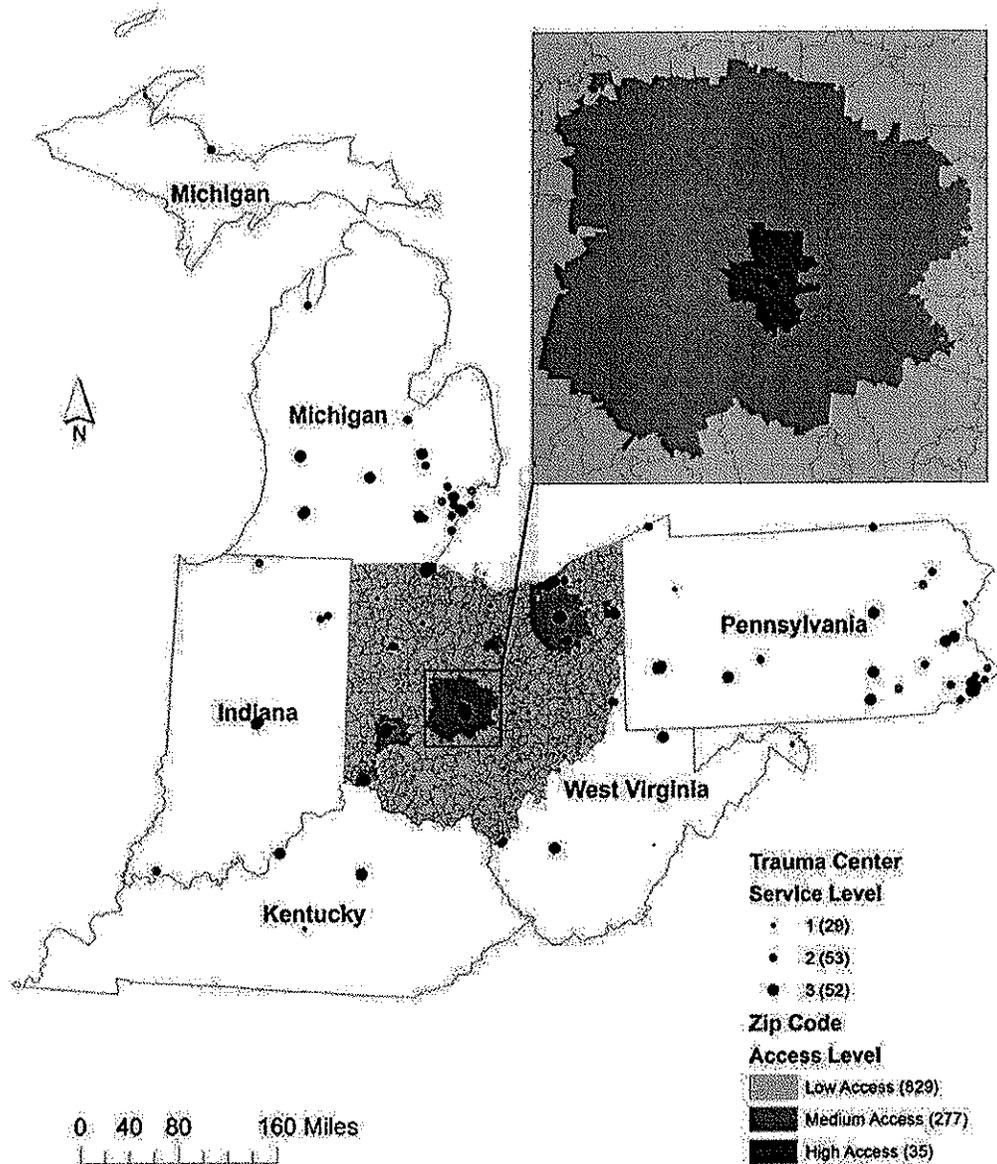


Figure 3. Access to trauma centers in Ohio by zip code¹.

Accessibility results by the zip code were mapped to the county level as shown in Figure 4.

County level accessibility pattern was similar to the one at the zip code level in which areas of

¹ In the legend, graduated size symbols were used to represent trauma center locations with the size proportional to their levels. The number in the parenthesis was the number of zip codes in the corresponding class.

good access clustered around urban centers (Cincinnati, Columbus and Cleveland). Additionally, northeastern regions had overall better access than other parts of Ohio due to a high concentration of trauma centers at different levels. Available access to out-state trauma centers might have met some of the needs for border populations such as those in northern part of the state that is adjacent to Michigan.

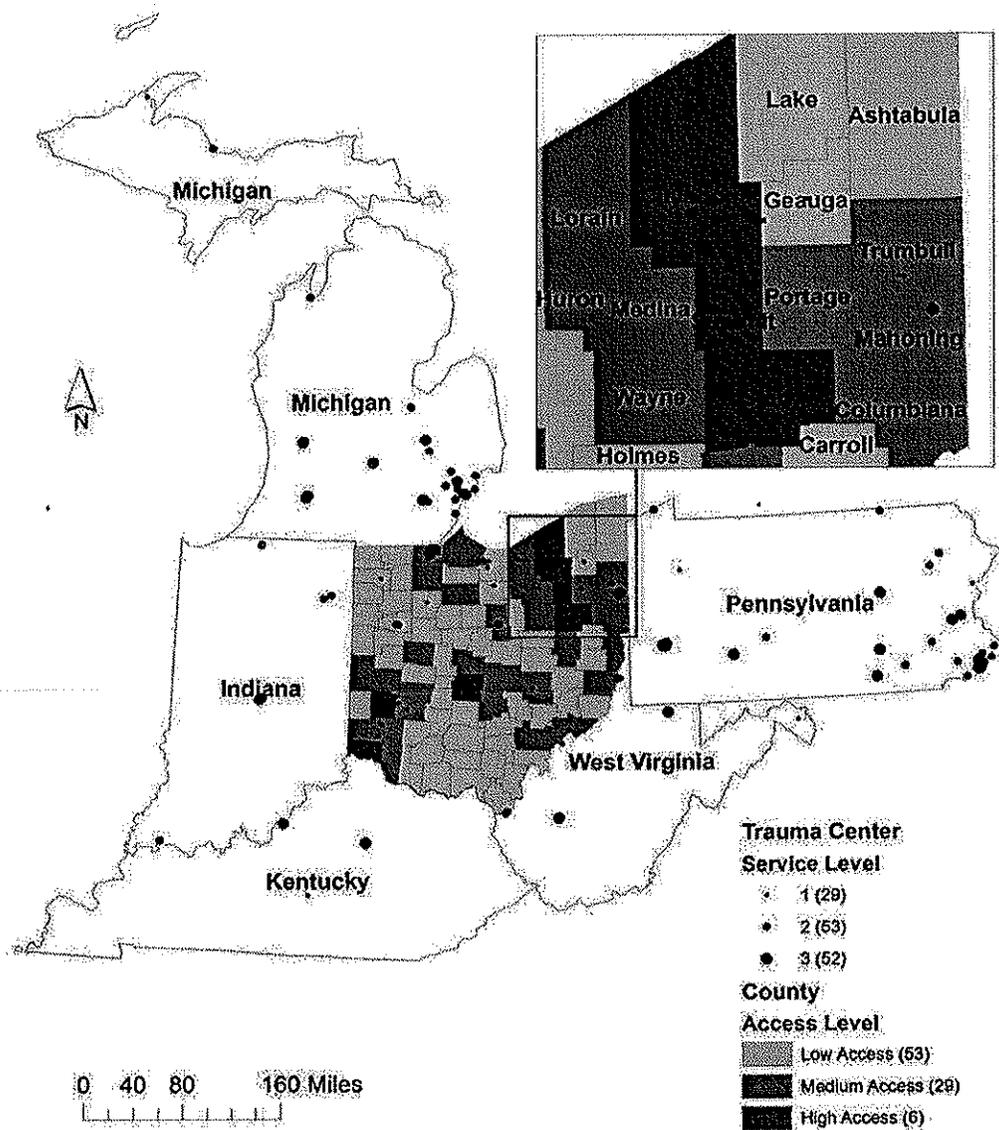


Figure 4. Access to trauma centers in Ohio by county.

The underserved index map of Ohio counties (Figure 5) identified counties of different underserved levels. The underserved levels range from high to low; high score indicated that the county was in a great need of service (high hospital trauma patient discharge volume and low access) while a low score indicated that the county was relatively well served (low hospital trauma patient discharge volume and high access).

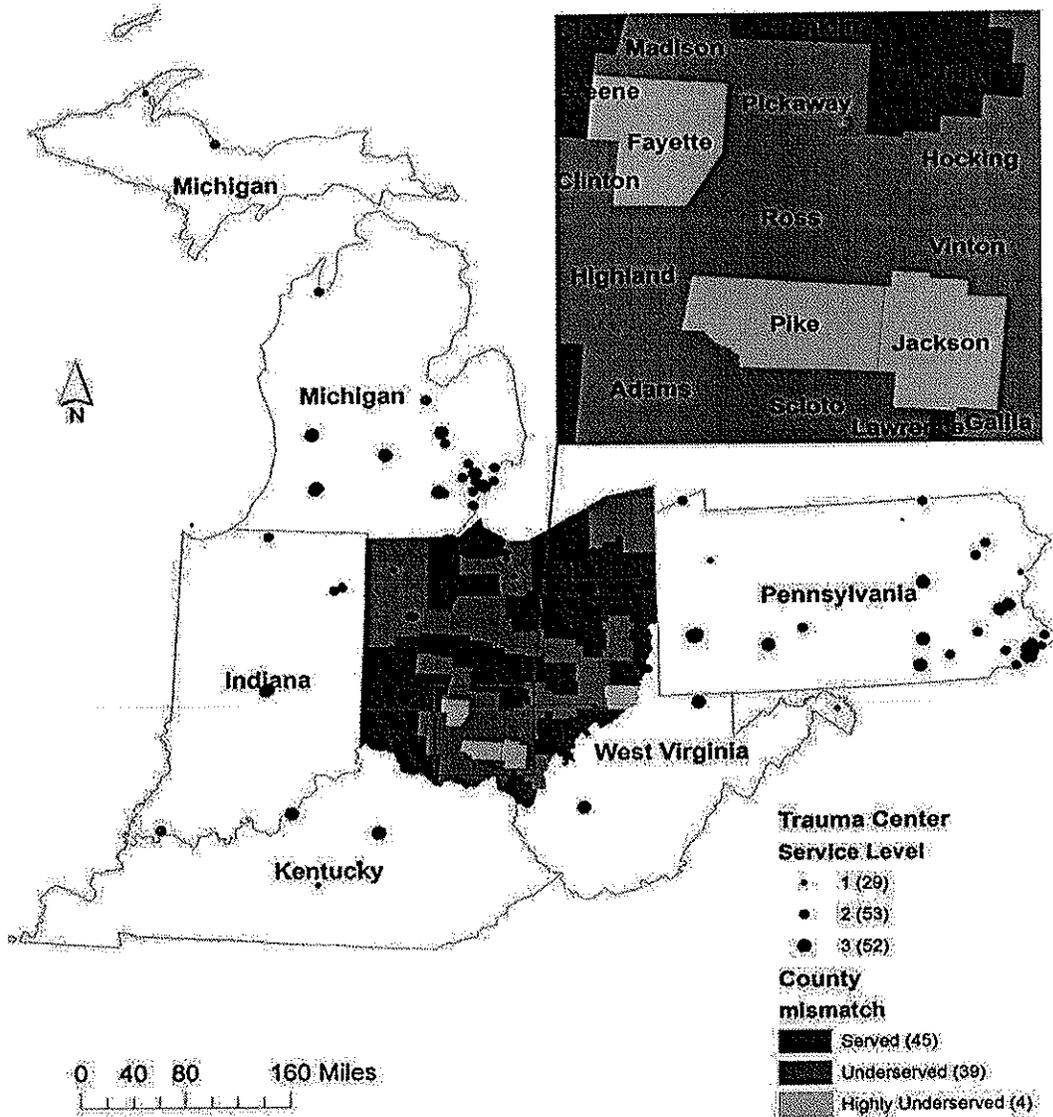


Figure 5. Underserved Counties

Table 1 shows the ranking of top 10 served and underserved counties, respectively. The degree of being served or underserved was calculated for each county by comparing the underserved index (UI) of that county with the mean and median UI of all counties. For example, Franklin County was about 10 times better served than an average county (percentage of mean UI=10%) while Monroe County was about 4 times underserved than an average county (percentage of mean UI=388%). If one chooses only one subregion to develop a new trauma center, Southern Ohio should be among the first region to consider.

Table 1. Ranking of served and underserved counties

Served Counties Top 10				
County	UI	Rank	Percentage of Mean UI	Percentage of Median UI
Franklin	3	1	10%	12%
Hamilton	3	2	12%	13%
Cuyahoga	3	3	12%	14%
Summit	4	4	16%	19%
Montgomery	4	5	17%	20%
Stark	6	6	23%	26%
Wood	8	7	32%	36%
Mahoning	8	8	33%	38%
Lucas	9	9	33%	38%
Belmont	10	10	37%	42%
Underserved Counties Top 10				
County	UI	Rank	Percentage of Mean UI	Percentage of Median UI
Monroe	100	1	388%	443%
Fayette	84	2	326%	372%
Jackson	77	3	298%	341%
Pike	68	4	266%	304%
Hocking	51	5	200%	228%
Morgan	51	6	199%	228%
Adams	51	7	197%	225%
Defiance	48	8	188%	214%
Coshocton	44	9	169%	194%
Crawford	42	10	164%	187%

5. Discussion

Results of the gravity model at the zip code level suggested that location of trauma centers and travel times were the two biggest factors in deciding accessibility. This finding is consistent with the conclusion from previous research (20) which also identified distance to service location as the most important factor. High access regions correlated well with clusters of trauma center locations and overall accessibility tapered off from the center of the cluster.

Based on the parameter setting recommended by a previous research (14), we obtained a 60 minute drive time accessibility pattern by using 0.6 as the travel friction coefficient. The distance decay pattern looked reasonable on the Ohio map when using this coefficient threshold. Our results confirmed the viability of using a travel friction coefficient as an effective proxy to calculate drive time. This is much more economical way of estimating travel time than using network-based measure.

Given the available hospital trauma patient discharge data we identified underserved areas by comparing revealed accessibility with potential accessibility. Previous studies identified underserved areas by aggregating variables that represented disadvantageous population groups (21). Those variables worked well to some degree but they were still demographic measures rather than actual clinical measures. In our study, we incorporated hospital patient discharge data into identifying underserved regions, which has not been done previously. The underserved counties map revealed big mismatch between real access (total hospital trauma patient discharge) and potential access (accessibility index) at the county level. Such results may be used by policy makers to identify counties with unmet need.

Our study has several limitations. Discrete classification of accessibility values was subject to interpretation as the classification results largely depended on the classification method chosen. The supply capacity variable was set to be a same constant for all supply locations in our analysis because we did not have comprehensive data about the capacity of each trauma center. This study was also restricted to spatial accessibility evaluation, demographic factors like income, which could potentially affect access to transportation, were not considered.

Nonetheless, GIS has been shown to be a powerful tool in integrating different sources of data and visualizing results on a map. Hospital location data and demographics data could be easily integrated on a spatial basis using GIS. Spatial patterns could be quickly identified by looking at clusters on a map rather than by querying raw data tables. Accessibility can be modeled and analyzed using capabilities of a GIS, which may not be always available elsewhere.

6. Conclusions

Ensuring good accessibility is an important first step to improve trauma care. However, evaluation of trauma center accessibility is difficult when both spatial and nonspatial factors are involved. This study implemented a GIS-based gravity model to evaluate accessibility to trauma centers in Ohio and further identified the distribution of underserved counties. In this study, we adapted the classic gravity model and introduced two modifications: the introduction of a weight parameter for factoring trauma center service levels and a method of transferring the accessibility results to different geographic levels. Both modifications were shown to be necessary for the final step of identifying underserved areas at a county level.

By incorporating hospital discharge data, for the first time we have identified the mismatch between simulated results and real world situations. Based on the ranking of underserved areas, policy makers are provided with scientific evidence to potentially develop more clear destination protocols to ensure appropriate triage of injured patients from the field to the appropriate trauma center based on trauma center level, proximity, and patients at risk. Local agencies with statutory authority in Ohio can also use these findings to establish a transparent evidence-based process for future designation of trauma centers and ongoing re-designations.

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