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Spatial methods for evaluating critical care and trauma transport: A scoping review

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ABSTRACT

Purpose: The objective of this scoping review is to inform future applications of spatial research regarding transportation of critically ill patients. We hypothesized that this review would reveal gaps and limitations in the current research regarding use of spatial methods for critical care and trauma transport research.
Materials and methods: Four online databases, Ovid Medline, PubMed, Embase and Scopus, were searched. Studies were selected if they used geospatial methods to analyze a patient transports dataset. 12 studies were included in this review.
Results: Majority of the studies employed spatial methods only to calculate travel time or distance even though methods and tools for more complex spatial analyses are widely available. Half of the studies were found to focus on hospital bypass, 2 studies focused on transportation (air or ground) mode selection, 2 studies compared predicted versus actual travel times, and 2 studies used spatial modeling to understand spatial variation in travel times.
Conclusions: There is a gap between the availability of spatial tools and their usage for analyzing and improving medical transportation. The adoption of geospatially guided transport decisions can meaningfully impact healthcare expenditures, especially in healthcare systems looking to strategically control expenditures with minimum impact on patient outcomes.

Contents

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1. Introduction

Medical transportation, which for the purposes of this paper refers to the movement of both critical care and trauma patients to care using ground or air vehicles, is affected by a breadth of environmental variables such as weather and seasonality, time of the week and day, population density, built environment, traffic patterns, and many other factors [1-5]. Prompt travel time allows for patients to arrive at definitive care within an appropriate time frame, critical for improved patient outcomes [6]. Due to the geographical nature of medical transportation and the importance of timely transportation, spatial methods, often implemented in Geographic Information Systems (GIS) that allow for the organization and analyses of spatial data, have only recently and sparingly been used to study the use of medical transportation.

While the tools for developing, and implementing more robust spatial methodologies are in place, the extent to which a majority of studies in this subject area have analyzed medical transportation involves the relatively simple task of using a GIS to measure travel time and distance. Spatial effects (e.g., spatial autocorrelation of data) and more complex spatial analyses are rarely considered in this field, as researchers predominantly use *aspatial* modeling methods. This occurs, despite a rich literature in the fields of public health and epidemiology, transportation, and medical geography that employs a wide range of sophisticated spatial methodologies that allow for more accurate predictions and assessments [7-9].

Given other health fields have successfully accounted and controlled for spatial heterogeneity in their analyses, the objective of this review is to investigate research regarding the transportation of trauma and critically ill patients to determine the types of geographic methods used in this distinct field. The intention of this scoping review is to serve as a resource to inform future applications of spatial research regarding transportation of critically ill patients. We hypothesized that this review would reveal gaps and limitations in the current research, as well as provide suggestions for future directions. Ultimately, as healthcare systems continue to seek opportunities to curtail costs while improving patient safety and outcomes, this work establishes the current state of the art regarding geospatial methods that may have utility for the evaluation of critical care and trauma transport.

2. Methods

2.1. Eligibility criteria

The “PICO” question for this review was: for trauma or critical care patients requiring emergency transportation to a care facility (P), do geospatial analyses (I), as compared to conventional aspatial analysis (C), provide additional information (O) that can help inform decisions, epidemiology, and planning for emergency medical services researchers? Prospective (i.e., randomized controlled trials) and retrospective studies were included (i.e., cohort, case-cohort, and case-control) for this review. Eligible studies for this review included those that employed a geospatial analysis on a dataset of patient transports to evaluate either the travel aspect of emergency medical services in a prehospital setting (travel to reach the incident scene, travel from incident scene to hospital, or both) or patient transfers in an inter-hospital setting. Eligibility was not limited based on participant condition since the objective of this review was aimed at evaluating the geospatial methods used in each study and excluding studies based on this criterion would potentially lead to the exclusion of important methodological contributions. Therefore, all studies that involved trauma and critical care, as well as adult and pediatric participants were included. No language, year of publication, or publication status restrictions were applied when considering studies for inclusion.

2.2. Information sources

The following four electronic databases were searched on January 4th, 2017:

- Scopus (1960 to 4 January 2017)
- Ovid MEDLINE (1946 to December Week 1 2016) + Ovid MEDLINE In-Process & Other Non-Indexed Citations (1946 to 4 January 2017)
- Ovid Embase Classic + Embase (1947 to 4 January 2017)
- PubMed (1964 to 4 January 2017)

2.3. Search

For each database, the title and abstract fields were searched using the keywords: (“emergency medical services” OR “air ambulance” OR “ground ambulance” OR “patient transfer” OR “ambulance”) AND (“geographic information systems*” OR “G.I.S.” OR “GIS” OR “spatial analysis” OR “spatial statistics” OR “spatial information” OR “spatial model”). The keywords were selected by two authors (Y.V. and M.W.) and were narrowed down to the above through preliminary searches and assessment of results. The above search strings provided the most relevant results for this review.

2.4. Study selection

The results from each of the databases were downloaded and aggregated together into a single file, after which any duplicates were removed. Two authors, (Y.V., M.W.) screened all the articles by title and abstract using the above inclusion criteria and sorted the articles into “include,” “exclude,” and “uncertain” categories. The results for each of the categories were compared and discussed between the two authors. Articles in the “uncertain” category were assessed for inclusion using the full-text and included if they were found to fit the criteria. One additional article was added to be a part of the review because it was referenced in one of the articles identified via the previously described search query and it fit the selection criteria. Studies were primarily excluded if they did not focus on medical transportation. Those with a focus on medical transportation were further excluded if they were

Table 1
Summary of findings.

Authors	Study area	Scale	Focus	Mode	Type	Dataset	Sample size	Consider health outcomes?	Spatial methods	Statistical model	Dependent Var in stat model	Environmental Var considered?	Spatial dependence considered?
Doumouras et al. [10]	Toronto, Canada	CT	HB	G	IC	R	898	No	N	Logistic regression	P(triaged to a trauma center)*	No	No
Acosta et al. [11]	California, USA	S	HB	G	IF	R	2798	No	ED	Generalized linear model	1. Transfer in-catchment 2. Transfer out-of-catchment	No	No
Earnest et al. [2]	Singapore	CT	SV	G	RT	R	2252	Yes	N	Conditional autoregressive	Ambulance response time	Yes	Yes
Lerner et al. [12]	USA	C	TM	B	FP	R	2516	No	N, SU	–	–	No	No
Widener et al. [13]	Maryland, USA	S	TM	B	IC	R	2208	No	N, ED, SU	–	–	No	No
Patel et al. [4]	Calgary area, Canada	CT	AV	G	FP	R	29,765	No	N	–	–	Yes	No
Asimos et al. [14]	North Carolina, USA	S	HB	G	ICl	R	2624	No	N	–	–	No	No
Taylor et al. [5]	New South Wales, Australia	S	HB	H	FP	R	464	No	N	Logistic regression	P(transported to closest facility)	Yes	No
Chen et al. [1]	Kaohsiung City, Taiwan	CT	SV	G	IC	R	4967	Yes	N, SU	Logistic regression	P(patient survival)	Yes	Yes
Patel et al. [15]	North Carolina, USA	S	HB	G	IC	R	301	No	N	–	–	No	No
McMeekin et al. [3]	Northeast England	RE	AV	G	IC	R	10,156	No	N	Generalized linear model	Prediction error	Yes	No
Cudnik et al. [16]	Parts of Canada and USA	RE	HB	G	IC	P	7540	Yes	N, ED	Logistic regression	P(survival to hospital discharge)	No	No

Scale: CT = City, S = State, RE = Regional, C = County.
Focus: HB = Hospital bypass, AV = Actual vs GIS predicted transfer times, TM = Transport mode selection, SV = Spatial variation.
Mode: G = Ground transportation, H = Helicopter transportation, B = Both ground and helicopter.
Type: IC = Scene of trauma incident to care, RT = Response time, FP = Full pre-hospital time (activation to care), IF = Inter-hospital.
Dataset: R = Retrospective, P = Prospective (observational, multi-center, population-based cohort study).
Spatial methods: NA = Network Analysis, SU = Surface Interpolation, ED = Euclidean Distance.
* P(outcome) = Probability of that outcome.

found to not used any spatial methods, focused on simulation, spatial optimization of or access to services, or did not analyze a patient transport dataset. Additionally, studies that were classified as reviews were excluded.

2.5. Data collection process

Data were collected by one author (Y.V.) into a summary of findings table (Table 1). Upon completion, all articles were reviewed a second time to confirm the validity of the data collected.

2.6. Data items

A list of all summary variables can be found in Table 1.

2.7. Risk of bias in individual studies

The common sources of bias that were identified across several studies included missing records, data validity, and missing confounding variables. However, given the primary focus of this review is to understand the scope of spatial methodologies used in medical transport research, the authors did not perceive these sources of bias to have any impact on the results of this review.

2.8. Summary measures

The principal summary measures were the types of spatial methods, statistical models, and environmental variables, as well as whether spatial dependence was considered. Studies were evaluated based on the extent to which they used spatial methods and spatial modeling, the breadth of environmental variables considered, and whether the authors acknowledged the potential for spatial dependence in their datasets and how this was dealt with.

2.9. Synthesis of results

The measures for each of the studies were organized into a summary chart found in Table 1. A description of each of the characteristics collected can be found in the “Data Items” section. Based on the results of this chart, common themes were developed and studies were categorized for a better understanding of how and why previous methodologies were used.

2.10. Risk of bias across studies

Publication bias and selective reporting were assessed, but were found to have no effect on the results of this review since the objective of this review is to assess methodology and not outcomes.

3. Results

3.1. Study selection

Fig. 1 depicts the screening and selection process, including the articles that were excluded at each stage. A total of 314 records were identified by searching the four databases using the search strings outlined in the “Search” section. All the records were aggregated and any duplicates were removed. After this step, the remaining 157 articles were screened by title and abstract by two authors (Y.V. and M.W.) against the exclusion criteria. The exclusion criteria were developed to help guide the authors in assessing which articles were inappropriate for the review and for what reasons. The criteria were used in a logical

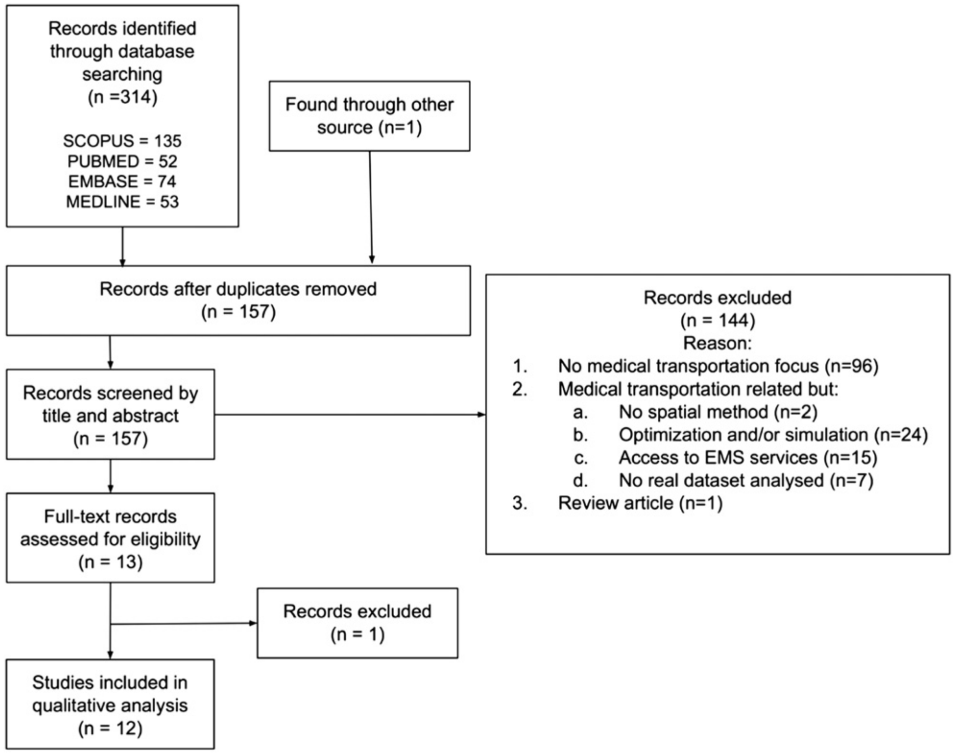

Fig. 1. PRISMA diagram of the selection process.

order where each article was compared against each criterion and excluded if met any of the conditions.

3.2. Study characteristics

A summary of the characteristics extracted from each of the articles included in this review can be found in Table 1. A majority of studies were found to have a "hospital bypass" focus [5,10,11,14-16] in which the primary objective was to evaluate the situations in which medical teams bypassed the closest hospitals to travel further to care. All but one study [5] in this focus category examined ground transportation. Only one of the studies looked at health outcomes [16]. With the exclusion of Acosta et al. [11], all studies in this category used network analysis tools to calculate road network distances (as opposed to straight-line distance). Four out of the six studies used statistical modeling [5,10,11,16]; however, none considered spatial dependence in their datasets and out of all the articles in this category only Taylor et al. [5] considered environmental variables other than travel time or distance.

Two studies [3,4] were found to have a common focus of comparing the predicted transport duration using GIS software to recorded travel times to determine when GIS software under- or over-predicts travel times. Both studies examined only ground transportation, used network analysis tools to calculate network distances, and one of the two papers used a statistical model for modeling prediction error [3], but did not consider the potential of spatial dependence in the observations. Due to the nature of these two studies' focus, extensive consideration was given to various environmental variables and how they might affect under- or over-prediction.

Studies classified as having a "transportation mode selection" focus [12,13] compared travel times between ground and air travel. Both studies used network analysis to calculate network distance for ground travel times and used straight-line distance to estimate air travel times. Surface interpolation was used in both to evaluate when either mode yields shorter travel times. Neither of the studies used any statistical modeling, or considered any environmental variables other than distance and time in their analyses.

The spatial modeling category included two articles [1,2] that had a common goal of understanding why medical transfers vary in space in relation to environmental variables. Both studies looked at patient outcomes, focused only on ground transportation, and used network analysis. Chen et al. [1] also used kriging, a spatial statistical method that considers spatial dependence between observations, and used a logistic regression model to predict patient survival to discharge. Earnest et al. [2] used a conditional autoregressive model, considering spatial dependence in the observations, to predict ambulance response time. Both studies looked at a variety of environmental variables, such as traffic conditions, population density, place of incident (residential, commercial, transportation accessible etc.), day of the week and time of day. These were the only two studies in this review that considered spatial dependence in the observations and attempted to correct for any violation of assumptions caused by such dependence.

3.3. Risk of bias within studies

Bias within individual studies was assessed for but was not found to have any effects on the results of this review.

3.4. Synthesis of results

In this section the main findings that relate to spatial variables will be reported for each study to assess how effective each methodology was at revealing the effects of environmental variables on medical transportation.

3.4.1. Hospital bypass

Using logistic regression to predict triage to a trauma center for trauma patients, Doumouras et al. [10] found that a lower difference in distance between the closest hospital to an incident site and the nearest trauma center results in patients being more likely to be triaged to the trauma center. Acosta et al. [11] did not find a significant difference between using straight-line and network distances, and therefore used straight-line distances in their analysis and found inappropriate triage decisions for "out-of-catchment" and "in-catchment" transfers. Asimos et al. [14] calculated network distances to the facility where patients were taken to, in addition to all the facilities bypassed, to assess rates of hospital bypass before and after a policy implementation. Taylor et al. [5] calculated network distances between trauma incident sites and the closest hospital and closest trauma center. The researchers found that trauma patients are less likely to be transported to the nearest hospital if it is classified as rural or regional, and if the transfer is handled by an urban helicopter EMS provider. Patel et al. [15] used network distance to find that facilities are more likely to be bypassed in an urban setting where distance to specialized care is shorter. Finally, Cudnik et al. [16] found that survival for Out-of-Hospital Cardiac Arrest (OHCA) patients is not associated with travel distance and that instead transport to a closer non-specialized care facility results in lower odds of survival.

3.4.2. Actual vs GIS predicted travel times

Patel et al. [4] used ArcGIS software (a popular commercial GIS; ESRI, Redlands, CA) to predict the time lapse from ambulance activation to care facility and compared the results to actual recorded times. The authors found systematic under prediction when using the GIS software to estimate transport times, and that the extent of under prediction varies with different built environments. However, the authors did not report whether they adjusted road network speeds to accommodate faster ambulance travel times, which potentially affects the accuracy of their results. McMeekin et al. [3] had similar findings to Patel et al. [4] where they found systematic under prediction of travel times for long rural transports, very short urban transports, winter months, and transports that occurred during peak traffic hours. However, McMeekin et al. [3] failed to report what GIS software they had used for their analysis, making it difficult to compare findings.

3.4.3. Transportation mode selection

Widener et al. [13] used network analysis tools to interpolate a geographic surface showing the spatial differences in travel times associated with helicopter and ground EMS transportation modes. The authors suggest that helicopter EMS does not always provide faster travel, and in certain cases the time trade-off between the two modes is negligible. Similarly, Lerner et al. [12] used the same methods to designate regions as "air zones" and regions as "ground zones" to guide decisions regarding EMS transportation mode selection.

3.4.4. Spatial modeling

Earnest el al [2]. found that ambulance response times are lower in light to moderate traffic conditions, weekends, outside of morning and evening peak hours, and depend on place of incident. The authors also found spatial dependence in their dataset and stressed that ignoring this dependence will lead to artificially low standard errors for the regression coefficients. Therefore, they used a statistical model that considered this dependence. Chen et al. [1] dealt with spatial dependence in their dataset by using kriging, a spatial statistics method which interpolates a geographic surface that accounts for spatial autocorrelation in the data. The authors found that environmental variables, such as built environment and population density, have a significant effect on the odds of OHCA patient survival.

4. Discussion

4.1. Summary of evidence

In the past seven years, the use of spatial methods for studying medical transportation has become more popular. However, the variety of spatial methodologies used remains somewhat limited. Common topics have been hospital bypass (6), comparing actual vs. predicted travel times (2), transportation mode selection (2), and spatial modeling of transfers (2). Amongst these articles, spatial methods are commonly used solely to calculate travel distance and time, except for Earnest et al. [2] and Chen et al. [1], who employed more sophisticated spatial statistical methodologies to reveal important findings about the effects of environmental variables on medical transportation.

There appears to be no consensus on whether travel time, straight-line distance or network distance is the best measure to study, even though previous research has found straight-line distance to be a poor estimator for evaluating medical transportation [17]. In addition to this, distance, as a measure, should be used with caution since some of the studies included in this review have found that environmental variables have a significant effect on transportation times [1-5]. This means that although distance remains static, the time it takes to traverse that distance fluctuates through time as environmental variables change. Therefore, using distance to assess medical transportation may not be methodologically sound. For instance, Cudnik et al. [16] found that distance does not impact OHCA patients, and that patients transported to specialized care that bypass community hospitals have higher odds of survival. These authors acknowledge that travel time is affected by various environmental variables and yet use this as their main argument to use distance as their primary measure. Chen et al. [1], had similar findings in that OHCA patients' outcomes are better if community hospitals are bypassed. However, by using travel time instead of distance, the authors found that longer travel times decrease survival odds of OHCA. This demonstrates that using distance and time can lead to different findings, mainly because, in the reality of medical transportation, transfer time will always fluctuate in relation to environmental variables (e.g. traffic conditions, road network structure, weather) and therefore using time instead of distance will allow for a more accurate understanding of medical transportation.

As demonstrated by the articles included in this review, spatial methods can be effective at revealing important aspects about medical transportation. However, there remains a gap between the availability of spatial tools and their usage in medical transportation research, where, as was shown with this review, environmental variables and spatial dependence in observations are often overlooked. While in many of the reviewed articles GIS was only used for calculating distance and time, this tool can also be useful for linking patient transport datasets to important environmental variables such as population density, built environment, traffic, and weather. Data on these variables is increasingly available and accurate, especially with the development of tools such as historic and real-time traffic and weather feeds. For assessing spatial dependence in the observations, spatial statistical methods, such as Global and Local Moran's I [18] can be employed. Spatial regression models such as spatial econometrics and heterogeneity models [19,20], can be used to model medical transportation while accounting for spatial dependence in the observations, thus allowing for improved estimates.

Spatial methods offer advanced analytic options for prehospital medicine researchers. Since many transportation decisions in emergency medical services cannot be randomized, it is important to employ state-of-the-art observational analytic methods that may advance the science by carefully examining the specific elements of distance, time, and speed in relation to patient outcomes and use of expensive resources such as helicopters. One of the most advanced and promising methods that may be advantageous to use in this field is instrumental variable regression analysis. Instrumental variables may be used when random assignment of patients into exposed and unexposed groups is not possible. These methods have been shown to be effective for controlling selection bias in observational studies [21]. For instance, with a group requiring helicopter transport (exposed group), whether a patient is flown to a trauma center may depend on certain characteristics. If these characteristics are not measured, a variable may be omitted that may help explain the effect of the exposure and the positive or negative outcomes. Spatial modeling holds great promise for instrumental variable analysis because distance from a Level I trauma center can be treated as an endogenous variable (i.e., one whose variation is explained by other exogenous or endogenous variables in the model). Distance to a

Level I trauma center may be correlated with improved mortality because of helicopter transport (exogenous variable) and may be likely to be highly correlated with improved survival.

Spatial methods hold great promise for future work in this area because these methods allow researchers perform advanced analyses. Modern GIS software can precisely estimate time, distance, and speed, thereby controlling for multiple potential confounders. Unfortunately, as described in this review, the use of these methods remains sparse and limited.

4.2. Limitations

This review has several limitations, the first being that literature in this area is limited given that this is a relatively new application of spatial methods. Further, a meta-analysis and other advanced methods for pooling results was not possible since this review focused on describing the methods that have been used to date. Finally, one of the articles that fit the review criteria by Arthur et al. [22] was not available even after an interlibrary loan was requested.

5. Conclusion

This review revealed that there is a gap between the availability of sophisticated spatial methodologies and the extent to which they are employed in understanding medical transportation. In addition, except for Earnest et al. [2] and Chen et al. [1], none of the studies considered spatial dependence in their datasets and did not use any spatial modeling techniques to account for modeling and analysis issues that may arise because of such dependence. Based on the findings from this review, we recommend that future research focusing on medical transportation include environmental effects and account for spatial autocorrelation.

Increasing granularity within this research field offers a window to better deployment of resources. This can have infrastructure and financial implications for regional health settings as more efficient inter-facility transport may result in less overall cost and less total time taken for the scarce resources within a specific health system. Even if evaluating aspatial dependent variables like patient survival, transportation is inherently geographical and past work has found environmental effects to have a significant effect on medical transportation [1-5]. Ultimately, this review calls for the integration of more advanced and robust spatial methods for the evaluation of environmental effects on medical transportation.

Conflicts of interest

None.

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