Evaluating Spatial Associations in Inpatient Deaths Between Organ Procurement Organizations

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INTRODUCTION

In the United States, the Organ Procurement Organizations (OPOs) are responsible for the evaluation and procurement of deceased donor organs within their assigned donation service areas (DSAs). Eligible deaths, the current common denominator for many OPO performance metrics,1 are vulnerable to selective reporting and therefore biasing the results.2 The consequences of a self-reported measure that is underinclusive of true potential are only compounded by the differences between the OPOs: OPO performance is further influenced by differences in donor availability,3,4 DSA geography and demographics,5 and organ acceptance patterns of transplant centers in neighboring DSAs.6,7 Many of these are consequences of the geographic borders and locally oriented organ allocation.

To address these shortcomings, the 2019 Executive Order on Advancing American Kidney Health8 contained a mandate to improve OPO performance metrics. In response, the Centers for Medicare and Medicaid Services (CMS) proposed “inpatient deaths” to replace eligible deaths by changing “the OPO donation rate measure to the number of organ donors in the OPO’s service area as a percentage of inpatient deaths among patients 75 years old or younger from any cause of death that would not preclude donation (eg, organs from those with metastatic cancer and a recent history of cancer cannot be transplanted).”9 As with any new metric that would have wide-ranging effects, further evaluation with both traditional and novel methods is essential.

Geography, conceived as both the geographic borders that define organ allocation as well as the populations, resources, and infrastructure that these spaces contain, influences organ allocation and the practice of transplantation. It has been studied in access to transplantation,10,11 local measures of socioeconomic status,12 and spatial organization of transplant...
centers. Donations are also influenced by geographical and special characteristics, from geographic variation between state policies encouraging organ donation, local variation in donor registration, and social capital. Prior spatial analysis specific to OPOs reinforced the poor validity of eligible deaths: Cannon et al demonstrated spatial autocorrelation of potentially donation-eligible mortality patterns that was not observed for eligible deaths, but the analysis was not advanced to incorporate a spatial regression approach. Extending these spatial analytic principles, accounting for the fact that certain population characteristics of geographically proximate OPOs are more similar than OPOs that are further apart (Tobler’s first law of geography) and as demonstrated in Cannon et al could lead to a better understanding of the geographic variability in possible organ donors and therefore lead to increased deceased organ donation. The application of spatial analysis has potential applications as allocation shifts away from the OPO territories and to broader sharing.

Here, we aim to utilize spatial analysis to better understand and to appraise the CMS proposal of inpatient deaths. First, we explore the spatial relationships and patterns between the OPOs, causes of donation-eligible deaths, and inpatient deaths. We then extend the work of Cannon et al by modeling these in a bivariate fashion to determine if spatial analysis is appropriate. Next, we use clustering to create groups of similar OPOs to adjust the number of inpatient deaths, understanding their varying levels of donor potential, by accounting for the additional information available from geographic analysis based on its constituent parts. This approach to analysis would enable an assessment of how cause of death, the racial and ethnic demographics, and geography overlap and contribute to organ donation in the United States. Ultimately, this work aims to demonstrate how spatial relationships affect inpatient deaths and to argue for future spatial analysis in setting transplant performance metrics.

METHODS

Data Sources

Eligible deaths, OPO demographic characteristics, and a list of counties served by each OPO was obtained from the January 2018 OPO Specific Reports from the Scientific Registry of Transplant Recipients. This served as the source for eligible deaths for 2016 for each OPO, which was used for comparison to the prior work of Cannon et al.

Matching prior work, the top 5 causes of death among organ donors (gunshot, blunt trauma, overdose, cerebrovascular disease, and cardiovascular disease) were aggregated from counties using CDC WONDER20 from 2014 to 2016. To estimate the number of inpatient deaths according to the CMS proposal, we followed the CDC WONDER query of Snyder et al covering 2014 to 2016. In CDC WONDER, deaths are attributed to the home county of the decedent, not where death occurs, and data are not available to assign deaths to the counties in which they occur.

These data were derived from the following resources available in the public domain: OPO-specific reports (https://www.srtr.org/reports-tools/opo-specific-reports/) and CDC WONDER (https://wonder.cdc.gov/).

Statistical Analysis

Organ Donor Center of Hawaii (HIOP) was excluded due to distance affecting spatial weights, and Life Link of Puerto Rico (PRL) was excluded due to missing death cause data; this left 56 OPOs for analysis. Moran’s I (using queen contiguity) assessed spatial autocorrelation and identified geographic clusters of similar inpatient and cause-specific death rates. Bivariate analyses, measuring the spatial association between the inpatient death rate and each of the cause-specific death rates separately, were conducted to further understand the relationship and identify areas of geographic variability using bivariate local Moran’s I.

After establishing both univariate (global) spatial dependencies with Moran’s I and bivariate (local) spatial dependencies with bivariate local Moran’s I, we executed a clustering procedure using all those 6 variables to investigate existence of clusters. To do that, we have considered 3 different clustering procedures, and then they were compared based on the tool called “within cluster sums of squares” (WCSOS); and the final clustering procedure will be selected based on smallest value of WCSOS. Here, we have considered 3 well-known methods: K-means clustering, hierarchical clustering, and ClustGeo, a hierarchical clustering with spatial constraints within R. We chose to proceed with ClustGeo as it produced smallest WCSOS compared with 2 other clustering procedures. Because ClustGeo contains spatial constraints and was the best-fitting model, we elected to use this method to account for all relevant variables, including the spatial clustering and causes of death consistent with organ donation. As ClustGeo incorporates spatial information in the clustering method, we find that it can be useful to use in the models to develop clusters among the OPOs. In this clustering procedure, for comparison of magnitude of relative contributions, we have standardized all the variables: by subtracting the group mean and dividing by the SD, giving each measure a mean of 0 and a SD of 1.

In the next phase, we used a multivariable linear regression procedure to examine the association between the inpatient death rates, the top 5 causes of death among organ donors, and the clustering variable. This regression model was also adjusted for other demographic variables of the OPOs. Given the large number of covariates and limited number of observations, a stepwise regression procedure was used to find the final parsimonious model, selected by Akaike Information Criterion. Further descriptions of the methods are included in the Appendix (SDC, http://links.lww.com/TXD/A305).

A P value <0.05 was used as criteria for statistical significance. No adjustments were made for multiple comparisons. All statistical analyses and data linkages were performed using R 4.0.2 (R Core Team, Vienna, Austria). Basic spatial analysis was conducted with GeoDa 1.14, and clustering was performed with the R package ClustGeo. Maps were made with QGIS 3.12.1 (QGIS Development Team, Open Source Geospatial Foundation Project, http://qgis.osgeo.org).

IRB Approval and Data Access

The Institutional Review Board of Partners Healthcare approved this study under a human subjects exemption, as it uses publicly available data. The compiled data that support the findings of this study are available in Harvard Dataverse at https://doi.org/10.7910/DVN/J1A4KS.

RESULTS

Establishment of Spatial Autocorrelation

First, we explored basic univariate measures of global spatial autocorrelation. The eligible death rate (per 100,000
population) was first mapped for each OPO (Figure 1A), which did not show significant spatial autocorrelation (Moran’s $I = 0.14$, $P = 0.109$). The lack of autocorrelation indicates a random association of eligible death rates among the OPOs, meaning that there is no spatial relationship in the data. The inpatient death rate (per 100,000 population) was then mapped (Figure 1B); here, significant spatial autocorrelation was observed (Moran’s $I = 0.54$, $P = 0.001$), which suggests that the data are subject to spatial analysis. Of note, the difference between eligible death rates and inpatient death rates was nearly 100-fold.

Next, we moved from univariate to the bivariate analysis, using bivariate local Moran’s I. This measurement identifies OPOs that have a high inpatient death rate and are surrounded by those with either a low- or high cause-specific death rate (e.g., gunshot wounds), as well as those with a low inpatient death rate and surrounded by a low- or high cause-specific death rate (Figure 2A–E). This demonstrated significant associations between all 4 types of outputs: high inpatient death rates with both high and low cause-specific death rates, as well as lower inpatient death rates that had both high and low cause-specific death rates ($P < 0.05$ for all

![Figure 1](image-url)
associations). The OPOs of high inpatient death rates generally had higher component death rates except for overdose deaths (Figure 2A). For OPOs with lower inpatient death rates, there are a number of high component death rates compared with lower inpatient death rates for overdose (Figure 2A), gunshot (Figure 2B), and blunt trauma (Figure 2C).

**Creation of the OPO Clusters**

The clustering analysis created 4 groups based on the relationship between geography, the 5 causes of death, and inpatient death rates: group A had 7, B had 13, C had 27, and D had 9 OPOs (Table 1; individual OPO categorization available in data repository). Inspecting the standardized means (Figure 3A), there were multiple associations between different death rates and inpatient deaths. There was also a clear geographic pattern (Figure 3B).

As noted in Table 1, the OPOs in group A were in the South, had the highest inpatient death rate, and were also significantly above average in gunshot, blunt trauma, cerebrovascular disease, and cardiovascular disease death rates. Group B was largely in the west and was significantly lower than the average in all rates, whereas group C was near the average for all rates and comprised OPOs in the Midwest and
actual inpatient deaths, indicating that the model could dis-
(12.5%) OPOs whose prediction was >10% different than 
actual and predicted inpatient deaths), which identified 7 
sus without. We also applied a percentage prediction error 
which suggested a better performance with clusters ver-
ification, the only group with a significant association (in 
spatial relationships in the assessment of common OPO per-
the number of organ donors within an OPO, but that 
number will vary between OPOs due to differing causes of 
death between the OPOs. Prior work has demonstrated a spa-
tural relationship between the pattern of eligible deaths among 
the OPOs; we undertook this work to (1) assess this relation-
ship among inpatient deaths and (2) demonstrate the role that 
geography and spatial associations play in the number of pos-
sible organ donors within an OPO and to understand how it 
could be used in future risk adjustment/performance assess-
ment. In this article, we propose a method to assess spatial 
relationships of inpatient deaths between OPOs to fully cap-
ture the benefit of geographical data in this new metric.

We began by examining spatial associations between the 
eligible death rate and the inpatient death rate among the 
OPOs. In agreement with Cannon et al,18 we failed to find a 
geographic pattern in the eligible death rate (Figure 1A), but 
there was a significant geographic association related to the 
ineligible death rate (Figure 1B). This significant association 
prompted us to pursue further spatial analytic methods; if 
Moran’s I had not been indicative of a spatial relationship/ 
component between inpatient deaths and geography, we 
would have otherwise proceeded with standard bivariate and 
multivariate analysis. We then measured the bivariate 
association patterns (Figure 2), which were ultimately simi-
lar to the patterns consistent with the regression analysis. 
This extension to bivariate spatial analysis is an important 
extension of prior work because it strengthens the cause for 
performing clustering and ultimately regression analyses.

Clustering was used to create cluster groupings based on 
the 5 most common causes of death for deceased organ 
donors and inpatient deaths. This identified a group of OPOs 
(Table 1 and Figure 3) with a greater rate of inpatient deaths 
(groups A and D), average rate (C), and lower rate (group 
B). The groupings were largely driven by the cause-specific 
death rates (Figure 3A), and identifying them as groups allows 
for further adjustment of the number of inpatient deaths and 
 donor potential. Moreover, there were significant geographic 
associations in the race/ethnicity makeup, as well as the age 
distribution (Table 2).

After combining all analyzed factors into a multivariate 
model, the cluster groupings remained significantly associated 
with inpatient deaths (Table 3); in other words, even when the 
demographic characteristics and death rates are accounted for, 
a spatial relationship persists and helps to better explain the 
number of inpatient deaths. This analysis argues for including 
spatial relationships in the assessment of common OPO per-
formance measures. Moreover, this shows which OPOs have 
more potential donors and therefore could be used to iden-
tify high- and low-performing OPOs to better understand and 
define best practices. These techniques can be extended to take 
advantage of more rich geographic data in the future, consid-
ering healthcare resource availability, differential patterns of 
infection and causes of death, and socioeconomic data.

### TABLE 1.
Components of spatial clustering by grouping

| Death rates (per 100 000 OPO population) | Overall (n = 56) | Group A (n = 7) | Group B (n = 13) | Group C (n = 27) | Group D (n = 9) |
|------------------------------------------|-----------------|----------------|-----------------|-----------------|----------------|
| Inpatient                                | 299.1 (8.99)    | 425.1 (13.1)*  | 224.4 (7.3)*    | 290.2 (6.8)     | 335.6 (6.3)*    |
| Gunshot                                  | 33.6 (1.52)     | 49.1 (2.9)*    | 27.2 (2.3)*     | 33.7 (2.1)      | 30.3 (3.1)      |
| Blunt trauma                              | 75.7 (2.44)     | 90.2 (3.8)*    | 67.0 (4.1)*     | 80.0 (4.0)      | 76.3 (4.6)      |
| Overdose                                  | 53.3 (3.03)     | 49.4 (7.0)     | 35.6 (3.4)*     | 55.1 (4.2)      | 77.7 (6.4)*     |
| Cerebrovascular disease                   | 135.1 (3.25)    | 157.8 (5.0)*   | 106.1 (3.7)*    | 136.2 (3.7)     | 156 (4.0)*      |
| Cardiac disease                           | 619.9 (17.8)    | 754.0 (16.3)*  | 440.4 (13.7)*   | 611.2 (10.7)    | 801.0 (15.5)*   |

Values are mean death rates (per 100 000 OPO population) of the components of the spatial clustering with standard errors presented parenthetically. Asterisks indicate significant associations relative to the group mean ($P<0.05$).

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There are limitations to the current work. Spatial statistics is subject to data quality and the ecological fallacy, as an individual may die in a hospital within an OPO’s DSA that differs from the OPO that covers the area inclusive of the decedent’s place of residence. Therefore, the dataset as utilized could misattribute death to the OPO where the decedent resides rather than where the decedent’s death actually took place (and therefore, where the opportunity for donation would have occurred). In the absence of other information, we would expect that effect to be relatively small among the 56 OPOs included in the study, although we note this could include deaths that occur while an individual is traveling as well as circumstances where a decedent lived on the border of 2 different OPO DSAs and underwent medical treatment in a different OPO’s service area than the decedent’s residence.

The present study intentionally does not assess the validity or usefulness of inpatient deaths as the denominator for OPO performance metrics, which would most likely be better assessed with direct patient-level characteristics that would not require other adjustments for OPO performance measurement. The process of converting inpatient deaths to an actual

FIGURE 3. A, Standardized mean values of the component rates of the grouping. Errors indicate a 95% confidence interval. B, Clustered map based on the inpatient death rate for the 56 continental OPOs. The groups were created via a hierarchical spatial clustering method with the inpatient death rate and top 5 causes of donation-eligible death rates within each OPO. Map created with QGIS 3.12.1.
organ donor is complex, and therefore it is not particularly sensitive to all the parts of the donation process that affect the final outcome of donors and the organs recovered (e.g., critical care, consent from donor or family, optimization of recoverable organs). This analysis cannot account for population growth and changes over time, nor can it assess for out-of-hospital deaths that may be appropriate for uncontrolled donation after circulatory death. Ultimately, we believe that these weaknesses are overcome because this approach is novel, is supported by prior work, and provides a method for more refined comparisons between OPOs.

In conclusion, we found a significant spatial/geographic component associated with inpatient deaths. This is to be interpreted in the context of the other contributing factors, namely the cause of death, age distribution, and racial/ethnic composition; these overlaps with the geographic component. Our analysis is timely and important because this modeling approach represents a method to assess policy and practice change by both the Organ Procurement and Transplantation Network and CMS. This method provides a useful platform for understanding geographic patterns among possible organ donors to drive quality improvement by improving the risk adjustment used to evaluate OPO performance. Ultimately, it is hoped that this will ultimately increase deceased donation and organ availability in the United States.

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