Spatial Analysis of Drug Poisoning Deaths and Access to Substance-use Disorder Treatment in the United States

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Abstract: Mortality rates from drug overdose have increased exponentially throughout the US for the past 30 years. Age-adjusted death rates from drug poisoning for 1999-2016 were analyzed at the county level using space-time cube and hot spot analysis, and a composite index of patient access to substance-use disorder treatment and services per each county has been calculated. More than two-thirds of all US counties have been classified as hot spots. Combining mortality hot spots with the accessibility index highlights 81 counties with high disease burden and low access to treatment providers. These areas deserve special attention as state and local government and public health organizations seek new prevention and intervention strategies to address the opioid epidemic.

1 INTRODUCTION

Substance-use disorder epidemic continues to rage through the United States, and the mortality rates from drug overdose have been increasing exponentially over more than 30 years (Jalal et al., 2018). According to the Center for Disease Control, the age-adjusted rate of drug overdose deaths in the country was more than three times higher in 2016 than in 1999 (Hedegaard et al., 2017), with considerable variation in mortality rates across the United States (Rossen et al., 2013). While scientific evidence suggests that medication-assisted treatment (MAT) is effective in treating substance-use disorders, only ten percent of people with this disorder receive any type of specialty treatment (U.S. Department of Health and Human Services, 2016). Three medications - methadone, buprenorphine, and naltrexone – are safe and effective in treating substance use disorder and opioid addiction, but their availability at treatment facilities in the U.S. is still limited (Jones et al., 2018). A recent survey of facilities providing addiction treatment services revealed that “61% of counties in the U.S. did not have any treatment programs that offered at least one MAT drug” (amfAR, 2018).

While several studies used GIS to analyze spatial patterns of the opioid epidemic (Jalal et al., 2018; Jones et al., 2018; Rossen et al., 2013; Stewart et al., 2017), only one study used GIS and clustering to examine spatial access to treatment and services, focusing on buprenorphine provider availability (Jones et al., 2018). In this research, spatial and temporal patterns of drug poisoning death rates are compared with patterns of access to facilities with MAT, with the goal of identifying priority areas for improving access to MAT. Specifically, this paper addresses the following two research questions: Where are the hot spots of drug poisoning death rates? How are resources for treatment and recovery distributed within these hot spots? The unit of analysis is a United States county, a political and administrative division within a state.

2 DATA

To understand where the drug overdose epidemic is the most pronounced, age-adjusted estimates of drug poisoning deaths per 100,000 per county were obtained from the amfAR Opioid and Health Indicator Database (https://opioid.amfar.org/). These estimates are based on deaths resulting from the following underlying causes: unintentional poisoning, intentional/suicidal poisoning; homicidal poisoning; and poisoning from undermined intent

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(Rossen et al., 2017). Annual estimates of death rates covered period from 1999 to 2016, allowing for a spatio-temporal analysis and identification of hot spots.

To characterize availability and access to treatment and services, the study used the following indicators about medical facilities and providers:

- Number of Facilities Providing Substance Abuse Services;
- Distance to Nearest Substance Abuse Facility providing MAT;
- Number of Facilities Providing at least one, at least two, or all three medications used in the treatment and Accepting Medicaid (three indicators);
- Number of Providers Licensed to Administer Buprenorphine.

Higher number of facilities and shorter distance to the nearest substance abuse facility providing MAT means better availability and access to treatment and services.

As of March 2017, private for-profit organizations operated 60 percent of facilities with opioid treatment programs certified by the Substance Abuse and Mental Health Services Administration

(Substance Abuse and Mental Health Services Administration, 2017), meaning that some parts of the country lack affordable options for any treatment (U.S. Department of Health and Human Services, 2016). To include the affordability aspect, this research analyzes facilities that provide MAT and also accept Medicaid, a government health care program. It is important to differentiate between the facilities that provide only one, or two, or all three medications because providing multiple options for MAT increases chances of a successful treatment. A separate variable on buprenorphine providers is also included, because buprenorphine has several advantages over the other two medications, including the option of receiving weekly or monthly prescriptions in the general office setting (Jones et al., 2018). Physicians, physician assistants, and nurse practitioners who have received specific training and obtained a waiver to prescribe buprenorphine for treatment of opioid use disorder are separate from providers working at the substance abuse facilities, so it is important to include them in the analysis.

All indicators mentioned above were downloaded in a tabular format from the amfAR Opioid and Health Indicator Database. To map these indicators, GIS layer of county boundaries was downloaded from the U.S. Census Bureau (https://www.census.gov/geo/maps-data/data/cbf/cbf_counties.html), and indicator tables were joined to GIS layer using county FIPS codes. There are 3142 counties in the United States. Table 1 provides details about data used in this study.

3 METHODS

To identify spatio-temporal hot spots of drug poisoning mortality, first a space-time cube was created in ArcGIS Pro (ESRI, 2019). Space-time cube approaches were previously applied to analyze spatio-temporal patterns of traffic accidents (Cheng et al., 2019; Rahman et al.,, 2018), crimes (Bunting et al., 2018), and anthrax epidemics in livestock (Abdrakhmanov et al., 2017), but haven't yet been applied to drug overdose mortality.

Table 1: Indicators used in the study.

Description	Year
Age-adjusted Drug Poisoning Deaths per 100,000 (Modeled)	1999-2016
Number of facilities that provide substance abuse services (per 100,000)	2017
Average geographic distance in miles to travel to a substance use disorder treatment facility providing at least one form of MAT	2017
Number of substance abuse treatment facilities offering all three MAT services (Buprenorphine, Methadone, Naltrexone) and accepting Medicaid (per 100,000)	2017
Facilities providing at least two of the three forms of MAT and accepting Medicaid (per 100,000)	2017
Facilities providing at least one form of MAT and accepting Medicaid (per 100,000)	2017
Number of healthcare providers licensed to administer buprenorphine (per 100,000)	2018

Space-time cube is a collection of spatial units (in this case, counties) layered vertically according to time. The bottom layer of the cube corresponds to 1999, the earliest year in the dataset, and the top layer of the cube corresponds to 2016, the latest year. Thus, a particular county at a given year is referred to as a bin within the space-time cube. Following this, Emerging Hot spot analysis tool in ArcGIS Pro was applied to identify hot spots and cold spots of mortality. A hot/cold spot has mortality that is significantly higher/lower at a given time than the mean mortality for the entire space-time cube. This tool uses the Getis-Ord Gi* statistic and Mann-Kendall test (Getis and Ord, 1992) and categorizes hot/cold spots into several categories based on their temporal trends: new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, and historic (ESRI, 2019). To be considered a hot/cold spot, each bin is evaluated in the context of its spatial and temporal neighbors. Selection of the neighborhood parameter can influence the results, so the tool was applied multiple times with different neighborhood parameters to explore variation in the outcome.

To identify different levels of availability and access to treatment and services, a composite index of six indicators was created using the following procedure. First, indicators measuring the number of facilities or providers per county, were recalculated per 100,000 persons. It was necessary to normalize by population, because some counties are much more populated than others. Second, all six indicators were standardized to a range of 0-100 to be comparable, using the following formula:

$$X_{inew} = (X_{ioriginal} - X_{imin}) / (X_{imax} - X_{imin}) * 100$$

Where X_{inew} is the standardized value of an indicator *i* for each county, ranging from 0 to 100;

$X_{ioriginal}$ is the original value of an indicator *i* for a county;

X_{imin} is the minimum value of an indicator *i* for the entire country;

X_{imax} is the maximum value of an indicator *i* for the entire country.

Third, these standardized indicators were aggregated (using averaging) into a composite index of access to treatment and services (from here on referred to as "access index" for brevity). Averaging approach was used as the aggregation method because it weighs all indicators equally, is intuitive, and allows maintaining the same scale (0-100).

To answer the second research question ("How are resources for treatment and recovery distributed within hot spots?"), the access index and the hot spots were overlaid and examined using various "select by attribute" queries in GIS. The level of access to treatment and services for counties that fall inside hot spots was further evaluated state by state.

4 RESULTS

Space-time cube consisted of 3142 locations (counties) and 18 time slices resulting in 56,556 space-time bins. Emerging Hot Spot Analysis tool was used several times, with different configurations of neighborhood (contiguity with edges and corners; contiguity with edges only; eight nearest neighbors) to evaluate sensitivity. Resulting spatio-temporal patterns of hot/cold spots were very similar, with minor variations. Results reported below are based on the contiguity with edges and corners because this conceptualization of neighborhood was used in a previous study of the drug overdose epidemic in the United States (Jalal et al, 2018).

Figure 1 and Table 2 show distribution of hot and cold spots over the 18-year period. More than two-thirds of the counties (68%) experienced hot spot trends; 30% of counties did not show any pattern, and only 2% of counties experienced cold spot trends. Of the counties with hot spots, 50% were an "oscillating" hot spot, 37% - a "consecutive" hot spot, 11% - a "new" hot spot, and 1.5% - an "intensifying" hot spot. While significant hot spots are present in every state, there is considerable variation in the extent of the hot spots within each state (Map 1). For example, some states have only a few counties in hot spots (Dakotas, Nebraska, Kansas, Iowa, New York), while other states are entirely covered with hot spots (Washington, California, Nevada, Utah, New Mexico, Michigan, Oklahoma, Florida, Tennessee, West Virginia, Vermont, New Hampshire, Maine, Massachusetts). There was a small number of counties with cold spots, clustered in North Dakota, South Dakota and Nebraska. Even though these areas show rates lower than the national mean, they are in diminishing and historic cold spot categories, meaning that the rates are increasing and areas are becoming less cold over time.

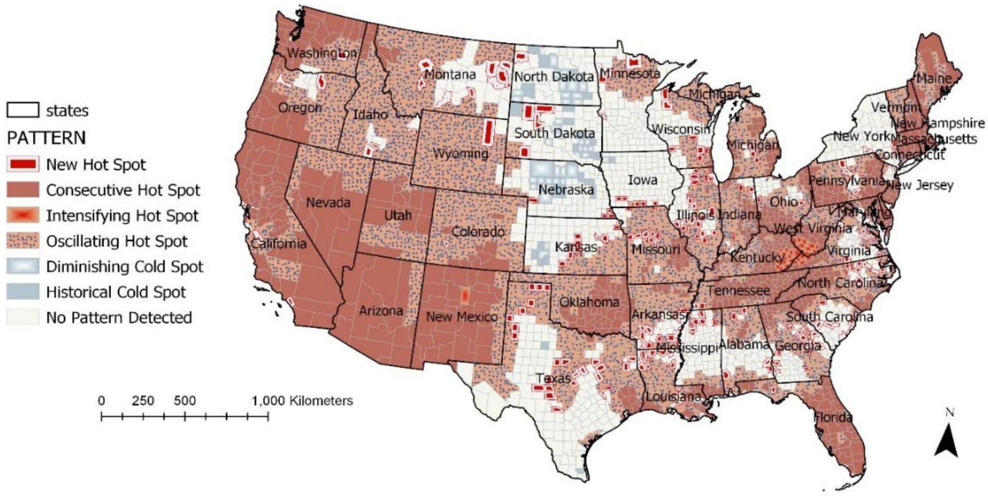

Figure 1: Hot/cold spots of Age-adjusted Drug Poisoning Deaths per 100,000.

Table 2: Number of counties in Hot/cold spots of Age-adjusted Drug Poisoning Deaths per 100,000 (1999-2016).

Type	Hot spot	Cold spot	Description (ESRI, 2019)
New	237	0	A location that is a statistically significant hot spot for the final time step and has never been a statistically significant hot spot before.
Consecutive	794	0	A location with a single uninterrupted run of statistically significant hot spot bins in the final time-step intervals. The location has never been a statistically significant hot spot prior to the final hot spot run and less than ninety percent of all bins are statistically significant hot spots.
Intensifying	32	0	A location that has been a statistically significant hot spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high counts in each time step is increasing overall and that increase is statistically significant.
Oscillating	1080	0	A statistically significant hot spot for the final time-step interval that has a history of also being a statistically significant cold spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant hot spots.
Diminishing	0	43	A location that has been a statistically significant cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is decreasing overall and that decrease is statistically significant.
Historical	0	28	The most recent time is not cold, but at least ninety percent of the time-step intervals have been statistically significant cold spots.

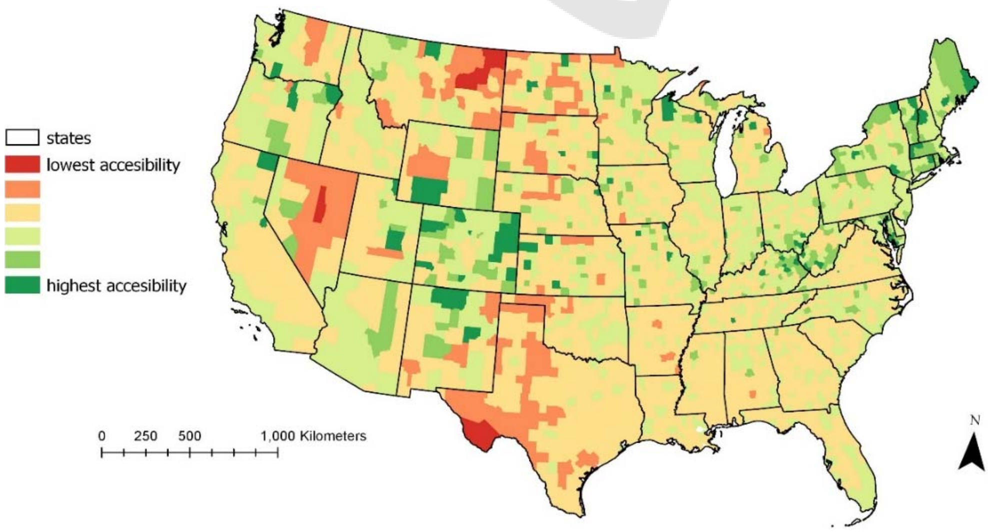

Figure 2: Composite index of access to substance-use disorder treatment and services.

The access index ranges from 2.8 to 57.8, representing the worst/the best availability and access to treatment and services respectively. The mean value of the access index for the entire country is 17.4, and the median – 16.9. To facilitate the analysis, composite index values were mapped using standard deviation classification – three below the national mean and three above the national mean, each class corresponding to one standard deviation (Figure 2). On this map, the darker the color the further away from the mean is the value: dark red corresponds to the lowest index value, and the dark green – to the highest index value. The map shows that access to treatment and services is distributed unevenly throughout the country. Northeastern states and selected counties within West Virginia, Kentucky, Ohio, Wisconsin, Colorado, New Mexico, and Oregon have the best access. The lowest access is observed in the Plains region, especially Montana, and in Texas and Nevada.

To explore access to treatment and services within the hot spots only, the access index and hot spots were overlaid, and three classes with access index values below the national mean were mapped separately (Figure 3). This map reveals that 55% of the hot spot counties have access index below the national mean. Of particular importance are 81 counties that fall within two lowest access categories: 72 counties that have very low access (i.e. their access index is between one and two standard deviations below the national mean), and nine counties that have extremely low access (i.e. their access index is below two standard deviations from the national mean). These 81 counties account for 3% of total U.S. population and are primarily located in Texas (26 counties), Montana (13 counties), Alaska (11 counties), Oklahoma (six counties), Nevada (six counties) and New Mexico (five counties). A smaller number of counties in this category are located in Washington, Wyoming, Utah, Arkansas, South Dakota, Michigan, Kansas, Iowa and Idaho.

5 DISCUSSION

This study of data from 3142 counties found a significant geographic variation in the concentration of the drug poisoning deaths, with the majority of counties (68%) falling inside a hot spot – an area where the death rates are statistically significantly higher than the national average. Among all types of hot spots, new and intensifying hot spots are of particular concern. The new hot spots are counties that were never a hot spot in previous years, and became a hot spot in 2016. These new hot spots are often located at the fringes of previously existing hot spots and symbolize a current frontier or opioid epidemic. The majority of the new hot spots are located in the South – in Texas, Georgia, Arkansas, Louisiana, but also in Illinois and Virginia.

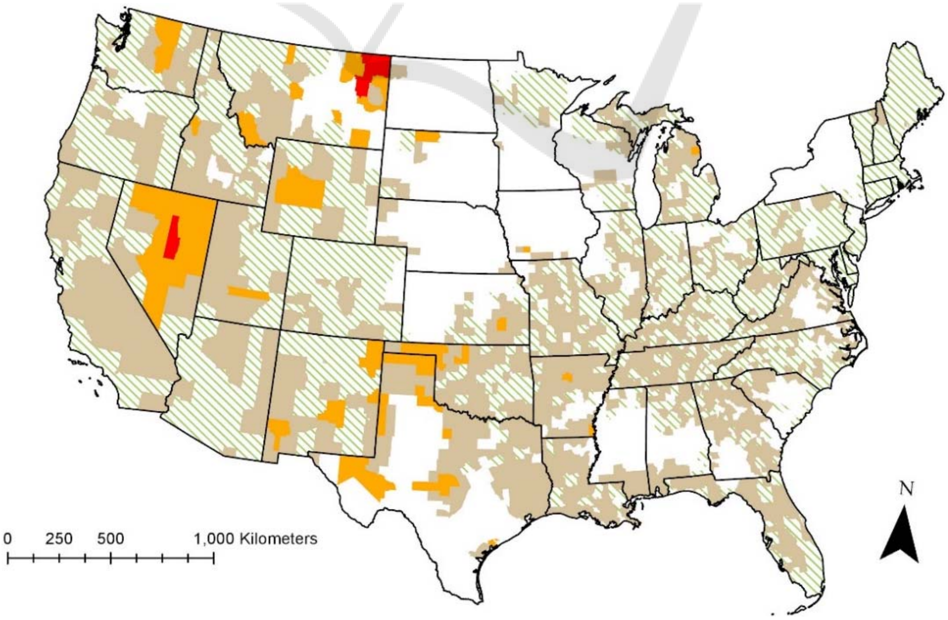

Figure 3: Composite index in hot spot counties. Red color shows hot spots with the lowest access to treatment and services; orange color shows hot spots with second lowest access. Light brown color shows hot spots with access within one standard deviation below the mean. Hatched green shows hot spots with access above the national mean.

The intensifying hot spots are counties that experienced increasing intensity of clustering of high mortality rates in each time step. There are two distinct areas of intensifying hot spots – a big cluster of contiguous 30 counties in the Appalachia region (Kentucky, West Virginia, Virginia) and a small cluster of two counties in north-central New Mexico.

This study aggregated six indicators into one composite index of availability and access to treatment and services, instead of analyzing access-related data separately. The averaging approach used here is an intuitive and easy to understand, especially when relative importance of contributing variables is unknown. One limitation of this approach is that it potentially compensates low scores in one variable with high scores in another variable, thus masking a more nuanced distribution and interaction between the variables. Future research will consider other ways of creating an access index.

The final index map shows that the availability of treatment and services varies widely. When it is overlaid with the hot spot map, some alarming patterns of high drug overdose deaths and low availability of treatment become evident. The study identified 81 hot spot counties that have extremely low access to treatment and services. In these counties, the average distance to the closest facility with MAT is 90 miles (minimum = 52 mi, maximum = 415 mi). Sixty-five of these counties have no facilities providing substance abuse services. The remaining 16 counties have 29 such facilities, and only one of them provides MAT with one medication. Only seven of 81 counties have Buprenorphine providers (total of 28 providers). These areas in Texas, Montana, Alaska, Oklahoma, Nevada and New Mexico need immediate attention for the local and state public health organizations.

6 CONCLUSION

This study used a novel approach to analyze opioid overdose death rates concurrently through space and time, by creating a space-time cube and identifying hot spots using GIS. Resulting hot spot maps provide a comprehensive assessment of the geographical patterns of death rates from drug overdose. This study also illustrates how a composite indicator can facilitate the assessment of accessibility and availability of treatment and services. Combining mortality hot spots with accessibility index spotlights areas with high disease burden and low availability of treatment centers and providers. These areas deserve special attention as state and local government and public health organizations seek new prevention and intervention strategies to address the opioid epidemic.

REFERENCES

Abdrakhmanov, S., Mukhanbetkaliyev, Y., Korennoy, F., Karatayev, B., Mukhanbetkaliyeva, A., and Abdrakhmanova, A. (2017). Spatio-temporal analysis and visualisation of the anthrax epidemic situation in livestock in Kazakhstan over the period 1933-2016. *Geospatial health, 12*.

amfAR, t. F. f. A. R. (2018). *Toward an Effective Strategy to Combat, HIV, Hepatitis C and the Opioid Epidemic: Recommendations for Policy Makers.* Retrieved from Washington, DC.

Bunting, R. J., Chang, O. Y., Cowen, C., Hankins, R., Langston, S., Warner, A., Roy, S. S. (2018). Spatial Patterns of Larceny and Aggravated Assault in Miami–Dade County, 2007–2015. *The Professional Geographer, 70*(1), 34-46. doi:10.1080/00330124.2017.1310622

Cheng, Z., Zu, Z., and Lu, J. (2019). Traffic Crash Evolution Characteristic Analysis and Spatiotemporal Hotspot Identification of Urban Road Intersections. *Sustainability, 11(1):160.*

ESRI. (2019). ArcGIS Pro Help. Retrieved from https://pro.arcgis.com/en/pro-app/help/main/welcome-to-the-arcgis-pro-app-help.htm

Getis, A., and Ord, J. K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis, 24*(3), 189-206. doi:doi:10.1111/j.1538-4632.1992.tb00261.x

Hedegaard H., Warner, M., and Miniño AM. (2017). *Drug overdose deaths in the United States, 1999–2016. CHS Data Brief, no 294.* Hyattsville, MD: National Center for Health Statistics.

Jalal, H., Buchanich, J. M., Roberts, M. S., Balmert, L. C., Zhang, K., and Burke, D. S. (2018). Changing dynamics of the drug overdose epidemic in the United States from 1979 through 2016. *Science, 361*(6408), eaau1184. doi:10.1126/science.aau1184

Jones, C. W., Christman, Z., Smith, C. M., Safferman, M. R., Salzman, M., Baston, K., and Haroz, R. (2018). Comparison between buprenorphine provider availability and opioid deaths among US counties. *J Subst Abuse Treat, 93*, 19-25. doi:10.1016/j.jsat.2018.07.008

Rahman, M. K., Crawford, T., and Schmidlin, T. W. (2018). Spatio-temporal analysis of road traffic accident fatality in Bangladesh integrating newspaper accounts and gridded population data. *GeoJournal, 83*(4), 645-661. doi:10.1007/s10708-017-9791-x

Rossen, L. M., Bastian, B., Warner, M., Khan, D., and Chong, Y. (2017). Drug poisoning mortality: United States, 1999–2016. Downloaded from National Center for Health Statistics https://www.cdc.gov/nchs/data-visualization/drug-poisoning-mortality/

Rossen, L. M., Khan, D., and Warner, M. (2013). Trends and geographic patterns in drug-poisoning death rates in the U.S., 1999-2009. *Am J Prev Med, 45*(6), e19-25. doi:10.1016/j.amepre.2013.07.012

Stewart, K., Cao, Y., Hsu, M. H., Artigiani, E., and Wish, E. (2017). Geospatial Analysis of Drug Poisoning Deaths Involving Heroin in the USA, 2000-2014. *J Urban Health, 94*(4), 572-586. doi:10.1007/s11524-017-0177-7

Substance Abuse and Mental Health Services Administration (2017). *National Survey of Substance Abuse Treatment Services (N-SSATS). Data on Substance Abuse Treatment Facilities.*

U.S. Department of Health and Human Services, O. o. t. S. G. (2016). *Facing Addiction in America: The Surgeon General's Report on Alcohol, Drugs, and Health.* Retrieved from https://addiction.surgeongeneral.gov/sites/default/files/report-highlights.pdf.