Spatio-Temporal Predictive Modeling for Placement of Substance Use Disorder Treatment Facilities in the Midwestern U.S

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Abstract. The inappropriate use of illegal and prescription drugs is an ongoing public health crisis across the United States and beyond. The demand for treatment services quickly outstrips the available supply, limiting access to care. Thus, a data-driven approach to assessing where new treatment facilities are to be built is an essential way to ensure new investments are strategically and optimally located. In this exploratory research, we report the findings of using 24 different public data sets to create three index variables used within a spatio-temporal modeling approach to predict what urban, suburban, and rural counties would most benefit from new substance use disorder treatments across the state of Indiana in the United States. Finally, we discuss the importance and potential limitations of taking this type of approach to develop policies that address complex societal issues.

Keywords: substance use disorder · treatment · predictive model · public policy · community health

1 Introduction

Substance use disorder (SUD) includes the continuous use of drugs and alcohol despite negative consequences. Criteria for diagnosing include the inability to stop even though you want to, neglecting responsibilities and using more of the substance than intended or using it for longer than you are meant to [11]. Approximately one in 12 adults in the U.S. has experienced a SUD in the last year, struggling with illicit drugs, alcohol, or both [12]. Indiana has the 10th worst drug problem in the nation [13] and the 14th worst overdose death rate [18]. In addition to this human tragedy, this epidemic imposes a significant burden on the healthcare system—approximately \$11.3 billion annually in hospital

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care for overdose clients. Healthcare systems struggle to deliver care to people needing substance use treatment with only 17% of individuals with SUD receiving any treatment in 2018 [14]. Those with SUD are at greater risk for long-term medical issues [15], and the relapse rate of 40–60% means that many cases are chronic, which positions SUD alongside other chronic illnesses [16]. Engaging clients in treatment, especially early, is critical to long-term recovery. SUDs are often multifactorial; hence, client-centered care, including shared decision-making and strong therapeutic alliance with healthcare providers, is a key strategy for effective treatment and whole-person, 360-degree care [17].

It is estimated that over 3.8 million Americans aged 12 and older receive treatment each year, representing only 8.4% of those in need [9]. Access to treatment is a major barrier to fighting this increasing epidemic. Financial/costs, stigma, geographic location, and co-occurring disorder treatment are some of the most common [10]. Geographic access is considered one of the key barriers [8]. Most treatment centers are located in urban/population settings, creating even more disparity for those in rural areas [36]. Current approaches to data-driven decisions on where to invest recovery resources use various data indicators for their assessments [37], but often lack the nuance and complexity of taking into consideration various aspects of community decay. For the purpose of this paper, we are defining community decay as a broad category of deterioration in the foundation of a specific county or region of a state. While in the strictest terms community decay refers to the break down of physical structures to a point where it is a threat to the health of a community, we look more broadly at the breakdown of social infrastructure as well.

Connected to the geographic location of treatment centers are the types of treatments offered at centers. The use of medication assisted treatment (MAT) has become the standard in long-term treatment [7] as it has been shown to reduce overall mortality and healthcare utilization [3–5]. However, it is estimated that only 41% of facilities offer one form of MAT (methadone, buprenorphine, and naltrexone) and only 3% offer all forms [2]. Geographical proximity is important as it has been found that the presence of a treatment facility is connected with decreased county-level overdose fatalities [6]. The level of care is also a further differentiation of treatment centers. Treatment facilities are broken into three levels of intensity: high, moderate, and low intensity [1].

To better understand the potential needs across different regions and counties in our state that are related to quickly evolving on-the-ground trends, we devised an exploratory analysis of various categories of social and community decay in an effort to better predict where new SUD treatment should be placed around the region to better support those in need of treatment using a spatio-temporal approach. This research makes the following contributions: connect various levels of community, social, and infrastructure decay to levels of substance use disorder in a given a specific geographic location and provide outputs of spatio-temporal predictive modeling of recommendations for a specific geographic region.

2 Related Work

There are many facets to the nature of a community in decline and/or collapse. Traditional markers include increased poverty rates [19], decreases in graduation rates [20], and increased overdose and incarceration rates [21]. Historically, various urban studies initiatives have looked at combining spatial economic and social differences to measure urban decline [22], however with the help of computational modeling approaches, these approaches can be expanded across larger regions that represent various levels of population density. Other popular theories of social decline include the reduction of in-person, social interactions. In Putnam's seminal work, he charts how declines in inter-personal community engagement maps to the rise in personal technologies as one of the factors including other aspects related to modernization [23].

There are also more unique, non-traditional ways to measure social and community decline. The Dollar Store has become a focus of interest of late related to measure of poverty and the role the store plays in trying to combat issues like food deserts [25], access to vaccines [26], and tobacco sales [24] to name a few. By creating index variables of multiple factors, it allows us to manipulate and align data, assigning weights or understanding to classes of phenomenon.

Substance use disorder has a rippling and compounding impact on individuals, families and communities [27]. There are many ways to measure the impacts of SUD on communities, including the calculations associated with loss of productivity [28], loss of life [29], and costs taken on by the healthcare systems and safety nets within the community [30,31]. Additionally, there are aspects related to impacts of substance use and abuse like erosion of trust [32], and how it relates to other social factors related to decay like decreases in high school graduation rates [33].

One way to computationally analyze the types of measures outlined above is the use of Latent class analysis (LCA). LCA is a modeling technique based on the idea that individuals can be divided into subgroups based on an unobservable construct(s) at a given point in time. Latent transition Analysis (LTA) is an extension of LCA [34]. The power of LTA is it can be used with longitudinal data, allowing to take into consideration the dynamic nature of human behavior [35]. The epidemic of SUD (including opioid use disorder) is continually evolving, thus methods like these that take nuance and complexity into consideration are critical.

3 Methods

3.1 Clinical Setting

This research was based in the state of Indiana, located in the Midwestern United States. The state is a majority rural – 70.65% of all counties are designated as rural with only 5.4% designated as urban (see Fig. 1). The total population is estimated at 6.8 million (17th most populated in the U.S.) [38]. Indiana is ranked 10th most severe state with respect to drug problems and drug related deaths, which have been consistently climbing since 2000 (see Fig. 2).

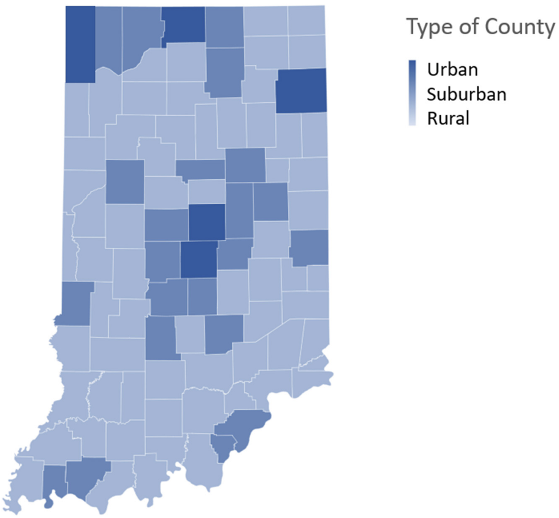

Fig. 1. Population Designation by County (Urban/Suburban/Rural) [38]

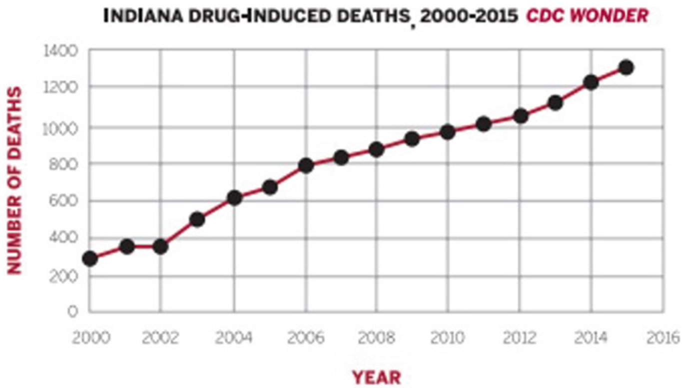

Fig. 2. Drug Induced Deaths in Indiana: 2000–2016 [18]

3.2 Data Collection

This analysis used publicly available data collected by the State and Federal governments. This is done for two key purposes - first, data collected by the government is deemed as a gold standard and is highly reliable and thus valid data for data-driven experiments. Second, publicly available data will ensure that the model can work well over a period of time and can be updated as newer iterations of collected data are updated, further reducing potential for model shift over time.

Thus, we created three index variables for this experiment: physical community decay, social community decay and addiction. The data that will comprise the initial index variables are located in the table below. Data collected for all elements were collected at the county level from 2015–2019 (See Table 1).

Table 1. Overview of data elements within each index variable and the data sources

Index Variable	Individual Data Elements	Sources
Substance Use (7)	Overdose deaths Overdose/Opioid hospitalizations Opioid prescriptions Non-fatal overdoses Fetal dependency rates Fetal death rates Proximity to current treatment	Indiana State Department of Health (ISDH) US Centers for Disease Control (CDC) US Department of Health and Human Services (DHHS)
Physical Community Decay (7)	Bankruptcy (Business) Density of low-price shopping Housing vacancy rates Job opportunities Labor turnover Housing Price Index (HPI) Foreclosure rates	US Bureau of Labor and Statistics (BLS) US Department of Justice (DOJ) US Federal Financing and Housing Agency (FHA) STATS Indiana
Social Community Decay (10)	Bankruptcy (personal) Poverty level Incarceration rates School drop out rates High school graduation rates Unemployment rates Divorce rates Child protective service placement Free/reduced lunch rates TANF (food stamps) rates	US Bureau of Labor and Statistics (BLS) US Department of Justice (DOJ) US Department of Education (DOE) Indiana Department of Child Services (IDCS) STATS Indiana ERS

3.3 Data Analysis

The analysis was conducted using a local, linear spatial regression model with multinomial outcomes for each county. Specifically, we assumed a stationary, (d+1) dimensional spatial process with a geodesic metric observed over a rectangular domain adapted from Hallin et al. 2004. We trained the resultant kernel estimator on a re-sampled training set using a standard SMOTE algorithm ($n = 1000$) using a 80-20 split. Further we used a 10-fold cross-validation to validate our results.

4 Results

Data from all 92 counties across the time period were collected and run through model. The outcomes of the model are presented here for the top three in each category of urban, rural and suburban locations. On an average, we achieved 78% accuracy with a 82% precision rate. The social and SUD related variables had more of an impact on predictions when compared to the community/physical variables (see Table 2). The demographics of the counties are the most influential as they correlate with levels of SUD recovery support in the model. Rural counties were more influenced by indicators of SUD, suburban counties were more influenced by the social decay factors and urban counties were consistently more influenced by physical decay factors.

Table 2. Outcomes of predictive model on where new SUD treatment facilities are needed based on county-level data. SD=Social Decay; PD=Physical Decay; SU=Substance Use

Type of Region	County	Influential Indicators	Model Accuracy Rate
Urban	1. Marion 2. Allen 3. Vanderburgh	- Homeownership rate (PD) - Incarceration rate (SD) - Child welfare referral rate (SD)	77%
Suburban	1. LaPorte 2. Hancock 3. Johnson	- Unemployment rate (SD) - HS graduation rate (SD) - School dropout rate (SD)	79%
Rural	1. Crawford 2. Putnam 3. Fayette	- Opioid prescription rate (SU) - Overdose deaths (SU) - Unemployment rate (SD)	73%

Additionally, two of the suburban counties are part of the greater Indianapolis (Marion County) region, the largest population center in the state. As highlighted on Fig. 3, half of the six non-urban counties have no SUD treatment facilities as of 2021, thus bolstering the outcomes of the model. Crawford and Fayette Counties are the only regions not located within a 60-minute drive of an urban population center. Interestingly, there was one urban county in the state that did not predict a high need – Lake County – which the model output showed there was a moderate need for new SUD treatment facility development. Within the *Suburban* category, Warrack was the only county that predicted having a low need for new facilities.

5 Discussion and Limitations

Complex societal issues are at the heart of many public policies, thus having a data-driven approach to address them is advantageous. The predictive model built for this analysis shows how different facets of SUD coupled with indices of decay impact are connected with population density. By understanding the impacts different indices have on need, potential biases are removed from the policy and decision making process [39]. Additionally, by taking into consideration many different types of data in the analysis, we also hedged against the

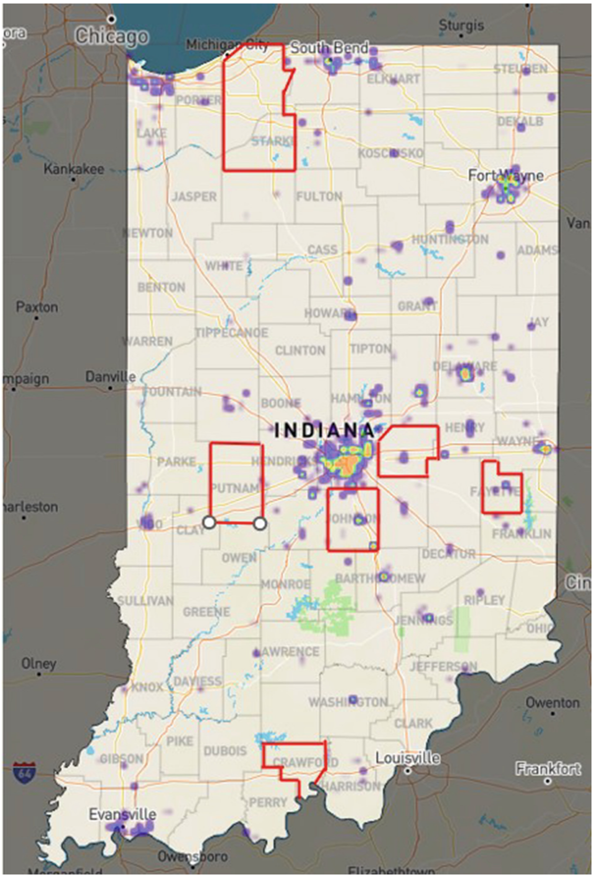

Fig. 3. Map of SUD treatment facilities in Indiana with suburban and rural outcomes of the predictive model

potential to have bias within the model outcomes because of a lack of data [40]. Making the output from the predictive model even more robust, accessible and actionable is essential. The differences in how local, state, and federal governments report various statistics is often highly variable, requiring immense levels of post-production of the data.

SUD is a rapidly evolving and ever-changing crisis. Street drugs and their complications can quickly evolve, leaving some medical complications under-recognized [41]. This coupled with the rise in prescription drug misuse [42] can leave communities scrambling as to how to get their hands around this public health issue. Utilizing computational approaches – like the one used in this analysis – on a regular, cyclical basis could provide decision makers with actionable data to inform near-term investments. Ensuring that action is taken to mitigate biases and ongoing measurements to catch potential issues as they arise are essential for the ethical integration of computing into the policy making process.

There are several limitations related to this exploratory analysis. First, computationally there are potentially biases of low populations within the model optimizations. More data and analyses would be needed to know the extent of the impact this has on the model. Additionally, we only used a 5 year time interval for this analysis. Looking at data and investments in treatment over a longer time horizon (e.g., 20 to 30 years) could provide enough window to account for other confounding impacts. While doing an analysis at a zip code level provide acceptable geographical boundaries, going even deeper to the zip code level would provide more nuance and attenuation to the results. However, due to the varying datasets used, the minimum specificity that could be obtained was to the county level. We chose to use government websites as they are perceived as gold-standard data that is more trusted and repeatedly updated than datasets curated by other special interest groups.

6 Conclusion

Data-driven decisions are critical in resource constrained environments like our state governments in the United States. Utilizing previous scholarship on the factors that go into substance use as well as social and community/physical decline of our local regions can offer unbiased and real-time information for policy makers, investors, and healthcare systems as to where investment is needed for expanded SUD treatment services. Future work on how telemedicine, mobile treatment, and other out-of-the-box treatment modalities can address the gap in access to care beyond large urban population centers and meet the last-mile healthcare needs of rural populations struggling to help individuals in their community enter into recovery.

References

1. Center for Health Policy (CHP). Treatment and Recovery for Substance Use Disorders in Indiana (2016)
2. Jones, A., Honermann, B., Sharp, A., Millett, G.: Where multiple forms of medication-assisted treatment are available. Health Affairs Blog. https://doi.org/10.1377/HBLOG20180104.835958
3. Samples, H., Williams, A.R., Crystal, S., Olfson, M.: Impact of long-term buprenorphine treatment on adverse health care outcomes in Medicaid. Health Aff. **39**, 747–755 (2020). https://doi.org/10.1377/hlthaff.2019.01085
4. Larochelle, M.R., et al.: Medication for opioid use disorder after nonfatal opioid overdose and association with mortality. Ann. Intern. Med. **169**, 137–145 (2018). https://doi.org/10.7326/M17-3107
5. Wakeman, S.E., et al.: Comparative effectiveness of different treatment pathways for opioid use disorder. JAMA Netw. Open **3**, e1920622 (2020). https://doi.org/10.1001/jamanetworkopen.2019.20622

6. Swensen, I.D.: Substance-abuse treatment and mortality. J. Public Econ. **122**, 13–30 (2015). https://doi.org/10.1016/j.jpubeco.2014.12.008
7. Volkow, N.D., Frieden, T.R., Hyde, P.S., Cha, S.S.: Medication-assisted therapies — tackling the opioid-overdose epidemic. N. Engl. J. Med. **370**, 2063–2066 (2014)
8. Substance Abuse and Mental Health Services Administration, 2020. FAQs: Provision of methadone and buprenorphine for the treatment of Opioid Use Disorder in the COVID-19 emergency. https://www.samhsa.gov/sites/default/files/faqs-for-oud-prescribing-and-dispensing.pdf
9. Center for Behavioral Health Statistics and Quality, 2017 Center for Behavioral Health Statistics and Quality 2016 National Survey on Drug Use and Health: Detailed Tables Substance Abuse and Mental Health Services Administration, Rockville, MD (2017). https://www.samhsa.gov/data/sites/default/files/NSDUH-DetTabs-2016/NSDUH-DetTabs-2016.pdf
10. Ashford, R.D., Brown, A.M., Curtis, B.: Systemic barriers in substance use disorder treatment: a prospective qualitative study of professionals in the field. Drug Alcohol Depend. **189**, 62–69 (2018)
11. Diagnostic and statistical manual of mental disorders (5th ed.). Arlington, VA: American Psychiatric Association (2013). ISBN 978-0-89042-554-1. OCLC 830807378
12. Taber, M.: Programs Can Adjust to Wraparound Model. Addiction Professional (2006). https://www.hmpgloballearningnetwork.com/site/ap
13. SAMHSA. National Survey on Drug Use and Health. (2018). https://www.mobihealthnews.com/news/innovation-substance-use-disorder-treatment-5-keys-impact
14. Inc. Premier. (2019). Opioid Overdoses Costing U.S. Hospitals an Estimated $11 Billion Annually. https://premierinc.com/newsroom/press-releases/opioid-overdoses-costing-u-s-hospitals-an-estimated-11-billion-annually
15. Kiernan, J. S.: Drug Use by State: Problem Areas. WalletHub, Washington, May 2022. https://wallethub.com/edu/drug-use-by-state/35150
16. Welty, L.J., et al.: Health disparities in drug-and alcohol-use disorders: a 12-year longitudinal study of youths after detention. Am. J. Public Health **106**(5), 872–880 (2016). https://doi.org/10.2105/AJPH.2015.303032
17. National Institute on Drug Abuse. Drugs, Brains, and Behavior: The Science of Addiction: Treatment and Recovery (2018). https://nida.nih.gov/publications/drugs-brains-behavior-science-addIction/treatment-recovery
18. Center for Disease Control ADN Prevention. Drug Overdose-2020 Drug Overdose Death Rates (2020). https://www.cdc.gov/drugoverdose/deaths/2020.html
19. Albrecht, D.E., Albrecht, S.L.: Poverty in nonmetropolitan America: impacts of industrial, employment, and family structure variables. Rural. Sociol. **65**(1), 87–103 (2000)
20. Belfield, C.R., Levin, H.M.: The Return on Investment for Improving California's High School Graduation Rate. California Dropout Research Project, Santa Barbara, CA (2007)
21. Nosrati, E., Kang-Brown, J., Ash, M., McKee, M., Marmot, M., King, L.P.: Economic decline, incarceration, and mortality from drug use disorders in the USA between 1983 and 2014: an observational analysis. Lancet Public Health **4**(7), e326–e333 (2019)
22. Cheshire, P., Carbonaro, G., Hay, D.: Problems of urban decline and growth in EEC countries: or measuring degrees of Elephantness. Urban Stud. **23**(2), 131–149 (1986)

23. Putnam, R.B.: Bowling Alone: The Collapse and Revival of American Community. Simon & Schuster, New York (2000). ISBN: 978-0-7432-0301-3
24. Hall, J., Cho, H.D., Maldonado-Molina, M., George Jr, T.J., Shenkman, E.A., Salloum, R.G.: Rural-urban disparities in tobacco retail access in the southeastern United States: CVS vs. the dollar stores. Prevent. Med. Rep. **15**, 100935 (2019)
25. Chenarides, L., Cho, C., Nayga, R.M., Jr., Thomsen, M.R.: Dollar stores and food deserts. Appl. Geogr. **134**, 102497 (2021)
26. Chevalier, J.A., Schwartz, J.L., Su, Y., Williams, K.R.: EQuity Impacts Of Dollar Store Vaccine Distribution. arXiv preprint: arXiv:2104.01295 (2021)
27. Sartor, R.: The social impact of drug Aubse on community life **10**, 205–208 (1991)
28. Sorge, J.T., et al.: Estimation of the impacts of substance use on workplace productivity: a hybrid human capital and prevalence-based approach applied to Canada. Can. J. Public Health **111**(2), 202–211 (2020)
29. Naumann, R.B., et al.: Impact of a community-based naloxone distribution program on opioid overdose death rates. Drug Alcohol Depend. **204**, 107536 (2019)
30. Bahorik, A.L., Satre, D.D., Kline-Simon, A.H., Weisner, C.M., Campbell, C.I.: Alcohol, cannabis, and opioid use disorders, and disease burden in an integrated healthcare system. J. Addict. Med. **11**(1), 3 (2017)
31. Ryan, J.L., Rosa, V.R.: Healthcare cost associations of patients who use illicit drugs in Florida: a retrospective analysis. Subst. Abuse Treat. Prevent. Policy **15**(1), 1–8 (2020)
32. Hamrick, H.C., Ehlke, S.J., Davies, R.L., Higgins, J.M., Naylor, J., Kelley, M.L.: Moral injury as a mediator of the associations between sexual harassment and mental health symptoms and substance use among women veterans. J. Interpers. Viol. **37**(11–12), NP10007-NP10035 (2022)
33. Swaim, R.C., Beauvais, F., Chavez, E.L., Oetting, E.R.: The effect of school dropout rates on estimates of adolescent substance use among three racial/ethnic groups. Am. J. Public Health **87**(1), 51–55 (1997)
34. Hagenaars, J.A., McCutcheon, A.L. (eds.): Applied Latent Class Analysis. University Press, Cambridge (2002)
35. Lanza, S.T., Flaherty, B.P., Collins, L.M.: Latent Class and Latent Transition Analysis. Handbook of Psychology, pp. 663–685 (2003)
36. Pullen, E., Oser, C.: Barriers to substance abuse treatment in rural and urban communities: counselor perspectives. Subst. Use Misuse **49**(7), 891–901 (2014)
37. Congressional Research Serrvce. Location of Medication-Assisted Treatment for Opioid Addiction. In Brief. Report no. R45782., June 24 2019. https://sgp.fas.org/crs/misc/R45782.pdf
38. U.S. Census Bureau. Quick Facts: Indiana. 2020. https://www.census.gov/quickfacts/IN
39. Hutchinson, J.W., Alba, J.W., Eisenstein, E.M.: Heuristics and biases in data-based decision making: Effects of experience, training, and graphical data displays. J. Mark. Res. **47**(4), 627–642 (2010)
40. Williams, B.A., Brooks, C.F., Shmargad, Y.: How algorithms discriminate based on data they lack: challenges, solutions, and policy implications. J. Inf. Policy **8**(1), 78–115 (2018)
41. Wurcel, A.G., Merchant, E.A., Clark, R.P., Stone, D.R.: Emerging and underrecognized complications of illicit drug use. Clin. Infect. Dis. **61**(12), 1840–9 (2015). https://doi.org/10.1093/cid/civ689
42. SAMHSA. Rise in Prescription Drug Misuse and Abuse Impacting Teens, April 2022. https://www.samhsa.gov/homelessness-programs-resources/hpr-resources/rise-prescription-drug-misuse-abuse-impacting-teens