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# Methods for jurisdictional vulnerability assessment of opioid-related outcomes

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## Abstract

In 2020, an estimated 2.7 million people in the US had opioid use disorder, increasing their risk of opioid-related morbidity and mortality. While jurisdictional vulnerability assessments (JVA) of opioid-related outcomes have been conducted previously in the US, there has been no unifying methodological framework. Between 2019 and 2021, we prepared ten JVAs, in collaboration with the Council of State and Territorial Epidemiologists, the Centers for Disease Control and Prevention, and state public health agencies, to evaluate the risk for opioid-involved overdose (OOD) fatalities and related consequences. Our aim is to share the framework we developed for these ten JVAs, based on our study of the work of Van Handel et al. from 2016, as well as a summary of 18 publicly available assessments of OOD or associated hepatitis C virus infection vulnerability.

We developed a three-tiered framework that can be applied by jurisdictions based on the number of units of analysis (e.g., counties, ZIP Codes, census tracts): under 10 (Tier 1), 10 to <50 (Tier 2), and 50 or more (Tier 3). We calculated OOD vulnerability indices based on variable ranks, weighted variable ranks, or multivariable regressions, respectively, for the three tiers. We developed thematic maps, conducted spatial analyses, and visualized service provider locations, drive-time service areas, and service accessibility relative to OOD risk. The methodological



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CRediT authorship contribution statement

**Shikhar Shrestha:** Conceptualization, Methodology, Writing – original draft. **Ric Bayly:** Data curation, Visualization, Writing – review & editing. **Jennifer Pustz:** Data curation, Writing – review & editing. **Jared Sawyer:** Data curation, Visualization, Writing – review & editing. **Michelle Van Handel:** Supervision, Writing – review & editing. **Cailyn Lingwall:** Writing – review & editing. **Thomas J. Stopka:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2023.107490.

framework and examples of our findings from several jurisdictions can be used as a foundation for future assessments and help inform policies to mitigate the impact of the opioid overdose crisis.

**Keywords**

Opioid overdose; Injection drug use; Jurisdictional vulnerability assessment

## 1. Introduction

Nearly 565,000 Americans have died from opioid-involved overdoses (OOD) from 1999 to 2020.(National Center for Health Statistics, n. d.) In 2020, an estimated 2.7 million people in the US had opioid use disorder (OUD).(Substance Abuse and Mental Health Services Administration, 2021) People with OUD are at increased risk for malnutrition, liver disease, depression, self-harm, and exposure to infections, including the hepatitis C virus (HCV), HIV, and overdose.(Ronan and Herzig, 2016; Ross et al., 2012; Wang et al., 2011; National Institute on Drug Abuse, 2020) Curbing the opioid crisis and mitigating its consequences requires understanding the predictors of OOD, including the underlying social determinants of health. Analysis at a sufficiently local level allows for careful assessment of the local risk landscape and can inform targeted responses to improve access to substance use treatment, harm reduction services, social and mental health services, and opioid education and naloxone distribution (OEND) programs.(Van Handel et al., 2016) Building on the development of the Centers for Disease Control and Prevention's (CDC) Social Vulnerability Index (SVI), the Van Handel et al. vulnerability assessment identified six indicators associated with HCV infection, a proxy for injection drug use (IDU), which were ultimately used to calculate a vulnerability score.(Van Handel et al., 2016)

In 2018, the CDC provided emergency funding for jurisdictional vulnerability assessments (JVAs) in 41 states and the District of Columbia.(Centers for Disease Control and Prevention, n.d.) These JVAs were intended to examine local vulnerabilities to opioid overdose and/or bloodborne infections by identifying relevant indicators and locating and inventorying services for people who use drugs.(Georgia Department of Public Health, 2018; Iowa Department of Public Health, 2019; Maine Department of Health and Human Services, 2019; Mercadel and Schneider, 2019; Nevada Department of Health and Human Services, 2020; Rickles et al., 2018; Missouri Department of Health and Senior Services, n.d.; Sharareh et al., 2020; West Virginia Department to Health and Human Services, n.d.; Wisconsin Department of Health Services, 2020; Washington State Department of Health, 2020; Bureau of Epidemiology Pennsylvania Department of Health, 2020; Hernandez et al., 2020; Arkansas Department of Human Services, n.d.; Schneider et al., 2020; Wesner et al., 2020; Michigan Dept. of Health and Human Services, n.d.; Bergo et al., 2021) Because these assessments were produced at the state level, considerable variability existed in the methods employed, including differences in focal geographic scales and sample sizes, such as the number of counties in a state, rurality versus urbanicity, and population density, availability of data; and the indicators that were selected in response to local concerns and practices. In collaborating with the Council of State and Territorial Epidemiologists (CSTE) and the CDC to conduct JVAs for ten states, we took advantage of the opportunity to extend, develop, and standardize methodologies and apply them across, and in collaboration with a variety of states with a goal of replicability and ease of repeatability.(Council of State and Territorial Epidemiologists, 2019) The objectives of this paper are to provide a brief overview of published state-level vulnerability assessments that were used to inform our framework and to report the methodological framework we developed in analyzing OOD vulnerability in ten states between 2019 and 2021.

To develop our methodological framework, we evaluated 18 publicly available state-based JVAs published from 2017 to 2021 (Appendix A) that focused on OOD or HCV infection vulnerability. We noted units of analysis, data sources, variables examined, analytical platforms, and methodologies, including the use of geographic information systems (GIS), presentation of results, and recommendations. The JVAs used data between 2011 and 2019, with most assessments utilizing data from 2016 to 2018. The most common unit of analysis was the county. Exceptions included the use of sub-divided county areas analyzed with ZIP Code Tabulation Areas (ZCTAs) in Maine, Rhode Island, and Wisconsin,(Maine Department of Health and Human Services, 2019; Wisconsin Department of Health Services, 2020) census tracts in Pennsylvania, (Bureau of Epidemiology Pennsylvania Department of Health, 2020) and “small areas,” which combined some ZCTAs, in Utah.(Sharareh et al., 2020) Data used in the JVAs included the American Community Survey (ACS),(U.S. Census Bureau, n.d.) the Substance Abuse and Mental Health Services Administration (SAMHSA) Treatment Locator, (Substance Abuse and Mental Health Services Administration Treatment, n.d.) CDC WONDER,(National Center for Health Statistics, n.d.) Behavioral Risk Factor Surveillance System,(Centers for Disease Control and Prevention (CDC), n.d.-a) Youth Risk Behavior Surveillance System, (Centers for Disease Control and Prevention (CDC), n.d.-b) National Emergency Medical Services Information System,(Dawson, 2006) Centers for Medicare and Medicaid Services National Plan and Provider Enumeration System,(Centers for Medicare and Medicaid Services (CMS), n.d.) and Drug Enforcement Administration High-Intensity Drug Trafficking Area designations.(Perl, 1988)

These JVAs employed a variety of methods to identify potential covariates for final models focused on OOD and other outcomes, including consultation with state-level public health researchers and the use of statistical methods. Final covariates commonly included opioid prescription rates, drug or OOD mortality, drug or OOD emergency department visits, and drug or opioid-related arrests, along with mental health care, primary care, and OUD treatment availability. States used various methods to calculate final vulnerability scores and rankings, including weighted rankings,(Missouri Department of Health and Senior Services, n.d.) the calculation of an SVI,(Sharareh et al., 2020) and regression models.(Iowa Department of Public Health, 2019; Maine Department of Health and Human Services, 2019; Bureau of Epidemiology Pennsylvania Department of Health, 2020; Hernandez et al., 2020) Some states used factor analysis to model the complex relationship between predictors of opioid vulnerability and quantified overall vulnerability at the county level.(Rickles et al., 2018) We found the most common visual representations of results to be descriptive GIS maps identifying vulnerable areas,(Georgia Department of Public Health, 2018; Iowa Department of Public Health, 2019; Maine Department of Health and Human Services, 2019; Mercadel and Schneider, 2019; Rickles et al., 2018; Missouri Department of

Health and Senior Services, n.d.; Sharareh et al., 2020; West Virginia Department to Health and Human Services, n.d.; Wisconsin Department of Health Services, 2020; Bureau of Epidemiology Pennsylvania Department of Health, 2020; Hernandez et al., 2020; Arkansas Department of Human Services, n.d.; Schneider et al., 2020; Wesner et al., 2020; Michigan Dept. of Health and Human Services, n.d.) treatment accessibility,(Mercadel and Schneider, 2019; Wisconsin Department of Health Services, 2020; Arkansas Department of Human Services, n.d.; Wesner et al., 2020) and the spatial distribution of indicators used in the analysis.(Iowa Department of Public Health, 2019; Mercadel and Schneider, 2019; West Virginia Department to Health and Human Services, n.d.; Wisconsin Department of Health Services, 2020; Washington State Department of Health, 2020; Bureau of Epidemiology Pennsylvania Department of Health, 2020; Arkansas Department of Human Services, n.d.; Wesner et al., 2020) States typically used descriptive maps to display vulnerability rankings, categorized by quintiles or Jenks natural breaks.

Our review of the JVAs found significant variations in the scope of the assessments, data sources and methods, statistical and spatial analyses, and reporting of findings. In response to these vast differences, our overarching goal was to develop a consolidated set of methodologies that we applied systematically to the ten JVAs conducted.

## 2. Methods

We developed algorithms for several analytical models and a framework to select the appropriate model to ensure consistency while conducting ten state-level JVAs (Alaska, Delaware, Florida, Hawaii, Idaho, Indiana, Kansas, Massachusetts, Texas, and Wyoming) in collaboration with the CSTE, CDC, and participating state public health agencies. We summarize key components of vulnerability and accessibility assessments and mapping methodologies to clearly communicate JVA findings to stakeholders in the section that follows.

### 2.1. Data framework

We defined a set of core measures based on the vulnerability assessment conducted by Van Handel: opioid overdose death rates, opioid prescription rates, HCV infection rates, per capita income, and drug-related crime rates,(Van Handel et al., 2016) additionally selecting covariates based on a review of macro forces that shaped the opioid use environment, consultation, and feedback from state partners highlighting local factors, state-level variation in data availability, and prior JVAs (Table 1). Understanding the history of the opioid overdose epidemic was key to the identification of opioid-related measures of vulnerability. The introduction of the concept of pain as a “fifth vital sign”(Van Zee, 2009; Morris, 1991; Pellegrino, 1998) and the subsequent increase in opioid prescribing was followed by a surge in opioid-related deaths between 2005 and 2010, making opioid prescription rates a core measure in our JVAs.(Dart et al., 2015) The use of heroin, an available and less expensive alternative, began a sustained increase, followed by the spread of synthetic opioids such as fentanyl beginning in 2013.(Zibbell et al., 2015) Underlying socioeconomic factors that are synergistic to the opioid overdose crisis, such as high unemployment rates, low socioeconomic status, drug-related crime, and low education level were also useful indicators of opioid vulnerability.(Perlman and Jordan, 2018; Shrestha et al., 2022; Monnat et al., 2019)

## 2.2. Geographic information system (GIS) framework

The combination of exploratory spatial data analysis, spatial analysis of the vulnerability, and integration of accessibility models were critical to the development of a strong and holistic understanding of the underlying socioeconomic, cultural, political, and geographic context that affected opioid use, misuse, treatment, and harm reduction environment in study areas.(Shrestha et al., 2022; Stopka et al., 2021) GIS analyses utilizing a variety of mapping techniques were used to depict the spatial distribution of core indicators and covariates, analyze accessibility to service providers, and vulnerability scores at varying geographic levels, including the census tract, ZCTA, and county, depending on data availability, with a preference for maximum spatial granularity. However, the effects of many policy decisions or interventions were observed at a much larger spatial scale (county-level or even state-level differences) when a larger spatial scale for analysis might be sufficient.

## 2.3. Vulnerability assessment model selection

In conducting JVAs for the ten states, we identified wide variability in data availability, local epidemiology, population and geographic size, and potential units of analysis requiring different algorithms and models. Larger sampling sizes (greater counts for the unit of analysis) allowed the application of more advanced algorithms and models. Accordingly, we developed a tiered framework for the selection of one of three vulnerability ranking models based on the count of the jurisdictional unit of analysis: rank-based, weighted rank-based, and multivariable regression-based (Table 2).

## 2.4. Rank-based approach (Tier 1)

For jurisdictions with a unit of analysis count of <10, we applied a rank-based method to calculate vulnerability scores (Table 2). We ranked each unit of analysis based on the observed values of core opioid vulnerability measures and calculated vulnerability scores as the summed rankings of each of the core variables.

## 2.5. Weighted-rank approaches (Tier 2A and 2B)

For jurisdictions with a unit of analysis count of at least ten but <50 (e.g., 35 census tracts), we used a weighted rank-based approach. When the unit of analysis was at least ten but <25 (2A in Table 2), we calculated vulnerability scores as the sum of the weighted ranks (percentile or quintile rank) of the core measures and chosen covariates determined for inclusion a priori. To account for the higher predicted impact of core indicators such as opioid prescription rates or high-dose opioid prescriptions (>90 morphine milligram equivalent units/day), HCV infection rates, and crime rates, we applied higher weights, also determined a priori to the core indicators similar to a prior published study.(Missouri Department of Health and Senior Services, n.d.)

When the unit of analysis was at least 25 but <50 (2B in Table 2), we used bivariate regression models to estimate weights for the core variables and covariates. We selected statistically significant covariates in the bivariate regression models with the outcome measure of interest – OOD death (count) and then used the selected coefficients to individually weight the rank score of each core measure and covariate. We calculated vulnerability scores as the sum of the weighted quintile rank of the core measures and selected covariates (Table 2).

### 2.6. Multivariable regression-based approach (Tier 3)

We used a multivariable regression-based approach to assess opioid vulnerability when the unit of analysis was 50 or more (e.g., 65 ZCTAs). We standardized the core measures and covariates selected for analysis, followed by the examination of the association between the variables under study (core measures and covariates) and opioid overdose death (count), using either Poisson or negative binomial distributions. The bivariate model was specified as follows:

$$\text{Negative binomial: } Y \sim X, \text{ offset (log-population)}.$$

Where,

Y = opioid overdose deaths (count).

X = standardized predictor.

We selected covariates significant at a pre-specified cut-off of $p < 0.1$ or $p < 0.2$ from bivariate models for inclusion in the final vulnerability score calculation. We fitted a multivariable model, with OOD death counts as the outcome and core measures and selected covariates shown to be non-collinear as the predictors, and assessed the model fit using model diagnostics. Finally, we used the regression coefficients to calculate vulnerability scores (Table 2).

### 2.7. Service location and service accessibility maps

We mapped the location of medication for opioid use disorder (MOUD) prescribers (buprenorphine-waivered physicians), methadone clinics (opioid treatment programs), substance use treatment clinics, and harm reduction services, including syringe services programs (SSP) and OEND programs using addresses from the SAMHSA Treatment Locator and data from state public health partners. We used drive-time maps to measure accessibility to MOUD, SSP, and OEND sites. The selected drive times were chosen based on factors such as the average commute times, urban/rural balance, and population density of the study jurisdiction, as well as expert opinion from local state health partners. Additionally, we used an enhanced two-step floating catchment area (E2SFCA) method to examine relative accessibility to treatment programs and harm reduction services.(Luo and Qi, 2009) The E2SFCA method is based on drive-times to service providers weighted for proximity but also accounts for both the supply (the number of providers and their service capacity) and the demand (the population or the number of patients) to show accessibility levels throughout a jurisdiction.(Luo and Qi, 2009)

## 3. Results

We conducted seven out of ten of our JVA in strong collaborations with state partners, the CDC, and the CSTE. The other three assessments had the technical support and collaboration of the CDC and CSTE. The state teams typically included epidemiologists (usually with expertise in HCV, HIV, and opioid overdose surveillance), GIS analysts, and program managers. The collaborative process helped ensure that the conducted JVAs would be used to inform public health planning, intervention targeting, and policy changes to address the opioid overdose crisis.

In response to a wide range in sample sizes, from four counties in Hawaii to 254 counties in Texas, we developed a framework to apply varying algorithms for vulnerability score calculation using three tiers based on the unit of analysis count. This tiered approach was designed to suit all state, territorial, county, sub-county, and municipal jurisdictions and provide structure to future analyses. We focused on the analysis of data for the three most recent years for which surveillance data were complete. This approach considered the suppression rules for the given unit of analysis (e.g., county, ZIP Code; larger date ranges were used if counts of events/outcomes were low, ensuring that we could obtain estimates without compromising suppression rules). We used median state values for other random missing observations. Eight of the ten JVAs were conducted at the county level. However, our collaborators in Alaska recommended analyzing data at the level of the seven Alaska Public Health Regions after considering both limited data availability and low counts in the sparsely populated regions of the state.(Agley and Xiao, 2021) In Delaware, which has only three counties, ZCTAs were used as the unit of analysis. ZCTAs with fewer than 300 people were combined to create a total of 58 ZCTAs.

Fatal OOD data were used as a core indicator or to calculate weights for other core indicators and covariates based on the complexity of the model. Opioid prescription data was another core indicator that we used in our JVA; we either used the total opioid prescription rate, total MME, or high-dose opioids (>90MME/day) as a core indicator. Prescription rates had a statistically significant positive association with opioid vulnerability in four states (Table 3). In five of the eight states where HCV infection was used as a core measure, we found positive correlations between HCV cases and OOD (Table 3). Both opioid-related arrest rates and opioid-related crime report rates were similarly strong predictors, with six positive correlations and one negative correlation in our JVAs. Income was negatively associated with OOD in four out of six states (Table 3). Among other core measures, opioid-involved emergency department (E.D.) visits were positively associated with OOD in five out of five states, with a statistically significant finding in one of the four states where regression models were constructed. The percentage of female head of households and the percentage of the population that was white were both commonly positively correlated with OOD.

For the Indiana JVA, we used a series of choropleth maps that consisted of OOD rates, opioid prescription rates, overdose-related emergency department visits, chronic HCV rates, opioid-related arrest rates, and median income with the values classified by quintiles (Fig. 1). The selection of the indicators for the descriptive maps was based on the importance of the indicator (core vs. covariates) and input from participating states. We also presented the vulnerability scores using choropleth maps and, based on the recommendation from the state-level DPH, highlighted areas at the highest risk (Fig. 2, Appendix B).

Spatial mapping of service locations such as methadone clinics, buprenorphine providers, SSPs, and harm reduction centers was vital in identifying gaps in services (Fig. 3). When supplemented with drive-time maps or more advanced, gravity-based models, such as E2SFCA, the maps highlighted micro-level deficiencies in the supply of critical OUD treatment services. We performed extensive drive-time analysis to show accessibility to methadone clinics – these analyses were critical in highlighting a severe gap in access in crucial regions. For example, in Wyoming, there were no methadone clinics, and patients seeking methadone for OUD treatment needed to travel in excess of two hours round-trip to methadone clinics in adjacent states. We also used E2SFCA analyses in combination with an opioid vulnerability index to identify areas with high vulnerability but low accessibility to substance use treatment in Indiana.(Sawyer et al., 2021)

## 4. Discussion

Our team had a unique opportunity to conduct JVAs for ten states based on the evaluated strengths and limitations of previous JVA approaches. In conducting these JVAs, we developed a structured procedure for selecting data sources, core indicators and covariates, analytical methods, and the presentation and visualization of findings. Using statistical and GIS-based methods, we calculated opioid vulnerability scores and mapped the scores, along with the location of services, to identify areas in significant need of additional interventions. The framework we developed provides a framework and range of methods for other public health jurisdictions that may have varying levels of available data and methodological expertise.

The unique features of jurisdictions, including demographics, urban/rural geography, opioid treatment and harm reduction policies, and availability of data at an appropriately granular unit of analysis, were considered when selecting core indicators and additional covariates. The decision-making process involved an overview of existing literature, identification of variables needed, and consultation with participating states to establish agreements for data access. In addition, each indicator was thoroughly examined not just for statistical quality control but also to account for the process of data collection, suppression rules, and its relationship with the OOD epidemic. For example, while acute HCV infection is more closely associated temporally with opioid injection than is chronic HCV infection, counts for diagnoses of acute HCV cases tend to be low, requiring the use of the measure of chronic HCV infection in younger adults as a proxy in most of our JVAs.(Zibbell et al., 2015; Hofmeister et al., 2019) In Idaho, the high prevalence of chronic HCV infection in prisons and in several sparsely populated counties containing prisons required imputation of chronic HCV case rates for those counties, removing corrections-related infections by use of a computed algorithm followed by a sensitivity analysis.

Drug-related crime rates, along with other crime statistics, have been shown to be associated with opioid-related outcomes such as emergency department visits, hospitalizations, and overdose deaths.(Dave et al., 2021; Chen et al., 2022) Substance use has been shown to be associated with involvement with the criminal justice system.(Winkelman et al., 2018) However, it is essential to consider the limitations of drug-related crime data since local variation in the enforcement of drug-related behaviors and racial inequities in policing can skew crime rate data.(Szalavitz and Rigg, 2017; Donnelly et al., 2022; Donnelly et al., 2021) In addition, law enforcement agency participation in the Federal Bureau of Investigation's reporting systems has been inconsistent and may not be complete enough for practical use. (Comer et al., 2021)

Opioid prescription data has been considered a strong indicator of opioid use and misuse and has been subject to several policies and regulations that have aimed to curtail their use.(Finley et al., 2017; Ponnapalli et al., 2018) Interventions such as Prescription Drug Monitoring Programs (PDMPs) have been shown to reduce the number of opioid prescriptions and also reduce the rate of prescription opioid overdose deaths.(Fink et al., 2018) However, a decrease in prescription opioid-related deaths after the implementation of PDMP programs has been followed by an increase in heroin overdoses.(Fink et al., 2018) In recent years, fatal OODs associated with fentanyl and other synthetic opioids have surpassed prescription opioid and heroin overdose deaths. (Hedegaard et al., 2021; O'Donnell et al., 2022; O'Donnell et al., 2017) However, our analysis was limited by the lack of precise data on fentanyl use and drug seizure data which is a stronger indicator of the current opioid crisis.

The assessment of opioid vulnerability on a state level can aid in targeting overdose reduction interventions, but there are limitations to these assessments. The state is a natural jurisdiction to assess due to the government infrastructure that requests these assessments, provides data, and implements state-wide interventions. However, limiting analyses to within one state's borders may over- or underestimate risk where interstate travel for OUD treatment, drug purchasing, or drug use may be common.(Van Handel et al., 2016) In state-level JVAs, the county is the most common unit of analysis due to the ease of accessing and aggregating data at this level without loss due to suppression.(Iowa Department of Public Health, 2019; Missouri Department of Health and Senior Services, n.d.; Wisconsin Department of Health Services, 2020; Wesner et al., 2020; Sawyer et al., 2021) While convenient, using the county as the unit of analysis can mask local areas of vulnerability for demographically and socioeconomically heterogeneous counties. (Openshaw, 1984; Kim et al., 2021; Joudrey et al., 2022) In addition, our methods did not consider spatial autocorrelation and the application of spatial models for the calculation of the vulnerability index.

Accessibility analysis, in combination with vulnerability assessment, provides researchers and policymakers with strong evidence to suggest interventions or policy decisions to improve access to substance use treatment programs and harm reduction services in areas with high vulnerability and limited access. However, the limitations of these accessibility assessments also need to be considered. Floating catchment area accessibility does not include access domains such as accommodation, affordability, and acceptability.(Penchansky and Thomas, 1981) Furthermore, the SAMHSA treatment locator provider list only contains information on providers who shared their information with the registry and is typically not a complete list.(Anyanwu et al., 2022) The vulnerability assessments also did not consider the availability of intramuscular naltrexone, which is another approved medication for MOUD. (Comer et al., 2021; Tetrault and Fiellin, 2012) Therefore, we strongly suggest accessing and combining information from state-level stakeholders to identify MOUD providers correctly. Our study also did not include a quantitative measure of urbanicity, limiting the examination of how urban-rural status affects opioid vulnerability.

The OOD crisis in the US has arisen from a complex mixture of opioid-prescribing practices from around 2000 to 2012,(Guy Jr. et al., 2017; MMWR Morb. Mortal. Wkly Rep., 2011; Boudreau et al., 2009; Sullivan et al., 2008) the increase of illicitly manufactured fentanyl in local drug supplies since 2013, ongoing socioeconomic challenges, and racial and ethnic disparities in access to prevention and treatment services.(Perlman and Jordan, 2018) Understanding the collective impact of these factors will help inform the allocation of resources and interventions. JVAs have been a strong tool in assessing these factors and have helped inform intervention planning, resource allocation, and targeted research efforts. However, the literature on opioid JVAs has shown considerable variation in analytic and methodological framework, data sourcing, and visualization of findings.(Van Handel et al., 2016; Rural Opioid Initiative Research Consortium, n.d.) This structured data analysis framework and related algorithms, implemented in practice via collaboration with state public health agencies, can help pave the way toward much-needed consistency in future JVAs focused on opioid-related risk factors.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.


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### Disclaimer

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

## Data availability

The authors do not have permission to share data.

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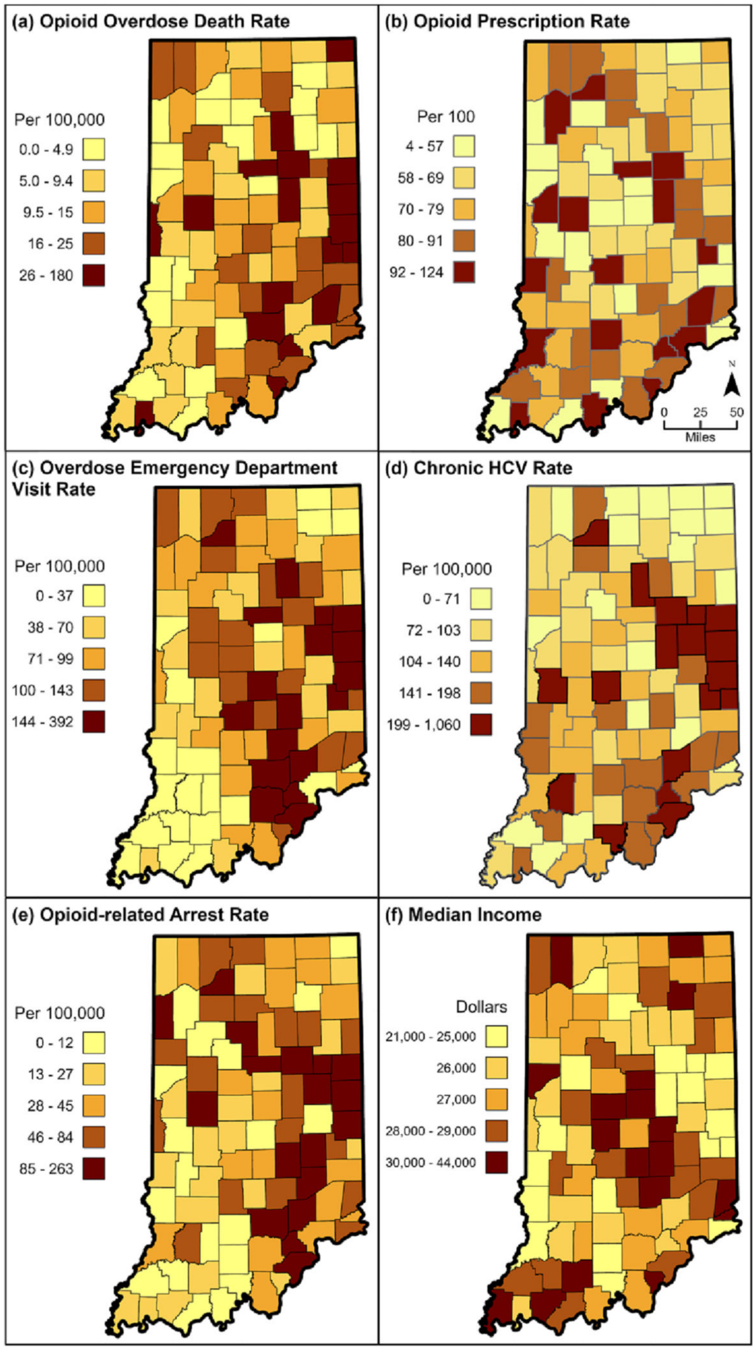


**Fig. 1.**

Indiana counties, 2017: core measures of vulnerability (quintiles breaks).

Notes: Data sources: (a - d) Indiana Department of Health; (e) National Incident-Based Report System (f) US Census Bureau American Community Survey 5-Year Estimates (2014–2018).

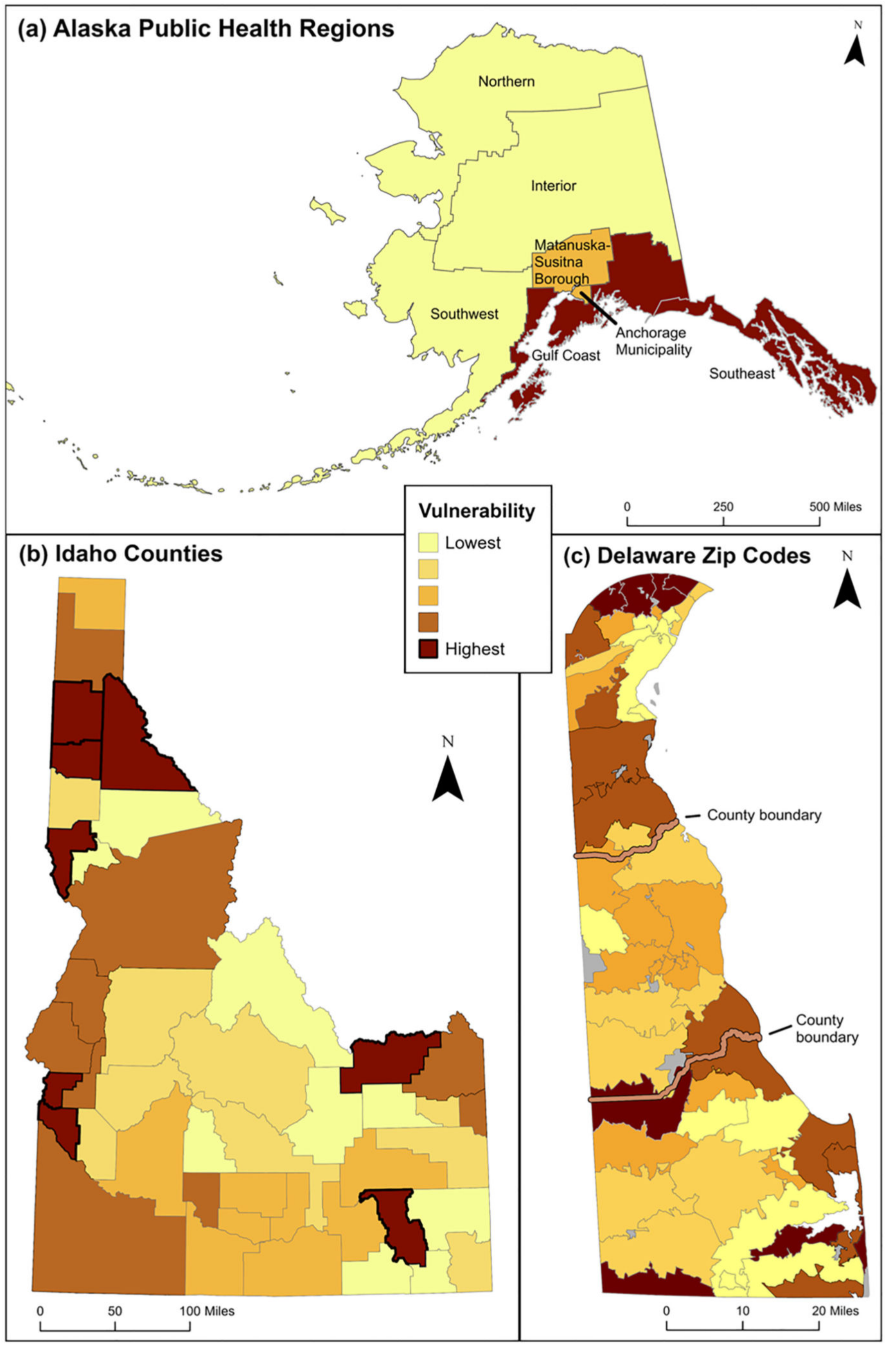


**Fig. 2.**

Opioid-involved overdose vulnerability assessments (quintile breaks).

Notes. (a) Alaska. Unit of analysis: Public Health Regions, $n = 7$, Tier 1 rank-based vulnerability scoring was used and tertiles classes are shown. Data sources: Alaska Department of Health and Social Services, Crime in Alaska Report, Centers for Disease Control and Prevention.

(b) Idaho. Unit of analysis: county, $n = 44$, Tier 2 weighted-rank based vulnerability scoring was used and quintile classes are shown. Data sources: Idaho Department of Health and Welfare, Bureau of Vital Records and Health Statistics, Bureau of Pharmacy, State Police.
(c) Delaware. Unit of analysis: ZIP Code Tabulation Area, $n = 57$, Tier 3 regression weighted-rank based vulnerability scoring was used and quintile classes are shown. Data source: Delaware Department of Health.
(a – c) Data included US Census Bureau American Community Survey 5-year Estimates.

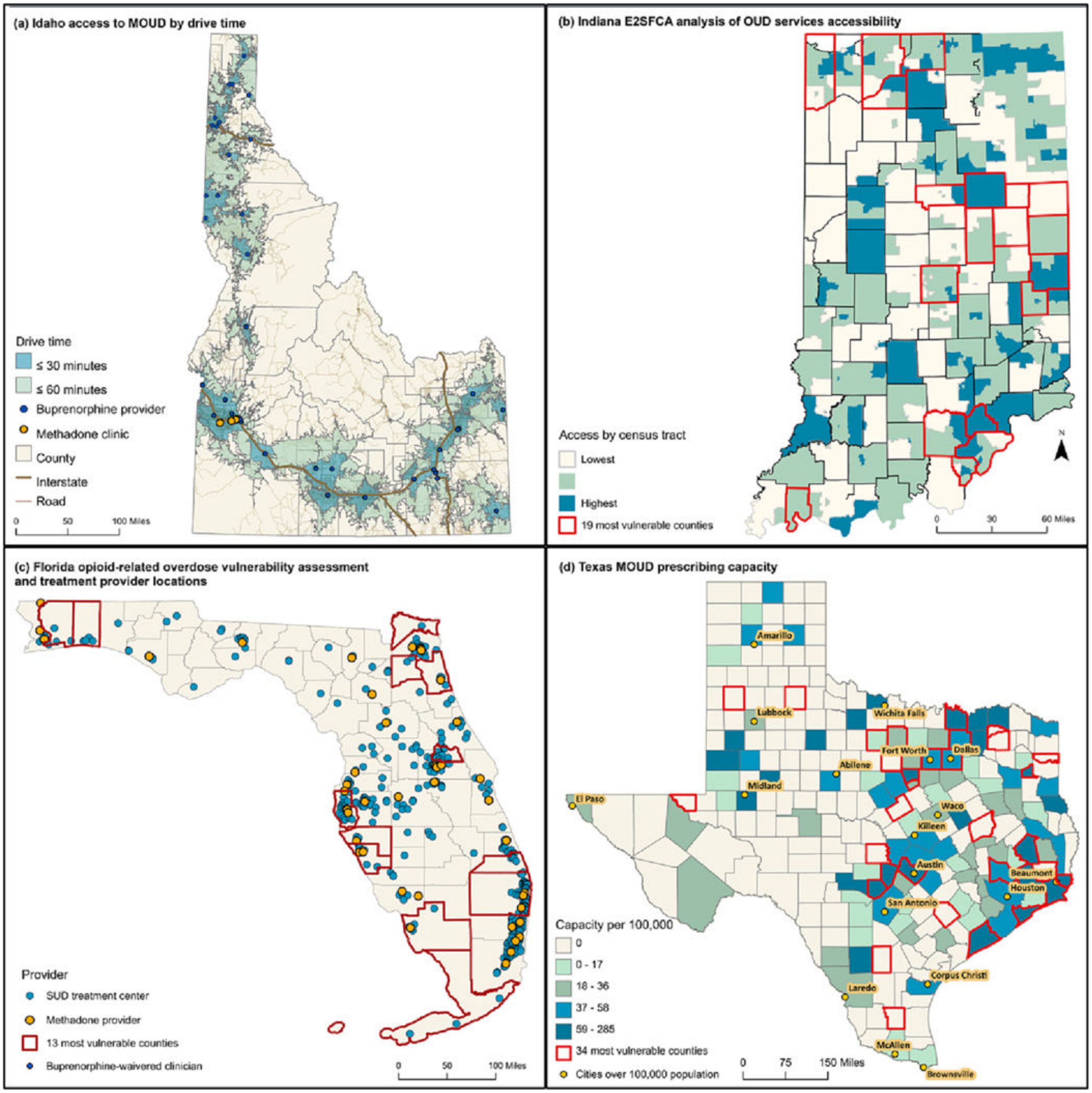


**Fig. 3.**

Mapping and analyzing opioid-related resources.

Notes. (a) Idaho. Access to Medicine for Opioid Use Disorder (MOUD, specifically buprenorphine) by prescriber drive-time service areas. For clarity, only selected prescriber locations are shown for each town and city. Data sources: Idaho Department of Health and Welfare, US Drug Enforcement Agency.

(b) Indiana. Enhanced two-step floating catchment area (E2SFCA) Opioid Use Disorder services provider analysis at census tract unit of analysis. Overlay of top quintile (19) of counties ranked highest on opioid vulnerability scale. Data source: Indiana Department of Health.

(c) Florida. Opioid vulnerability scale ranks in quintiles overlaid with substance use disorder treatment and methadone provider locations. Data sources: Substance Abuse and Mental Health Services Administration, National Vital Statistics System 2014–2018, American Foundation for AIDS Research (2017), Florida Department of Law Enforcement (2018).

(d) Texas. MOUD (buprenorphine) prescribing capacity rate overlaid with 34 most opioid-involved overdose vulnerable counties. Data sources: Texas Department of State Health Services, US Drug Enforcement Agency.

(b – d) Data included US Census Bureau American Community Survey 5-year Estimates.

**Table 1**

Core and covariate measures for opioid vulnerability assessments.

| Core variables | Data sources | Notes |
|---|---|---|
| Opioid-involved overdose mortality | State department of public health (DPH), state registry of vital statistics, public data warehouse, Centers for Disease Control and Prevention (CDC) wide-ranging ONline data for epidemiologic research (WONDER) | |
| Opioid prescriptions (total prescription [Rx], total morphine milligram equivalent [MME], or counts of high MME Rx) | DPH, state prescription drug monitoring program, CDC opioid prescribing map(CDC, n. d.) | |
| Crime or arrest rates | National Incident-Based Report System (NIBRS) | Due to local law enforcement agency variation in crime reporting to NIBRS, some states had limited or unreliable data. |
| Hepatitis C virus (HCV) (adults ages 18 to 45) | DPH (alternatively, if necessary, HepVu.org or AmFAR.org) | Due to low or zero counts of acute HCV in most counties, we used chronic HCV, antibody + ribonucleic acid testing confirmed, younger adults as a proxy for recent infection. |
| Per capita or median household income | American community survey (ACS) | Typically from 5-year estimates |
| **Covariate** | | |
| Emergency department visits | DPH, various | Opioid-involved overdose |
| Emergency medical service calls | DPH, various | Opioid-involved overdose |
| Buprenorphine prescription capacity | DPH | |
| Covariates based on ACS 5 or 3-year estimates<br>Social vulnerability index (SVI) | | Composite of ACS measures in four domains |
| Gini index<br>Population never married<br>Teen birth<br>Unemployment<br>Population with a disability<br>Over 25 years of age with no high school diploma<br>Uninsured<br>Over 25 years of age and living in poverty<br>Female population<br>Renter occupied households<br>Non-Hispanic white<br>Hispanic<br>Non-Hispanic black<br>Families with married head of household<br>Female-led household<br>No vehicle access | | A measure of inequality |

### Table 2

Opioid vulnerability assessment model selection.

| Count of unit of analysis (e.g., counties or zip code tabulation areas) | Tier | Scoring model (algorithm) and Description | Formula |
|---|---|---|---|
| <10 | 1 | Rank-based: Ranked by summation of indexed measures | $V_c = \sum CorR_{c,j}$<br>Where,<br>$V_c$ = vulnerability score for unit of analysis c<br>$CorR_{c,j}$ = rank of core measure j in county c |
| 10 to <25 | 2A | Weighted rank-based: Ranked by summation of weighted indexed measures selected by expert consensus | $V_c = \sum W_i R_{ci}$<br>Where,<br>$V_c$ = vulnerability score for unit of analysis c |
| 25 to <50 | 2B | Regression-weighted rank-based: Ranked by summation of bivariate regression coefficient weighted indexed measures selected by statistical significance | $R_{ci} =$ = rank of the $i^{th}$ covariate/core measure<br>$W_i$ = weighting factor for covariate/core measure i |
| 50 or more | 3 | Regression-based: Ranked using multivariable regression | $V_c = \sum \beta_i X_{ci}$<br>Where,<br>$V_c$ = vulnerability score for the unit of analysis c<br>$X_{ci} =$ = standardized covariate/core measure (i) value at the unit of analysis c<br>$\beta_i$ = regression coefficient for covariate/core measure i from the multivariable regression model |

## Table 3

Core and covariate indicators and service access evaluated across 10 states.

| State | Indicators used in regression model* | | Indicators used without regression model** | Buprenorphine access | SSP Access |
|---|---|---|---|---|---|
| | Positive association | Negative association | | | |
| Alaska | | | Crime, Rx, HCV, SVI | Low access, rurally | Low access, rurally |
| Delaware | **Crime, Rx, HighSchool, Unemp, FemHH, Hisp** | **Inc, White** | | Low access, rurally | Low access, rurally |
| Florida | Rx, **Inc**, MarrHH, White, Hisp | Crime, HCV, **HighSchool, Unemp, black** | | Access tracks vulnerability | Low access, generally |
| Hawaii | | | Crime, Rx, SVI | Low access, generally | Strong, with gaps |
| Idaho | **Crime**, Rx, E.D., **EMS**, HighSchool, **Unemp**, **FemHH**, White, black, Hisp | Inc, HCV | | Low access, generally | Low access, generally |
| Indiana | **Crime, Rx, HCV, ED,** HighSchool, **Unemp**, **FemHH**, black | | | Low access, rurally | Low access, rurally, but access tracks vulnerability |
| Kansas | Crime, **Rx, HCV,** E.D., **HighSchool, Unemp, WNH** | MarHH | | Low access, generally | Low access, generally |
| Massachusetts | | | Crime, Rx, HCV, HighSchool, FemHH, MarHH, White, black, Hisp; Inc. (negative) | Low access, rurally | Strong, with gaps |
| Texas | **Rx,** HCV, E.D., **Inc, White**, black | HighSchool, Unemp, **FemHH, Hisp** | | Low access, rurally | Illegal |
| Wyoming | | | Crime, Rx, HCV, ED, EMS, FemHH; Inc., White (negative) | Low access, rurally | Illegal |

Notes.

* **bolded** are significant to $p < 0.10$.

** positive association unless otherwise noted as "(negative)". SSP = Syringe Services Program. ***Indicators, opioid-related:*** Crime = Drug-related arrests or crime; Rx = High-dose opioid prescriptions, total opioids prescriptions, or total MME (morphine milligram equivalents) prescribed; HCV = chronic HCV (except acute in Florida); ED = emergency department opioid-involved non-fatal overdoses; EMS = opioid-involved non-fatal overdose runs. ***Indicators, socioeconomic covariates:*** Inc. = Per capita or median income; HighSchool = No high school diploma; Unemp = unemployed; MarHH = married head of household; FemHH = female head of household; SVI = Social Vulnerability Index; White = non-Hispanic white; Black = non-Hispanic Black; Hisp = Hispanic.