The author(s) shown below used Federal funding provided by the U.S. Department of Justice to prepare the following resource:

Document Title:	Building Drug Intelligence Networks to Combat the Opioid Crisis in Rural Communities: A Collaborative Intelligence-Led Policing Strategy
Author(s):	Andy Hochstetler, David J. Peters, Kyle Burgason, Jeff Bouffard, Glenn Sterner III, and Shannon Monnat
Document Number:	307534
Date Received:	September 2023
Award Number:	2018-AR-BX-0004

Building Drug Intelligence Networks to Combat the Opioid Crisis in Rural Communities:

A Collaborative Intelligence-Led Policing Strategy

September 2023

Investigators: Andy Hochstetler[1,2], David J. Peters[1], Kyle Burgason[1], Jeff Bouffard[1], Glenn Sterner III[3], Shannon Monnat[4]

Awardee: IOWA STATE UNIVERSITY OF SCIENCE AND TECHNOLOGY, 1138 Pearson Hall, 505 Morrill Road, Ames, IA, 50011-2103

Award: 2018-AR-BX-0004

1. Iowa State University, Department of Sociology and Criminal Justice
2. Project Director, e:mail: hochstet@iastate.edu, phone:515-451-1005, 203B East Hall, 510 Farm House Lane, Ames, IA, 50011-1070
3. Pennsylvania State University Abington, Department of Criminal Justice
4. Syracuse University, Sociology Department

This project was supported by Award No. 2018-AR-BX-0004, awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. The opinions, findings, and conclusions or recommendations expressed in this publication are those of the authors and do not necessarily reflect the official position or policies of the Department of Justice.

Collaborating agencies include: Tennessee-5th Judicial District Drug Task Force, Lafollette Police Department, Oneida Police Department, Missouri- Missouri State Highway Patrol, Lake Area Narcotics Enforcement Group, Crawford County Sheriff's Office, Maries County Sheriff's Office, Pennsylvania-Office of the Attorney General, New Wilmington Police Department, and Wyoming County District Attorney's Office.

Table of Contents

List of Tables and Figures

Appendices

Abstract

Introduction: The goal of this project was to identify rural jurisdictions with high drug overdose rates and collaborate with resourced mentors to create law enforcement intelligence responses to local opioid problems.

Methods: The first part of the strategy was to control for known contributors to opioid death that are largely beyond the control of law enforcement, and thereby focus on jurisdictions that are outliers in terms of drug problems. (Work products include a Non-Metropolitan County Opioid Overdose Calculator that allows one to examine how demographics and other county conditions affect overdose risk.) Use of maps of drug overdose deaths identified high overdose places by drug type with a classification technique to group places with like drug problems (latent profile analysis) and a multiple regression data analysis to identify outliers. A survey of law enforcement agencies provided an understanding of intelligence resources available in rural areas and agencies. This information informed recruitment of enthusiastic participant agencies. A small scale, intelligence strategy appropriate to resource deprived, rural departments was developed in collaboration with participating agencies, leaving them great flexibility in design. Evaluation of outcomes included a survey, qualitative interviews providing anecdotal feedback, and official data that each department had decided would speak to successful implementation.

Conclusions: Variables significantly predicting death rates include population, indicators of ethnic diversity, natural resource amenities, and labor market characteristics. Lagged indicators of drug deaths and prescribing rates are the most consistently significant and convincing block of variables as predictors of current death. The most successful departments implemented efforts based on what they had learned in previous collaborations with better resourced areas, where efforts led to arrests and judges supported use of intelligence in court proceedings, and either information sharing or use of electronic surveillance was supported such as using cell phone opening software. Also, closed network iPads were used in relation to controlled buys, search warrants, pre and post raids, evidence and picture recording during searches, overdose mapping, surveillance photos and messaging to the narcotics officer, confidential informant files and referencing files, and notes from scenes. ODMAP can inform efforts but proved difficult to use on mobile devices, lagging in time, and imprecise to use as daily actionable intelligence. Funds can be well spent in rural places, but investments in departments with little resource slack, lacking in administrative capacity, and where there are few personnel or hours of investment to spare are risky and make for difficult collaborations. Analytics and predictive problem solving are near impossible. Therefore, immediate and accessible intelligence for patrol officers without investment in analytics likely should be the goal.

Statement of the Problem

For more than two decades, opioid use disorders (OUDs) and related mortality rates have increased dramatically (Florence et al. 2016; Rigg & Monnat 2015a; Weiss et al. 2016). The age-adjusted rate of drug overdose deaths involving any opioid increased from 2001 to 2021 in the U.S., especially for fentanyl and non-methadone synthetic opioids (Center for Disease Control and Prevention, CDC, 2022). The opioid epidemic grew markedly during COVID, along with a general epidemic of drug abuse. Based on provisional data from CDC (2022), drug overdoses grew by 15.7 percent between 2020 and 2021—half the 2019 to 2020 rate when they grew 30 percent. Of the roughly 108,000 overdose deaths recorded at the end of 2021, about 65 percent were attributable to "illicit" opioids (e.g. heroin, non-prescription synthetic, and unknown opioids), continuing a trend that began in 2013 (CDC 2022; Drug Enforcement Administration, DEA, 2021). The Substance Abuse and Mental Health Services Administration (SAMHSA) estimated that in 2021, 3.1 percent or 8.1 million people aged 12 or older in the U.S. misused prescription pain relievers, compared with 1.1 million who used heroin (SAMHSA 2023). While opioids, due to their lethality, remain the crux of the mortal drug danger, there has also been a rapid rise in overdoses from other drugs. Deaths where methamphetamine and cocaine contributed sharply increased and now account for 19.8 percent and 19.4 percent of overdose deaths, surpassing deaths from prescription opioids (17.2 percent) (CDC 2022). A polysubstance epidemic has placed heavy burdens on local police, emergency personnel, the courts, corrections system, and social services agencies (Lurie 2017, Moghe & Drash 2017). In 2019 and 2020, opioid deaths were about 70,000 per year (CDC 2021).

Findings from U.S. research are mixed on whether opioid use disorder (OUD) rates are higher in rural or urban areas of the U.S., with some studies finding higher rates in rural areas (Cicero et al. 2007; Monnat & Rigg 2016; Paulozzi & Xi 2008) and some in urban areas or no difference (AHRQ 2017; Lenardson et al. 2016; Rigg & Monnat 2015a; 2015b). Opioid-related mortality clearly has increased at a faster pace in rural areas. The age-adjusted opioid-related mortality rate increased 185 percent in large central metro areas, 693 percent in micropolitan areas, and 725 percent in noncore/rural areas between 1999-2015 (CDC 2016); however, after the pill problem peaked and fentanyl proliferated, death rates grew rapidly in urban areas (Peters and Hochstetler 2023). Methamphetamine remains a problem disproportionately affecting rural parts and contributing in a great and recently increasing number of drug deaths (Peters and Hochstetler 2023). It is clear that the U.S. drug problem and drug death problem can no longer be characterized as an urban problem.

Many communities have begun to respond to the opioid and thereby the overdose crisis aggressively (U.S. Attorney, Northern District of Ohio 2018). Comprehensive responses include improvements in intelligence data systems and analysis, intelligence gathering techniques, targeted enforcement strategies, and legal changes, as well as enforcement efforts to support new regulations and laws. They also include public health responses such as treatment oriented drug courts, Naloxone availability, follow-up for overdose survivors, and locally supported treatment options. However, comprehensive responses are difficult to implement in rural communities where resources for basic law enforcement often are strained. Therefore, a first step in a viable rural response is information and intelligence improvement for police, the front-line in drug and opioid response. However, rural police often are resource deprived, and need even the most basic drug responses buttressed.

The goal of this integrated research, practice and extension project is to identify and disseminate effective intelligence strategies to reduce drug death and opioid risks and increase enforcement outcomes in *rural* communities. We mapped the spatial distribution of the drug death problem, identified high opioid hazard communities, then screened locations to gauge intelligence response, match mentors with departments with scant intelligence resources and response, facilitate mentoring, observe implementation of intelligence strategies, and track outputs with qualitative and quantitative data. This project operated on the assumption that local narcotics police are able to prioritize their needs and develop a response with only limited advisory input from outside experts. The project aimed toward intelligence-centered responses feasible for rural areas, premised on the notions that local law enforcement understands the needs of their community and how to respond best, and that a collaborative design where stakeholders have control is effective particularly for areas that cannot easily emulate responses in urban centers due to limited resources.

Research questions follow:

(1.) What is the spatial distribution of drug death by substance in the U.S.? (2.) What factors best indicate opioid risk in rural places? (3.) What responses are rural communities and their police making to the drug and particularly the opioid epidemic, especially for police intelligence and information gathering? (4.) What intelligence-centered approach do rural police departments find most useful and how do they respond when primed to initiate one with a small investment of resources? (5.) What benefit is yielded with new initiatives in opioid response and drug intelligence for rural police? (6.) Where should taxpayers invest resources for maximal outcomes?

Our process for understanding and responding to the deadly drug problem in rural areas had four steps. First, understand the spatial distribution of drug deaths in the U.S. Second, develop a statistical model to identify places that were outliers for drug problems based on known predictors of opioid deaths. By modeling out this variation, we removed known structural predictors and other controls related to the opioid problem, presumably accounting for things that largely are beyond law enforcement's control. We highlighted locations (counties) that had large differences, or residuals, from predicted values but that also had a significant opioid death problem that needed addressing. Third, we conducted a survey to get an initial understanding of law enforcement intelligence efforts in rural police departments, including potential implementation sites to make sure each had resources typical of a rural department, which are scant. We included both very rural and somewhat rural places. Fourth, we recruited departments based mainly on high death rates and scores on the residuals indicating that they were unusual given their economic and demographic characteristics. We also selected places of varying resource availability, the feasibility of travel to the location, and willingness for participation in the project and working in a mentor and mentee relationship during a project that spanned the worst of the COVID-19 epidemic. Once departments were selected and successfully recruited, we cultivated relationships with local partner agencies providing services to the area. Mentor agencies already had some relationship to the selected departments, but intelligence initiatives were not centered locally in these smaller and rural departments; the project successfully inspired a new initiative in all sites. Sites provided official data before and after implantation and a final executive survey, but implementation efforts mainly were evaluated using site visits, intermittent contact with officers and employees involved in the project, and qualitative interviews.

Intelligence Led Policing in Rural Areas

Rurally located departments "often lack the resources for training and equipment accessible to larger departments" (International Association of Chiefs of Police, IACP, 2018). However, "the needs of agencies—from the very small to the very large—must be considered if intelligence-led policing is to be established in the United States" (U.S. Department of Justice, DOJ, 2005). *Intelligence-led policing* is the use of data and formal analysis to form strategy and facilitate gathering additional information for still further analysis. Rural departments may need investment in rudimentary intelligence, rather than in cutting edge analytics. For example, when the Bureau of Justice Assistance (BJA) established a new intelligence-driven policing model in Evans County Georgia, a community of 12,000 with twelve officers, during an initiative aimed mainly at large departments, they initiated an e-roll call. Officers in Evans County did not brief before shifts or communicate across shifts. Another measure was staffing a daily e-mail exchange for informational mailings to larger adjacent departments (BJA 2008). Underdeveloped intelligence is partially an effect of a small tax base for many small town police departments; a study in Pennsylvania, found that small town departments spend 62 percent of what urban areas spend on policing per capita (Center for Rural Pennsylvania 2006).

The origins of intelligence-led policing lie in concern with investment of limited enforcement dollars, use of analysts and planners to combat particular problems, the recognition of improved data value and access, and in the value of multiple sources of information, ranging from surveillance, to mapping, to police informers for managing crime's risk (Ratcliffe 2016). Because it results in a tailored response, intelligence-led policing requires local data and information inputs, and often ties closely with community policing. It focuses on collaboration between analysts with inclination and time to craft broader, proactive responses with line officers, and also multi-jurisdictional partnership to improve information flows. Strategic intelligence involves "big picture" strategy such as allocation of resources toward intelligence driven objectives (i.e., staffing an analyst position). Evidential intelligence involves leveraging information toward more information (i.e., incentivizing paid informants, or use of the National Virtual Pointer System, a system for checking agencies working cases with the goal of target deconfliction). Operational intelligence involves targeted responses aimed at a particular type of case or group of similar offenders (i.e. doctor shoppers, pain clinics, or a gang) (Ratcliffe 2016).

The most common means of collecting drug intelligence information are by physical surveillance, electronic surveillance, cultivating and using confidential informants, and undercover operations. Any operation designed to develop sources and gather information for use beyond a current case is an intelligence operation, if the aim is a larger effort of investigating and building cases for future arrest or for strategy-making. Sources of information may include arrestees, community members, social service agencies and public safety workers. Data gathering almost necessarily is intelligence, and "intelligence is a product that is immediately or potentially significant to client decision making" (Australian Customs Service 2000, p. 15; Ratcliffe 2016).

Intelligence building encompasses more of law enforcement than most people imagine. It has several possible broad strategies composing it as well. The five intelligence strategies are:

1. Confidential informants: Strategies that focus mainly on informants (by building confidential informant relationships, and networks, or incentivizing larger returns from confidential informants already developed).
2. Training: Strategies focused on sending key officers to drug enforcement and intelligence training.
3. Analysis and communication: Strategies focused on analysis of available data. Alternatively, agencies might develop or enrich ties and communication systems with adjacent areas and/or state intelligence such as drug task forces.
4. Community policing and information: Measures focused on developing community provided information such as providing and enhancing tip-lines or by advertising and disseminating information about such as emergency dispatchers, private paramedics, volunteer firemen, hospital security workers, and non-governmental social service providers.
5. Interdiction: Measures focused on interdiction such as retraining of K-9 animals for opioid detection, or training by state-police experts in traffic interdiction and searches. Other measures could be targeted pursuit of a type of offender, such as prescription fraudsters, larger traffickers, or pill distributors.

Drug Deaths by Time and Place

In the immediately following sections, we describe how we mapped the spatial distribution of the deadly drug problem, including the variables used, the statistical technique for grouping like places (Latent Profile Analysis, LPA) and for comparing mean differences. *Data and Modeling* describes data sources and variables used for this study and the statistical technique for grouping places (LPA). We then present descriptive trends in drug mortality by place in a section called *Trends in Drug Mortality*. Next we present the statistical grouping identified and key differences between them in *Identifying Drug Epidemics*. These analyses provided broad understanding of drug problems throughout the U.S. that contributed to choosing states for site selection.

Data and Modeling

First, we examined the spatial distribution of the deadly drug problem in the U.S. to identify the most pressing regional problems. Units of analysis are counties in the 48 conterminous states based on 2000 Census geographies, with modifications to prevent breaks in the spatial time-series.[1] Drug mortality is defined as any underlying (primary) cause-of-death that involved one or more of the following drugs as a contributing cause (International Classification of Diseases, Tenth Revision or ICD-10 codes in parentheses): prescription opioids (T40.2, 40.3), illicit opioids like heroin and synthetics (T40.0, 40.1, 40.4, 40.6), cocaine (T40.5), methamphetamine (T43.6), hallucinogens (T40.7, 4038, 40.9), sedatives of the central nervous system (T42.3, 42.4, 42.6, 42.7), anti-depressants (T43.0, 43.1, 43.2), and anti-psychotics (T43.3, 43.4, 43.5, 43.8, 43.9). By not limiting the underlying cause-of-death to only overdoses, we create a more comprehensive measure of drug mortality, and hence a broader indicator of drug abuse. That said, the majority of drug deaths are from overdoses, especially for opioid class drugs. The expanded measure allows us to capture the impact of drug-related deaths that are often not the result of overdoses, as is the case for methamphetamine and hallucinogens.

Data are obtained from confidential cause-of-death mortality files from the National Vital Statistics System (NVSS) maintained by the CDC (2017). Opioid mortality rates per 100,000 population (based on 2000 Census) are by residence of the decedent and are pooled over three-year periods between

2000 and 2016 to reduce annual fluctuations in small counties, as is standard in public health research (Rothman, Lash, and Greenland 2008). One limitation is a recognized drug mortality undercount on death certificate data, where synthetic opioid analogs and other unknown drugs go undetected in toxicology reports (Ruhm 2018). Since there is no agreed upon method to correct this problem, our measures represent a lower-bound estimate of drug mortality.

Latent profile analysis (LPA) is used to identify drug epidemics by classifying counties into classes so that places with similar mortality rates and growth are grouped, based on mortality rates per 100,000 across eight drug types (prescription opioids, illicit opioids, cocaine, methamphetamine, hallucinogens, sedatives, anti-depressants, and anti-psychotics) in 2016-18 and change from 2000-02. Mortality rates are normalized using *z*-scores to remove scale differences for comparisons. LPA is sensitive to extreme score, like all classification techniques, so data are Winsorized at the 0.5 and 99.5 percentiles, roughly corresponding to ±2.6 standard deviations. LPA is part of a broader technique called finite mixture models. The procedure assumes observed data form a multivariate mixture collected from a number of mutually exclusive profiles, each with its own distribution (Lanza, Tan, & Bray 2013). We refer to the profiles as classes as this term is more common across disciplines. LPA offers some advantages over more common classification techniques like hierarchical cluster analysis (Morgan et al. 2016). The estimated LPA density function is presented in equation 1, where $\mathbf{x}_i$ are the 16 drug mortality variables for county i, $\boldsymbol{\lambda}_k$ are the mixture weights for each variable in class k, and $\boldsymbol{\theta}_k$ are the mean vectors and covariance matrices for each class or $\boldsymbol{\theta}_k = (\boldsymbol{\mu}_k , \boldsymbol{\Sigma}_k)$ (Collier & Leite 2017). The LPA is identified by having positive degrees of freedom, an information matrix that is positive definite, and uncorrelated indicators (Abar & Loken 2012; McLachlan & Peel 2000).

$$f\left(\mathbf{x}_i \mid \boldsymbol{\theta}\right) = \sum_{1}^{K} \boldsymbol{\lambda}_k f_k\left(\mathbf{x}_i \mid \boldsymbol{\theta}_k\right)$$

To describe the demographic, drug risk, social disorganization, and economic characteristics of counties affected by different drug epidemics, a multivariate general linear model (traditionally MANOVA) is used to explore unconditional mean differences across a number of variables using the

Games-Howell test, which is robust to unequal group sizes and variances (Johnson & Wichern 2007). Current indicators and change from 2000 are primarily obtained from the U.S. Census Bureau's American Community Survey (2012-16 ACS, 2014-2018) and previous decennial Census periods, unless otherwise noted. We use 2003 Core-Based Statistical Area (CBSA) definitions for primary metropolitan and micropolitan counties.

Demographics include population, shares of those 25 and younger and 65 and older, minority population shares (Hispanic of any race, African-American, and other/multiple races), and residence in another county five years previous. A number of locational factors are also explored. Natural amenities have been found to either help or hinder economic development (Pender et al. 2014), which may indirectly affect drug overdose fatalities as documented in the literature (Betz & Jones 2018). Using data from USDA's Economic Research Service, amenities include topographic variation and water area (*z*-scores). Density of interstate road lengths per square mile are calculated using, Environmental Systems Research Institute (ESRI) files to model transportation access and drug trafficking corridors (DEA 2017, ESRI 1998). ESRI shapefile format is a special-purpose dataset for storing non-topological geometry and attribute information for spatial features in a data set (ESRI 1998). *Drug risk factors* are selected based on extant research (Monnat 2019; Rigg, Monnat & Chavez 2018). Prescription opioid dispensing rates per 100 people is used to measure supply, taken from QuintilesIMS Transactional Data Warehouse with modifications. Work disabled individuals as a percent of the population is from the Social Security Administration's OASDI program. To measure healthcare infrastructure, we use County Business Patterns (U.S. Census 2020; Upjohn Institute 2019) place-of-work employment per 10,000 in retail pharmacies, physician offices, mental health and substance abuse centers, hospitals, and family social service organizations. These variables are used to control for the availability of prescribers and pharmacists that may exacerbate drug deaths, or social and addiction service providers that may inhibit them.

From the U.S. Census we include the person poverty rate, the 80:20 income gap to measure inequality (quotient of income shares owned by the top and bottom 20th percentiles), and the percentage of housing units that are vacant to measure physical disorganization. Although single-headed families is found to be a significant predictor of drug overdoses in previous studies, we drop it from consideration due to its high correlation with poverty. Property crime rates per 100,000 people in the jurisdiction come from the Federal Bureau of Investigation's Uniform Crime Reports, with modifications. Crime is typically an outcome in disorganization research, but we view property crime (includes burglary, larceny, vehicle theft, and arson) as an indicator of community disorder contributing to drug use and mortality. Social capital is measured using employment per 10,000 (from County Business Patterns, U.S. Census 2020; Upjohn Institute 2019) in religious organizations, and in community, social, and civic organizations. Charitable contributions per capita measure local giving, and is taken from Internal Revenue Service Data (U.S. Department of the Treasury 2019).

Lastly, *employment and economic restructuring* is measured using current employment shares from the 2012-16 ACS and change from the 1990 Census. We include change over two decades to capture long-term consequences of economic restructuring on drug mortality. Census employment is defined as employed persons (16 years and older) by place of residence in two-digit North American Industry Classification System (NAICS) industry codes. Some services sectors are aggregated for comparability to 1990 data. Our use of place-of-residence person employment is unique from existing studies that use place-of-work job counts. The former is preferable since it is consistent with CDC mortality data that is also reported by residence. Blue-collar employment sectors, with NAICS codes in parentheses, include: agriculture, forestry, and fishing (11); mining (21); construction (23); manufacturing (31-33); and transportation and warehousing (48-49). Lower skilled jobs characteristic of the postindustrial economy is measured by retail trade and leisure services (44-45, 71-72, 81). Additional notes on methods appear in Appendix A-3.

Trends in Drug Mortality

Drug overdose mortality has grown markedly over the past two decades, as shown in Figure 1. During 2000-2002, high drug mortality of 25 deaths per 100,000 were rare and confined to only a few areas of the U.S. These includes areas in central Appalachia, New Mexico, and reservations in the northern Plains. By 2016-2018, however, large swathes of the nation were experiencing high rates of overdoses, primarily driven by illicit and prescription opioids. This included the Ohio River valley, Appalachia, most of the northeast, Missouri and Oklahoma, Florida and Louisiana, and the southwestern states.

Opioids, from ill-gotten prescriptions to illegal narcotics like heroin and synthetics, account for most drug deaths (see Figure 2). Illicit opioids mortality is fast rising in urbanized America, while prescription opioid deaths have fallen across the Nation. In the largest metropolitan areas, cocaine and methamphetamine account for one-third of drug deaths, while the most rural places these drug account for 45 percent or fatalities involving drugs.

Figure 1. Drug Mortality per 100,000 2002 and 2018.

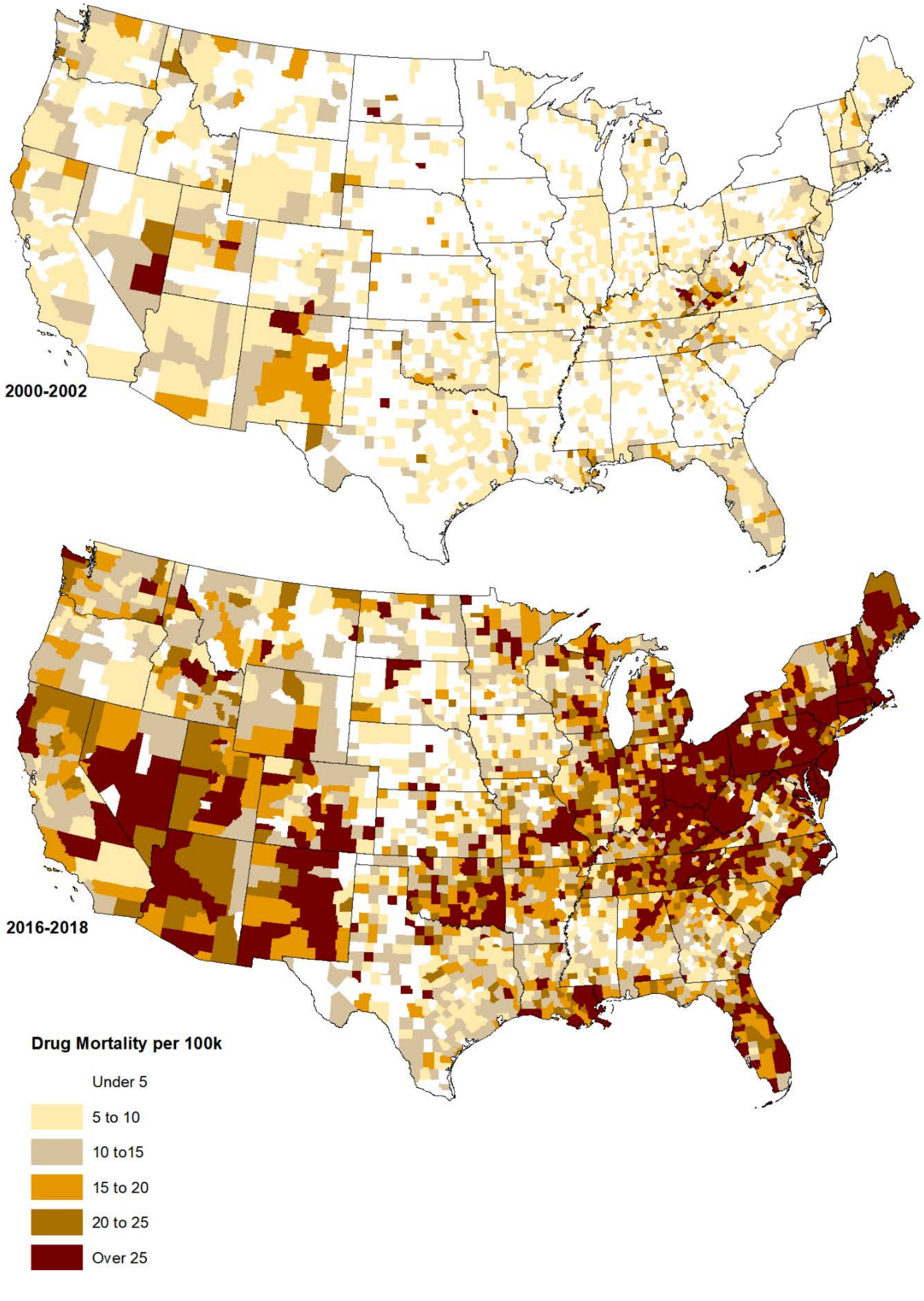
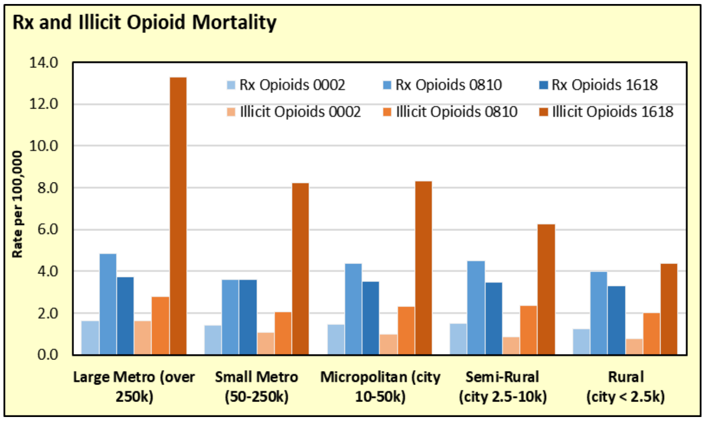
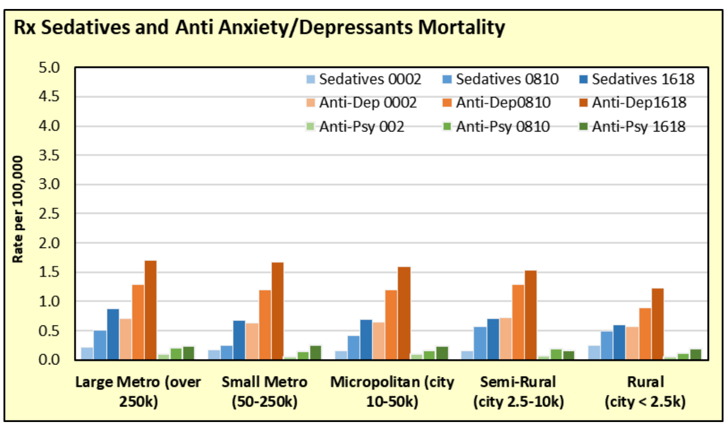


Figure 2. Mortality by drug type per 100,000 (age-adjusted) by modified Core-Based Statistical Areas between 2000-2002 and 2016-2018 for: prescription, and illicit opioids (heroin and synthetic opioid



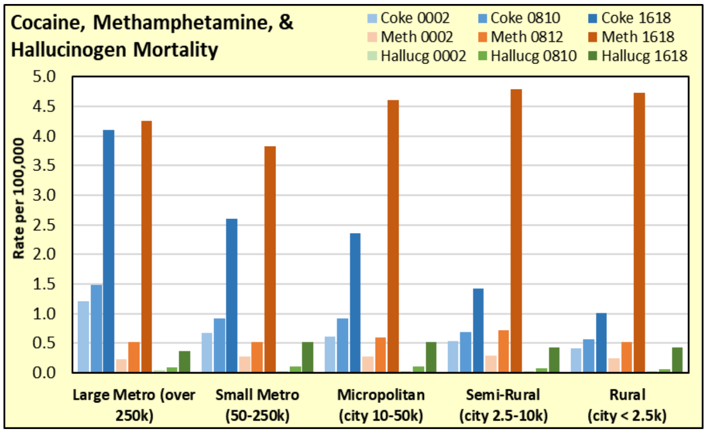
Mortality from other prescription drugs that are often abused are low, including sedatives and anti-psychotic medications (see Figure 3). However, deaths from prescription anti-depressants are trending upward (Figure 3).

Figure 3. Mortality by drug type per 100,000 (age-adjusted) by modified Core-Based Statistical Areas between 2000-2002 and 2016-2018 for: Rx Sedatives and Anti Anxiety/Depressants Mortality by Rural-Urban



Cocaine deaths remain largely an urban problem and is increasing across rural and urban placed while methamphetamine deaths have spiked and are more common in rural areas (Figure 4**).**

Figure 4. Mortality by drug type per 100,000 (age-adjusted) by modified Core-Based Statistical Areas between 2000-2002 and 2016-2018 for: cocaine, methamphetamine, and hallucinogens



Identifying Drug Epidemics

This section is about understanding distinct drug problems and where they occur in the U.S. by classing counties with Latent Profile Analysis (LPA) so that counties with similar death rates by drug and growth in death rates group together. We identify drug mortality epidemics at the county level using LPA. The procedure classified counties into eight latent classes, each having a distinct distribution of drug mortality. Each latent class represents a distinct drug epidemic. The initial LPA estimated seven classes, but examination of class means indicated the polydrug class, where deaths are high for all substances. The polydrug class has a small yet distinct subpopulation. For substantive interpretation, we extracted the polydrug class, resulting in eight classes. Detailed results of the LPA are presented in Table 1, where Bayesian Information Criteria (BIC) is a criteria for model selection; lower numbers are preferred and significance indicates difference in fit from previous model as classes are fit to data. To ensure high internal consistency, we exclude any county not having a posterior probability (i.e. likelihood of correct classification) above 0.90 on at least one latent class, resulting in 236 unclassified counties. Means of standardized drug mortality rates in 2016-18 and change from 2000-02 across the eight latent classes is presented in Table 2. The spatial distribution of the drug mortality classes is shown in Figures 3-4 and mapped in Figure 5.

Table 1 Fit Statistics from Latent Profile Analysis

Class Stage	BIC	Adjusted BIC	AdjBIC Change	Relative Entropy	VLMR Test	LMR Test
1	113,148	113,047	n.a.	n.a.	n.a.	n.a.
2	103,949	103,793	-8.186%	0.961	9,336 ***	9,268 ***
3	97,959	97,749	-5.823%	0.967	6,126 ***	6,081 ***
4	93,774	93,511	-4.336%	0.969	4,322 ***	4,290 ***
5	90,262	89,944	-3.815%	0.973	3,649 ***	3,622 ***
6	87,370	86,999	-3.274%	0.975	3,028 ***	3,006 ***
7	85,243	84,817	-2.508%	0.967	2,264 ***	2,248 ***
8	83,361	82,882	-2.281%	0.970	2,018	2,003
9	81,909	81,375	-1.818%	0.970	1,589	1,577
10	81,054	80,466	-1.117%	0.964	992	985
11	80,275	79,633	-1.035%	0.959	567	563
12	78,800	78,104	-1.920%	0.967	996	988

*p<0.05, **p<0.01, ***p<0.001

The majority of counties in the U.S. (*n*=1,666) have *low to average drug* mortality, with standardized rates ranging from -0.30 to -0.50 below the national average. The remaining counties are classified into specific drug mortality classes. The 228 counties in the *emerging hallucinogen* class have above average fatalities (*z*=0.82), but are not yet at crisis levels. By contrast, the *high hallucinogen epidemic* class (*n*=112 counties) has extremely high hallucinogen fatalities (*z*=2.37), with methamphetamine being a co-abused drug with above average mortality (*z*=0.74). Hallucinogens include drugs like LSD, MDMA, psilocybin, mescaline, DMT, and PCP.

The *methamphetamine epidemic* consists of *n*=205 counties where methamphetamine (or variants like blue, crystal ice, and speed) mortality is well above average (z=1.69). Prescription opioids (z=0.58) also appear to be abused in meth counties, either alone or in combination. The *prescription sedatives and opioids epidemic* (n=119) includes counties where these two prescription drug are frequently abused at a level to cause death. Deaths from sedatives are *z*=2.22 standard deviations above the national average; and prescription opioids are also above the national rate at *z*=0.98. Commonly abused sedatives or depressants include Xanax, Ambien, Lunesta, Valium, GHB, and other barbiturates. In addition, a *prescription anti-psychotic and anti-depressant epidemic* also exists in *n*=156 counties. Instead of prescription sedatives, deaths are attributable to anti-psychotic medications (*z*=1.99) and anti-depressants (*z*=0.82). The primary anti-psychotic with abuse potential is quetiapine/Seroquel (Susy Q, quell, baby heroin), but also includes Clozaril, Zyprexa, Abilify, and Zeldox. Common anti-depressants include Prozac, Zoloft, Paxil, and Colexa. Like other prescription epidemics, pharmaceutical opioids are also co-abused resulting in above average death rates (*z*=0.56).

The *illicit opioids and cocaine epidemic* reflects the public narrative of the opioid crisis and illegal drug trade. Both cocaine (*z*=1.68) and illicit opioids like heroin, fentanyl analogs, and other unknown narcotics (*z*=1.42) result in deaths in these *n*=322 counties. These illegal drugs are smuggled into the U.S. by drug trafficking organizations. Highly potent in pure form, small quantities are brought into the country, then cut with other substances to vary potency and maximize profit. Communities in this group are part of the “powder” epidemic. The preceding classes can be termed epidemics, as only one or two opioids are responsible for most overdose fatalities. However, our analysis finds a group of counties with co-occurring epidemics that overlap and reinforce each other (Ciccarone 2019). The *n*=35 counties in the *polydrug* class have coinciding epidemics involving anti-psychotics (*z*=2.13), hallucinogens (*z*=1.77), anti-depressants (*z*=1.49), prescription opioids (*z*=1.21), illicit opioids and methamphetamine (both *z*=1.00), and cocaine and prescription sedatives (both *z*=0.76).

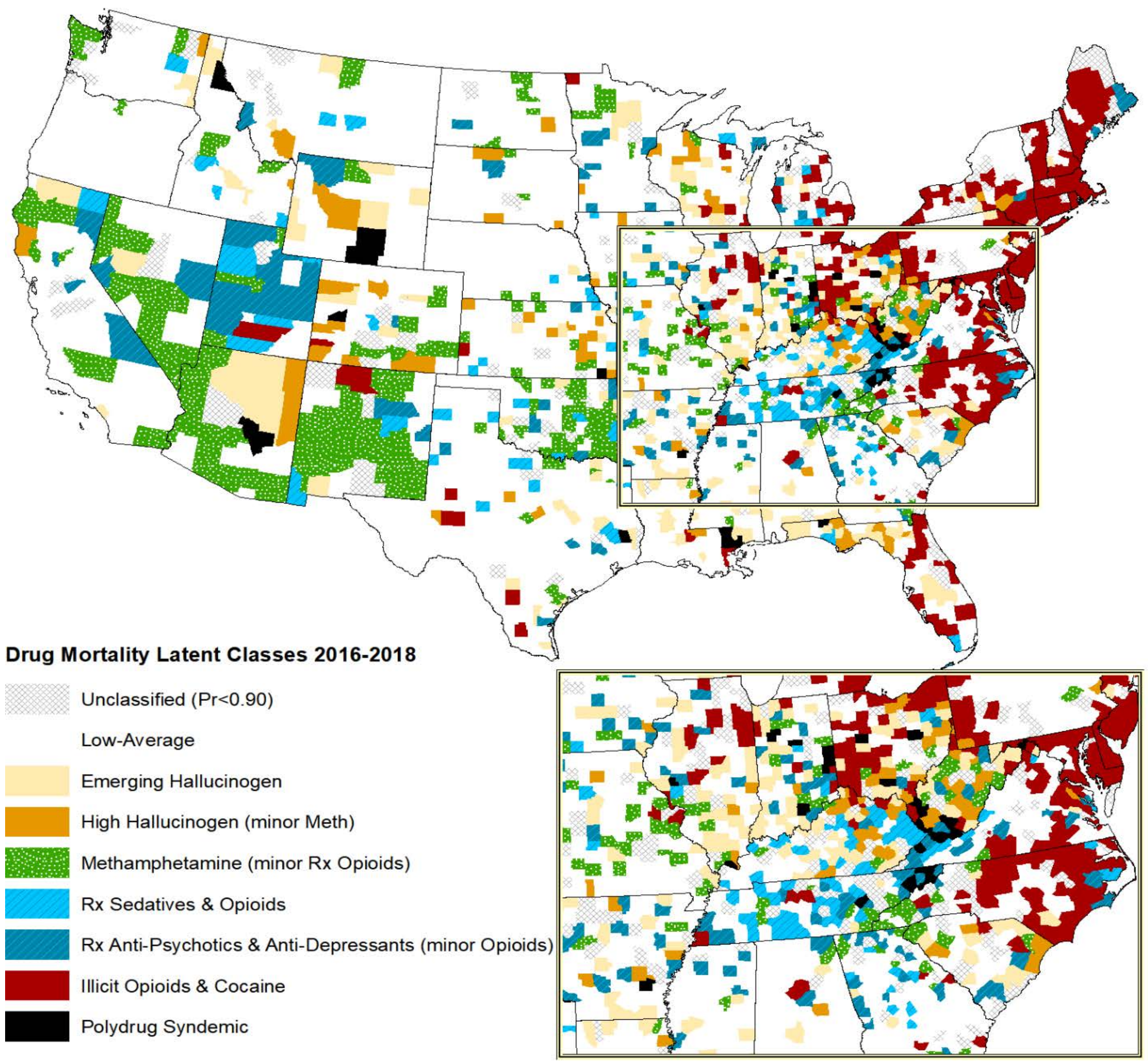
Table 2 Means of Standardized Drug Mortality Rates by Drug Mortality Latent Classes

	Drug Mortality Latent Classes															
	Low to Average (n=1,666)		Emerging Hallucinogen (n=228)		High Hallucinogen (n=112)		Methamphet-amine (n=205)		Rx Sedatives & Opioids (n=119)		Rx Anti-Psychotics / Depressants (n=156)		Illicit Opioids & Cocaine (n=322)		Polydrug (n=35)	
Drug Mortality	*Base*	*Chg*	*Base*	*Chg*	*Base*	*Chg*	*Base*	*Chg*	*Base*	*Chg*	*Base*	*Chg*	*Base*	*Chg*	*Base*	*Chg*
Rx Opioids	-0.38	-0.26	0.08	0.11	0.41	0.37	**0.58**	**0.35**	**0.98**	**0.79**	**0.56**	**0.39**	0.11	0.06	**1.21**	**1.04**
Heroin & Synthetic Opioids	-0.44	-0.43	0.07	0.10	0.48	0.49	0.09	0.05	0.13	0.10	0.04	0.02	**1.42**	**1.38**	**0.98**	**0.93**
Cocaine	-0.37	-0.34	0.00	0.05	0.17	0.25	-0.33	-0.43	-0.16	-0.19	-0.11	-0.07	**1.68**	**1.58**	**0.76**	**0.72**
Methamphetamine	-0.39	-0.39	0.20	0.22	**0.74**	**0.73**	**1.69**	**1.67**	0.27	0.29	0.23	0.21	-0.30	-0.27	**1.03**	**1.06**
Hallucinogens	-0.28	-0.26	**0.82**	**0.82**	**2.37**	**2.35**	-0.28	-0.30	-0.26	-0.28	-0.24	-0.24	-0.22	-0.22	**1.77**	**1.78**
Sedatives (CNS)	-0.31	-0.23	-0.04	-0.01	0.28	0.21	-0.19	-0.20	**2.22**	**2.06**	0.37	0.31	0.09	0.07	**0.76**	**0.54**
Anti-Depressants	-0.32	-0.22	0.02	0.02	0.04	-0.08	0.29	0.15	0.32	0.23	**0.82**	**0.68**	0.30	0.25	**1.49**	**1.21**
Anti-Psychotics	-0.24	-0.17	-0.18	-0.16	-0.25	-0.29	-0.19	-0.19	-0.22	-0.32	**1.99**	**1.87**	-0.03	-0.02	**2.13**	**1.79**

Bold indicates above average z-score.

Distribution of the drug mortality classes varies across the rural-urban continuum, as shown in Figures 3-4. The high hallucinogen epidemic tends to cluster spatially in Appalachia, south Atlantic states, and parts of the Midwest and Great Plains. The methamphetamine epidemic tends to occur in the Mountain West, Great Plains, and Midwestern states. Counties in the prescription sedatives and opioids epidemic are concentrated in Appalachia, especially in Tennessee, Kentucky, and portions of western Virginia and West Virginia. The prescription anti-psychotics and anti-depressants epidemic also occurs in Appalachia, but also includes places in the Mountain West in Utah. The illicit opioid and cocaine epidemic is spatially clustered along the eastern seaboard and large cities near the Great Lakes. Lastly, the polydrug counties occur in remote parts of Appalachia, ground-zero of the opioid crisis, as well on reservation counties in the western and Great Plains states. Figure 5 maps the drug classes. (Appendix A-4 contains a map of the drug classes if only opioid types are classed and other drugs are excluded, showing opioid death rates specifically.)

Figure 5. Drug mortality latent classes in 2016-2018 and change from 2000-2002



Analysis to Identify Drug Death Outlier Counties

This section explains how we identified statistical outlier locations to guide site selection. In conjunction with exploratory understanding of the geographic and spatial distribution of the drug problem in the U.S., we aimed to understand which places might benefit most from a locally designed intelligence building initiative. Our logic for selecting places was to control for known structural predictors of drug death. In other words, we predicted death rates by opioid types using many known covariates, and then examined variation that is left unexplained to identify outlier counties. It would make little sense to select only places where structural conditions, like poverty, drive the opioid problem entirely, as these ordinary (average) predictors often are beyond the control of policymakers and police who can do little about things like the labor market or poverty in their communities. It would make less sense to select places that have no problem at all. At least, we should want to understand variation in community context, on how communities are faring against the drug problem *given the economic and social structure of their locale*. We selected places with a high opioid death rate, but varied them on the type of opioid driving the problem and whether they were doing better or worse than expected given the model. Only nonmetropolitan (n=2013) counties and opioid deaths were used in our key analysis for site selection (Appendix A-1, 2, 4).

Our logic rested on the fact that one would not want to take what works for addressing opioid problem that is affluent and educated, say a small university town, with one that has a large population of displaced and impoverished industrial workers in a former factory town with extremely high crime rates. To help select places, we developed a conventional model predicting overdose death using Centers for Disease Control and Prevention (CDC) mortality files for the dependent (outcome) variable and extant social, economic and demographic variables for the independent (predictor) variables. We used this model to predict death rates in rural counties and then identified places that were outliers in Pennsylvania, Tennessee and Missouri, states with varying types of opioid problems on death rates (Tennessee=largely pills; Pennsylvania= largely fentanyl and heroin, and Missouri=pills becoming fentanyl at project's outset). Appendix A-2 shows the results of this analysis with urban influence codes (UIC) reported. UIC codes score counties on a 1-12 scale with 12 being most rural. UIC of four or greater might be considered rural places and entail (4 - noncore adjacent to a metro, 5 - micropolitan and adjacent to a small metro, 6 - noncore adjacent to a small metro with a town of at least 2,500, 7 - noncore adjacent with no town of at least 2,500, 8 - micropolitan not adjacent to a metro, 9 - noncore adjacent to a micro area and does not contain a town of 2,500 to 19,999 residents, 10 - noncore not adjacent to a micro area and does not contain a town of 2,500, 11 - noncore not adjacent to a metro or micro area and contains a town of 2,500, and 12 - noncore not adjacent to a metro or micro area and does not contain a town of 2,500 residents). The columns provide (1.) the z scores for actual deaths by substance, (2.) the z scores for the predicted estimate of the deaths by substance and (3.) and the scores of the residual above or below the estimate as indicated by the numerical sign. Highlights in the table indicate places of interest based on residual sizes. These were calculated using data for the Nation rather than for each state. There is variation in the type of drug leading to fatal overdoses in rural areas by state, even when the analysis is limited to opioid death, with Tennessee being largely pills, Pennsylvania being largely heroin and fentanyl and Missouri being a mix. The regression data analysis provided us a guide for selecting appropriate places for implementation using to the extent possible observable criteria and official statistics.

Statistical analyses include a negative binomial Poisson regression used to predict mortality rates in 2016-2018 with lagged covariates from 2010 and change between 2000 and 2010. The negative binomial model helps account for overdispersion of data toward zero. The model, presented in Appendix A-1, accounts for approximately 40 percent of the variation in mortality rates, taking pills as the example. Negative binomial regression coefficients are reported in Appendix A-1. Appendix A-6 (Artifacts and Dissemination Efforts) contains a web link to a data tool based on this analysis shown in Appendix A-7 (Non-Metropolitan County Opioid Overdose Calculator). Covariates significantly predicting death rates include population, indicators of ethnic diversity, natural resource amenities, and labor market characteristics. Lagged indicators of drug deaths and prescribing rates are the most consistently significant and convincing block of variables as predictors of current death.

Police Agency Intelligence Resources in Rural Areas: Survey Results

As a final screen before site recruitment, we set out to understand resource availability for drug intelligence in rural as compared to urban areas. Our goal was to recruit places that needed assistance but with greater and less resources. To get a sense of the resources available in a community, we used a survey to select locations, allowing us to examine and understand varying resources available to police departments before applying our program and to make sure that we had a wide variety of rural departments. A pretest was used to refine an initial draft of the survey. We pretested the survey with 4 experts on opioid law enforcement (a Chief Deputy of a Sheriff's Department in a county of 91,000, a Police Chief of a town of 27,000, and two public health experts in Iowa and Pennsylvania). We also administered the survey at a national meeting of National Guard Counter Drug programs in Reno, Nevada, 2019 (32 U.S. Code § 112 - Drug interdiction and counter-drug activities). We administered the survey to all participating guardspersons (n=130), and asked that they provide written comments and critiques in the margins and also add any comments about the survey to a 45 minute discussion time that we had with them pertaining to a presentation that we gave on spatial results that day resulting from analysis from another project on spatial drug patterns in the nation. These guardspersons provide a litany of law enforcement and treatment support services, and also advise on widely varying communities and responses to the drug problem in both rural and urban communities, with many of the guardsmen assigned to under-resourced and rural parts of their states. Based on their feedback, we refined our instrument. Then we used a purchased list of all police departments in the U.S. to conduct via a phone or mail survey to garner participation from police departments in five states, across all five regions (West, Midwest, Southwest, Southeast, and Northeast) of the U.S. A mailer provided the option of responding to the survey by mail, phone, or by access to a web site that we created. We also allowed participants to fill out the survey on-line who heard about the survey from one of our law enforcement advisors who was not only a high ranking Sheriff's Department Executive but also an officer of a national police officers' organization; we allowed this in the interest of building sample size so that we could learn about as many departments as possible, but also knowing that these departments outside the mailer sample would not be selected as intervention sites. Each Department received an initial invitation and a reminder postcard to recruit for the survey. The final sample size of survey responses was 232 or 9 percent of the 2,490 departments that we attempted to contact. However, this sample was purposive to choose sites for study in a few states and sufficient to accomplish that goal; it was not intended to draw a representative sample of departments. Figure 8 presents a map of the counties where respondent departments were located and the number of responding agencies in that county. It shows that coverage was greatest in Iowa, Missouri and Pennsylvania where academic investigators had the strongest state-level and state police contacts.

While the survey of departments indicated mainly the presence of basic resources and not the number or investment in those resources, it provided evidence that rural places are more under-resourced than urban places. Appendix A-5 reports averages and comparisons for urban and rural places with rural being urban influence codes (UIC) of 5 or greater. For example, 56 percent of rural agencies reported having funds for confidential informants compared to 71 percent of urban located departments. Sixty-six percent of rural located departments assigned officers specifically to drug enforcement compared to 83 percent of more urban departments. Only 37 percent of rural departments had a designated drug officer or unit compared to 49 percent of urban departments. For only 6 of 36 items in our battery of resource availability and use questions did rural places score higher and only one was significantly higher (assigning officers to surveillance). Urban scores were significantly higher on 14 of the 36 items. On all summary measures (created by adding individual items thematically), rural places had fewer resources than urban places including equipment and resources, community resources, overdose response resources, and management and information sharing and differences were significant for all but response resources (see Appendix A-5).

Participant Recruitment for Program Implementation

This section lists participants and collaborating organizations in the project and explains their recruitment.

Participants and Collaborating Organizations

Mentor agencies in the project include: The Lake Area Narcotics Enforcement Group, Missouri; Attorney General's Office, Commonwealth of Pennsylvania; and, the Tennessee Attorney General's 8th Judicial District Drug Task Force. *Mentee* (mentored) agencies include: the Lafollette Police Department (Tennessee); Oneida Police Department (Tennessee); Wyoming County District Attorney's Office (Pennsylvania); New Wilmington Police Department Pennsylvania; Crawford County Sheriff's Office (Missouri); and Maries County Sheriff's Office Missouri. Other collaborating agencies that supported the project through intelligence sharing with main sites or other support include: the Missouri Highway Patrol; Tennessee Attorney General's Office; Westminster Campus Patrol (a campus police department in Pennsylvania); and the Tunkhannock Township Police, Pennsylvania.

Recruitment

Using information from department surveys and the statistical analyses described above as a guide, we selected sites in three states, and began attempts to recruit participants. States varied on the central opiate drug overdose problem at project outset with pills being the key problem in rural Tennessee and Missouri with an emerging illegal synthetic opioid problem in the latter, and synthetics and heroin driving death rates in Pennsylvania. Recruiting agencies proved to be much more difficult and time consuming than we expected largely due to COVID-19. As it turns out, rural departments which are not expecting to be selected for a project, often are skeptical about changing procedure and becoming involved in a project using federal funds. This is often due to budget complications, as rural departments have no accounts for special use during the project and must get political support in order to set them up, making their cost-benefit analysis for new financial and contractual agreements troublesome for new initiatives. As a result, we had to contact eleven agencies and begin recruitment in order to recruit our six mentee agencies, which was no easy task in the COVID-19 pandemic years. State-level law enforcement proved essential in finding participants in two states and the mentor site in Pennsylvania assisted in recruitment of Wyoming County which fit our criterion as being rural but is part of the Scranton-Wilkes-Barre-Hazleton metro. It is small at 26,000 population and was known to have a high synthetics and heroin overdose problem for a small area. It was selected at the suggestion of the mentor agency that we selected based on Lawrence County after recruitment concerns. Participant sites varied on resources with agencies in Campbell (TN), Wyoming (PA) and Crawford Counties (MO) being relatively resource rich. Campbell had lower than expected pill deaths, even though pills were the crux of the problem there, but worse were synthetics. Crawford (MO) was significantly worse than expected for heroin, and the problem there is severe by rural standards. Maries (M0) showed high levels of heroin and unexpectedly high levels for synthetics. Scott (TN) was worse than expected synthetics and a little better on pills, again with pills being the central problem there. Lawrence (PA) was better than expected on heroin but much worse on synthetics, although heroin and synthetics have driven the problem there historically.

Changes in Approach from Original Design

Initially, we proposed to select locations and partner city or county police departments with other police departments based on differences in death rates in Iowa, Missouri and Pennsylvania. The plan was to select places that were significantly higher and lower based on a ratio of death rates to arrests. We stayed generally true to the initial modeling strategy, albeit drug arrest rates as a variable did not play as key a role in models as we planned. This was due to a lack of reliable local level drug arrest data. We maintained a modeling strategy based on higher and lower than expected death rates, according to the statistical model, in places where death was still common by comparison to other rural places. We also changed recruitment strategies. We excluded Iowa as a location due to the low occurrence of opioid deaths in rural areas, with heroin in the large cities and counties adjacent to large cities being the crux of the problem. We replaced Iowa with Tennessee where the rural pill problem was extreme and noticeable in the models and maps we generated.

We changed our mentor/mentee-building strategy to some degree as well. We learned from law enforcement involved in our recruitment attempts that local police had little interest in working with distant departments that we deemed to have better outcomes, our initial plan. We did not have sufficient funds budgeted to incentivize reluctant mentors to work with distant departments on a one time basis. The more immediate need for mentees was for connection to state-level law enforcement with whom they already had some geographic and formal connection, but that did not focus sufficient services on very rural places. Mentors already had ideas about places that were underserved, and we needed to accommodate their suggestions. In other words, drug enforcement networks needed building locally, and our efforts would be better spent connecting agencies that could continue to work together enthusiastically and try new initiatives that had potential to be extended than in short term connections to distant locales. We also had to accommodate varying state financial and organizational structures. In keeping with our ground-up philosophy for this project, we followed the advice of potential participants given during our recruitment efforts. An additional reason for modifying the recruitment strategy was the timeline of the project. Willing participants had to be encouraged to come on the project quickly by easing their network and initiative building effort; this was challenged by the COVID-19 pandemic and some bureaucratic difficulties with allowing expensive procurement of data across multiple states and getting local governments' approval for the project slowed our start. During the project both Missouri and Pennsylvania had periods where only essential police operations were allowed.

The Programs

Missouri

Crawford County and Maries County Sheriffs' Departments

Missouri's final plan most significantly involved the training and use of a technology manufactured by the Cellebrite Corporation for opening cell phones of drug suspects with permission granted by search warrants or owners of phones. This commercially available system has proven as effective as comparable software and hardware (Kong 2015). This was applied to both participant counties. Officers were loosely familiar with the capabilities of this technology because they had worked with the National Guard to open phones in the past. Having the technology available quickly and locally made a tremendous difference according to the officers, however. Working with the National Guard, the lag time of up to several weeks for having a phone opened meant that intelligence gathered was no longer operational. Judges in the area typically allowed phones on sites into their search warrants; and it was almost certain that phone access would be included in warrants if the numbers were listed as known contact numbers for persons targeted by the warrants, such as when a confidential informant provided the number(s) used by suspected dealers. Moreover, phones could be gathered from the legal owners in they provided consent or if they were deceased from drug overdose and family members provided consent.

The second intelligence effort was a combined plan by our sites to map all calls related to opioids in the counties where the Sheriff's departments operated. They used an Overdose Detection Mapping Application Program (ODMAP) which links first responders and relevant record management systems to a mapping tool to track overdoses. During the project, this was expanded to all of the areas policed by our mentor agency, the Lake Area Narcotics Enforcement Group (LANEG), which essentially is a drug task force. As part of this effort, a task force officer was assigned to liaison with emergency services and the county ambulance services. The officer presented the importance of logging all overdose cases that the departments responded to and after a few weeks departments routinized the provision of calls for service reports involving overdoses to the task force officer, so that they could be logged into ODMAP mapping software. Crawford and Maries County Sheriff's departments were the mentee agencies.

Tennessee

Lafollette Police Department

Lafollette, in Campbell County, Tennessee opted for a hybrid of increased use of computer communications technology between patrol and narcotics officers, a shared communication system with local departments, and enhancing support for additional K-9 services and training. Lafollette City Police implemented a shared call and data system with Caryville and Jacksboro. The system is by a company called Agisent located in Tullahoma, Tennessee and includes dispatch, mobile command and record keeping systems. The city shares a county, Campbell, with these two very small, adjacent towns. Police resources are sometimes shared with the departments but the call and data systems from the police were not shared before this project. The implementation of this measure made data shareable across departments and also allowed for executive officers to see development of incidents across towns. This is important mainly for tracking developments in real time. AGISENT allows departments to share arrests, warrants written (both served and not served), citations written, drug activity documented, drug arrests and drug activity noted on warrants. Feasibly, it encourages intelligence sharing across jurisdictions. However, it was difficult for us to track the implications of the effort for drug intelligence specifically, and we could identify no case where the collaborative data sharing resulted in a specific arrest that would not have been made otherwise. Support of police dog services also were slightly enhanced with this project, but because the department already had K-9 units, this too was difficult to garner any evidence of improvements as a result of specific design. Lafollette also participated in ODMAP. Mapping incidents was assigned to an employee in the records unit who also was assigned to be liaison for this project.

Lafollette also was interested in improving communications between patrol officers and their designated narcotics officer(s). One idea was to formalize information sharing in regular meetings, but soon they concluded that larger gains would be had by deploying new equipment for communications. So, they purchased some simple equipment and allowed their narcotics officer to deploy it as he saw fit. His goal was to place the equipment in the hands of the patrol officers that already showed the greatest interest in providing drug intelligence to him. This idea came from the lone narcotics officer, at the time, who also was reluctant to propose the idea for fear of not looking innovative or of not showing an understanding of what a drug intelligence strategy might be. After the initial planning meeting that he attended, he requested that his superiors ask if this was an appropriate drug intelligence strategy and we conferred to come to agreement that it was. The Department previously was unaware of the need. Six computer pads (iPads) and a compatible laptop were purchased by the Department. The narcotics officer kept one and the computer, and five iPads were dispensed to the patrol officers that he deemed the most proactive at working drug cases and providing him intelligence based on past experience. One printer was also placed in a patrol car to be used to disseminate information to officers such as descriptions of vehicles and persons who needed apprehension, copies of documents needed at scenes and intelligence information on persons and activities in households under surveillance or about to be raided. As he put it, "There is no shortage of drug cases to make in this community and the best information you get comes from conversation with officers who live here and are out patrolling in the community." Software on the tablets includes TCA plus, Mobile Patrol, CASPER (controlled buys), Drugs.com, ODMAP, and Covert Track.

Oneida Police Department

Oneida Tennessee Police Department, Scott County, was our smallest department involved in the project. Oneida decided to support narcotics intelligence with the use of a police K-9 unit and also increased use of basic K-9 equipment, a standard temperature controlled enclosure, in a patrol car partially designated to narcotics enforcement. They also conducted some drug interdiction training for the single officer with the most time devoted to narcotics enforcement. In the initial plan and logic model, Oneida Police Department intended to use ODMAP but that effort was modified over two years into the project, as we will discuss in the Outcomes section (below). Today, they share an emergency response reporting data system in common with the Scott County Sheriff that they report was in part inspired by this effort. It provides overdose addresses to officers.

Pennsylvania

The mentor agency, the Office of the Attorney General, identified several concerns with local to state intelligence capacities in the Commonwealth of Pennsylvania. First, they indicated that there was a lack of capacity at the local scale in terms of knowledge and resources, particularly in more rural areas, for using intelligence techniques in drug-related investigations and drug market interruption. Second, they also noted that those agencies applying intelligence techniques in drug investigations did not always share that knowledge with their office, which can help to ensure that data is utilized to connect investigations across localities. Therefore, they identified the need for developing a set of trainings to ensure that local agencies were made aware of state-based intelligence resources (e.g., databases, analytical support, investigatory assistance), legal parameters of drug-related intelligence for investigations, intelligence techniques for drug investigations, emergent technology for consideration, and agency specific capacity development (identified through conversations with local agencies). They also identified the need for developing a model for reciprocal data sharing of drug related intelligence. These became the primary goals of the mentor agency connection to the mentee agencies in the project, and the mentor agency developed outcomes, activities, and measures to meet these goals, as identified in their logic model. The most significant themes of information shared in trainings is included in the section labelled 'Outcomes' below. Lawrence County was the location that met the criterion for selection and was our initial contact. Wyoming County and the Wyoming County District Attorney's Office was also selected as suggested by the mentor agency due to evident resource needs.

New Wilmington Police Department

The New Wilmington Police Department in Pennsylvania, Lawrence County, identified several key needs to increase its capacity for addressing drug-related supply issues within its jurisdiction. First, due to the small size and limited resources associated with the Department, they noted a need for increasing capacity for their officers to understand resources, techniques, and technology associated with drug-related investigations. Second, the college that is within their jurisdiction has historically not shared crime-related information with the Department. They noted a need for increasing collaboration with the college's administration and public safety office to share criminal justice related information across entities, including drug-related intelligence, to increase the safety of the community and disrupt drug-related activities that spill over from the college to the community. Finally, they noted a need for technological improvements to advance their ability to engage in drug-related investigations. As such, they administered trainings on drug-related intelligence investigatory resources and techniques offered by the mentor agency, the Attorney General's Office. They also developed key partnerships and information sharing between their department and the local college.

Wyoming County District Attorney's Office

The DA's Office identified a need for drug-related intelligence gathering capacity. Due to their county-wide jurisdiction, there was a need to both develop investigations to disrupt drug markets as well as to provide support for local agency drug-related investigations. They identified two primary and related goals for the project. The first was to increase their office's capacity for investigations with lessons on available investigatory tools in the state. The second goal was to understand external and state-based resources for their office to use for drug-related investigations and when they should be used, so they may also connect local agencies to those resources. To increase capacity and gain awareness of intelligence techniques and resources, they relied on the mentor agency, the Attorney General's drug intelligence unit, to provide trainings and access to these resources. Furthermore, they purchased a K-9 unit that was trained for drug investigations as part of invigorating their intelligence gathering effort.

Outcomes

Tennessee

The most beneficial change for drug intelligence networks in Tennessee, implemented by the Lafollette Police Department, seemed to be the distribution of iPads to motivated patrol officers for regular communication on a closed network with the narcotics officer. This simple measure proved invaluable. The officers were able to use the iPads as they worked to leave communications for the narcotics officer in hours when he was not working. These included secure text messages and photographs of suspicious activities and evidence of drug activity in the community, including found paraphernalia and unusual amounts or suspiciously stored cash found on crime suspects, that they saw during their ordinary patrols, investigations, and stops. The computers were also handy to photograph crime scenes and drug evidence securely. The computers were used on a daily basis by the department with narcotics officer receiving several pieces of information per day and allowing him to see developments on his days off that might not have merited a personal call or text. He reported that just having the computers in officers' hands encouraged communications that likely would have been lost in transition or thought not noteworthy enough to pass on in person. In several instances they also provided visual prompts to discuss with confidential informants in the community. The computers were used in almost all of the investigations that involved the narcotics officer in some capacity and for communication on a daily basis. Officers reported that the iPads were most useful once a narcotics officer identified and began to work a case, and for typing up warrants from the field. They reported the most beneficial software was the Casper software, available to law enforcement officers but not others at Sur-

Tec Corporation headquartered in Shawnee, Kansas (surtec.com) which allowed confidential informants and undercover buyers to record and transfer video, audio and location from their phone to the narcotics officer's iPad. This was done about 20 times in the last year of the project. The iPad not only allowed the officer to see and hear information from the Casper system but also, being designated for the task, to stop interruptions during drug operations. The information gathered on these computers in controlled drug purchases was also used to construct power points before a police forced entry or search team served search warrants on drug houses, with the information being used to construct instructional power points for the search. The iPads are used in relation to controlled buys, search warrants, pre and post raids, evidence and picture recording during searches, OD mapping, surveillance photos and messaging to the narcotics officer, confidential informant files and referencing files, and notes from scenes. There are on average 20-30 photographs taken per case.

Once confidential information is on an electronic pad they are brought to the stations physically for download and deleted from tablets as is the case for other sensitive information. All uses of tablets must be case related. The information from the tablets and transferred from the narcotics officer's computer also can be sent to in-car printers that officers may use to print for other officers directly in the field such as when an identified address seems to call for further surveillance at shift change or in providing identifying information and suspect background before a raid. While the city had purchased the printer, COVID-19 delayed acquisition and installation. The site was installing the printers as this project ended in October of 2022. However, the department was confident that it would continue its mapping effort and surveillance equipment effort in some form. Administration and staff changed dramatically in November of 2022, but the iPads and mobile printers will certainly continue service, and the Department plans to continue mapping overdoses.

Oneida Police Department increased hours of officers devoted to narcotics, sent the officer to a drug law and drug interdiction training offered by the state, and purchased a K-9 and an enclosure to support its use. They were reluctant to start a drug hotline service even though advised that this would probably be a cost advantageous program for a small city, in part because they felt concerned citizens already could contact police with matters of concern and the manpower needed to track and investigate anonymous tips. ODMAP use reportedly led to less return on investment in Oneida, according to the officer responsible for the mapping effort, as problem areas were known and Oneida spans about 9 square miles with 398 people per mile, an area that is fairly easy to keep track of informally. According to the narcotics officer, the problem population of heavily drug involved persons was already well-known to police.

However, as a result of the failure to keep OD data up to date in ODMAP, the department ultimately invested in a commercial software for police that allows officers to see emergency calls on their telephones from the previous night. This software reportedly was a boon for the small department and narcotics operations. It is used daily by the chief and was used for intelligence by all officers including the narcotics officer as they begin their shifts. Although there is no time or available resource for analytics in this department, just seeing the addresses reportedly did lead to increased patrols in some parts of town such as a large trailer park in the community and might have contributed to increased probably cause search and arrest there.

The K-9 was in use 47 weeks a year for 30-40 hours a week for the last two years of this project and was sometimes used in the County on loan. The department had previously had a dog but had eliminated its use in 2015 due to cost, and decided to reinstate it as part of their effort in this project, setting it to work by 2019. When active, the dog is used in home or car searches routinely, 1-4 times per week, or about 50 times a quarter, primarily when the handler has suspicion in traffic stops and also with a warrant for home searches. The K-9 has reportedly failed to locate drugs only three times in its term with the officer who handled it during this project with most being marijuana possession locations.

The approach in Oneida was more haphazard and difficult to track throughout the project. The effort was heavily dependent on a single officer, a young narcotics and K-9 officer who was also assigned the mapping task. This officer failed to track deployments of the K-9 formally. The officer also left the employ of the police department in September of 2022 near the end of this project and on short notice. A new hire narcotics officer and K-9 officer was in training at the end of this project in November 2022.

Implementation in this area was confronted with delays, communication difficulties, incomplete reports, technology difficulties for communication, and this was particularly true during the 2020-2021 COVID-19 period. The implementation was impromptu and the department had more difficulty staying true to the original design than did other areas. In one example, on the advice of the research team and our expert consultant, the department had seemed enthusiastic about investing in a drug hotline and data collection for it, but never did. In another example, the department had agreed verbally to invest in updated surveillance equipment but never did. In a third example, the department agreed to invest in a K-9 unit; they did accomplish this but later explained that deployment records had been misplaced. Too much of this department's effort was placed on a single officer with only part of his time devoted to narcotics and K-9 policing, who simply had too much to do. This officer was also tasked with most of the communications with our team for this project, and with assembling data for the project.

There is a lesson here about the prospects for building intelligence and intelligence analysis in extremely rural counties and small towns with modest investments when the baseline is very little capacity. The lesson for us was that funds can be well spent in rural places, but investments in departments with little resource slack, lacking in administrative capacity, and where there are few personnel or hours of investment to spare are risky and make for difficult collaborations. The most successful efforts in such a department are the least burdensome and most apparent such as K-9 use. Analytics and predictive problem solving are near impossible. Therefore, immediate and accessible intelligence for patrol officers without investment in analytics likely should be the goal.

Missouri

Missouri sites include the Crawford County and Maries County Sheriff's department, although the mapping program was implemented in all counties in LANEG jurisdiction.

The greatest benefit to the Missouri departments was hardware and software for opening phones. It seems to have been the best investment made by any of the departments in this project. The officers involved had plentiful access to phones containing such intelligence. Indeed, the departments had always had many phones from drug cases. However, they had to turn over the phones to the area task force officer, who would then provide them to state police, who would in turn provide them to the National Guard. The Guard would then send all accessed content back to the task force officer who would examine the downloaded information and work with local police to pull the evidentiary portions. The lag time was simply too long to provide actionable intelligence in many cases. The problem had never been the legal difficulty or technical inability to get an abundance of such information.

By the end of our project, judges in the area were writing warrants that covered all electronics in a house in many cases where evidence showed clear indications of drug dealing. As had always been the case, there were plenty of phones with potential intelligence on them available. Between May 1 of 2021 and October 1 of 2021, when use of the technology was fully implemented and local officers had become aware of it, more than 60 phones were opened. Officers report that the intelligence gathered in this way was invaluable. Indeed, the officer responsible for opening phones reported that he loathed the job because it took so much office time and he preferred to be doing more active things, however he soon learned that the intelligence gathered from phones far surpassed what he gained from confidential informants, cooperators, or other sources such as the drug hotlines at local police departments. This intelligence often included incriminating texts, ability to track travel through photos and messages, evidence of various forms of drug use and sells, and ability to understand much about the network of the owner of the phone. The evidence was useful in many investigations and drug cases. It had direct effect on two drug overdose homicide cases almost immediately, and also identified a case of severe child victimization where authorities were later able to prioritize the offender on other unrelated charges. In one of the homicides, incriminating text messages were recovered where a dealer and customer considered whether to call for help for their associate who had overdosed, but decided not to due to the fact that there were criminal warrants active for persons at the scene. The same series of texts even clarified the exact nature of the substance (fentanyl) that caused the overdose when the dealer made clear that he had delivered exactly what had been ordered (fentanyl) and communicated that the customer should seek medical attention. In addition, task force officers gained a great deal of understanding of drug networks and distribution in their area and the persons involved, which although not always legally actionable in the immediate, did provide officers better understanding of priorities and persons endangered by deadly substance abuse.

Officers reported that few drug dealers in the area used burner phones for their illegal businesses because cell phones had become such a part of their ordinary lives. In addition, while phones manufactured by some companies were nearly impossible to open without suspects volunteering codes, the high cost of these types of phones meant that many in the heroin/fentanyl trade in the area could not afford them. Suspects often used messaging services that were accessible. The typical arrangement for opioid distribution in the area was for a dealer who had contacts in St. Louis to drive the short distance to the city to purchase fairly small amounts of heroin and fentanyl—a few hundred fentanyl-loaded pills at most at a near retail price of $2.00 to $3.00 cost. These traffickers return to the area to resell them for about 50 percent more to fund their own habit. At times, the driver/dealer would raise money from customers and friends before the trip in order to make the purchase worthwhile, only hoping for a few pills in the exchange. Identifying these key players in decentralized and generally small drug networks, and connecting larger dealers in metropolitan areas to these smaller markets, was key for local authorities. By project's end, 148 phones had been opened, 140 of those were in drug cases, and in excess of 70 to 75 percent contained information officers deemed useful for cases or intelligence.

We also advise localities that would acquire such technologies that powerful but affordable computers that can deal with large stores of video, audio and text data should accompany the purchases of the technology. The agencies in our project sites learned that opening such stores of data requires more than the cheapest of computers if it is to be done in a time-efficient manner that does not require too much officer time. The purchase of a mid-priced computer designed for entertainment and gaming cleared this hurdle for this locality. An additional purchase that proved indispensable was charging equipment for a variety of electronic phones and devices and high quality, and durable bags (such as Faraday bags) which prevent signals from transmitting from digital devices and can be sealed to maintain chain of custody. This both saves power on devices for ready access and prevents remote access once electronic equipment is in the custody of law enforcement, a lesson learned on implementation of this technology. Of course, an array of charging devices also is needed.

Officers reported that intelligence from phones was particularly useful due to the hidden nature of opioid abuse locally. Officers contrasted intravenous opioid addicts with methamphetamine addicts who they believed to be unable to hide their activities and condition in the same way, and that opioid addicts belong to smaller and more isolated and less criminally troublesome networks. They observed meth houses and addicts often are seen by concerned community members much more than opioid addicts who often sleep, exist in small, insular drug trading networks, and do not cause as much disruptive trouble as persons very intoxicated on methamphetamine. Because most drugs in the community come from a few entrepreneurial drivers with drug contacts in the city, identifying hubs in these networks and a constant stream of intelligence is critical to interrupting fentanyl and heroin supply. Missouri's mapping effort is discussed in the section on mapping below.

Pennsylvania

Pennsylvania implementation sites include The Wyoming County Districts Attorney's Office and the New Wilmington Police Department. The Wyoming County District Attorney's Office developed a K-9 unit within the County, which was a stated goal from the outset. It also participated in a series of seminars offered by the Pennsylvania Office of the Attorney General's Intelligence Unit. These included trainings on regional drug trends, drug stamp laws and stamp reports, ion scan training for identifying substances, interviewing drug distribution suspects and use of electronic information, local drug pricing, Alcohol Tobacco and Firearms (ATF) Internet-Based Firearms Tracing and Analysis (eTrace) programs (ATF, 2009), using social media and open source for intelligence, explaining technologies available in certain cases to the intelligence unit including phone password breaking, FBI National Crime Information Center-offline, Vigilant Clear Car Rental Companies data base, and Prescription Drug Monitoring Program (PDMP) database that records prescriptions written (see CDC 2022), U.S. Treasury Department Financial Crimes Enforcement Network (FinCEN) suspicious banking activity reports, and collecting photo and video evidence. These trainings also offered the small department's officers a chance to interact with members of the intelligence unit regularly, increasing the chances of future collaborations and cases. Investigators did not evaluate each of the lessons or programs but agency leadership, officers and staff were made aware of a wide array of services. The Office of Attorney General also offered analytic support and data pulls and these were utilized in three drug cases in the implementation year; perhaps the scant use is indicative of a split in modern, electronic intelligence analytic capabilities as opposed to need in rural locations. Yet, it is essential that rural officers understand that available capacity. For example, access to FinCEN and other resources led to successful prosecution of a human trafficking, prostitution and suspected drug trafficking enterprise that had been operating for more than a decade when officers involved in the trainings referred it for a collaborative investigation.

In addition to these mentor efforts, the New Wilmington Police Department had monthly meetings and as needed interactions with a local college police department; each agency also devoted a computer to storing drug case information and shared access at the meeting. These meetings have reportedly been useful and led to one collaboration on a narcotics related "operating while intoxicated" case with shared investigatory and expert resources for prosecution. The Wyoming County District Attorney developed a new K-9 unit during this project, which was a stated goal. The K-9 was owned and operated by Tunkhannock Borough police in the County seat of Wyoming County and was utilized daily there and was also available to loan for other departments in the county. There had been no K-9 in the county for more than a decade. It was the only K-9 in Wyoming County. Volunteer private entities offered vet services for the K-9, perhaps indicating how thin resources are in rural policing in the U.S.

On Mapping Across Sites

Project participants indicated in site visit interviews that intelligence from ODMAP sometimes is too abstract to be directly actionable. One reason is simply time delay until activities are mapped. Another is that maps are difficult to disseminate in real time to patrol officers using this software. Missouri officers reported that the mapping technology was difficult to use on mobile devices and too clunky, lagging and imprecise for patrol officers to use as daily actionable intelligence. All sites had difficulties with the interface and were particularly disappointed with it on patrol officer equipment and telephones in the field. Another reason that maps contribute only to abstract intelligence are Good Samaritan laws, which are present in two states in this project: Pennsylvania and Missouri. Missouri's Good Samaritan Law (RSMO 195.205), for example, states that a person who actively seeks emergency medical help in the instance of an overdose (or other medical emergency) and the person experiencing the medical emergency will be protected legally from minor drug and alcohol violations. The law provides immunity from: Possession of a controlled substance (RSMO 579.015), possession of drug paraphernalia (RSMO 579.074), possession of an imitation controlled substance (RSMO 579.078), keeping or maintaining a public nuisance (RSMO 579.105), sale of alcohol to a minor (RSMO 311.310), possession of an altered identification (RSMO 311.320), purchase of alcohol by a minor (RSMO 311.325) or violation of a restraining order or violation of probation or parole. This meant that emergency calls effectively could not be used to directly make drug cases. Officers found this to be a troublesome law since they did know of locations where several emergencies had occurred, and thought that frequent calls for service might offer some protection to drug houses. However, they understood the reason behind the law and also noted that over time judges had learned to use the law to forbid immediate arrest but still allow record of information in some proceedings.

In Missouri, judges were receptive to the introduction of evidence of overdose emergency calls as one piece of information in the process of issuing a search warrant when other evidence of a new incident/case was strong or in affidavits. This increased the value of mapping efforts for officers. Reportedly, information from mapping had been used to in a small number of cases to establish that offenders' involvement spanned multiple incidents and time, and officers believed that this contributed to drug arrestees (alleged dealers) being denied bail. Early on, executive level participants in Missouri (Sheriffs' offices, and drug task force members) noted that mapping was handy for making decisions, and communicating with the public and state officials about the drug problem and the extent of it locally, since many citizens assume that rurality insulates from the problem until presented with evidence to the contrary. In addition, collecting overdose data required a level of communication with emergency personnel that was not present before this project, and might be useful for general intelligence purposes such as being aware of emergent drug problems and where they concentrate.

In Tennessee, Lafollette Officers also found their mapping to be useful, although in a more abstract strategic sense than in Missouri where it was used in cases. Mapping benefitted the department as a general intelligence source for officers within each of three patrol zones, pointing officers to areas within their beat. The narcotics officer consulted the developing maps regularly and identified high drug traffic streets and homes from overdoses. This information was conveyed to patrol officers almost daily or whenever an overdose occurred and also when repeated overdoses in an area were noticed. The narcotics officer reported that occasionally it was surprising where overdoses happened, which he did not expect at the project's outset, assuming officers knew the community well. Officers were then encouraged to give extra attention to these areas in their beats and to continue to make probable cause stops, in accordance with their duties. The maps provided an additional source of information and to officers who used their own local expertise of traffic expectations to homes and streets, and conducted casual surveillance of known drug users and suspected homes accordingly. The maps were never used as evidence and reportedly did not lead directly to cases, but officers say they are reluctant to share their general methods in court. The maps were also used as part of the local citizens' police academy and this sometimes led to additional intelligence and information exchange from concerned community members. The greatest use of the maps as we saw in other places was the requisite step to document addresses and not necessarily the geo-coding or graphics provided.

Mapping in Oneida, Tennessee did not go as well. Oneida found mapping to be relatively burdensome and redundant since officers can access emergency call information each morning. It was clear from the beginning that this department had fewer resources than others and that the project was a burden for them. It was fortuitous, however, that as a result of their largely unsuccessful attempts to keep up with OD mapping, the department discovered, at the county Sheriff's suggestion, a real time software that allows officers to see emergency calls on their phones from the previous 24 hours and to store those deemed important. In such a small community, sometimes going for several days without an emergency, this was a much better use of officers' time than a mapping effort. Reportedly, the shared data system with the Sheriff's office has proved beneficial and sufficient for local intelligence that can be managed by a single narcotics officer and the 1-3 officers on patrol at any given time.

Pennsylvania already had their own mapping software, Overdose Information Network (ODIN) in place when this project began (Pennsylvania Office of the Attorney General 2023). ODIN provides summary information on OD responses and naloxone administrations by Pennsylvania criminal justice agencies and some third-party (i.e., EMS, Fire, Medical Staff, etc.) first responders voluntarily entering incident data. They found it useful mostly in the abstract and at the state-level, and mapping was not part of their effort in this project.

Discussion

Rural police departments are resource deprived. The survey revealed that on many measures of intelligence, communications and equipment, they are lacking even the most basic resources, including things that almost all urban police departments have such as K-9s and narcotics units. Rural departments have little analytic capacity, and often lack basic intelligence gathering equipment as well as access to state provided support. Narcotics policing in rural areas is very likely to be incidental and reactive, rather than strategic and proactive. Even modest investment, therefore, is sorely needed if there is to be a drug intelligence effort that yields results or drug intelligence networks that span jurisdictions.

Some strategies that might work well in well-resourced urban locales do not yield as great a return in rural areas. For example, all of our participant departments thought that mapping would prove useful to them, but some overestimated the actionable intelligence provided and in one instance their capacity to do it. Mapping makes more sense in places where intelligence might contribute to abstract and broad strategies about resource deployment, say how to deploy patrols or arrange police beats in cities, as distributions on maps shifts. In rural areas, it is more likely that the spatial distribution of crime can be comprehended intuitively by police managers, narcotics officers, and patrol officers. Beats are small, the area is well-known to all who work there, and in some places there are not enough cases to form clear aggregates on maps; moreover, there is little room to re-deploy additional resources strategically as they already are in full use.

Nevertheless, most of our participant departments were interested in mapping and it did offer them new or renewed access to streams of information that they might have otherwise overlooked. They reported that mapping provided few surprises concerning where drug and other crime areas were located. For example, local residents and patrol officers were already aware of drugs and crimes in a large impoverished community of mobile homes. Respondents were somewhat surprised at the frequency of calls represented by concentration on the maps. An additional problem noted was that participation in ODMAP and similar programs is not incentivized and often voluntary, so that no comparisons were available in some states. Ranking officers on the drug task force and the highest officers in the Sheriff's departments and city police chiefs that we spoke with did see strategic utility in the maps but mainly to reinforce to officers the importance of concentrating patrol and attention in certain areas. The maps were seen as a valuable tool for communicating with the public about the degree of the drug problem in their area and importance of their work, as police executives reported that some community members are tempted to idealize their rural communities and deny the extent of the problem. While one site did report that some mapping information was used in criminal cases, mapping as a drug intelligence strategy occurs post-hoc; it is only generally practicable for strategy-making and community relations, and its current voluntary and sporadic nature serves little scientific or comparative value. It is likely that it would fare better as a strategy in urban environments where officers may not have a detailed sense of the communities that they serve or locally acquired knowledge, and where beats and patrol routes may be designed for large populations and geographies such as metropolitan areas and large, urban police departments. Furthermore, there is no clear motivation for small rural departments to spend manpower on tracking data for federal or larger geographic trends analysis. These efforts do not inform their investigations which require timely data that are sensitive to local drug market shifts. Also, the sustainability of large projects for long time periods is questionable when resources are scarce, budgets sparse, and all efforts are contingent on personnel and administrative priorities that shift. Turnover and staffing problems in small departments has been a persistent problem in rural police agencies for the last decade as salaries are low.

Breaking phones provided actionable intelligence that was not available to these sites before our project. One of the central conclusions of this research is that rapid access to intelligence technologies and the availability of a specialist officer familiar with working with them is essential for building drug intelligence in rural areas. Officers in Missouri would not have had the time to break and analyze intelligence on seized telephones without a drug task force employee whose freedom from other more routine duties allowed an officer to spend considerable time on the task. Another important conclusion, with larger ambition and implication, is that our federal government should strive to encourage electronic communications companies to allow law enforcement affordable and quick access to law enforcement officials when legal possession of the communication device and the right to access it has been granted by a court or the current legal possessor of the device. Such authority seems necessary in an age when most criminal conspiracies and documents pertaining to them occur via electronic transfer.

Trainings on high-level surveillance technologies such as banking information, state PDMPs, car rental, and criminal record information may only be relevant to rural police work in a few cases. We did not hear convincing evidence in our qualitative interviews that these had great payoff in daily operations. Nevertheless, the increased contact between police departments and state-level intelligence units was viewed as valuable as was the information that local police learned about resources available to them. In the future, they know what is available should they refer a case to state police or need a resource in a particular investigation.

A key lesson of this project is that rural agencies can design and implement projects with relatively little outside oversight and financial support. Academics can manage grant and report writing, help with project design, correspond to keep agencies on task without burdening senior management and acquire grants before implementation locations are selected so that small agencies need not sink resources into competitive grant efforts that they may not win. Implementation in rural places likely should involve efforts where departments already see a need and were on the cusp of implementing before a small incentive nudged them toward doing so. Participant agencies here responded with only the incentive of some extra money offered for data for the project. Individual rural jurisdictions are unable to access resources via competitive grant programs and may be neglected in state funding which tends to be used in larger more urban areas that generally garner the lion's share of funding. Locations for projects must be selected carefully, however, and hurdles, red-tape and paperwork for participation in new initiatives must be fairly low. Executives in resource deprived departments are often off put by burdensome costs of entry and regulatory 'red tape' for federal and state projects. They do not have grant writers on staff, and if they did, these would have a difficult time competing for large sources of revenue with professional grant writers in large cities. They cannot afford the time and effort investment at the risk of a grant rejection. Yet, when approached with offers of some small incentives, rural places can be willing participants in surprisingly large efforts. That is, small amounts of funds and support can spark them to truly innovative initiatives or push them beyond thresholds that make them consider a new investment. As our main coordinator in Missouri, put it, "it's amazing how people respond, when you put a little bit of money behind it."

Systematic site selection is a good first step. At least, it should be empirically documented that there is a significant problem in an area and that there is pre-existing local interest in doing something about the problem. It also helps to understand if the problem is unusual, which justifies our use of divergent cases (statistical outliers). All of our participating jurisdictions reported high opioid death rates, of a particular sort varying by place, and this was true beyond what should be expected based on demographic and social statistics. We cannot prove that our selection of sites makes better sense than simply selecting places with the worst problem and further study of the method to find out would be worthwhile. However it intuitively makes sense that the drivers of an opioid or drug problem are largely beyond the capacity or duties of law enforcement to manage alone. The police cannot undo poverty, but they can perhaps address crime and drug problems that are worse than the norm based on their economic conditions. In essence, the residual crime problem holding most drivers constant may reflect an array of unmeasured variables and error; but a large residual potentially indicates what drug problem is unusual and the addressable problem for front line public health and safety. Admittedly, we have much less evidence that the form of residuals leads to policies that translate across areas. For example, Lafollette likely was low on pills due to the regional and local crackdowns on opioid overprescribing in the last 5 years that was beyond control previously. Lawrence was low on heroin but high on synthetics, possibly because synthetics have so come to dominate the opioid problem in Pennsylvania. These seem to be idiosyncratic, historical and regional differences and not necessarily indications of how well law enforcement is doing. In some places, being an outlier might indicate something about responses. However, certain drugs were never the crux of the local problem in some outlier places. It probably is better to understand outliers as indicators of especial unmeasured local conditions.

All sites that we selected seemed interested enough in our project to begin serious discussion as soon as they learned about this project, and key stakeholders that we met immediately helped carry it through. This, of course, is the most important criteria for selection. Additional lessons that we learned about selecting sites seem now to be as important as statistical selection criteria. First, departments should have clear needs that a small investment might help address. It is helpful to have experts measure what a local drug and intelligence effort entails. We also think that it is as important to have local experts spend some time reflecting and designing additional intelligence related responses that suit their current needs, desires and situation, and allowing them voice in the design certainly seemed to help executive and officer buy-in. Another lesson is that it takes time and many contacts to carry an effort through in a rural area, and merely gathering simple data is difficult given the extant burdens on personnel.

While departments must have clear needs, it should also come as no surprise that the best investment is into departments that are not so under-resourced that they struggle to support a new initiative. Here, intelligence building may be reduced to suggesting basic equipment purchases and gathering of simple intelligence as there are no resources for analytics and strategy beyond basic law enforcement. For example, when the mentor drug task force dissolved in Tennessee it had little effect on the larger mentee agency participating in the project, yet the project became difficult for the smaller agency to maintain. Indeed, the larger department took on much of the mentor's role in assisting us with communications and data collection. Professional and consistent office staff assigned to support the project, and a full time narcotics officer and large and well-trained patrol division accustomed to complex drug investigations, made all the difference. It was easy for larger and relatively less rural places and region-level agencies, such as LANEG, to begin the simpler tasks of the project, such as overdose mapping, but difficult for very rural places. It took a significant amount of time to get the project off the ground in the more rural and under-resourced of the two mentee departments. One conclusion is that while new initiatives may be a larger denominator over other departmental efforts in severely under-resourced places, prospects for successful implementation and throughput of projects are significantly lower and it is better to have departments with more support personnel. One must strike a balance between need and resource availability that future researchers should strive to identify. Established markers for site selection by departments for projects such as this would be a useful data product.

Another thing that may be misunderstood by state and federal officials removed from law enforcement in rural communities are the potential benefits of investments given the local baseline. Law enforcement in these places generally are intimately familiar with their own jurisdictions. Local police are confident that they have a good idea of which homes, families and individuals are involved in drug trafficking. Many of the key culprits are not the first generation in their family to have participated in illegal drug markets, long term drug use usually leads to identification as a user or dealer at a fairly early age by law enforcement; and confidential informants and drug operations eventually raise the same names to law enforcement's attention. Moreover, the lifestyle and activities of those heavily involved in use and distribution of illegal drugs in small communities makes drug involvement difficult to hide from neighbors. It goes without saying that police in rural communities often went to school with persons involved in drug offenses and thereby have reasonable suspicions about persons' behaviors. The assembly and communication of drug intelligence often occurs quite casually in conversations between officers. Indeed, there may be little added benefit to formally tracking networks (especially post hoc), not as much to mapping areas where drug use is heavy, or to designating great resources to analytics, storage and retrieval capacities for drug intelligence data. We advise against abstract, strategic data gathering in very small locales. Rural agencies simply cannot spare resources. State-level agencies and scholarly institutions may be a better placement of such resources.

The most basic measures offered the greatest return of participation in the project. Basic intelligence gathering equipment is the best investment of small amounts of funding into opioid plagued rural communities for law enforcement. Academics and funding agencies may far overestimate the amount of organizational and resource slack in small police departments for improvements and special efforts. This is not to say that departments are without resources, but those resources already are fully deployed and budgeted. It is difficult for departments to commit to new allocations and investments that extend beyond a funding stream. Changes in the 'war on drugs' such as the fragmented and small-time scale of many distributors, large stores of money in locations now out of local law enforcement reach, and procedures for asset forfeiture that have a higher bar to pass have depleted local resources for drug intelligence and enforcement even further recently. Rural departments are in need of basics for drug intelligence gathering.

There is great utility, however in gathering operational data as cases are made. The most convincing evidence for this is found in the Missouri sites which implemented the phone opening software and accordingly received enhanced support from judges who wrote inclusive warrants for electronic devices. This yielded intelligence that was almost unimaginably rich to investigators, including clear indications of the drug purchases and sales under current investigation, information on the social networks of users and ties between them, cars driven by dealers seen in photos, evidence of ongoing non-drug related crime, indications of who was making large amounts of money on drugs, phone numbers used by users and dealers, and also indications in travel records and photos of how drugs were moving into the community and key players in the transport. Even when phone breaking was conducted by outside state and federal agencies for police, they did not get as much actionable or basic intelligence as a result of the time lag for return, and the specific information required in the request to open an electronic device to agencies preferring restrictive and narrow requests for information.

Intelligence efforts without great immediate benefit to current investigations can aid in some respects. By inputting information into maps, communications with paramedic and emergency rescue teams improved as a tertiary benefit; overdose calls that occurred in off-shift times made it into the record, as indicated by Missouri officers. In Tennessee, the department that used computer iPads learned immediately that officers were naturally incentivized to take more photos for narcotics officers and prosecutors, and to leave a formal record of things they had seen that might otherwise have gone unrecorded or only received casual mention. Information that might have been deprioritized when meetings with patrol officers and narcotics officers were informal, made a more convincing suspicion when sent immediately to the narcotics officer. The mere gesture of giving motivated officers additional equipment for narcotics investigations brought their drug investigatory and surveillance aims to the fore; patrol officers who already were doing an aggressive job on the narcotics front and communicating well with the designated narcotics investigator were encouraged and incentivized to further their efforts. We suggest that such small equipment purchases or support of information gathering efforts, with use designated toward narcotics policing teams, is the best way to support intelligence efforts in these communities. Here, very small investments can make significant differences.

Another conclusion is that rural departments benefit greatly from solid infrastructure at higher levels in effectively implementing new intelligence initiatives. The availability of a full-time paid employee manager working under the state police in Missouri made a tremendous difference. Few small departments can spare an officer’s time for tracking overdose data or even for breaking phones. Opening phones can take hours of supervision of a computer for each phone seized and sometimes without payoff, such as when several largely empty or long out of use burner phones are located in a seizure. And, that is only to glean the most basic message and photograph data. Yet, sending these phones off to be analyzed loses valuable time and may not yield important information that can only be seen as significant in the local context known to a local narcotics officer, like which dealers serve which customers. Our success in getting meetings set, getting data and a program in place when working with Lafollette Tennessee, and indeed in the entire area, only came about because the Chief of Police was able to assign a professional office manager as our key contact. At the least, investments in drug intelligence should be made in places that have a full time narcotics officer or someone from a superordinate agency that acts as one in the area. In less amply funded and very small departments, efforts do not tend to be as creative, guidance is more difficult to implement, data is more difficult to gather, and new intelligence efforts are likely to end up buttressing plans that were in the works already. Perhaps departments that were on the fence about a shared data system or supporting a K-9 can be moved in that direction, but on their own they do not have the inclination or resources to implement completely new approaches.

Recommendations

We recommend ground-up, locally designed or modified strategies with academic partners that contribute mainly by selecting appropriate sites and encouraging the effort. Institutional buy-in is difficult to garner in places that are resource strained, and this seems particularly true when stakeholders are confronted with burdens and demands from outside entities. Participation is attractive for such locales, however, when they are told that they will carry out plans that they devise with a modicum of interference and additional burden. This recommendation comes with the caveat, however, that those selecting sites must understand the level of institutional support and priorities. In example, most of our departments are as concerned with methamphetamine as opioids and this was a slight hurdle to overcome in initial discussions. It is key that some individual be available and able to work with investigators and to manage the plan that is designed, and that this individual be an experienced manager with ample time to invest in the project. In retrospect, we should not have included any sites without a full time narcotics officer and an office manager invested in the project from the beginning. We also recommend the extant Missouri model for building drug intelligence networks where the state police and employees of the local drug task force work together in contractual agreements with small police departments. They provide the services such departments demand when it comes to narcotics intelligence and law enforcement at a level they are prepared to pay for in an individualized contract. Such a model may be more financially sustainable for small places, compared to assigning officers to drug task forces or to paying for services that are not often needed in very rural areas, such as sophisticated surveillance equipment or full a time narcotics officer on the permanent payroll.

We recommend the construction of small, closed networks of communication between narcotics officers and patrol officers that do not distract entire communications networks from their daily duties. It would make little sense to overload extant communication systems with information based on observations of officers in the field and reports of suspicious activities. New designated lines of communication with experienced narcotics and patrol officers who are aggressive at working narcotics, ease and streamline the ability to pass information to a person who can analyze and prioritize it as part of their regular duties. For example, mapping efforts are a good source of basic intelligence, but without accessibility to officers and constant communication of working patrol and narcotics officers with those assembling the intelligence, they yield only occasional actionable information.

We recommend enhancing electronic surveillance capacities of all police departments and improving the turn-around time for intelligence on seized phones and computers. We also think it essential that agreements be reached so that police can access electronic records on commonly used electronic devices for communication in the same way that they can for similar electronic devices without near impassable security firewalls. Simply put, it makes little sense to write warrants for documents that few have in paper form any longer, and it makes as little sense to write warrants for electronic devices leaving whether the search of such devices will yield results contingent to the brand of the device. Also, local rules and procedures on what can be pulled and analyzed should be set at the maximum information allowed for an investigator to see by law. Officers can learn much from electronic surveillance if given the time and allowed to explore for evidence of continued crime and ongoing criminal collaborations.

We recommend the use of data that are independent of statistics collected by police to choose sites for intervention. Mortality statistics and death data have strengths in this respect because they are not easily manipulated and are not directly contingent on police data-keeping policy. These statistics revealed to us the complex and regional nature of drug problems in the U.S. We also suggest that site selection be at least partially contingent on methods that factor out contributors to local problems so that community comparisons make sense and differences are more likely attributed to local practices. For example, sites with very high rates of drug problems often cannot follow the lead of sites with low rates because they diverge on so many variables beyond the control of local policymakers. Disadvantaged places are likely to find efforts to become more like well-resourced or advantaged places futile. We suggest one method for identifying outlier patterns as a way of finding places with unexpected drug problems as a means of aiming toward things that can be addressed with focused efforts. To best yield the benefits that analysts of spatial data can bring to policing, the financial and contractual relationships between universities, funding agencies and police departments must be smoothed. Rural agencies cannot make use of scholars if the institutional barriers separating collaborations are too thick.

References

Abar, B. & Loken, E. (2012). Consequences of fitting nonidentified latent class models. *Structural Equation Modeling*, 19, 1-15.

Agency for Healthcare Research and Quality (AHRQ). 2017. Healthcare Cost and Utilization Project (HCU). Rockville, MD. Retreived, July 5, 2017. https://www.hcup-us.ahrq.gov/faststats/OpioidUseServlet.

Alcohol Tobbacco and Firearms (ATF). 2009. Etrace, Internet-based Firearms Tracing and Analysis. (2009). ATF pulication 3312.9. Retrieved August 10, 2023. https://www.atf.gov/firearms/docs/guide/national-tracing-center-%E2%80%93 -etrace-%E2%80%93-internet-based-firearms-tracing-and-analysis/download

Australian Customs Service. (2000). Intelligence Doctrine. Canberra, AU.

Betz, M. & Jones, L. (2018). Wage and Employment Growth in America's drug epidemic: Is all growth created equal? *American Journal of Agricultural Economics*, 100, 1357-1374.

Bureau of Justice Assistance (2008). Reducing Crime Through Intelligence Led Policing. Bureau of Justice Assistance: Office of Justice Programs. Washington, D.C. Retrieved 3/12/2018. http://www.rural.palegislature.us/small_town_police06.pdf

Center for Disease Control (CDC). (2016). Synthetic opioid data. U.S. Center for Disease Control and Prevention. Retrieved 7/7/2017. https://www.cdc.gov/drugoverdose/data/fentanyl.html

Center for Disease Control (CDC). (2017). Multiple Cause of Death Files, 1999-2016. U.S. Center for Disease Control and Prevention. Retrieved 3/23/2018. https://www.cdc.gov/nchs/data/databriefs/db294.table.pdf#page=4.

Center for Disease Control (CDC). (2022). U.S. Overdose Deaths in 2021 Increased Half As Much in 2020 – But Are Still Up 15%. Atlanta, GA: U.S. Department of Health and Human Services. Retrieved 6/9/2022. (https://www.cdc.gov/nchs/pressroom/nchs_press_releases/2022/202205.htm)

Center for Disease Control (CDC). 2021) . Drug Overdose Deaths in the U.S. Up 30% in 2020. Retrieved 7/19/2021. https://www.cdc.gov/nchs/pressroom/nchs_press_releases/2021/20210714.htm

Center for Disease Control (2022). Prescription Drug Abuse Monitoring Program. Retrieved August 10 2023. https://www.cdc.gov/opioids/healthcare-professionals/pdmps.html#:~:text=A%20prescription%20drug%20monitoring%20program,transitions%20to%20a%20new%20clinician.

Center for Rural Pennsylvania (2006). Survey of small town police departments. Center for Rural Pennsylvania: A Legislative Agency of the Pennsylvania General Assembly, March. Retrieved 3/12/2018. http://www.rural.palegislature.us/small_town_police06.pdf

Ciccarone, D. (2019). The triple wave epidemic: Supply and demand drivers of the U.S. opioid overdose crisis. *International Journal of Drug Policy*, 71, 183-188.

Cicero T.J, Surratt, H., Inciardi, J.A,, & Munoz A. (2007). Relationship between therapeutic use and abuse of opioid analgesics in rural, suburban, and urban locations in the United States. *Pharmacoepidemiol Drug Saf*.16 (8), 827-40.

Collier, Z. & Leite, W. (2017). A comparison of three-step approaches for auxiliary variables in latent class and latent profile analysis. *Structural Equation Modeling*, 24, 819-830.

Drug Enforcement Administration (DEA). (2021). *2020 National Drug Threat Assessment*. DEA-DCT DIR-032 21, Drug Enforcement Agency. Washington, DC: U.S. Department of Justice.

Drug Enforcement Administration (DEA). (2018). *2017 National Drug Threat Assessment*. DEA-DCT DIR-040 17, Drug Enforcement Agency. Washington, DC: U.S. Department of Justice.

Drug Enforcement Administration. (2017). Statistics & Facts. Retrieved 3/13/2018. http://www.dea.gov/resource-center/statistics/shtml.

Environmental Systems Research Institute. (1998). ESRI Shapefile Technical Description, An ESRI White-Paper. Retrieved 8/14/2023. https://www.esri.com/content/dam/esrisites/sitecore archive/Files/Pdfs/library/whitepapers/pdfs/shapefile.pdf

Florence,C.S., Zhou, C., Lou, F., & Xu, L. (2016). The economic burden of prescription opioid overdose, abuse, and dependence in the United States, 2013; *Medical Care* 54(10);901-6.

International Association of Chiefs of Police. (IAACP). (2018). Policing in Small, Rural and Tribal Communities. International Association of Chiefs of Police. Richmond, VA. Retrieved 7/20/2022. https://www.theiacp.org/sites/default/files/2018-11/IACP_PMP_SmallTribal.pdf

Johnson, R. & Wichern, D. (2007). *Applied Multivariate Statistical Analysis*. Upper Saddle River, NJ: Pearson Prentice Hall.

Kong, J. (2015). Data extraction on MTK-based Android mobile phone forensics. *Journal of Digital Forensics, Security and Law*, 10 (4), article 3. Retrieved 8/15/2023. https://commons.erau.edu/jdfsl/vol10/iss4/3

Lanza, S., Tan, X., & Bray, B. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling*, 20, 1-26.

Lenardson, J.D., Gale, J.A., & Ziller, E.C. (2016). Rural Opioid Abuse: Prevalence and User Characteristics. Research and Policy Brief (PB-63-1). Maine Rural Health Research Center. Accessed July 5, 2017 via http://muskie.usm.maine.edu/Publications/rural/Rural-Opioid-Abuse.pdf.

Lurie, J. (2017). Children of the Opioid Epidemic Are Flooding Foster Homes. America is Turning a Blind Eye. Mother Jones, July/August 2017 Issue. Accessed July 5, 2017 via http://www.motherjones.com/politics/2017/07/children-ohio-opioid-epidemic/.

McLachlan, G. & Peel, D. (2000). *Finite Mixture Models*. New York: Wiley.

Moghe, S. & Drash, W. (2017). ‘He’s blue’: Louisville rattled by 151 overdoses in four days. Cable News Network, Retrieved 7/20/2022. https://www.cnn.com/2017/02/14/health/heroin-overdose-louisville-opioid-responders-eprise/index.html

Monnat, S. (2019). The contributions of socioeconomic and opioid supply factors to U.S. drug mortality rates: Urban-Rural and Within-Rural Differences. *Journal of Rural Studies*, 68, 319–335.

Monnat, S.M., & Rigg, K.K. (2016). Examining rural/urban differences in prescription opioid misuse among U.S. adolescents. *Journal of Rural Health* 32(2), 204-218.

Morgan, G.B., Hodge, K.J., & Bagget, A.R. (2016). Latent profile analysis with nonnormal mixtures: A Monte Carlo examination of model selection using fit indices. *Computation Statistics and Data Analysis,* 93(C), 146-161.

Paulozzi, L.J., & Xi, Yongli. (2008). Recent changes in drug poisoning mortality in the United States by urban-rural status and by drug type. *Comparative Study of Pharmacoepidemiol Drug Safety*, 10, 997-1005.

Pender, J.L., Weber, J.G., & Brown, J.P. (2014). Sustainable rural development and wealth creation: Five observations based on emerging energy and opportunities. Economic Development Quarterly 28:73-86.

Pennsylvania Office of the Attorney General. (2023). Overdose Information Network Data CY January2018-Current Monthly County State Police. Retrieved, August 10, 2023. https://https://www.attorneygeneral.gov/data/overdose-information-network-data-current-county-state-police/data.pa.gov/Opioid-Related/Overdose-Information-Network-Data-CY-January-2018-/hbkk-dwy3

Peters, D.A, & Hochstetler, A. (2023, Forthcoming). Prescription opioid resiliency and vulnerability: A multi-method comparative case study. *American Journal of Criminal Justice*.

Ratcliffe, J.H. (2016). Intelligence-led policing. 2nd edition. Philadelphia: Routledge.

Rigg, K.K., & Monnat, S.M. (2015a). Comparing characteristics of prescription painkiller misusers and heroin users in the United States. Addictive Behaviors, 51, 106-112.

Rigg, K. K., & Monnat, S. M. (2015b). Urban vs. rural differences in prescription opioid misuse among adults in the United States: Informing region specific drug policies and interventions. *International Journal of Drug Policy*, *26*(5), 484-491.

Rigg, K. K., Monnat, S. M., & Chavez, M. N. (2018). Opioid-related mortality in ruralAmerica: Geographic heterogeneity and intervention strategies. *International Journal of Drug Policy*, 57, 119–129.

Rothman, K., Lash, T., & Greenland, S. (2008). *Modern Epidemiology*. Philadelphia: Lippincott, Williams & Wilkins.

Ruhm, C. (2018). Corrected US opioid-involved drug poisoning deaths and mortality rates, 1999-2015. *Addiction*, 113, 1339–1344.

Substance Abuse and Mental Health Services Administration (SAMHSA). (2023). 2021 National Survey on Drug Use and Health Annual National Report, with errata. U.S. Department of Health and Human Services. Washington D.C. Retrieved August 16, 2023. https://www.samhsa.gov/data/report/2021-nsduh-annual-national-report

U.S. Attorney's Office, Northern District of Ohio. (2018). Heroin epidemic: The U.S. Attorney's Office, Heroin and Opioid Task Force, action plan. Retrieved 3/12/2018. https://www.justice.gov/usao-ndoh/heroin-epidemic

United States Census, CBP. (2020). County Business Patterns (1986-2000) and Nonemployer Statistics (1997-2019). Washington, D.C.

United States Census, ACS (2020). American Community Survey. Washington, D.C. https://www.census.gov/programs-surveys/acs

United States Department of Justice (DOJ). (2005). *Intelligence-led Policing: The New Intelligence Architecture*. Office of Justice Programs, Bureau of Justice Assistance. Washington, D.C.

U.S. Department of the Treasury, Internal Revenue Service. (2019). Individual Income Tax Filing: Itemized Deductions: Charitable Contributions [IMZDCTCA], retrieved from FRED. Federal Reserve Bank of St. Louis. Retrieved July 15, 2019. https://fred.stlouisfd.org/series/IMZDCA,.

Upjohn Institute for Employment Research. (2020) WholeData County Business Patterns. Retrieved 7/17/2019. https://www.upjohn.org/data-tools/wholedata

Weiss, A.J., Elixhauser, A., Barrett, M.L., Steiner, C.A., Bailey, M.K., & O'Malley, L. (2016). Opioid related inpatient stays and emergency department visits by state, 2009-2014. HCUP Statistical Brief #219. Agency for Healthcare Research and Quality. Rockville, MD. Accessed June 29, 2017 via https://www.hcup-us.ahrq.gov/reports/statbriefs/sb219-Opioid-Hospital-Stays-ED-Visits-by-State.jsp.

A-1. Results from Negative Binomial Model Predicting Prescription Opioid Overdose Mortality in 2016-2018 Using 2010 Covariates for N = 2,013 Non-Metropolitan Counties in the Conterminous United States.

	Prescription Alone Opioid Deaths 2014-16			**Heroin Alone Deaths 2014-16**			**Synthetic & Multiple Opioid Deaths 2014-16**		
Covariates in 2000 and Change 2000-2010	b	exp(b)	p	b	exp(b)	p	b	exp(b)	p
Intercept	0.720			-3.424		+	-3.193		*
Demographics									
Population (1000)	0.000	1.000		0.006	1.006	*	-0.002	0.998	
Age 25 and under (%)	-0.003	0.997		-0.005	0.995		0.018	1.018	
Age 65 and over (%)	0.012	1.012		0.056	1.058	*	0.033	1.033	+
Hispanic (%)	-0.007	0.993		0.032	1.032	***	-0.009	0.991	+
African American (%)	-0.013	0.987	**	0.004	1.004		-0.008	0.992	+
Other Race (%)	0.001	1.001		0.035	1.035	**	-0.001	0.999	
Population (%chg)	-0.010	0.990		0.032	1.032	*	0.003	1.003	
Age 25 & under (%chg)	0.009	1.009		-0.019	0.981	*	0.000	1.000	
Age 65 and older (%chg)	-0.002	0.998		0.003	1.003		-0.006	0.995	+
Hispanic (%chg)	0.000	1.000		0.001	1.001	*	0.000	1.000	
African American (%chg)	0.000	1.000		0.000	1.000		0.000	1.000	
Other Race (%chg)	0.000	1.000		-0.002	0.998	**	0.000	1.000	
Spatial									
Natural Amenity, Jan Sun & Jul Humid (z)	0.042	1.043		-0.008	0.992		0.177	1.193	***
Natural Amenity, Topography (z)	-0.019	0.981		-0.006	0.994		-0.110	0.895	*
Natural Amenity, Water Area (z)	0.081	1.085	*	0.021	1.022		0.033	1.034	
Micropolitan	-0.128	0.880		-0.017	0.983		0.046	1.047	
Metro Adjacency	0.110	1.116		0.068	1.070		0.101	1.107	
Micro Adjanceny	-0.148	0.862	+	0.129	1.138		0.114	1.121	
Reservation Land (%)	-0.003	0.997		0.002	1.002		0.005	1.005	
Interstate Density (per sq.mi.*100)	0.015	1.015		0.002	1.002		0.026	1.026	+
Drug Risk									
Non-Opioid OD Deaths (100k)	0.021	1.021	*	-0.003	0.997		0.001	1.001	
Base Opioid Drug Deaths (100k)	0.056	1.058	***	0.297	1.345	***	0.052	1.053	*
Rx Opioid Drug Deaths (100k)		1.000	***	-0.030	0.971		0.038	1.039	*
Opioid Prescribing Rate (100)	0.001	1.001		0.002	1.002		-0.001	0.999	
Work Disabled Population (%)	0.114	1.121	*	-0.235	0.790	**	0.072	1.075	
Non-Opioid OD Deaths (chg)	0.004	1.004		-0.003	0.997		0.005	1.005	
Base Opioid Drug Deaths (chg)	0.020	1.020	*	0.155	1.168	***	0.023	1.023	+
Rx Opioid Drug Deaths (chg)		1.000	***	0.029	1.030	*	0.005	1.005	
Opioid Prescribing Rate (chg)	-0.001	0.999		0.008	1.008	**	-0.003	0.997	+
Work Disabled Population (chg)	-0.010	0.991		0.159	1.172		0.102	1.108	
Income									
Labor Income Per Job ($1000)	-0.009	0.991		-0.039	0.961		0.037	1.038	*
80:20 Income Gap	-0.029	0.972		-0.009	0.991		0.023	1.024	
Labor Income Per Job (%chg)	-0.002	0.998		0.004	1.004		0.003	1.003	
80:20 Income Gap (chg)	0.010	1.010		0.006	1.006		0.019	1.020	
Social Disorganization									
Violent Crimes (100k)	0.000	1.000		0.000	1.000		0.000	1.000	
Proprty Crimes (100k)	0.000	1.000		0.000	1.000		0.000	1.000	
Social Capital, Organization (z)	0.001	1.001		-0.005	0.995		-0.026	0.974	
Social Capital, Participation (z)	-0.044	0.957		-0.130	0.878	*	-0.068	0.935	+
Violent Crimes (chg)	0.000	1.000		0.001	1.001	+	0.000	1.000	
Proprty Crimes (chg)	0.000	1.000		0.000	1.000	+	0.000	1.000	
Social Capital, Organization (chg)	-0.033	0.968		0.035	1.036		-0.095	0.909	**
Social Capital, Participation (chg)	-0.034	0.967		-0.090	0.914		-0.041	0.960	

Employment in 2000									
Agriculture, Forestry, Fishing (%)	-0.024	0.976 *		-0.025	0.975		-0.042	0.959 ***	
Mining (%)	0.000	1.000		0.036	1.037 +		-0.039	0.962 *	
Manufacturing (%)	-0.004	0.996		0.035	1.036 **		-0.002	0.998	
Construction (%)	-0.003	0.997		0.086	1.090 **		0.012	1.012	
Transportation & Warehousing (%)	-0.025	0.975		0.016	1.016		-0.001	0.999	
Leisure Services & Retail Trade (%)	-0.001	0.999		0.020	1.020		0.014	1.014	
Business & Professional Services (%)	0.024	1.024		0.190	1.209 ***		0.000	1.000	
Healthcare Services (%)	0.034	1.035 *		-0.020	0.980		0.014	1.014	
Employment 1990-2000									
Agriculture, Forestry, Fishing (%chg)	0.000	1.000		-0.001	0.999		0.002	1.002 **	
Mining (%chg)	0.001	1.001 ***		0.000	1.000		0.001	1.001 *	
Manufacturing (%chg)	0.000	1.000		0.000	1.000		0.000	1.000	
Construction (%chg)	0.000	1.000		-0.002	0.998		0.001	1.001	
Transportation & Warehousing (%chg)	-0.001	0.999 +		-0.001	0.999		-0.002	0.998 **	
Leisure Services & Retail Trade (%chg)	0.001	1.001		-0.005	0.995 +		0.002	1.002	
Business & Professional Services (%chg)	0.001	1.001		-0.003	0.997		0.002	1.002	
Healthcare Services (%chg)	-0.001	0.999		-0.004	0.996 ***		0.001	1.001	
Employment 2000-2010									
Agriculture, Forestry, Fishing (%chg)	0.000	1.000		-0.004	0.996 **		-0.002	0.998 *	
Mining (%chg)	0.000	1.000		0.000	1.000		0.000	1.000	
Manufacturing (%chg)	0.000	1.000		0.001	1.001		0.000	1.000	
Construction (%chg)	-0.003	0.997 **		0.003	1.003 *		0.000	1.000	
Transportation & Warehousing (%chg)	-0.002	0.998 *		0.004	1.004 ***		-0.001	0.999	
Leisure Services & Retail Trade (%chg)	-0.001	0.999		-0.005	0.995 +		0.001	1.001	
Business & Professional Services (%chg)	-0.001	1.000		0.001	1.001		-0.001	1.000	
Healthcare Services (%chg)	0.002	1.002		-0.006	0.995 **		0.002	1.002	
Statistical Parameters		1.000			1.000			1.000	
Spatial Lag	0.022	1.022 +		0.203	1.225 ***		0.067	1.070 ***	
Dispersion	0.936	0.050	0.000	1.420	0.108	0.000	1.021	0.057	0.000
State Fixed Effects	Y			Y			Y		
Model Fit									
GFI Deviance	2278.971		0.000	1510.099		0.000	2188.753		0.000
GFI Pearson	2443.424		0.000	2410.368		0.000	2814.095		0.000
"-2LL"	-4484.041			-2390.781			-4141.815		
AIC	9192.083			5009.562			8511.630		
PRE	0.463			0.483			0.465		
null-2LL	-8346.162			-4623.608			-7748.075		
nullAIC	16694.323			9249.216			15498.150		

Notes: Mortality rate (age-adjusted) per 100,000 people. exp(b) = odds ratios; p=+<.1, *<.05, **<.01, ***<.001

Appendix A-2. Residuals by Opioid Overdose Drug Type for Rural Counties in Missouri, Pennsylvania and Tennessee for Rx Opioids, Heroin and Synthetic Opioids<u>Missouri</u>

FIPS	State	County	UIC_2003	zY	zYHAT	zRESID	DRUG	zY	zYHAT	zRESID	DRUG	zY	zYHAT	zRESID
29001	MO	ADAIR	8	-0.43805	-0.32356	-0.14639	HER	-0.20118	-0.44624	0.297064	RX	0.254615	-0.501	0.809508
29005	MO	ATCHISON	10	-0.43805	-0.29889	-0.17134	HER	0.798287	-0.45803	1.582203	RX	-0.67894	-0.49714	-0.31977
29007	MO	AUDRAIN	5	-0.43805	0.015323	-0.48911	HER	-0.54389	-0.26956	-0.35746	RX	-0.33885	-0.35024	-0.05714
29009	MO	BARRY	6	-0.24351	-0.17207	-0.08925	HER	-0.45587	-0.14097	-0.40487	RX	0.364311	-0.47417	0.914832
29011	MO	BARTON	6	-0.43805	-0.14138	-0.33063	HER	-0.71213	-0.41787	-0.38761	RX	-0.67894	-0.34793	-0.46944
29015	MO	BENTON	10	-0.43805	-0.09492	-0.37762	HER	0.5729	0.192487	0.489824	RX	0.313286	0.220768	0.15621
29017	MO	BOLLINGER	8	-0.43805	-0.31264	-0.15743	HER	-0.71213	-0.40074	-0.40884	RX	-0.67894	-0.3927	-0.42453
29023	MO	BUTLER	8	0.150459	-0.12098	0.285024	HER	-0.47678	-0.02454	-0.57569	RX	-0.08171	-0.21054	0.112691
29029	MO	CAMDEN	9	0.300887	0.131958	0.191863	HER	0.455341	0.136481	0.409762	RX	0.206219	0.4433	-0.19609
29031	MO	CAPE GIRARDE	8	-0.27937	-0.07095	-0.2303	HER	-0.64104	-0.24451	-0.512	RX	-0.67894	-0.25582	-0.56184
29033	MO	CARROLL	4	-0.43805	-0.21019	-0.26104	HER	-0.02287	-0.35099	0.405745	RX	-0.67894	-0.49937	-0.31753
29035	MO	CARTER	10	-0.43805	-0.42571	-0.04308	HER	-0.71213	-0.17929	-0.68317	RX	0.40836	0.324913	0.166352
29039	MO	CEDAR	6	-0.43805	-0.20019	-0.27115	HER	-0.71213	0.095213	-1.02322	RX	0.326128	-0.32227	0.716424
29041	MO	CHARITON	9	-0.43805	-0.33727	-0.13253	HER	-0.71213	-0.47037	-0.32257	RX	-0.67894	-0.57829	-0.23836
29045	MO	CLARK	8	-0.43805	-0.22339	-0.24769	HER	0.457496	-0.53743	1.24735	RX	-0.67894	-0.63125	-0.18524
29053	MO	COOPER	6	-0.43805	-0.2811	-0.18933	HER	-0.71213	-0.29222	-0.54326	RX	-0.67894	-0.3606	-0.45674
29055	MO	CRAWFORD	4	2.254969	0.797514	1.631504	HER	-0.41301	0.134086	-0.69113	RX	1.208229	0.594522	0.860146
29057	MO	DADE	7	1.452906	-0.21894	1.792286	HER	-0.71213	-0.32152	-0.50698	RX	-0.67894	-0.5412	-0.27557
29061	MO	DAVIESS	4	-0.43805	-0.44372	-0.02487	HER	-0.71213	-0.39134	-0.42048	RX	-0.67894	-0.21713	-0.60066
29065	MO	DENT	9	0.304807	-0.03397	0.363909	HER	0.233599	0.221964	0.021984	RX	0.743738	0.136893	0.75926
29067	MO	DOUGLAS	6	-0.43805	-0.36248	-0.10702	HER	-0.71213	-0.44421	-0.35498	RX	-0.67894	-0.62685	-0.18965
29069	MO	DUNKLIN	8	-0.43805	-0.23618	-0.23476	HER	-0.71213	-0.24377	-0.60329	RX	-0.67894	-0.29276	-0.52478
29073	MO	GASCONADE	4	0.779815	0.690252	0.14506	HER	1.00845	-0.32391	1.683216	RX	0.376122	-0.19042	0.644428
29075	MO	GENTRY	7	-0.43805	-0.47442	0.006174	HER	-0.71213	-0.01975	-0.88081	RX	-0.02687	-0.35126	0.319973
29079	MO	GRUNDY	11	-0.43805	-0.37605	-0.09331	HER	1.296692	-0.23714	1.942138	RX	1.611702	-0.49323	2.437683
29081	MO	HARRISON	11	-0.43805	-0.30845	-0.16167	HER	-0.28121	-0.35505	0.082349	RX	0.53731	-0.48921	1.138474
29083	MO	HENRY	4	-0.43805	-0.30455	-0.16561	HER	0.027763	0.07458	-0.0571	RX	0.154546	0.189318	-0.0036
29085	MO	HICKORY	7	-0.43805	-0.28926	-0.18108	HER	2.087898	-0.1874	2.886308	RX	0.074316	-0.24576	0.336113
29087	MO	HOLT	7	-0.43805	-0.35013	-0.11952	HER	-0.71213	-0.21669	-0.63684	RX	-0.67894	-0.44537	-0.3717
29091	MO	HOWELL	8	-0.43805	-0.21666	-0.2545	HER	0.345592	-0.10505	0.569451	RX	-0.26254	-0.32859	0.013121
29093	MO	IRON	4	-0.43805	-0.07022	-0.4026	HER	0.917947	0.554501	0.479987	RX	1.103042	0.655162	0.672515
29101	MO	JOHNSON	3	-0.43805	-0.20255	-0.26877	HER	-0.61829	-0.46282	-0.21263	RX	-0.48064	-0.27478	-0.30378
29103	MO	KNOX	10	-0.43805	-0.23287	-0.2381	HER	1.896856	-0.39134	2.896099	RX	-0.67894	-0.56619	-0.2505
29105	MO	LACLEDE	5	-0.43805	-0.12006	-0.35219	HER	-0.59924	-0.41566	-0.24684	RX	-0.67894	-0.3543	-0.46305
29109	MO	LAWRENCE	6	-0.43805	-0.23725	-0.23368	HER	0.782776	-0.11923	1.142777	RX	-0.48163	-0.18023	-0.39981
29111	MO	LEWIS	8	-0.43805	-0.21052	-0.26071	HER	0.500063	-0.40313	1.135086	RX	-0.67894	-0.47923	-0.33774
29115	MO	LINN	11	-0.43805	-0.30213	-0.16807	HER	-0.71213	-0.36426	-0.45403	RX	-0.67894	-0.41071	-0.40647
29117	MO	LIVINGSTON	4	-0.43805	-0.31194	-0.15814	HER	1.880877	-0.14115	2.565856	RX	-0.21788	-0.36055	0.099013
29121	MO	MACON	9	-0.43805	-0.37057	-0.09885	HER	-0.71213	-0.30457	-0.52797	RX	-0.67894	-0.32893	-0.48851
29123	MO	MADISON	9	-0.43805	0.355636	-0.83328	HER	-0.71213	-0.1465	-0.72379	RX	0.988553	-0.12649	1.318596
29125	MO	MARIES	7	2.421454	-0.12565	2.74512	HER	-0.71213	-0.23216	-0.61766	RX	1.225035	-0.36072	1.838631
29127	MO	MARION	8	1.277653	-0.14009	1.523065	HER	-0.2619	-0.25851	-0.01268	RX	0.582005	-0.2135	0.915783
29129	MO	MERCER	12	-0.43805	-0.46023	-0.00818	HER	-0.71213	-0.55365	-0.21941	RX	-0.67894	-0.68965	-0.12665
29131	MO	MILLER	6	-0.43805	-0.17189	-0.29978	HER	0.151875	0.010836	0.179642	RX	-0.67894	0.309115	-1.12854
29133	MO	MISSISSIPPI	9	0.355247	-0.11436	0.499747	HER	-0.29791	-0.53725	0.28684	RX	-0.67894	-0.4173	-0.39986
29137	MO	MONROE	9	-0.43805	-0.0743	-0.39848	HER	-0.71213	-0.57207	-0.19659	RX	-0.67894	-0.52431	-0.29251
29139	MO	MONTGOMERY	4	3.510379	0.230656	3.562116	HER	0.43737	-0.11886	0.703237	RX	0.190868	-0.11459	0.345036
29141	MO	MORGAN	6	-0.43805	-0.30878	-0.16134	HER	0.352827	0.238729	0.15278	RX	0.248629	0.234111	0.064881
29143	MO	NEW MADRID	9	0.306801	-0.44527	0.782017	HER	-0.71213	-0.52583	-0.25387	RX	0.073628	-0.41268	0.502729
29147	MO	NODAWAY	5	-0.43805	-0.29492	-0.17535	HER	-0.71213	-0.50059	-0.28514	RX	-0.13337	-0.45643	0.29708
29149	MO	OREGON	10	0.894312	-0.31275	1.283211	HER	-0.71213	-0.43574	-0.36548	RX	-0.67894	-0.37229	-0.44501
29153	MO	OZARK	10	-0.43805	-0.18251	-0.28903	HER	-0.71213	-0.05309	-0.8395	RX	-0.67894	-0.37306	-0.44423
29155	MO	PEMISCOT	9	-0.43805	-0.22174	-0.24937	HER	-0.71213	-0.22885	-0.62177	RX	-0.41948	0.652829	-1.16055
29157	MO	PERRY	9	-0.43805	0.194889	-0.67071	HER	-0.71213	-0.39926	-0.41066	RX	-0.28149	-0.3594	0.021191
29159	MO	PETTIS	3	-0.14782	-0.12767	-0.0307	HER	-0.30994	-0.33957	0.026662	RX	-0.1779	-0.39032	0.17708
29161	MO	PHELPS	8	1.793027	0.173239	1.763401	HER	-0.351	-0.32741	-0.0406	RX	-0.18126	-0.06321	-0.1551
29163	MO	PIKE	4	0.800617	-0.01453	0.880308	HER	-0.71213	-0.37679	-0.43851	RX	-0.31001	-0.42228	0.049887
29169	MO	PULASKI	8	1.987122	0.049251	2.098646	HER	0.111659	-0.35357	0.57995	RX	0.924482	-0.06753	1.182212
29171	MO	PUTNAM	10	-0.43805	-0.46206	-0.00632	HER	-0.71213	-0.52491	-0.25501	RX	-0.67894	-0.54577	-0.27098
29173	MO	RALLS	8	-0.43805	-0.32528	-0.14465	HER	-0.71213	-0.35413	-0.46658	RX	-0.30612	-0.28304	-0.08511
29175	MO	RANDOLPH	5	-0.43805	-0.14469	-0.32729	HER	-0.71213	-0.34344	-0.47982	RX	-0.16306	-0.4057	0.210408
29179	MO	REYNOLDS	12	-0.43805	-0.05169	-0.42134	HER	0.637586	-0.0144	0.828351	RX	-0.67894	-0.39115	-0.42609
29181	MO	RIPLEY	10	-0.43805	-0.28334	-0.18706	HER	-0.27335	-0.25169	-0.03569	RX	-0.09017	-0.15481	0.046595
29185	MO	ST. CLAIR	4	-0.43805	-0.32635	-0.14357	HER	-0.71213	-0.17524	-0.68819	RX	-0.67894	-0.34723	-0.47015
29186	MO	STE. GENEVIE	4	0.383923	0.401989	0.008553	HER	0.168985	-0.16787	0.422771	RX	0.313629	-0.23137	0.610174
29187	MO	ST. FRANCOIS	3	1.619459	0.612249	1.13176	HER	0.029864	0.02189	0.010846	RX	0.288653	0.362269	-0.01543
29195	MO	SALINE	3	-0.43805	-0.20876	-0.26249	HER	-0.71213	-0.16897	-0.69595	RX	-0.4828	-0.32431	-0.2567
29197	MO	SCHUYLER	8	-0.43805	-0.3848	-0.08446	HER	-0.71213	-0.40976	-0.39766	RX	-0.67894	-0.58782	-0.22881
29199	MO	SCOTLAND	10	-0.43805	-0.33639	-0.13342	HER	-0.71213	-0.56249	-0.20846	RX	-0.67894	-0.50883	-0.30804
29201	MO	SCOTT	8	0.999525	-0.24353	1.326966	HER	-0.38556	-0.31765	-0.09663	RX	-0.07221	-0.41458	0.328823
29203	MO	SHANNON	10	-0.43805	-0.45769	-0.01074	HER	-0.71213	-0.43961	-0.36068	RX	-0.67894	-0.44464	-0.37243
29205	MO	SHELBY	10	-0.43805	-0.22956	-0.24145	HER	-0.71213	-0.45121	-0.3463	RX	0.507196	-0.56004	1.173216
29207	MO	STODDARD	9	-0.43805	-0.25894	-0.21175	HER	0.358178	-0.45951	1.024556	RX	-0.67894	-0.34601	-0.47137

29209	MO	STONE	5	-0.43805	-0.43575	-0.03293	HER	1.089958	0.113268	1.245251	RX	-0.2987	1.024007	-1.38729	SYNMIX
29211	MO	SULLIVAN	10	-0.43805	-0.30955	-0.16056	HER	-0.71213	-0.50575	-0.27875	RX	-0.67894	-0.49281	-0.32411	SYNMIX
29213	MO	TANEY	5	-0.43805	-0.10333	-0.36911	HER	-0.44007	0.098714	-0.6817	RX	-0.54594	0.190071	-0.8488	SYNMIX
29215	MO	TEXAS	9	-0.43805	-0.3229	-0.14706	HER	-0.09233	-0.48253	0.480398	RX	-0.10687	-0.44727	0.319827	SYNMIX
29217	MO	VERNON	11	-0.43805	-0.29404	-0.17624	HER	0.066004	-0.04443	0.138949	RX	-0.20913	-0.36978	0.118835	SYNMIX
29223	MO	WAYNE	10	-0.43805	-0.37476	-0.09461	HER	-0.71213	-0.30659	-0.52546	RX	0.335168	0.065025	0.338819	SYNMIX
29227	MO	WORTH	10	-0.43805	-0.39843	-0.07067	HER	-0.71213	-0.55457	-0.21827	RX	-0.67894	-0.5997	-0.21688	SYNMIX
29229	MO	WRIGHT	6	-0.43805	-0.42314	-0.04569	HER	-0.37493	-0.35136	-0.04135	RX	-0.67894	-0.50003	-0.31687	SYNMIX

Pennsylvania

42001	PA	ADAMS	5	0.30938	0.920913	-0.59684	HER	-0.5721	-0.39263	-0.24086	RX	0.048672	0.649839	-0.5932	SYNMIX
42009	PA	BEDFORD	6	-0.30481	1.404954	-1.75042	HER	-0.4154	-0.27933	-0.18203	RX	-0.49012	0.514342	-1.10679	SYNMIX
42015	PA	BRADFORD	5	-0.43805	1.10434	-1.59046	HER	-0.59872	-0.33165	-0.35025	RX	0.18468	0.349047	-0.12751	SYNMIX
42023	PA	CAMERON	9	-0.43805	0.076122	-0.5506	HER	-0.71213	-0.45729	-0.33877	RX	-0.67894	-0.16847	-0.64947	SYNMIX
42031	PA	CLARION	4	0.671851	0.817621	-0.10048	HER	-0.71213	-0.27583	-0.56358	RX	0.385284	0.503599	-0.04071	SYNMIX
42033	PA	CLEARFIELD	5	0.095102	0.95554	-0.86354	HER	-0.3312	-0.28725	-0.06518	RX	-0.0605	0.519227	-0.59378	SYNMIX
42035	PA	CLINTON	5	0.141141	0.168717	-0.01803	HER	-0.54324	-0.25243	-0.37787	RX	0.44537	0.394618	0.141045	SYNMIX
42037	PA	COLUMBIA	5	0.896547	1.072617	-0.11543	HER	-0.57231	-0.25096	-0.41664	RX	-0.21354	0.682091	-0.94164	SYNMIX
42039	PA	CRAWFORD	5	1.612376	2.392958	-0.67677	HER	-0.27233	-0.20342	-0.09418	RX	1.447158	0.949562	0.792027	SYNMIX
42047	PA	ELK	8	0.588299	0.483042	0.14755	HER	0.62606	-0.36426	1.247099	RX	-0.01809	0.082281	-0.10434	SYNMIX
42053	PA	FOREST	10	1.670244	2.130242	-0.34851	HER	-0.71213	-0.1675	-0.69777	RX	-0.67894	0.239045	-1.05825	SYNMIX
42055	PA	FRANKLIN	5	-0.3033	1.074492	-1.41458	HER	0.322378	-0.29701	0.777753	RX	1.182867	0.513613	0.910736	SYNMIX
42057	PA	FULTON	7	1.659516	0.345858	1.444476	HER	-0.71213	-0.39245	-0.41911	RX	0.34706	0.472903	-0.056	SYNMIX
42059	PA	GREENE	4	0.618453	0.913194	-0.25487	HER	0.253545	-0.13471	0.489184	RX	1.519601	1.153185	0.675099	SYNMIX
42061	PA	HUNTINGDON	5	0.069864	0.256975	-0.18435	HER	-0.50786	-0.41363	-0.13319	RX	0.564633	0.116404	0.5639	SYNMIX
42063	PA	INDIANA	3	1.180004	0.511898	0.758113	HER	0.356813	-0.30899	0.836361	RX	1.068034	0.409468	0.876774	SYNMIX
42065	PA	JEFFERSON	9	0.951629	1.224174	-0.20914	HER	0.478986	-0.37384	1.072005	RX	0.075813	0.341318	-0.25099	SYNMIX
42067	PA	JUNIATA	7	-0.43805	0.309209	-0.78632	HER	-0.71213	-0.4011	-0.40838	RX	-0.00953	0.023245	-0.03481	SYNMIX
42073	PA	LAWRENCE	3	1.052579	2.186557	-1.07328	HER	0.497604	-0.07336	0.723435	RX	4.773742	1.741159	4.008174	SYNMIX
42083	PA	MC KEAN	8	0.85092	-0.00398	0.924026	HER	0.635899	-0.27509	1.149145	RX	-0.13264	-0.05681	-0.10291	SYNMIX
42087	PA	MIFFLIN	5	0.474661	0.698192	-0.1929	HER	-0.35922	-0.36186	-0.00837	RX	0.890405	0.168319	0.904543	SYNMIX
42089	PA	MONROE	3	0.436805	0.598281	-0.13279	HER	0.275394	-0.19311	0.589307	RX	0.009255	1.808094	-1.80259	SYNMIX
42093	PA	MONTOUR	5	0.867493	0.033849	0.903691	HER	-0.37129	0.298604	-0.8419	RX	1.157526	1.227387	0.164182	SYNMIX
42097	PA	NORTHUMBERLA	5	1.474636	1.111949	0.469821	HER	-0.40561	-0.09012	-0.40398	RX	0.429272	0.376973	0.139339	SYNMIX
42105	PA	POTTER	9	-0.43805	0.092149	-0.56681	HER	-0.36838	-0.49119	0.140205	RX	0.349244	-0.26428	0.686119	SYNMIX
42107	PA	SCHUYLKILL	5	1.743068	1.503982	0.363575	HER	0.44123	-0.17561	0.778438	RX	1.037819	0.550288	0.699089	SYNMIX
42109	PA	SNYDER	8	0.84088	-0.00592	0.915141	HER	-0.71213	-0.49396	-0.29336	RX	-0.57041	0.027474	-0.7152	SYNMIX
42111	PA	SOMERSET	5	0.139216	1.44469	-1.31053	HER	0.080977	-0.28412	0.454905	RX	0.67263	0.759355	0.049131	SYNMIX
42113	PA	SULLIVAN	7	2.276837	0.348762	2.108981	HER	-0.71213	-0.26791	-0.57339	RX	0.362673	0.165329	0.271359	SYNMIX
42115	PA	SUSQUEHANNA	7	2.27835	0.836258	1.617601	HER	0.687174	-0.10007	0.997512	RX	2.840608	1.675051	1.744084	SYNMIX
42117	PA	TIOGA	6	0.944787	0.459994	0.55629	HER	-0.71213	-0.34915	-0.47274	RX	-0.34657	-0.00317	-0.41461	SYNMIX
42119	PA	UNION	5	0.315466	0.133171	0.206398	HER	-0.71213	-0.47516	-0.31663	RX	-0.67894	0.039627	-0.85821	SYNMIX
42121	PA	VENANGO	3	1.022459	0.879523	0.21599	HER	-0.3942	-0.13581	-0.33286	RX	0.503778	0.633871	-0.02855	SYNMIX
42123	PA	WARREN	5	0.293976	0.590231	-0.27907	HER	-0.71213	-0.21632	-0.63729	RX	0.280886	0.281675	0.056055	SYNMIX

Tennessee

47003	TN	BEDFORD	3	0.356485	-0.01533	0.400936	HER	0.672452	-0.02214	0.882258	RX	-0.39076	-0.31318	-0.15691	SYNMIX
47005	TN	BENTON	9	-0.43805	0.03837	-0.51242	HER	0.046076	1.563164	-1.87788	RX	3.374569	0.425533	3.641199	SYNMIX
47007	TN	BLEDSOE	7	-0.43805	-0.36039	-0.10914	HER	0.08279	0.389061	-0.37673	RX	-0.20043	-0.13184	-0.10937	SYNMIX
47013	TN	CAMPBELL	5	-0.08022	-0.15119	0.066174	HER	2.170897	3.767668	-1.90773	RX	1.902709	1.472595	0.81653	SYNMIX
47017	TN	CARROLL	6	0.160843	-0.25555	0.432348	HER	-0.71213	1.177569	-2.36405	RX	-0.36657	0.402565	-0.84573	SYNMIX
47025	TN	CLAIBORNE	6	-0.05233	-0.35216	0.299559	HER	0.725648	1.471232	-0.90012	RX	0.309706	0.480753	-0.1089	SYNMIX
47027	TN	CLAY	4	1.761463	-0.06356	1.968756	HER	7.230471	5.233408	2.708292	RX	0.575351	0.284081	0.408621	SYNMIX
47029	TN	COCKE	5	-0.43805	0.190074	-0.66584	HER	1.584197	1.765633	-0.17342	RX	0.276801	0.467944	-0.13572	SYNMIX
47031	TN	COFFEE	3	-0.43805	0.232788	-0.70904	HER	1.93138	1.351298	0.781199	RX	-0.20959	0.622424	-0.87703	SYNMIX
47033	TN	CROCKETT	7	-0.43805	-0.31271	-0.15736	HER	-0.43312	0.177933	-0.77101	RX	-0.36463	-0.12657	-0.3126	SYNMIX
47035	TN	CUMBERLAND	8	-0.43805	-0.17685	-0.29476	HER	0.986762	1.26471	-0.31234	RX	0.204338	0.742731	-0.49872	SYNMIX
47039	TN	DECATUR	12	-0.43805	-0.37774	-0.0916	HER	1.412563	1.02042	0.531566	RX	1.635223	1.449797	0.516943	SYNMIX
47041	TN	DE KALB	4	0.228544	-0.36837	0.619636	HER	1.287176	3.235057	-2.37133	RX	0.958965	0.817637	0.335845	SYNMIX
47045	TN	DYER	8	-0.43805	-0.21354	-0.25766	HER	-0.71213	0.182907	-1.13186	RX	-0.4396	-0.18517	-0.3442	SYNMIX
47049	TN	FENTRESS	10	-0.43805	-0.43766	-0.031	HER	1.069204	0.400852	0.862607	RX	-0.32349	-0.00835	-0.3816	SYNMIX
47051	TN	FRANKLIN	5	0.221152	-0.15891	0.39982	HER	1.04757	0.688989	0.478161	RX	-0.0339	-0.22872	0.188563	SYNMIX
47053	TN	GIBSON	6	0.171915	-0.24596	0.434616	HER	0.498968	0.646432	-0.16651	RX	-0.16192	0.080093	-0.27554	SYNMIX
47055	TN	GILES	6	-0.43805	-0.26015	-0.21052	HER	1.352473	0.464227	1.144192	RX	0.3849	0.080507	0.383241	SYNMIX
47059	TN	GREENE	5	-0.28064	-0.07687	-0.22569	HER	1.239528	1.540503	-0.33268	RX	0.576383	0.37007	0.323606	SYNMIX
47061	TN	GRUNDY	7	-0.43805	-0.41413	-0.05479	HER	2.299048	1.606826	0.932034	RX	0.002945	0.238802	-0.236	SYNMIX
47067	TN	HANCOCK	7	-0.43805	-0.4177	-0.05119	HER	1.777807	1.147723	0.838164	RX	1.813844	0.050904	2.135536	SYNMIX

47069	TN	HARDEMAN	6	-0.43805	-0.32106	-0.14892	HER	-0.41793	-0.0214	-0.50476	RX	-0.42702	-0.246	-0.26801	SYNMIX
47071	TN	HARDIN	6	-0.43805	-0.28084	-0.18959	HER	3.806344	2.218104	2.090873	RX	0.948003	0.640895	0.499925	SYNMIX
47075	TN	HAYWOOD	5	-0.43805	-0.40509	-0.06394	HER	-0.71213	0.017284	-0.92668	RX	-0.15139	0.266873	-0.4502	SYNMIX
47077	TN	HENDERSON	6	-0.43805	-0.25548	-0.21524	HER	0.461212	1.029631	-0.68921	RX	0.306005	0.323989	0.043889	SYNMIX
47079	TN	HENRY	8	-0.43805	-0.13123	-0.34089	HER	0.469686	1.118062	-0.78799	RX	-0.29949	0.329482	-0.69155	SYNMIX
47083	TN	HOUSTON	4	-0.43805	-0.29125	-0.17907	HER	1.794001	0.859955	1.215239	RX	0.484383	0.231753	0.351448	SYNMIX
47085	TN	HUMPHREYS	4	-0.43805	-0.30404	-0.16613	HER	2.165959	0.579003	2.036121	RX	-0.0192	0.2275	-0.25136	SYNMIX
47087	TN	JACKSON	3	-0.43805	-0.27548	-0.19502	HER	3.137849	1.72197	1.855686	RX	1.681253	0.985606	1.038075	SYNMIX
47091	TN	JOHNSON	7	0.366216	-0.28092	0.680046	HER	0.540907	0.856455	-0.37337	RX	-0.33773	0.511838	-0.92058	SYNMIX
47095	TN	LAKE	10	-0.43805	-0.42251	-0.04632	HER	-0.71213	0.016178	-0.92531	RX	-0.67894	0.352522	-1.17209	SYNMIX
47097	TN	LAUDERDALE	4	1.395107	-0.30349	1.815298	HER	0.013005	-0.01182	0.031181	RX	0.311101	-0.20857	0.584257	SYNMIX
47099	TN	LAWRENCE	5	-0.43805	-0.21093	-0.2603	HER	0.477227	0.524655	-0.04329	RX	-0.14338	0.008906	-0.18178	SYNMIX
47101	TN	LEWIS	4	-0.43805	-0.39476	-0.07438	HER	-0.71213	1.190281	-2.3798	RX	-0.67894	-0.13991	-0.67811	SYNMIX
47103	TN	LINCOLN	6	-0.43805	-0.24342	-0.22743	HER	1.078127	0.311684	0.984411	RX	-0.14655	-0.17554	-0.00058	SYNMIX
47107	TN	MC MINN	5	-0.30416	-0.2385	-0.08766	HER	0.298339	1.852406	-1.91552	RX	0.239224	0.843497	-0.55775	SYNMIX
47109	TN	MC NAIRY	6	-0.43805	-0.26937	-0.20119	HER	2.251687	1.620828	0.854483	RX	-0.0296	0.618681	-0.65629	SYNMIX
47117	TN	MARSHALL	4	-0.43805	-0.35179	-0.11784	HER	3.144169	0.192487	3.75845	RX	0.231944	0.06133	0.218087	SYNMIX
47119	TN	MAURY	3	-0.28013	-0.31036	0.011006	HER	0.804517	0.423697	0.497834	RX	0.483392	-0.01885	0.601641	SYNMIX
47121	TN	MEIGS	7	0.859344	-0.21813	1.149715	HER	-0.71213	0.445436	-1.45708	RX	-0.05417	0.662113	-0.72948	SYNMIX
47123	TN	MONROE	6	-0.43805	-0.14289	-0.32911	HER	0.285664	1.318689	-1.27046	RX	0.453521	0.395736	0.149749	SYNMIX
47127	TN	MOORE	8	-0.43805	-0.42244	-0.04639	HER	0.209003	-0.02509	0.296767	RX	-0.67894	-0.31306	-0.50443	SYNMIX
47129	TN	MORGAN	6	0.035928	-0.41718	0.46075	HER	0.578089	1.317768	-0.89758	RX	3.205251	1.316487	2.543348	SYNMIX
47131	TN	OBION	8	0.05838	-0.31558	0.382274	HER	-0.27667	0.1608	-0.55091	RX	-0.41196	-0.16985	-0.32623	SYNMIX
47133	TN	OVERTON	8	0.245977	-0.38428	0.654581	HER	1.953984	1.347798	0.814269	RX	0.51573	0.148511	0.472741	SYNMIX
47135	TN	PERRY	4	-0.43805	-0.4417	-0.02691	HER	0.196328	1.395145	-1.47874	RX	0.243573	0.978971	-0.6884	SYNMIX
47137	TN	PICKETT	10	-0.43805	1.037035	-1.52239	HER	1.088163	0.251073	1.072256	RX	-0.67894	-0.05006	-0.76825	SYNMIX
47141	TN	PUTNAM	3	-0.43805	-0.26294	-0.20769	HER	1.719279	0.918909	1.047219	RX	0.272412	0.303841	0.023605	SYNMIX
47143	TN	RHEA	6	-0.43805	-0.32499	-0.14494	HER	0.271014	1.056345	-0.96409	RX	0.109668	0.031193	0.100915	SYNMIX
47145	TN	ROANE	5	0.16325	0.829127	-0.66201	HER	2.054828	1.662832	0.552198	RX	2.722802	1.62982	1.64744	SYNMIX
47151	TN	SCOTT	6	-0.43805	-0.42005	-0.04881	HER	0.839634	1.299161	-0.54205	RX	1.088602	1.062602	0.246393	SYNMIX
47155	TN	SEVIER	5	0.201588	0.21496	0.00056	HER	0.767282	0.632799	0.191464	RX	0.536217	0.183363	0.462477	SYNMIX
47175	TN	VAN BUREN	10	-0.43805	-0.50731	0.039445	HER	0.328142	0.162089	0.216341	RX	1.495393	1.12436	0.674831	SYNMIX
47177	TN	WARREN	3	-0.10886	0.075754	-0.19431	HER	0.482684	0.729151	-0.28968	RX	-0.06297	-0.07086	-0.00482	SYNMIX
47181	TN	WAYNE	6	-0.43805	-0.30727	-0.16286	HER	1.595831	1.155645	0.597021	RX	0.302041	0.126296	0.237421	SYNMIX
47183	TN	WEAKLEY	9	-0.01486	-0.25831	0.245172	HER	0.55308	0.515259	0.064776	RX	-0.01342	0.155535	-0.17219	SYNMIX
47185	TN	WHITE	9	-0.43805	-0.32363	-0.14632	HER	3.178783	1.537924	2.135719	RX	0.197158	0.582491	-0.34664	SYNMIX

Appendix A-3. Notes on Methods and Measurement

Spatial scales

Several changes were made to the county units of analysis. First, independent cities in Virginia with populations under 65,000 were merged back into their respective counties, resulting in 29 fewer county-level equivalents. Second, Broomfield County in Colorado, newly created in 2003, was disaggregated back into its four original counties based on population-weighted geographic shares. The above modifications result in a time series of 3,079 counties back to 1999, down from the original 3,109 counties, but with no loss of information as data was merged and not dropped. Data used in this study conformed to these spatial units, but regression models for selection are only on rural counties and only opioid deaths were used for selection (Appendix A-1, 2, 4).

Variables

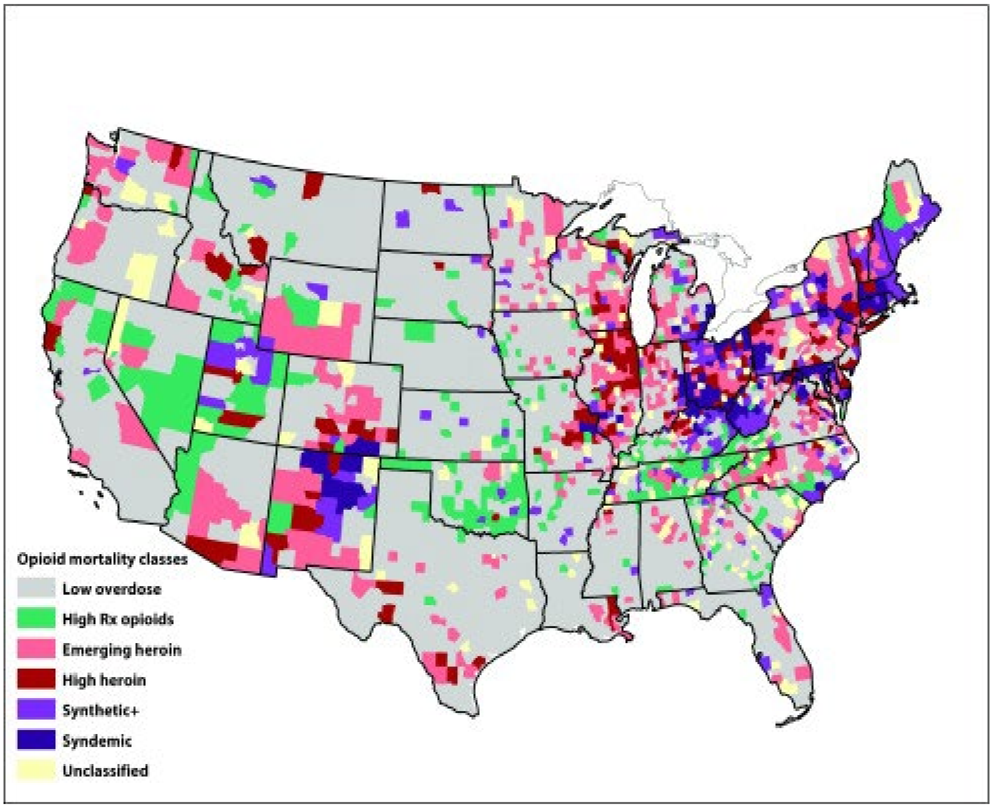
Demographic and economic variables are primarily obtained from the U.S. Census Bureau's American Community Survey (2012-2016, 2014-18 ACS). ACS estimates for most counties exhibit relatively low error, even in counties with small populations, with most coefficients of variation around 25 percent and only a few nearing 50 percent. We dropped two counties (Kenedy and Loving counties in Texas) due to large errors. Demographics include population, shares of those 65 and older, Hispanics of any race, African-Americans, other or multiple races, and residence in another county five years previous. Economic structure is measured as the percent of employed persons 16 years and older in the following industries: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation and warehousing; and retail trade and leisure services. Employment is by place-of-residence. Rural-urban continuum codes and topographic variation is from the U.S. Department of Agriculture; and density of interstate road lengths per square mile are calculated using GIS to model drug trafficking corridors.

We use U.S. Census County Business Patterns data for 2018 (U.S. Census 2020) to measure place-of-work employment per 10,000 in mental health / substance abuse centers and in family social service organizations. We also measure social capital producing organizations by employment per 10,000 in religious organizations, and employment in community, social, and civic organizations.

Statistical procedures

Latent Profile Analysis (LPA) provides hypothesis tests of class structure and model fit statistics, whereas cluster analysis relies on subjective heuristics. Cluster analysis can result in very different solutions depending on the type of distance metrics and linkage rules used, whereas LPA relies on a single estimation technique. More importantly, LPA estimates classification uncertainty using posterior probabilities obtained using Bayes theorem. By contrast, cluster analysis incorrectly assumes perfect certainty in classification, failing to recognize that cases may fit into multiple clusters. Fit statistics for the initial LPA indicated five classes were optimal, but examination of class means indicated that two classes (the prescription drug class and the illicit opioid and cocaine class) had high heterogeneity, indicating distinct subpopulations had not been identified. For substantive interpretation and to marginally improve fit, we extracted the two additional classes resulting in the seven classes.

Appendix A-4. Spatial Distribution of Drug Classes of Opioid Types Excluding other Drugs



Appendix A-5. Survey Responses for Resource Availability and Use Schedule for Agencies in Urban and Rural Counties

	All		Urban		Rural		
	Mean	SD	Mean	SD	Mean	SD	Difference
	2.671	2.671	2.729	0.579	2.587	0.744	0.142
Carry naloxone off duty	1.361	1.361	1.4	0.565	1.303	0.509	0.097
Use CIs repeatedly	2.238	2.238	2.293	0.613	2.156	0.517	0.137 *
Has CI funds	2.049	2.049	2.187	0.86	1.846	0.829	0.341 **
Has buy bust operations	2.188	2.188	2.301	0.826	2.022	0.816	0.279 **
Emergency responders carry naloxone	2.787	2.787	2.842	0.386	2.705	0.506	0.137 **
Suspects offered proffer opportunity	2.05	2.05	2.045	0.271	2.056	0.232	-0.011
Officers carry test kits	2.147	2.147	2.083	0.686	2.242	0.672	-0.159 *
Call K-9 for search	2.027	2.027	2.015	0.425	2.044	0.515	-0.029
Has tip lie	2.254	2.254	2.398	0.843	2.044	0.942	0.354 **
Secures jail treatment	1.608	1.608	1.589	0.657	1.636	0.61	-0.047
Refers to non-mandated treatment	1.689	1.689	1.708	0.603	1.663	0.583	0.045
Participates in education efforts	2.147	2.147	2.15	0.723	2.143	0.607	0.007
Officers serve on task force	2.227	2.227	2.343	0.777	2.055	0.794	0.288 **
Has drug coalition	1.921	1.921	2.031	0.896	1.759	0.777	0.272 **
Overdose follow-up	2.400	0.566	2.414	0.566	2.38	0.571	0.034
Anonymous tips pursued	2.529	2.529	2.541	0.500	2.511	0.524	0.03
Overdose death family follow-up	2.295	2.295	2.25	0.646	2.359	0.604	-0.109
Assign Officers to drug intelligence	2.505	2.505	2.542	0.558	2.451	0.582	0.091
Assign Officers to drug surveillance	2.214	2.214	2.311	0.763	2.076	0.829	0.235 **
Conducts road blocks	2.165	2.165	2.25	0.681	2.043	0.61	0.207 **
Assigns officers to surveillance	1.304	1.304	1.25	0.484	1.38	0.552	-0.13 **
Formally identifies drug dealers to target	2.263	2.263	2.303	0.641	2.207	0.688	0.096
Records source of seized Rx pills	2.252	2.252	2.285	0.707	2.207	0.688	0.078
Trains officers for OD response	2.662	2.662	2.722	0.466	2.576	0.559	0.146 **
Utilizes communications for drug intel other agencies	2.493	2.493	2.545	0.597	2.418	0.539	0.127 *
Shares drug intel with federal agencies	2.29	2.29	2.368	0.596	2.176	0.55	0.192 **
Shares drug intel with other local depts.	2.46	2.46	2.481	0.502	2.429	0.54	0.052
Shares drug intel with state police or task force	2.442	2.442	2.489	0.531	2.374	0.509	0.115 *
Stores intel of designated computer	1.662	1.662	1.715	0.828	1.584	0.736	0.131
Works with National Guard task forces	1.55	1.55	1.621	0.694	1.444	0.583	0.177 **
Uses state task force resources	1.982	1.982	2.053	0.624	1.879	0.574	0.174 **
Analyzes drug intel from past cases	2.162	2.162	2.191	0.622	2.121	0.593	0.07
Works cases with state police or task force	2.229	2.229	2.265	0.591	2.176	0.55	0.089
Equipment	21.513	21.513	22.127	3.241	20.62	3.646	1.507 **
Community	9.396	9.396	9.604	2.492	9.088	2.042	0.516 *
Response	22.48	22.48	22.699	3.768	22.163	3.414	0.536
Management Information	19.161	19.161	19.579	4.088	18.549	3.078	1.030 **
	n=232		n=135		n=97		

1=never, 2=sometines, 3=always

t-test *=p<.10*, **=p<.05

Appendix A-6. Artifacts and Dissemination Efforts

Products

Hochstetler, A. & D.J. Peters. (2023). Geography of Polysubstance Mortality. *Journal of Criminal Justice*. Pre-published. https://doi.org/10.1016/j.jcrimjus.2023.102044.

Hochstetler, A., D.J. Peters, S.M. Monnat. (2022). Prescription opioid resiliency and vulnerability: A mixed-methods comparative case study. *American Journal of Criminal Justice* 47:651-671.

Peters, D.J. (2023). Opioid Scenario Tool. – A tool for predicting death risk by county with user input. Submitted as part of this project to National Institute of Justice. Upon final submission and acceptance of products from this grant, also available at https://ruralopioids.soc.iastate.edu/nij.

Data Sets

Quantitative and Qualitative Data Sets from this project will be archived and searchable by investigator name or project title at the National Archive of Criminal Justice. https://www.icpsr.umich.edu/web/pages/NACJD/

Dissemination Activities

Hochstetler, A., Peters, & G. Sterner, III. (2023). Building opioid intelligence networks to combat the opioid crisis in rural communities: A collaborative intelligence led policing strategy. National Institute of Justice Research Conference, May 23, 2023. Washington, D.C.

Hochstetler, A., Peters, & G. Sterner, III. (2023). Building opioid intelligence networks to combat the opioid crisis in rural communities: A collaborative intelligence led policing strategy. National Institute of Justice-Bureau of Justice Assistance/COSSUP, regular internal meeting, On-line, May 8, 2023. Washington, D.C.

Hochstetler, A. & D.J. Peters (2022). Understanding county-level, spatial and temporal distribution of drug abuse as indicated by causes of death. American Society of Criminology. November 15-18. Atlanta, GA.

Hochstetler, A. (2021). Exploring opioid prescription overdose: remoteness and response in the rural U.S. American Society of Criminology. November 15-18.

Peters, D.J. & A. Hochstetler. (2021). The opioid epidemic in the nation and Iowa. Presentation to Extension Working Group on Drug and Alcohol Abuse. On-line. October 14, 2021.

Peters, D.J. & A. Hochstetler. (2019). The Opioid Hydra: Identifying Opioid Clusters and Implications for Counterdrug Efforts. Invited. The National Guard, Counterdrug Task forces. Reno, NV. (We gave a presentation on mapping and predicting before pre-testing and getting feedback on the survey used herein).

Appendix A-7. Non-Metropolitan County Opioid Overdose Calculator

NON-METROPOLITAN OPIOID OVERDOSE SCENARIO TOOL

Purpose: This tool allows local leaders to see how changes in local conditions may impact opioid overdose deaths. Tool allows decision makers to run "what-if" scenarios to anticipate changes or to assess program impacts.

Instructions:
1. Select your state and county
2. Change local conditions by entering the percent change to change in rates.
3. Tool automatically calculates changes in opioid overdose rates.

STEP 1 - SELECT YOUR STATE AND COUNTY

Select your STATE ...

New_York

Select your COUNTY ...

Seneca County, New York

STEP 2 - MODEL COUNTY CHANGES

	Current		Change	New Scenario
Demographics				
Population (number)	35,036	Percent Change	0	35,036
Percent Age 65 and older	17.20 %	Change	0	17.20
Percent Hispanics	3.21 %	Change	0	3.21
Percent Black/African American	4.31 %	Change	0	4.31
Percent 2+ or Other Races	3.05 %	Change	0	3.05
Social Conditions				
Percent in Poverty	12.38 %	Change	0	12.38
Property Crimes per 100,000 people	513.40	Percent Change	0	513.40
Church Jobs per 10,000	27.97	Percent Change	0	27.97
Community Organization Jobs per 10,000	8.28	Percent Change	0	8.28
Drug Risk Factors				
Non-Opioid Drug Deaths per 100,000	3.21	Percent Change	0	3.21
Rx Opioid Dispensing Rate per 100 people	38.87	Percent Change	0	38.87
Percent Work Disabled	3.87 %	Change	0	3.87
Retail Pharmacy Jobs per 10,000	19.98	Percent Change	0	19.98
Treatment Provision				
Physicians per 10,000	20.55	Percent Change	0	20.55
Mental Health and Substance Abuse Jobs per 10,000	0.01	Percent Change	0	0.01
Family Social Services Jobs per 10,000	132.15	Percent Change	0	132.15
At-Risk Employment				
Percent Employed in Agriculture and Forestry	3.28 %	Change	0	3.28
Percent Employed in Mining	0.09 %	Change	0	0.09
Percent Employed in Manufacturing	15.47 %	Change	0	15.47
Percent Employed in Construction	7.08 %	Change	0	7.08
Percent Employed in Transportation/Warehousing	3.77 %	Change	0	3.77

STEP 3 - VIEW OPIOID OVERDOSE ANALYSIS

	Overdose Risk Percentiles		
	Current	Scenario	Change
Perscription Opioids Alone	**36%**	**36%**	**0%**
Heroin Alone	**21%**	**21%**	**0%**
Synthetic Opioids and Mixtures	**47%**	**47%**	**0%**

Percentile	*Scale*
1-20%	Bottom 20%, LOW overdose rates
21-40%	BELOW AVERAGE overdose rates
41-60%	Middle 20%, AVERAGE overdose rates
61-80%	ABOVE AVERAGE overdose rates
81-100%	Top 20%, HIGH overdose rates
	Based on U.S. averages

IOWA STATE UNIVERSITY

Tool was developed by the Department of Sociology and Criminal Justice at Iowa State University.

For more information, contact Dr. Andrew Hochstetler at hochstet@iastate.edu

This project was supported by Award No. 2018-AR-BX-0004, awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. The opinions, findings, and conclusions or recommendations expressed in this publication/program/exhibition are those of the author(s) and do not necessarily reflect those of the Department of Justice.