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Poisson Probability Count Variable Model and An Eigen-Bayesian Semi-Parametric Eigen-Autocorrelation for Optimizing Mapping Fentanyl Mortality in Hillsborough County, Florida

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ABSTRACT

Background: Currently, there is a lack of precision count variable models for mapping fentanyl fatalities. The primary objective of this article is to develop a predictive count variable model for mapping county-level fentanyl-related deaths using scalable zip code capture point census data.
Subjects and Method: This ecological study focused on all zip codes within Hillsborough County, Florida. The target population included residents across these zip codes, with fentanyl-related mortality data aggregated per area. Total population sampling was applied using secondary data from census and mortality records. The dependent variable was the count of fentanyl-related deaths, while independent variables included sociodemographic indicators obtained from the U.S. Census Bureau. Variable measurements were based on standardized public data sources. Data were analyzed using a multi-count Poisson regression model. As no overdispersion was detected (variance inflation factor <10), neither negative binomial regression nor stepwise regression was required. Spatial analysis and autocorrelation were conducted using ArcGIS, with the primary predictor further interpolated to identify geographic patterns.
Results: Variable selection for the primary predictor was performed by observing the relationship between the standard error of each tested independent variable and its associated Z score. Given the identified relationship between fentanyl mortality and white populations, from the selection process, a spatial autocorrelation hot and cold spot analysis was conducted. This analysis identified zip codes with the highest and lowest predicted likelihood of fentanyl-caused deaths (as opposed to deaths where fentanyl was merely present). The identified zip code locations were 33647 and 33810 for the hot spots.
Conclusion: Count variable models and autocorrelation hot/cold spot mapping offer a methodological framework for future modeling efforts to predict locations of fentanyl mortality for preventative means.

Keywords: Fentanyl-caused Deaths, Poisson Regression, Spatial Autocorrelation

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BACKGROUND

Fentanyl is a potent synthetic opioid analgesic that is primarily used for severe pain management, often in cases of advanced cancer or post-operative recovery due to its rapid onset and high efficacy (Stanley, 2014). Fentanyl acts on the body by binding to the μ-opioid receptors in the central nervous system, which results in the inhibition of pain signaling and induces analgesia and euphoria. The drug is approximately 50–100 times more potent than morphine, and even small doses can be fatal, making it a major contributor to the ongoing opioid crisis (Centers for Disease Control and Prevention, 2024). While initially developed for controlled medical use, fentanyl's illicit analogs have increasingly entered the black market, affecting a broad demographic, particularly in individuals with substance use disorders. It disproportionately impacts communities with limited access to healthcare and addiction support services, exacerbating mortality rates among young and marginalized populations.

Unfortunately, thus far in scholarly literature, multi-count variable Poisson regression models are not employed frequently due to the untreated overdispersion displayed in their end result; an issue that was not encountered within this paper. As such, a predictive model for fentanyl mortality within Hillsborough County, Florida, at the zip code level was generated. The practice of fentanyl research in contributions in literature is commonly associated with the utilization of a dichotomous logistic regression model, which does not allow for proper natural handling of count data nor the development of second-order spatial autocorrelations.

Furthermore, even though there exist databases that can create predictive fentanyl mortality maps, commonly these models do not look at regression violations assumptions in space, time, and geography (i.e., spatial heteroscedasticity, zero non-Gaussian autocorrelation [geographic chaos], multicollinearity). Hence, it would be pertinent to detect anomalies in a fentanyl mortality model as violations of regression assumptions in space, time, and geography can generate biased, skewed outputs. Geospatial heteroscedasticity and multicollinearity commonly occur in spacetime epidemiological models (Jacob et al., 2023).

Geostatistical analyses may be integral to examining spatial and temporal patterns in count data, [e.g., rapid detection of fentanyl analog interpolated signatures for on-site or laboratory statistical-based analyses]. For example, Lim et al. (2024) analyzed count data from 11,940,207 samples to determine if fentanyl occurred concurrently with all examined substances and increased monotonically over time (Mann-Kendall $p<0.001$). The authors found that fentanyl co-occurred most commonly with heroin, and its presence in stimulant supplies revealed increasing trends in some areas. However, this model output did not portray where geolocations exactly posed a disproportionately high risk of overdose nor define a suitable location for a potential intervention treatment site within an urban classified stratified map.

Often, epidemiological count data analysis relies on statistical modeling methods to quantify relationships between predictors and outcomes. The validity of these models depends on satisfying key assumptions, including equidispersion, independence of observations, and the absence of spatial or temporal zero autocorrelation in residuals. Overdispersion, where the variance exceeds the mean, violates the equidispersion assumption of Poisson regression and necessitates alternative approaches (Hosmer and Lemeshow, 2000). Similarly, non-Gaussian, zero spatial autocorrelation, where residuals are random across geospace, can create heteroscedasticity, i.e., unequal variance changes, which can bias estimates and reduce model reliability (Jacob et al., 2023).

Early fentanyl models, including the Poisson regression, assume equidispersion—that the mean and variance of the response variable are equal. While this assumption simplifies computation, capture point, zip code, county-level, fentanyl-related count variables may exhibit overdispersion due to unobserved heterogeneity, omission of key predictors, and outliers, necessitating alternative approaches like the Negative Binomial regression (Cameron and Trivedi, 1998). Kim and Kriebel (2009) demonstrated, through simulation studies, that Negative Binomial regression models with a non-homogenous gamma distributed mean consistently outperformed other methods for handling overdispersion regardless of its source, including population heterogeneity, omitted variables, and outliers. Scale-adjusted capture point, zip code, county-level, Poissonian models, while computationally simpler, may produce biased standard-error estimates by underestimating or overestimating standard errors in a covariant dataset of zip code-stratified, fentanyl-related capture points. Hence, the usage of flexible model-based approaches, such as Negative Binomial regression, may be mandatory in geostatistical analysis of count data for anomaly outlier detection in fentanyl-related scalable capture point county-level predictive models. Furthermore, georeferenceable fentanyl, overdose-related propensities may be heuristically delineated using non-heteroscedastic prognosticative Gaussianism in clustering/non-clustering estimators determinants in eigen-Bayesian eigenvector eigengeospace where overdispersion is likely to occur.

In statistics, Moran's I is a measure of spatial autocorrelation developed by Patrick Alfred Pierce Moran (Moran, 1950). Spatial autocorrelation is characterized by a correlation in a signal among nearby locations in space. Hot and cold spot analysis may be generated using a second-order eigenfunction eigendecomposition eigenspatial filter eigen-algorithm to reveal patterns of high and low intensities in georeferenceable, epidemiologically sampled fentanyl-related, zip code stratified spatial data (Griffith, 2003). In so doing, this would provide additional insights into geographic heterogeneity, and predictive error in these paradigms, thus providing insight into the potential volatility of the observations in eigenvector eigen-Bayesian eigen-geospace.

This study incorporated the methodology from Jacob et al. (2023) of error diagnostics in eigenvector eigen-Bayesian, eigengeospace, such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), deviance, and spatial metrics like Moran's I to inform model selection and refinement. Akaike's information criterion (AIC) and Bayesian information criterion (BIC) are criteria for model selection amongst a finite set of models (Gelman et al., 2013). Models with non-zero autocorrelation are preferred since zero autocorrelation would signify total spatial and temporal randomness (Griffith, 2003). The spatial filtering may be a general methodology supporting more robust findings in scalable, zip code-level, fentanyl count sociodemographic stratified data analytic work and may be based upon a posited linkage structure that ties together the capture point, data observations in an eigen-Bayesian eigenvector model framework. Constructed mathematical operators are applied to decompose the geographically structured noise from both trend and random errors in the data, enhancing analysis results with clearer visualization possibilities and sounder statistical inference. In doing so, nearby/ adjacent values are manipulated to help analyze attribute values at a given location [ex. geolocation of a fentanyl-related treatment facility]. Eigen-spatial filtering mathematically manipulates the eigenized-Bayesian data in order to correct for potential distortions introduced by such factors as arbitrary scale, resolution and/or zonation (i.e., surface partitioning). The primary idea is that some spatial proxy variables extracted from a spatial relationship matrix are added as control variables to a scalable, capture point, zip code-level, fentanyl sociodemographic stratified, county-level, data predictive model specification in Python. The principal advantage of this methodology is that these control variables, which identify and isolate the stochastic spatial dependencies among the georeferenced fentanyl-related observations, would allow model building to proceed as if these observations were independent in a Python iOS pipeline.

The objective of this study was to develop a predictive model for fentanyl-related mortality in Hillsborough County, Florida, USA to facilitate the identification of potential overdose outbreaks within the context of the ongoing opioid epidemic. By analyzing data at the zip code level, this model may provide enhanced spatial resolution, enabling more precise identification of intervention sites within the county. In contrast, models that aggregate data at the county level in fentanyl modeling literature fail to account for localized variations, treating the county as a homogeneous unit and thereby obscuring critical hot and cold spots. To address this limitation, we designed a methodological framework that builds upon established principles, drawing from the foundational work presented by Hosmer and Lemeshow (2000). We also developed an eigen-Bayesian eigenvector Markovian semiparametric model presented in Jacob (2023) to distinguish zero autocorrelation, heteroscedasticity, and multicollinearity in space-time and geography. A robust analytical foundation for accurate and actionable public health interventions is created through the approach.

This paper specifically examines fentanyl-caused deaths to determine mortality rates, explicitly excluding fentanyl-present deaths. This exclusion is necessary due to the potential influence of confounding variables that cannot be accounted for in cases where fentanyl was present but not confirmed as the primary cause of death. Although fentanyl may have been detected at the time of death, its role as the principal cause cannot always be substantiated, and it may not have directly contributed to the fatality. According to the Florida Medical Examiners Commission (2022), Hillsborough County reported a total of 410 fentanyl-caused deaths in 2021. Of these, 42 were attributed to fentanyl alone, while 368 involved a combination of fentanyl and other substances. For this study, a total of 410 fentanyl-caused deaths were utilized in constructing the population stratification, ensuring a comprehensive analysis of fentanyl's impact on mortality within the county.

This research aims to achieve several objectives to enhance the precision and reliability of predictive modeling for fentanyl-related mortality. First, a Poisson regression is constructed on sociodemographic, US census, Florida Medical Commission, and fentanyl-related data to identify a primary predictor covariate. Second, a georeferenced hot and cold spot cluster map is developed using a second-order eigen-spatial autocorrelation model according to the primary predictor noted. Third, causal covariates within the autocorrelated data are identified through a Markov Chain Monte Carlo (MCMC) sampling distribution algorithm. Fourth, a non-bilinear, non-parametric algorithmic signature interpolator is employed to forecast potential high-prevalence geolocations. Fifth, an eigen-Bayesian eigenvector uncertainty model is implemented to account for non-Gaussian uncertainty in the predictive mapping of fentanyl-related deaths in Hillsborough County. Finally, we identify suitable locations within or around the spatial autocorrelation hotspot(s) to place a fentanyl drug intervention site. We assumed that these methodologies would provide a robust framework for understanding and predicting spatial patterns of fentanyl mortality. The primary aim of this article is to identify specific trends in a georeferenced capture point zip code sociodemographic stratified dataset of fentanyl-related county-level estimator determinant data to determine optimal geolocation for a treatment center in Hillsborough County, Florida.

SUBJECTS AND METHOD

1. Study Design

Initially, a Poisson regression with statistical significance was calculated with 95% confidence in Python (scipy.stats.poisson). The Poisson process in our analyses was provided by the limit of a binomial distribution of the sampled zip code level, fentanyl-related covariate coefficient estimates.

This study used Python to generate, plot, and calculate the Poissonized zip code and stratified distribution which was then used to fit a generalized linear model (GLM) to the sampled fentanyl-related data by maximum likelihood estimation of the parameter vector β. The procedure estimated the zip code sampled parameters numerically through an iterative fitting process. The dispersion parameter was then approximated by the residual deviance and by Pearson's chi-square divided by the degrees of freedom (d.f.). Covariances, standard errors, and p-values were then computed for the sampled covariate coefficients based on the asymptotic normality derived from the maximum likelihood estimation.

Note that the sample size N completely dropped out of the probability function, which in this experiment had the same functional form for all the capture points, sentinel site, fentanyl-related, stratified, estimator determinants indicator values (i.e., ν). As expected, the Poisson distribution was normalized so that the sum of probabilities equaled 1.

2. Population and Sample

Hillsborough County is one of the most populous counties in the United States with an estimated population of 1,444,359 (U.S. Census Bureau, 2021). Hillsborough County is composed of urban and rural residential among other land uses like industrial, commercial, and agriculture. The racial makeup is composed of 45.8% non-Hispanic white, 30.4% Hispanic, 18.6% non-Hispanic African American, 4.9% Asian alone, and 0.3% other (U.S. Census Bureau, 2024b).

It is located in central Florida along the west coast of the peninsula. Hillsborough County belongs to the Tampa Bay Area, a metropolitan area that consists of Tampa, St. Petersburg, and Clearwater (State of the Region, 2024). The county has a total area of 1327.821 square miles (3439.041 km2), of which 1022.537 square miles (2648.359 km2) are land and 305.284 square miles (790.682 km2) (22.991%) are covered by water (U.S. Census Bureau, 2024a).

For this study, zip code-level data was gathered through the use of 2021 American Community Survey (ACS) U.S. Census data. Data with specific regard to fentanyl mortality was gathered from the 2021 Annual Report by the Florida Medical Examiners Commission (Medical Examiners Commission, 2022). Within the 2021 Census data sets that were used for this study, there existed a total of 58 classified zip codes, 2 of which contained estimated populations of 0 (33530 and 33550). The total estimated population of Hillsborough County was 1,444,359 (U.S. Census Bureau, 2021).

3. Study Variables

This study constructed zip code probabilities from population-stratified fentanyl-related socioeconomic and racial-related covariates (Table 1), which was acquired from U.S. Census Bureau (2021). To obtain the dependent variable that was regressed against with the covariates throughout this study, a population stratification had to be completed per zip code. For this to be accomplished, the total fentanyl mortality that was noted earlier, 410 deaths, was set equal to the estimated population of Hillsborough County, 1,444,359. Each zip code population was then set equal to an unknown variable X. To acquire X, the following equation was used for each zip code: X=(410*Zip Code Population)/1,444,359. This allowed for a predictive fentanyl mortality value to be found for each zip code in our area of study. Our covariates centered around sociodemographic details: age, race, and education.

4. Operational Definition of Variables

The age covariates followed a similar stratification as shown prior but also included age range deaths from fentanyl via the Medical Examiners Commission (2022). The education variable, X6 from Table 1, involved the total number of people from each zip code that met the criteria listed in the variable's name. This was then stratified as well for predictive deaths in each zip code. Lastly, race was a proportionality of the predicted deaths for each zip code by the racial makeup of the (U.S. Census Bureau, 2021).

Table 1. Sample of Data for Zip Code 33510

Covariates	Example Zip Code Values: 33510
Y1 = Stratified Fentanyl Deaths at Zip Code Level	8.41057521
X1 = Fentanyl Deaths (0<18)	0.041027196
X2 = Fentanyl Deaths (18-25)	0.615407942
X3 = Fentanyl Deaths (26-34)	2.256495788
X4 = Fentanyl Deaths (35-50)	3.487311673
X5 = Fentanyl Deaths (>50)	2.010332611
X6 = Educational attainment of 18 and above for bachelor's and above degrees	1.654637109
X7 = White Portion of Fentanyl Deaths per Zip Code	3.624957916
X8 = Black Portion of Fentanyl Deaths per Zip Code	1.412976635
X9 = Asian Portion of Fentanyl Deaths per Zip Code	0.437349911
X10 = Latino/Hispanic Portion of Fentanyl Deaths per Zip Code	2.61568889
X11 = Other Race Portion of Fentanyl Deaths per Zip Code	0.328012433

5. Study Instrument

This study employed satellite-sensed, signature, zip code-stratified, LULC capture point, and sentinel site surveys of the potential aggregation/non-aggregation-oriented, georeferenced covariates. The digital overlay revealed the georeferenceable, capture point, LULC-classified surface area (m2) of each georeferenced, epidemiological, remote, sampled sentinel site variable within a zip code intervention geolocation in Hillsborough County.

Utilizing publicly accessible Environmental Systems Research Institute (ESRI) data through ArcGIS Pro’s Atlas Portal, a USA National Land Cover Database (NLCD)

Land Cover raster file was overlayed on the site of interest: Hillsborough County, Florida. The thematic Map (Figure 1) shows the appropriate LULC of each zip code, helping give a better insight into the differences between each individual zip code's geographical makeup. This map utilizes 30-meter spatial resolution data from the Land Cover Classification (Landsat 8) (Fickas et al., 2023). This model is managed by ESRI and is trained on the 2016 NLCD. The thematic map we created encompasses a time extent from 2020 to 2024 which was last modified on 11/15/2023.

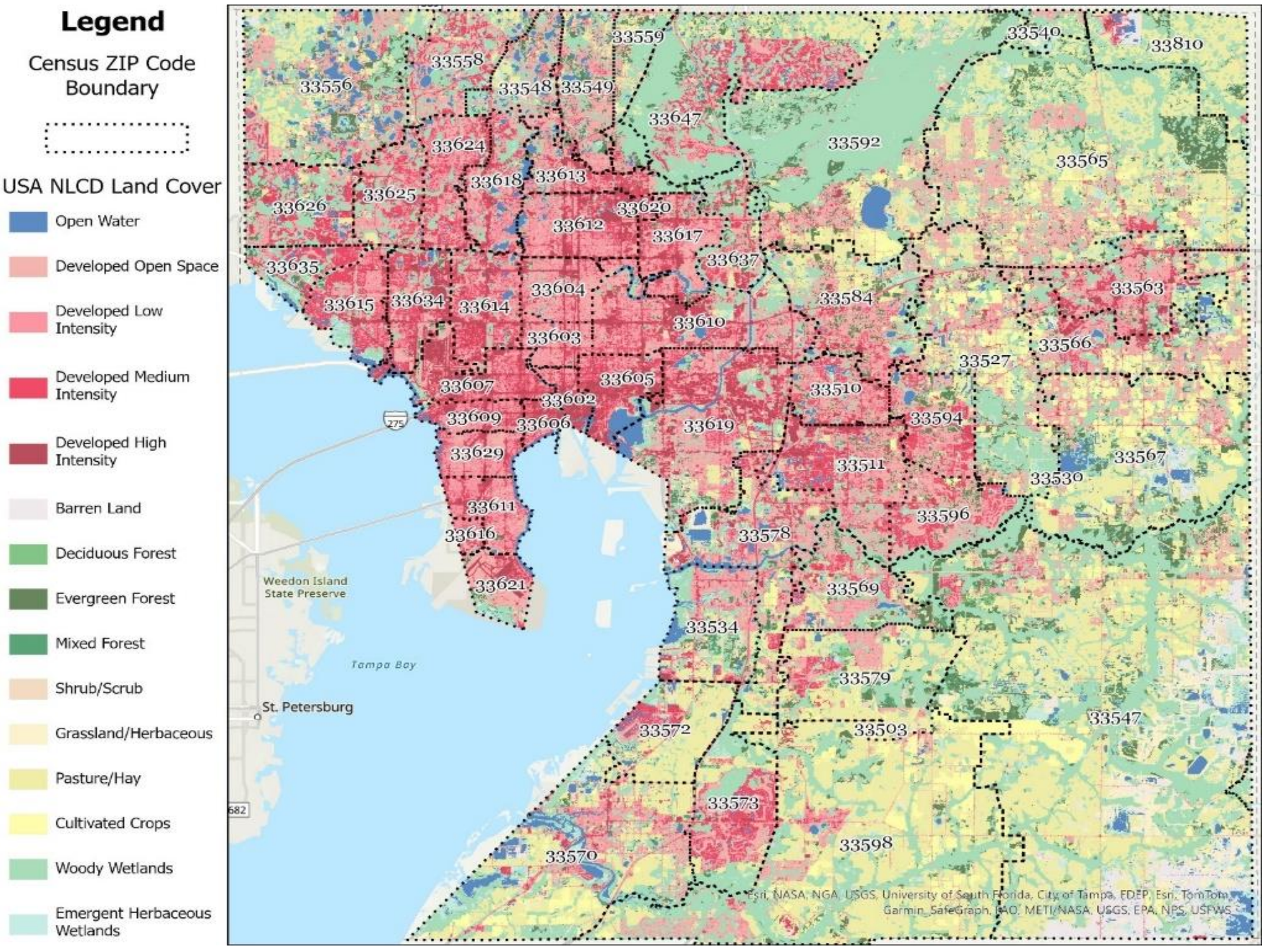

Figure 1. NLCD Land Cover Map of Hillsborough County by Zip Code

6. Data Analysis

A model was evaluated among the sampled fentanyl overdose-related covariates sampled at the Hillsborough County study site using Moran's I. In statistics, Moran's I is a measure of spatial autocorrelation (Griffith, 2003). We employed PySAL to compute Moran's I.

To compute Moran's I, we employed a weight matrix that represented the degree of relationship between the fentanyl overdose-related capture point zip code cells for which we verified autocorrelation. We examined the autocorrelation, which was arranged like a mosaic. We computed the weight matrix using the Contiguity-Based Weights method. We computed Moran's I for a two-dimensional dataset matrix.

We started with a random matrix, Z. In our instance, the outcome of Moran's I approximated 0, serving as an effective test. Once we validated the model employing the random Z data, we implemented it with the zip code-stratified fentanyl overdose variables.

An autocorrelation model specification was subsequently used to describe the Poissonized random autocorrelated, fentanyl overdose-related, sociodemographic variables. The resulting model specification took on the following form: $Y = \mu(1 - \rho) * 1 + \rho WY + \varepsilon$ (2.1) where μ was the scalar conditional mean of Y, and ε was an n-by-1 error vector whose elements were statistically independent and identically distributed (iid) normally random variates. Varying spatial, autoregressive parameters appeared in the covariance matrix, which for our fentanyl model specification was $\Sigma = [(I - \langle\rho\rangle diagW')(I - \langle\rho\rangle diagW)]^{-1}\sigma^{2}$ (2.2). The diagonal matrix of autoregressive parameters, $\langle\rho\rangle$diag, contained two sampled parameters: $\rho+$ for. those georeferenced, stratified sociodemographic covariates displaying positive spatial dependency, and ρ. for those displaying negative spatial dependency.

To identify georeferenceable, fentanyl-overdose-related clusters, Thiessen polygon surface partitioning was generated using Python 2.x script so as to construct geographic neighbor matrices, which were subsequently employed in the autocorrelation analysis. We generated spherical Voronoi polygons (Thiessen polygons). The Voronoi polygons were generated on a sphere under the consideration of a non-homogeneous slope coefficient surface.

Voronoi polygons were constructed from the data set of the latitude/longitude coordinates of zip code stratified, fentanyl overdose sociodemographic, data capture points Polygon geometries together with their geodesic area were saved in the ESRI Shapefile format.

7. Research Ethics

Given that our results identify a singular group of people as being in association with fentanyl deaths, it can be misconstrued that we are making any form of claim toward who causes fentanyl deaths. It should be clear that this article is purely about predicting fentanyl mortalities within space based upon sociodemographic data. We do not claim any group(s) responsible or associated to fentanyl-caused deaths.

RESULTS

A Poisson regression with statistical significance was calculated with 95% confidence in Python. The Pearson Chi-square value observed from the Poisson regression was 12.2, with a pseudo-R-squared value of 0.88. The Poisson process in our analyses was provided by the limit of a binomial distribution of the sampled zip code level, fentanyl-related sociodemographic, and racial stratified covariate coefficient estimates. We viewed the distribution as a function of the expected number of diagnostic, zip code, stratified, estimator determinant, and explanatory count variables (Jacob et al., 2014; Hosmer and Lemeshow, 2000). $\frac{n}{k}$ was used as a binomial coefficient, which was rearranged to achieve conditionally convergent series in our diagnostic, zip code, stratified, estimator determinant model. The plus and minus terms were first grouped in pairs of the sampled covariate coefficient estimates employing the resulting series based on the actual stratified sampled fentanyl-related, capture point, sentinel site indicator values.
In this experiment, the negative binomial regression models with variance function were not required as the variance inflation factor was below 10. According to Hosmer and Lemeshow (2000), there would be a requirement of a VIF >10 to use a negative binomial regression to rectify the over-

Poissonian variation. Our primary independent variable was concluded via association between standardized error and Z-score for each of the 11 covariates. Fentanyl deaths associated with white populations per zip code had a standard error of 0.051 and a Z score of 0.88.

We generated eigenfunctions of a spatial weighting matrix using the fentanyl overdose-related, sociodemographic stratified estimator determinants. Hence, in this experiment, the eigenvectors of Ω were vectors with unit norm maximizing Moran's I. The eigenvalues of this matrix were equal to Moran's I coefficients of spatial autocorrelation post-multiplied by a constant. Eigenvectors associated with high positive (or negative) eigenvalues have high positive (or negative) autocorrelation (Griffith, 2003). The eigenvectors associated with eigenvalues with extremely small absolute values corresponded to low spatial autocorrelation and were not suitable for defining spatial structures.

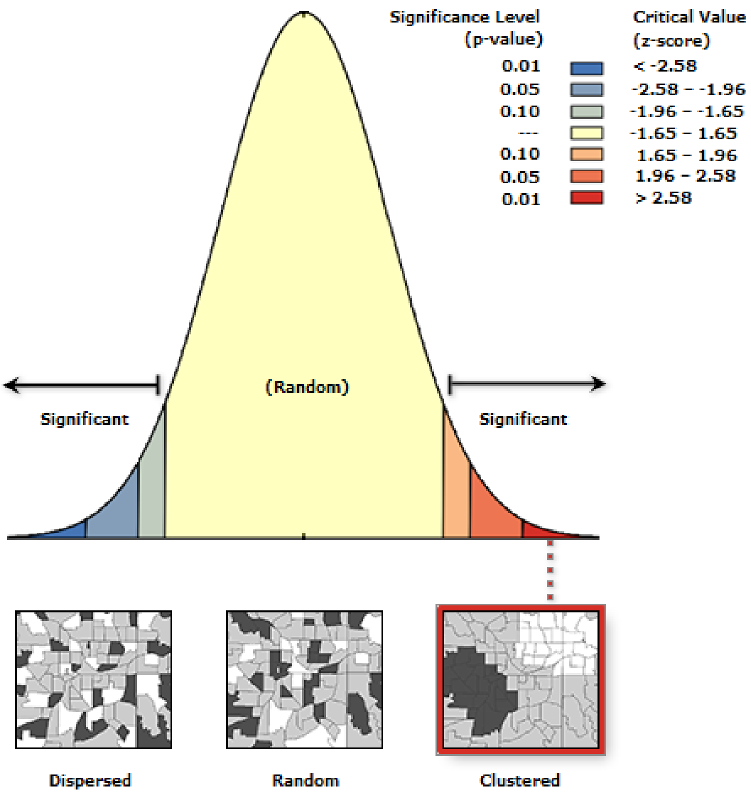

Figure 2. Spatial Autocorrelation Report

Table 2. Global Moran's *I* Diagnostic Summary of Georeferenced Zip Code Stratified Hot/Cold Spot Autocorrelated County Level Fentanyl Fatalities

Statistic	Value
Moran's Index	0.770851
Expected Index	-0.000411
Variance	0.000225
z-score	51.393087
p-value	0.000000

Table 3. Spatial Autocorrelation Dataset Information

Parameters	Description
Input Feature Class	Extract_habitat1_ExportFeatures
Input Field	RASTERVALU
Conceptualization	INVERSE_DISTANCE
Distance Method	EUCLIDEAN
Row Standardization	True
Distance Threshold	3635.9936 meters
Weights Matrix File	None
Selection Set	False

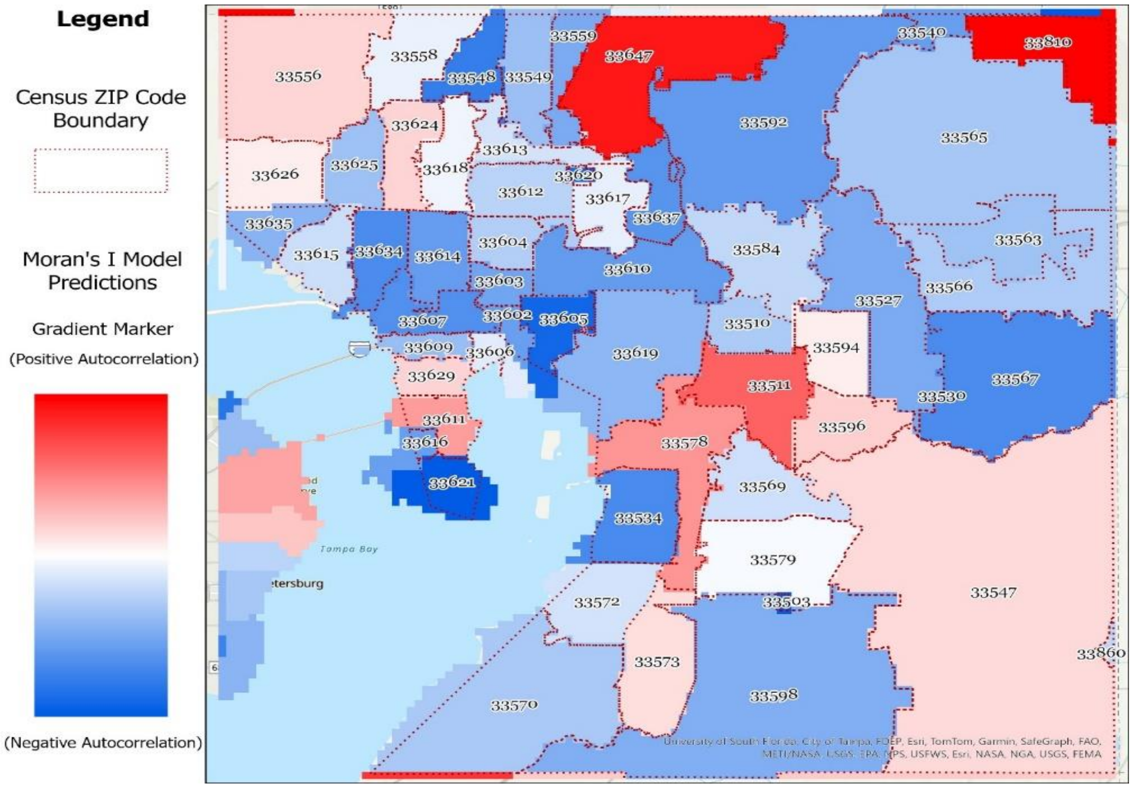

Figure 3. Second Order Spatial Autocorrelation Map of Study Site

In this experiment, we assumed that quantifying latent, non-normality due to violations of regression assumptions in geospace (i.e., multicollinearity, non-asymptoticalness, zero autocorrelation, heteroscedasticity) in an empirical geosampled dataset of regressed, georeferenced, fentanyl overdose-related, diagnostic, stratified, estimator determinants could be optimizable by employing a second-order, autoregressive, uncertainty-related, residual, vulnerability-oriented, prognosticative model and a probabilistic, eigen-Bayesian, Poissonian generalizable estimation matrix. In this experiment, the georeferenced, sub-county, zip code-level, diagnostically stratifiable, specifiable, geo-sampled characteristics were robustly and parsimoniously imposed, which allowed mapping the exact geolocations of treatment intervention centers for fentanyl overdose. We generated optimal locations for treatment intervention sites for fentanyl-related clients within both related major positive spatial autocorrelation zip codes (Figure 4 and Figure 5).

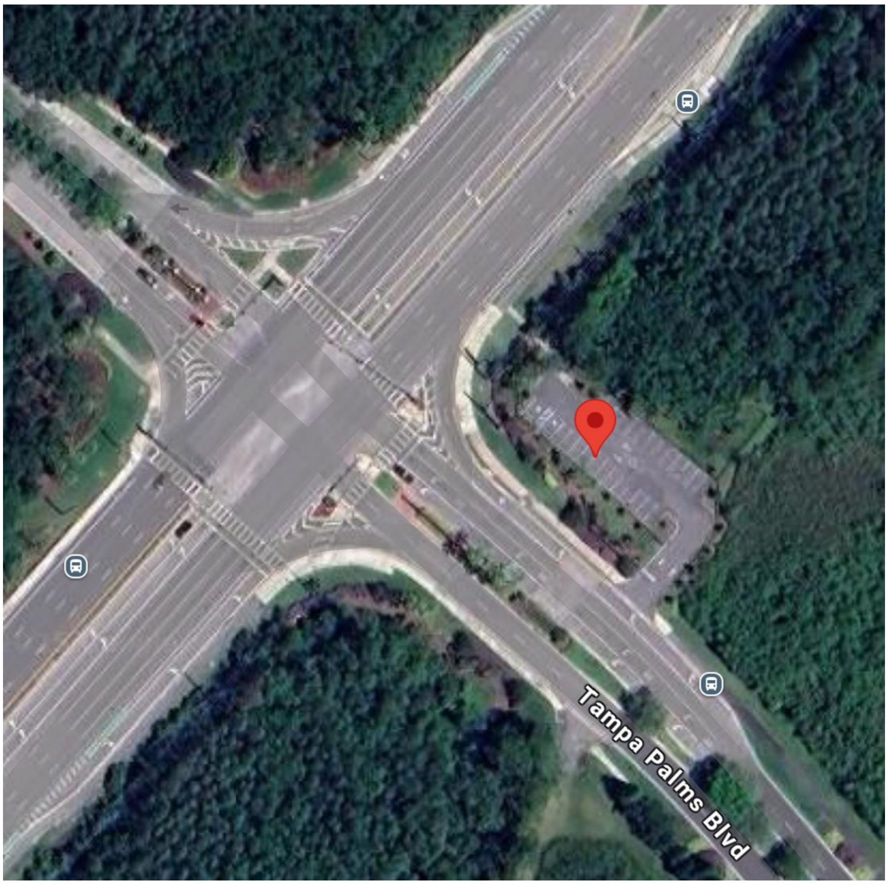

Figure 4. Google Maps Photo of 33647 Intervention Site

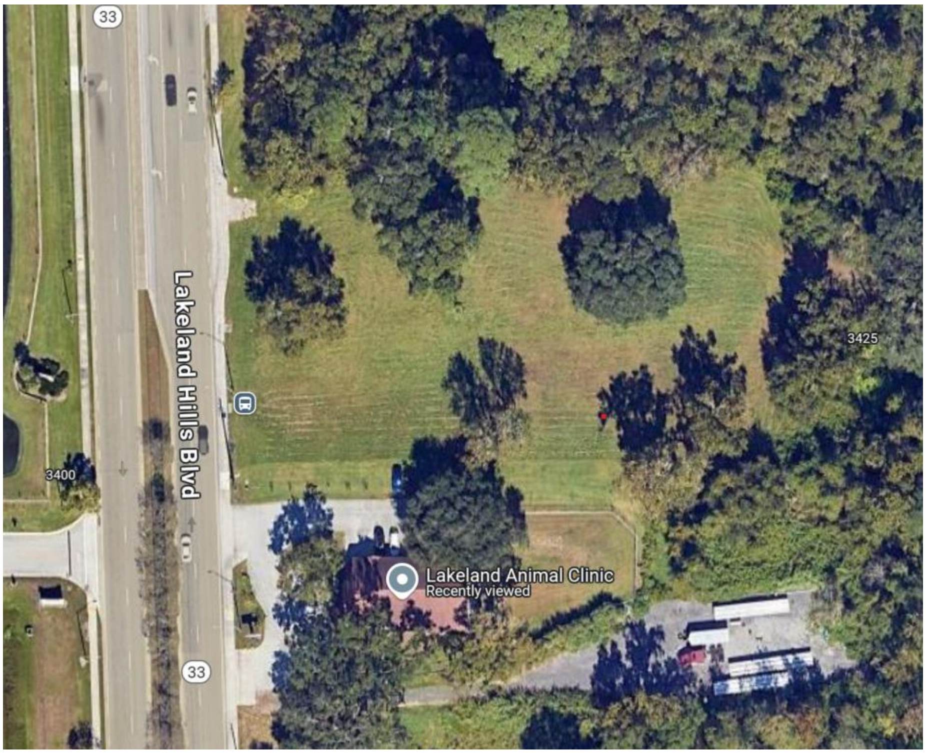

Figure 5. Google Maps Photo of 33810 Intervention Site

This study used county-level, census tract, zip code, and sociodemographic data to probabilistically forecast fentanyl-detected overdose deaths in Hillsborough County, Florida. To our knowledge, this is the first study to second-order spatially autocorrelate the distributions of fentanyl-detected overdose deaths in Florida and provide potential intervention locations based on said findings. The regression models at the capture point and zip code level, utilizing a Poisson regression approach, identified fentanyl-related deaths among non-Hispanic Whites as the most significant variable out of the 11 considered. This finding was determined through a rigorous variable selection process, based on the associated Z-scores and standardized errors for each sociodemographic variable. This result is consistent with the current fentanyl-related mortality statistics reported in Florida.

The Florida Drug-Related Outcomes Surveillance and Tracking (FROST) System, a collaborative initiative led by the University of Florida in partnership with the University of Kentucky and other key organizations, offers accessible data summaries through its dashboard. The Frost dashboard, while not differentiating between non-Hispanic Whites and Whites in general as our model does, provides established data within the same time frame, the year 2021, that supports our results. Their data from both years preceding and following 2021 further highlight that White populations are consistently the most prominent sociodemographic group in relation to fentanyl deaths. This alignment of data from FROST with our separate findings helps to rectify the validity of our results (Goldberger et al., 2025).

Given our findings, it is shown that non-Hispanic Whites are disproportionately affected by the waves of the fentanyl crisis.

This gives credence to the need for further research to address fentanyl deaths among White populations on both a local and national level to assist in harm reduction approaches and services. Our contribution to this is via the creation of a second-order spatial autocorrelation map of our target site, Hillsborough County, to pinpoint predicted fentanyl death hot spots (Hosmer and Lemeshow, 2000).

One of the benefits of using a spatial autocorrelation and eigen-Bayesian treatment post Poissonian, for fentanyl-related mortality, is the ability to cartographically and statistically delineate potential intervention sites for treatment. The need for an intervention site is crucial for helping people recover from their dependence. In so doing, we may achieve a better understanding of fentanyl addiction and potential treatment protocols. According to the Truth Initiative, opioid dependence can take as little as 5 days of use for individuals to have a lifetime of addiction (Truth Initiative, 2018). Fentanyl, like other opioids, has a highly addictive nature that without proper usage and management, can create a lifetime of dependence.

Fentanyl, due to its incredibly high potency, is commonly used as an adulterant within other illicit drug products. From a Drug Enforcement Administration (DEA) report in 2024, fentanyl was found in combination with Xylazine, also called Tranq, and cocaine (DEA, 2024). The problematic nature of this arises as Tranq is a sedative and not a synthetic opioid like fentanyl. This leads to a reduction in efficacy in Naloxone being administered thus increasing the probability of a fentanyl overdose. Mixtures between different illicit compounds are not uncommon, as fentanyl can be manufactured as a liquid or powder, allowing for it to blend in and go unnoticed by the user (Centers for Disease Control and Prevention, 2024). With all these combinations, those who engage in recreational drug usage may unknowingly consume/use a fentanyl-laced product, either immediately leading to an overdose or accelerating the process of addiction. The required amount of fentanyl to be consumed that leads to an overdose is as little as 2 milligrams, an amount that was found to be in 42% of fentanyl tablets analyzed by the DEA (DEA, 2021). Fentanyl is a product that can be found in practically any illicit drug, given the small amount needed to obtain efficacy.

Commonly, intervention sites focus on programs like syringe service programs (SSP) to help curb the spread of diseases like hepatitis C or HIV (Centers for Disease Control and Prevention, 2024). Through the usage of clean needles, people who use intravenous drugs will also be less likely to break their veins on injection. Drug overdose deaths, while tied to many other factors as well, are also tied to the availability of any given illicit drug (Jalal and Burke, 2021). As the incoming supply increases, so do the overdose-related deaths. This is one part too many for implementing drug intervention locations, particularly within 33647 and 33810, as if the demand for the drugs can be curbed the resulting supply will dwindle as well.

Our proposed intervention site not only focuses on drug tapering of fentanyl through actions like SSP but also the inclusion of social counseling to help provide structure back into their lives. Figures 4 and 5 show the intervention sites from Google Maps view with the satellite layer. Both sites have been selected while factoring in many variables including proximity to other healthcare centers/clinics, schools, residential zones, drug and liquor stores, comercial plazas, and law enforcement, along with access to bus routes, car routes, and walkability. This is all to ensure that the location can be accessible to those who need its services while also occupying a location that will not cause community unrest or impact local businesses.

The proposed location for a fentanyl intervention clinic in 33647 is at 8091 Tampa Palms Blvd, 33647 (Figure 4) which offers several potential benefits for addressing the predicted hotspot in the New Tampa area. One of the primary advantages of this site is its accessibility. Situated along a major thoroughfare, Tampa Palms Blvd, the clinic would be within reach of several key transportation routes, such as Bruce B. Downs Boulevard, which is a major county road connecting the suburban areas to the larger city of Tampa. This location is also relatively close to public transit stops, increasing accessibility for individuals without private transportation. Additionally, its proximity to the University of South Florida (USF) provides the opportunity for collaboration with local academic institutions, potentially enhancing the clinic's reach and effectiveness through research and partnership opportunities with healthcare programs.

However, there are certain challenges associated with placing a fentanyl intervention clinic at this location. One of the primary concerns is its proximity to residential areas, particularly in neighborhoods such as Tampa Palms and surrounding communities. While the area is suburban in nature, placing a harm reduction facility within such proximity to homes and schools could raise concerns among local residents regarding safety, stigma, and the potential for increased drug-related activity in the area (Creasy, 2021). Community opposition may arise, especially given the sensitivities surrounding public perceptions of drug use and intervention services. The clinic's presence in a relatively affluent and family-oriented area could potentially lead to resistance, complicating efforts to gain community support for the project.

This challenge can be addressed, however, if correctly approached. Stigmatization of substance use disorders (SUD) is, whether in regard to the individual afflicted or the place of treatment, not a new hurdle. This negativity is held not only by the general populace but also by those with SUDs themselves. The social stigma surrounding SUDs has been shown to be positively impacted by the usage of remission leaflets that document the succession of an individual who overcame addiction, for those with heroin dependence and alcoholism (Luty et al., 2008). While there are limitations that need to be further expanded upon, such as the small sample size within this study, there is promise in this avenue and those similar to improving public perception.

Another consideration is the proximity to healthcare services, which could be seen as both an advantage and a limitation. On one hand, the area benefits from being relatively close to major hospitals such as Advent Health Tampa and Tampa General Hospital's Wesley Chapel campus, ensuring that emergency medical services would be readily available in case of overdose or other health crises. Overdose treatment and prevetion centers should be proximal to hospital and clinics as they can provide additional support that the clinic itself may not be able to provide (Pikul, C., 2024). On the other hand, the clinic's location may be somewhat removed from areas with higher concentrations of individuals directly impacted by substance use, such as neighborhoods with lower-income populations or those with higher overdose rates. Therefore, while the clinic would serve the New Tampa community, it may not be as well-positioned to reach the populations most in need, necessitating additional outreach efforts to ensure that underserved individuals can access services effectively. Optimally, prevetion and treatment centers should be accessible to all members of society regardless of socioeconomic status (CDC, 2024). This is an issue not easily addressed given the land use previously identified as 33647. This is a zip code predominantly comprised of urban residential housing and commercial plazas off of State Road Bruce B Downs Boulevard. Drug intervention locations do not widely exist within this zip code, thus affirming the need for one. But the lack of open developmental areas that are both not within the immediate vicinity of housing, while also being close to underserved communities, is an issue we have not been able to reach.

The drug intervention site for the zip code 33810 would be directly north of 3421 Lakeland Hills Blvd. This specific address is in relation to a current bus station off of Lakeland Hills Boulevard and an animal clinic, but to further specify we are referring to the plot of land directly above said clinic (Figure 5).

The address 3421 Lakeland Hills Blvd offers a highly strategic location for a fentanyl intervention clinic due to its central positioning within the community and its accessibility to individuals in need of addiction treatment services. Situated in an area with high foot traffic and close proximity to public transportation, the site ensures that individuals struggling with opioid addiction, including fentanyl use, can easily access the facility. Accessibility to treatment centers is fundamental for recovery from drug addiction (CDC, 2024). This location is crucial in mitigating the barriers to care that many individuals face, such as transportation issues or long travel distances to receive help. Additionally, its visibility within the community ensures that the clinic can reach a broader population and provide services to those who may not otherwise seek out treatment due to geographical or logistical constraints.

Furthermore, the area surrounding 3421 Lakeland Hills Blvd includes both residential neighborhoods and local businesses, which enhances the potential for fostering community engagement and support. The clinic's proximity to residential areas allows for better outreach to local families affected by fentanyl addiction, fostering an environment where individuals can receive treatment close to home. Establishing a clinic in this community also presents an opportunity to collaborate with local social services, healthcare providers, and law enforcement to ensure a holistic, comprehensive approach to fentanyl addiction recovery. The presence of nearby social infrastructure could provide a robust support network for patients, improving long-term recovery outcomes and encouraging broader community involvement in combating the opioid crisis.

Finally, 3421 Lakeland Hills Blvd provides ample space for both clinical and supportive services, which is essential for the diverse needs of individuals affected by fentanyl addiction. The facility could accommodate various treatment modalities, including medication-assisted treatment (MAT), counseling services, and harm reduction programs, allowing for individualized care plans tailored to the specific needs of each patient. The ability to offer a multi-faceted treatment approach is critical in addressing the complex nature of fentanyl addiction (Blatt, A., 2024). By establishing a clinic at this location, the facility can also serve as a critical hub for education and prevention efforts, providing the community with resources to prevent future fentanyl misuse and promoting overall public health.

In conclusion, a Poissonian model can quantify overdispersed fentanyl-related sociodemographic variables at the county level. A second order autocorrelation model, thereafter, can cartographically and statically find hot and cold spots of georeferencedable fentanyl deaths. This research aimed to provide both a new methodology within fentanyl research and actionable public health directives based upon this methodlogy outcome for the betterment of our study site, Hillsborough County. In our future publiccation efforts, we plan to expand upon this methodology to contain more variables, models, and a larger study site, all of Florida. This is all with the purpose of allowing for better informative decisions to be made toward future harm reduction protocols and services.

This study is subject to several limitations. First, although we adjusted for sociodemographic and racial zip code stratified covariates in our autocorrelation space-time model, it possible that this analysis was obscured by individual-level relationships between place, and overdose risk. Second, we used population stratification to determine geographic weights based only on sociodemographic and racial covariates in space and geography but not on time, which may have led to misclassification. Lastly, while we investigated the spatial trends of fentanyl-detected overdose deaths, we did not explore the trends of overdose deaths that involved both fentanyl and other substances such as methamphetamine. Further studies are needed to investigate the spatiotemporal trends of polysubstance use with fentanyl in Hillsborough County.

AUTHOR CONTRIBUTION

Alexander Gambrell constructed the spatial autocorrelation model. Heather McDonald generated the NLCD LULC map of the study site. Namit Choudhari constructed the Poisson model. Sasha Mosichs edited the draft. Benjamin Jacob oversaw the manuscript

compilation. Caleb Jaramillo was in charge of the manuscript chapter developments, mapping the intervention sites for fentanyl-related overdose prevention and treatment, and prepared the final manuscript.

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CONFLICT OF INTEREST

The authors declare that the study was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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