

ORIGINAL RESEARCH ARTICLE

Deep learning-based spatio-temporal framework for opioid overdose monitoring in rural Alabama

Xue Wu¹, Shengting Cao², and Jiaqi Gong^{1*}¹Department of Computer Science, the University of Alabama, Tuscaloosa, Alabama, United States of America²Department of Computer Science, Knox College, Galesburg, Illinois, United States of America

Abstract

Timely and accurate monitoring of opioid overdose risks is critical for public health, particularly in underserved rural regions. Traditional surveillance systems often lack the spatial and temporal resolution needed to support proactive interventions. While socioeconomic indicators, such as the social vulnerability index and housing value, show moderate correlations with opioid-related outcomes, existing methods rarely incorporate high-resolution environmental data. Previous research relies largely on static census data and coarse geographic indicators, limiting its ability to detect localized risk patterns. Moreover, the connection between built-environment features and opioid overdose remains underexplored—especially in rural areas like Alabama’s Black Belt. To address this gap, we propose a multiscale spatio-temporal framework that integrates satellite imagery and machine learning to monitor opioid-related emergency room (ER) visit rates. We collected 201,967 housing images from Black Belt counties and classified them using computer vision models, including ResNet and external attention transformers. To overcome limitations in labeled data, we developed four unsupervised pipelines combining k-means clustering with autoencoders, masked autoencoders, VGG16, and household-image ratios. Our results show that unsupervised embeddings outperform supervised classification in capturing signals associated with ER visits. Descriptive features, such as roof type, road layout, and environmental openness, significantly inform predictions. Although Black Belt counties report lower absolute ER visit rates, they show faster year-over-year growth. Our study demonstrates the potential of combining satellite imagery with multimodal artificial intelligence to improve rural health surveillance and supports the development of scalable, interpretable monitoring tools for early intervention and policy planning.

***Corresponding author:**Jiaqi Gong
(jgong5@ua.edu)

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1. Introduction

The opioid epidemic has emerged as a major public health crisis in many countries, particularly in North America.¹ In the United States, it has profoundly affected community well-being, with significant social, economic, and environmental

consequences. Rising opioid misuse has driven an escalating overdose crisis characterized by reduced quality of life, criminal justice involvement, loss of economic productivity, and overdose deaths. In 2017, the estimated cost of opioid use disorder and fatal overdoses reached USD 1.02 trillion,² with opioids accounting for nearly 70% of all drug overdose deaths. Policymakers, community organizations, and local stakeholders face the urgent responsibility of addressing these challenges. Multiple funding agencies, non-governmental organizations, and local coalitions are working to implement harm-reduction strategies, especially in rural areas.³ Despite these efforts, opioid-related mortality continues to rise; from April 2020 to April 2021 alone, more than 100,000 deaths were attributed to opioid overdose—a 28.5% increase from the previous year.⁴ Yet, timely and localized information remains limited, particularly at the county level. Developing effective monitoring systems to support harm reduction and guide place-based interventions is, therefore, crucial in combating the opioid crisis.

To examine environmental determinants of opioid overdose, we use social vulnerability as a reference. The social vulnerability index (SVI) measures a community's capacity to withstand and recover from disasters or public health crises. At the local level, resilience shaped by socioeconomic and demographic factors plays a critical role in both research and policy. The SVI includes an overall score and four thematic dimension: socioeconomic status, household composition, race/ethnicity/language, and housing/transportation. These indices collectively reflect the community environment and are assessed for their correlation with opioid overdose patterns. Beyond the SVI, additional attributes—such as property values and satellite-derived housing features—provide valuable complementary measures for monitoring opioid risk.

Satellite data have gained increasing attention across diverse applications, including disaster response and environmental monitoring.⁵ Advances in high-resolution imagery and the expansion of public data resources have made satellite data more accessible than ever. When combined with artificial intelligence (AI), remote sensing imagery can provide valuable insights through deep learning (DL)-based feature extraction. By integrating satellite imagery with complementary datasets such as property values, it becomes possible to uncover socioeconomic patterns and geographic features associated with opioid risk.

Prior studies have demonstrated the value of integrating social, geographic, and image-based data to monitor public health crises, particularly opioid overdoses. Early work combined county-level socioeconomic indicators with

spatial statistics and data mining to capture spatio-temporal overdose patterns, such as a study in Virginia,⁶ while community-level virtual audits using Google Earth imagery in Kentucky⁷ showed that satellite-based observations can reveal rural environmental risk factors often missing from traditional datasets. Medical-data-driven approaches have further identified individual-level overdose risk factors to support clinical monitoring and counseling.¹ Beyond opioid-specific research, satellite imagery and machine learning have been widely adopted to characterize social and health-related conditions. Prior studies demonstrated that computer vision models can infer poverty and socioeconomic vulnerability from satellite images⁸ and support cost-effective community sampling for public health surveillance, such as COVID-19 vaccine studies in rural Alabama.⁹ Advances in AI have strengthened these efforts, with convolutional neural network (CNN)-based architectures, such as ResNet and VGG16, becoming standard backbones for satellite image classification and feature extraction.¹⁰⁻¹⁴ While these classification-oriented models effectively capture global visual patterns, they lack explicit spatial localization. Image segmentation methods, particularly U-Net, address this limitation by preserving fine-grained spatial structure through encoder-decoder architectures with skip connections, making them more suitable for extracting meaningful built-environment features for social science applications. Autoencoder-based approaches further enable unsupervised feature learning from heterogeneous remote sensing data.¹⁵ Finally, previous studies integrated Google Earth and community data to inform opioid crisis mitigation using AI tools,¹⁶ while recent work has emphasized the interpretability of visual features such as texture, shape, pixels, and frequency.^{17,18} A growing body of literature also highlights the importance of contextual and environmental factors in shaping health disparities. A study leveraged satellite data to monitor large-scale environmental changes, such as land use, meteorological patterns, and air quality, across East Asian cities.¹⁹ Community-level social determinants and social vulnerability have been shown to be strongly associated with nonfatal overdose risk.²⁰ Related research links environmental sustainability in healthcare systems to improved service quality and financial performance,²¹ emphasizing the broader role of environmental stewardship in public health outcomes. Urban livability and sustainability frameworks further demonstrate how built-environment indicators can inform resilient and healthy community planning.²²⁻²⁴ These studies collectively suggest that environmental conditions, healthcare operations, and community well-being are deeply interconnected and can be effectively assessed using integrated geospatial and AI-driven approaches.

Building on prior research, our study integrated satellite imagery, the SVI, and geographic information to monitor opioid overdose patterns. First, we applied supervised learning methods to classify satellite imagery and examine correlations between the classified image categories and opioid overdose emergency room (ER) visit rates. We then extracted housing features from satellite images using computer vision approaches, including VGG16, autoencoders, and masked autoencoders, and generated feature clusters through unsupervised learning. By combining satellite-derived features, SVI data, and housing values, we gained a deeper understanding of factors associated with opioid overdose. We further illustrated the distribution of housing features using clustering algorithms, in which the extracted feature vectors corresponded to distinct satellite-based patterns. Since housing features remain stable over time, we leveraged these satellite-derived features to monitor ER visit rates and demonstrated their correlations with opioid-related outcomes.

Our study examined Alabama, a state exhibiting elevated opioid-related risk. Alabama's opioid overdose rate surpasses the national average,²⁵ and it has historically maintained the highest opioid prescription rate nationwide.²⁶ Prior research has shown that counties with higher prescription rates tend to experience greater opioid-related mortality.²⁷ While drug overdose was historically more prominent in urban areas, recent trends indicate a shift toward rural communities, where overdose deaths now surpass those in urban settings.⁷ Rural Alabama, in particular, has experienced sharper increases in overdose rates, along with widespread opioid misuse and adverse health outcomes.²⁶ Contributing factors include limited resources—such as healthcare services, treatment and prevention programs, and available providers^{28,29}—as well as sociodemographic vulnerabilities, including poverty, underinsurance, and a predominance of working-class residents.²⁶ Despite these challenges, few studies have examined the spatial and temporal associations between socioeconomic conditions and opioid overdose rates. Our study addresses this gap by proposing a monitoring framework that can inform harm reduction strategies and guide future research to mitigate opioid-related harms.

We integrated high-resolution satellite imagery with geographic and social determinant data to monitor opioid overdose ER visit rates. This monitoring framework enabled a comprehensive analysis of ER visits by combining geographic representation, SVI measures, and features extracted from satellite imagery. [Figure 1](#) shows the workflow of the opioid overdose monitoring system. We obtained the correlation values for ER visit rates, SVI,

and housing value. We use calculated opioid overdose ER visit rates, SVI, and SVI themes to monitor the SVI of opioid overdose. We also used the calculated opioid overdose ER visit rates and extracted housing features to monitor the housing features of opioid overdose. We extracted visual features from the collected satellite dataset using DL techniques and then clustered them using clustering algorithms to create distinct feature clusters. Then we used the extracted percentage of visual feature clusters to correlate with the opioid overdose ER visit rates. The SVI was divided into four themes: socioeconomic status, housing/transportation, race/ethnicity/language, and household composition. To explore SVI themes, we considered property values and satellite images to analyze how SVI themes and housing features affected opioid overdose ER visit rates.

To our knowledge, no prior study has jointly incorporated geographic data, SVI, and satellite-derived features to examine and compare ER visit rates across counties and over time. Beyond opioid overdose, the proposed framework also has the potential to inform analyses of other health-related challenges, both emerging and ongoing. The contributions of this study are as follows:

- Propose a spatio-temporal monitoring framework that integrates opioid overdose ER visit data with geographic, social vulnerability, and housing-based indicators to support county-level overdose surveillance across Alabama.
- Develop an innovative multi-dimensional data integration approach that combines spatial features, social vulnerability measures, and housing characteristics to identify key determinants of opioid overdose ER visit rates.
- Demonstrate the utility of the proposed framework by analyzing spatio-temporal variations in overdose ER visit rates from 2018 to 2021, revealing rural disparities, lower ER utilization in high-risk counties, and spatial patterns associated with changes in ER visit rates over time.

The organization of the remainder of this paper is as follows: the data and methods section introduces the datasets and AI techniques for this monitoring framework; the results section presents the analysis; the discussion section; and the concluding remarks and future work are described.

2. Data and methods

More than 50 national governments have established data-driven strategies for science and engineering policy interventions.³⁰ According to a brief review of the unique features of rural risk environments that affect research

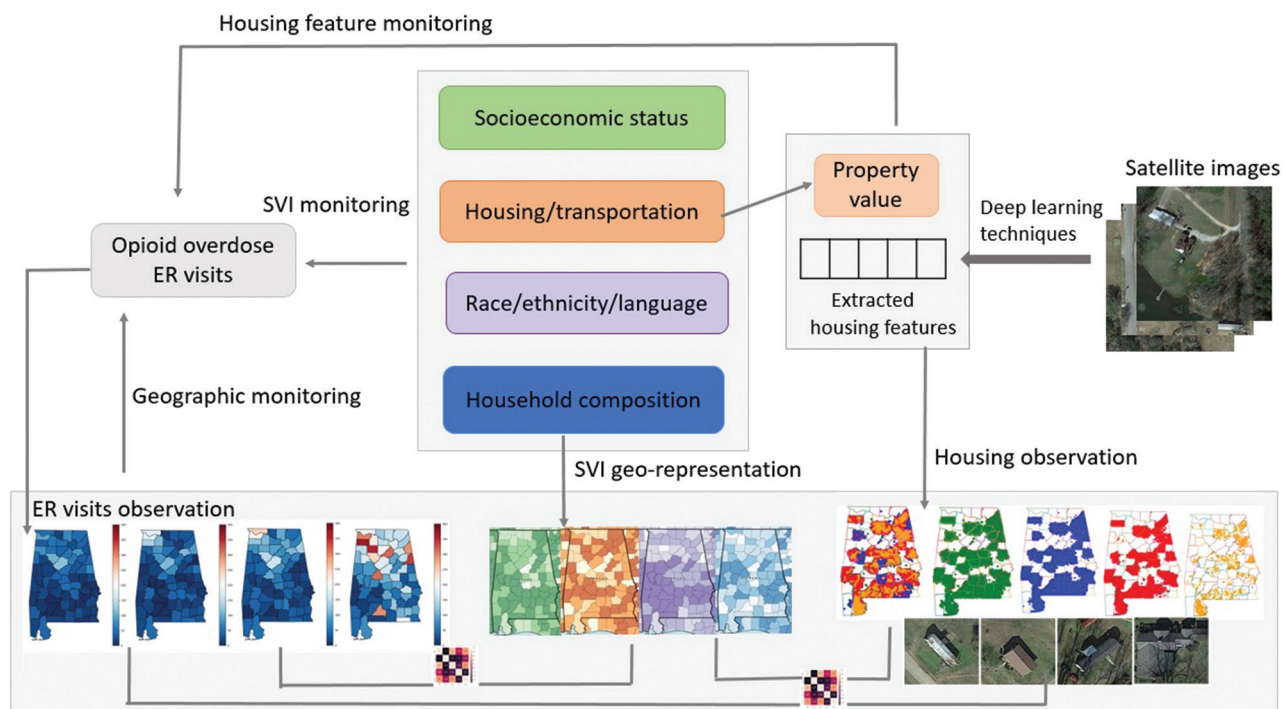


Figure 1. Workflow of the opioid overdose monitoring system
Abbreviations: ER: Emergency room; SVI: Social vulnerability index.

and policy planning,³¹ it is clear that local decision-makers are unable to raise revenue to supplement necessary infrastructure, creating an underprivileged policy environment. Rural areas also lack evidence-based pharmacotherapy and scalable treatments for drug use disorder; all the findings of our study have important policy implications for addressing the opioid crisis in rural areas. To address these gaps, our study integrated four complementary data sources: SVI, Alabama Black Belt satellite images, property values, and opioid overdose ER visit rates. This study received an institutional review board (IRB) exemption on the grounds that all data were publicly available, no identifiable individual-level records were collected, and all analyses were performed at the aggregated county scale. As a result, the IRB determined that informed consent was not required.

The Centers for Disease Control and Prevention (CDC) publishes the SVI³² in geographic information system (GIS) format,³³ providing county- and zip code-level data for all 67 counties in Alabama. Social vulnerability reflects a community's resilience in responding to public health crises, pandemics, or disasters.³⁴ The CDC releases SVI data in GIS format every 2 years,³⁴ offering a publicly available resource that enables researchers to capture geographic variation in rural areas and identify counties most in need of targeted interventions and policy support.

The SVI consists of four thematic domains: socioeconomic status, household composition, race/ethnicity/language, and housing/transportation.³⁴ Figure 2 illustrates these themes for Hale County, a rural county in Alabama. For example, lower SVI values for socioeconomic status represented stronger socioeconomic conditions, while higher values indicated greater vulnerability. In this study, we used the 2018 SVI data, which provided a complete set of theme values.

Satellite sensors provided synoptic data on a range of biophysical parameters and land-use/land-cover information that can be used for environmental monitoring and mapping.³⁵ To enable prospective monitoring of opioid overdose using geographic and satellite-derived features, we collected housing satellite imagery from Google Maps and other satellite databases,³⁶ focusing primarily on 17 counties in Alabama's Black Belt region in 2018. Our goal is to evaluate whether satellite imagery can represent socioeconomic status and housing-related geographic factors through spatial features. To this end, we calculated distributions of housing classifications and image-based features to assess their ability to validate our hypothesis. Using a custom Python crawler (Version 3.7, developed by authors using Google API, United States), we collected additional imagery with detailed features, including houses, roads, and yards,

resulting in a dataset of 201,967 housing images at a resolution of 768×768 pixels. Figure 3 shows the satellite data collection process. Figure 4 shows the number of households and satellite images. Since socioeconomic status strongly influences community health, housing and transportation characteristics serve as key environmental variables that may impact health outcomes. In rural areas, where traditional data sources are limited, satellite-based imagery provides a valuable means to analyze opioid overdose patterns and their association with underlying social and environmental factors.

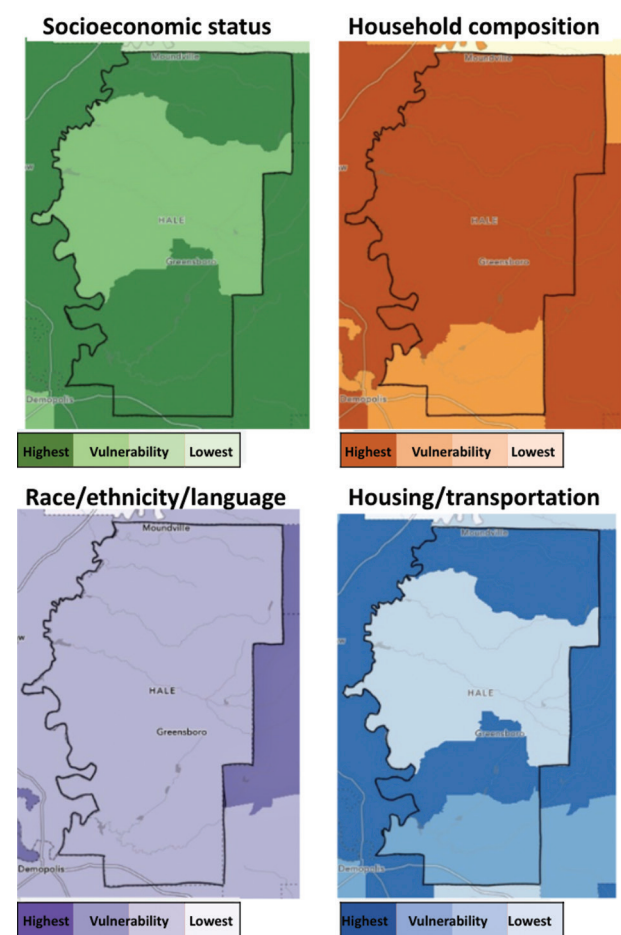


Figure 2. Four social vulnerability index themes of Hale County

Housing data retrieved from online sources has become an integral part of daily life. Zillow, for example, provided detailed property-level information that characterized houses through market transactions, including estimated prices. To illustrate the spatial distribution of housing across Alabama, we mapped properties in all 67 counties using latitude and longitude coordinates. There were 1,048,576 property data points, each representing a household with an associated property value. Several properties appear as outliers, as they were not fully aligned with Alabama CoreLogic Property records.

The ER visits dataset included county- and zip code-level opioid overdose data for all 67 counties in Alabama. It contained records from 2018 to 2021 on individual opioid overdose ER visits, including patient zip code, age, gender, race, and county of residence. Gong and Wu¹⁶ conducted a descriptive analysis of these variables. The ER visit rate was defined as the number of opioid-related ER visits per 100,000 population. Similarly, the opioid-related death rate was defined as the number of opioid-related deaths per 100,000 population. In some counties, death rates were reported as zero because health data are suppressed when there are fewer than 10 cases to protect confidentiality.

The state of Alabama consists of 67 counties and 645 zip code areas, which served as the units of analysis in this study. We examined ER visit rates and opioid-related death rates across counties and zip codes and assessed spatial autocorrelation of ER visit rates in 2018. Spatial autocorrelation refers to the tendency of values in one location to be similar to or different from those in nearby areas.⁶ In our analysis, we considered neighborhood adjacency for Alabama zip codes. Positive spatial autocorrelation indicated that neighboring areas shared similar values, whereas negative spatial autocorrelation indicated that neighboring areas exhibited dissimilar values.

This study analyzed potential geographic factors of opioid overdose and examined how social vulnerability shaped overdose rates in 2018. We explored different SVI themes to assess how socioeconomic status and housing features influenced opioid overdose. We also calculated

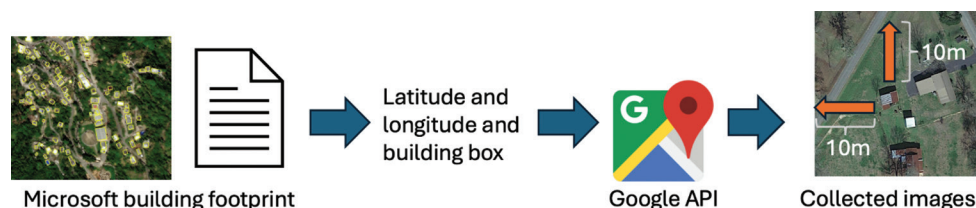


Figure 3. Satellite data collection process
Abbreviation: API: Application Programming Interface.

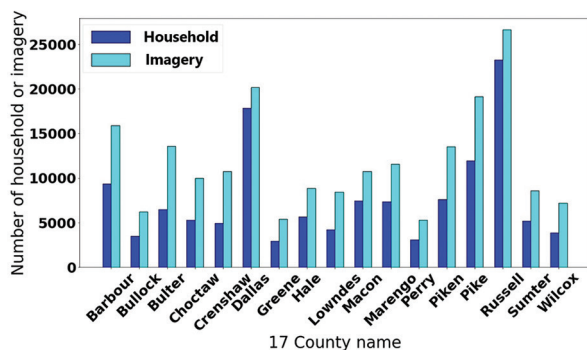


Figure 4. The amount of data collected for 17 counties in the Alabama Black Belt

the spatial autocorrelation of opioid overdose rates across Alabama counties using neighborhood adjacency and ER visit data in 2018. For temporal analysis, we tracked changes in ER visit rates by incorporating social vulnerability measures and satellite-derived features, and identified associations among ER visits, SVI themes, and environmental characteristics. For spatial analysis, we examined ER visit rates across counties and evaluated their relationships with satellite features, property values, and both local and global indicators of spatial association.⁶

2.1. Social vulnerability monitoring

We obtained county-level SVI data for 2018 in Alabama's Black Belt region to examine correlations between social vulnerability and opioid overdose ER visit rates. Among the SVI themes, socioeconomic status exhibited the strongest correlation with ER visit rates, followed by housing and transportation. These findings are consistent with prior research that highlighted a strong association between socioeconomic conditions and public health outcomes.⁶ By leveraging this approach, we assessed whether variations in social and environmental vulnerability are reflected in opioid-related health outcomes in rural Alabama counties.

2.2. Housing feature monitoring

2.2.1. Property value

We considered property value as a housing-related feature in analyzing opioid overdose. The raw data were obtained from CoreLogic Alabama Property Information, which provides official statistics on total assessed property values along with geographic coordinates (latitude and longitude). These data were aggregated from county and township government records across Alabama. We used the property dataset directly to examine the association between property values and opioid overdose ER visit rates.

2.2.2. Physical and neighborhood features

Supervised learning techniques require labeled data samples. To investigate the relationship between social vulnerability and opioid-related ER visit rates, we analyzed correlations between the SVI and satellite-derived housing imagery. In addition to housing structures, we included neighborhood-level features, such as road networks and greenery, when collecting satellite images. DL, a subset of machine learning, has proven effective at extracting meaningful features from satellite imagery,³⁷ particularly with CNNs. To monitor opioid overdose ER visit rates in relation to social vulnerability, we applied machine learning algorithms to high-resolution satellite imagery, focusing on housing and neighborhood characteristics. Specifically, we implemented CNNs, ResNet-18, ResNet-50, and the external attention transformer network (EANet) for satellite image classification. All images were labeled and classified into four categories—poor, common, good, and luxury—based on housing size, roof condition, yard characteristics, and road quality for training. The CNN models were trained on four classification tasks, with the input images appended, for 100 epochs. The ResNet-18 and ResNet-50 were trained with the Adam optimizer¹¹ and a mean squared error loss function. The ResNet-18 model is trained for 50 and 100 epochs, and ResNet-50 is trained for 100, 200, and 400 epochs. EANet was used as an image classification model. In the experiment, TensorFlow (Version 2.7, Google, United States) was used to train under this classification condition, observe the results, and validate the unlabeled data. We used an independent sample of the dataset for the prediction tasks, with 80% for training, 20% for testing, and an additional 20% subset for validation during model development.

2.2.3. Latent visual features

Unsupervised learning does not rely on labeled data; instead, it groups samples based on similarity.³⁸ Because labeling satellite imagery is both costly and time-consuming,³⁹ clustering algorithms are often employed for image classification tasks.³⁸ In our approach, we first extracted latent visual features from satellite images using models such as VGG16,⁴⁰ autoencoders, masked autoencoders, and a segmentation housing ratio. [Figure 5](#) shows the architectures of three neural network types: UNET-AutoEncoder, Masked AutoEncoder, and VGG-16. For VGG16, we removed the final classification layer to obtain a 4,096-dimensional feature vector. For both the Autoencoder and Masked Autoencoder, the encoder produced a 1,000-dimensional latent feature vector, representing the compressed visual information. These latent features, which captured high-level visual patterns

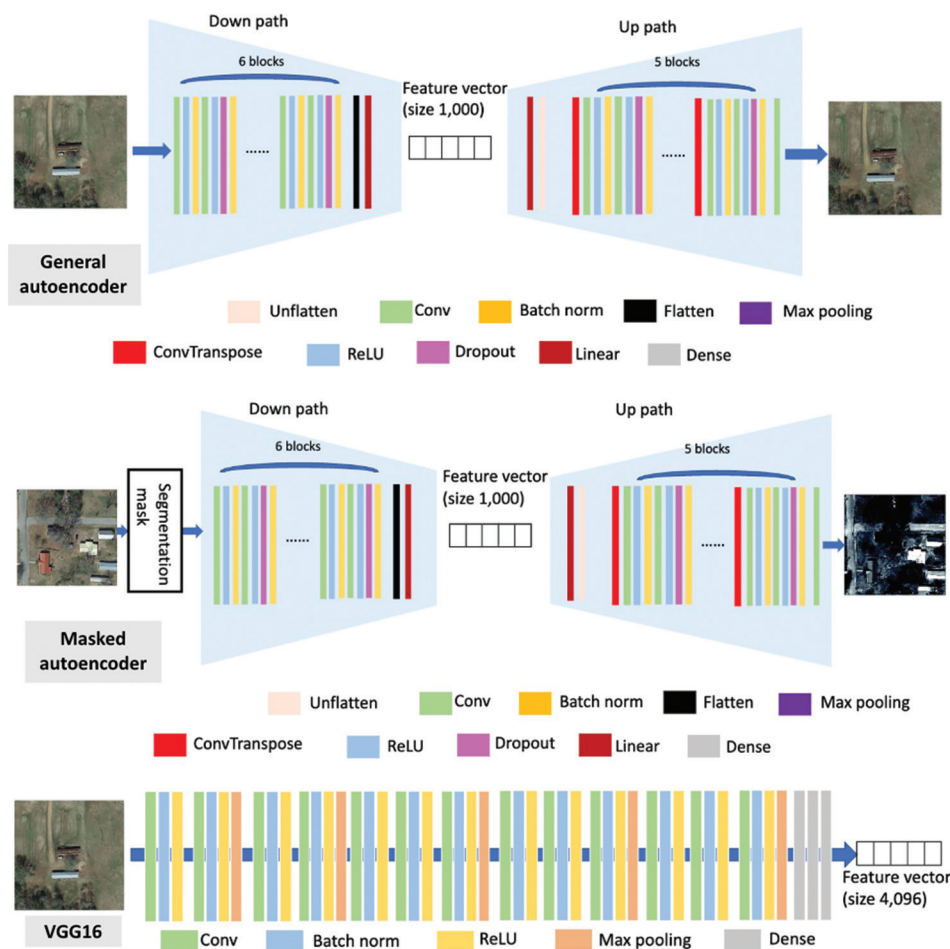


Figure 5. The architectures of three types of neural networks, UNET-AutoEncoder, Masked AutoEncoder, and VGG-16
Abbreviations: Conv: Convolutional; ReLu: Rectified linear unit.

rather than explicit categories, were clustered using the k-means algorithm. K-means initialized centroids with a fixed seed, assigned samples based on Euclidean distance, and iteratively updated centroid positions until convergence. We tested multiple cluster sizes (2, 3, 4, 5, and 6) and identified that four clusters provided the most distinct separation of housing image patterns.

2.3. Geographic information monitoring

Geographic information has attracted significant attention in spatial analysis,⁶ creating a growing demand for advanced techniques to analyze spatial data. In this study, we employed clustering, classification, and both local and global indicators of spatial association to monitor geographic patterns. With the increasing availability of large spatially referenced datasets and advances in data science, GISs enabled reliable monitoring and visualization of patterns across space and time.

2.3.1. Global indicator of spatial association

Global autocorrelation measures the overall spatial association within a dataset and is particularly important for analyzing large-scale patterns. We used Moran's I index to evaluate global autocorrelation and assess its statistical significance. The value of Moran's I ranged from -1 (strong negative spatial autocorrelation) to 0 (randomness) to +1 (strong positive spatial autocorrelation). Global autocorrelation also influenced local autocorrelation, except during outlier detection. A positive Moran's I indicated spatial similarity among neighboring areas, whereas a negative value indicated spatial dissimilarity. The spatial patterns revealed by the global autocorrelation index are shown in Section 3.

2.3.2. Local indicator of spatial association

Local indicators of spatial association (LISA)⁶ illustrate the distribution of each county's Moran's I index, providing

a quantitative measure of local spatial effects. LISA also identifies spatial outliers, allowing us to interpret locations as potential hotspots or coldspots. For 2018, the analysis distinguished five groups, each highlighted with a different color. The classification of counties into low or high opioid ER visit rates was based on whether their values fell below or above the mean ER visit rate. Both local and global spatial autocorrelation analyses of Alabama's opioid ER visit rates were conducted using the Python PySAL package.⁶

3. Results

Our results revealed discernible correlations between housing data and opioid overdose ER visit rates, highlighting their connection to broader public health outcomes. By integrating multiple SVI themes, satellite-derived features, and property values, policymakers can effectively identify underlying factors associated with opioid overdose fatalities and ER visit patterns. We used a DL approach to extract satellite-derived features from satellite imagery in rural Alabama counties. The full satellite imagery dataset used for feature extraction is approximately 275 GB. Visualization of model-derived features indicated that the DL models captured information closely aligned with the variation in SVI and ER visits, including driveways and sidewalks, overgrown vegetation, yard conditions, and the size and appearance of houses and roofs. These predictions provided insights into key SVI themes—socioeconomic status, household composition, and housing/transportation—offering a cost-efficient and potentially real-time strategy for estimating SVI values and monitoring ER visit rates. Overall, the findings suggest that DL-based analysis of satellite imagery can reveal fine-grained spatial patterns of social vulnerability and opioid-related health outcomes at the community level.

3.1. Social vulnerability monitoring

Table 1 presents the correlations between social vulnerability and opioid overdose ER visit rates across years. The results show that the socioeconomic status theme (T1) was consistently and moderately negatively

correlated with ER visit rates, with the strongest effect observed in 2020 ($r = -0.61$). This suggests that counties with greater socioeconomic vulnerability reported lower ER visit rates in that year. The household composition/disability theme (T2) also showed negative correlations across all years, though the effects were weaker than those of T1. The minority/language theme (T3) was generally weakly associated with ER visit rates, except in 2020, when a stronger negative correlation ($r = -0.58$) was observed. In contrast, the housing/transportation theme (T4) showed unstable associations, with small positive correlations in 2018 and 2021 but negative correlations in 2019 and 2020. Overall, these results indicate that the different dimensions of social vulnerability contribute unevenly to opioid overdose outcomes, and their relationships vary across time.

3.2. Feature monitoring

3.2.1. Property value

CoreLogic property value showed substantial variation across Alabama counties, reflecting differences in data collection practices and administrative records. Although relatively inexpensive, these data represented a valuable resource for monitoring when paired with scientific analysis. We found notable disparities in property values between counties, yet their influence on health-related outcomes remained uncertain. In several cases, significant differences in opioid overdose ER visit rates may partly reflect inconsistencies between property value records and satellite-derived measures. Even so, certain counties emerged as priority areas for targeted research and intervention.

We examined the potential of using property value as a proxy for estimating opioid overdose risk across geographic areas in the United States. In Alabama, property values may not directly capture overdose rates, but they provide a sound signal for monitoring county-level variation and temporal trends. **Table 2** reports correlations between ER visit rates and county-level property values, with the strongest correlation achieving 0.6. **Figure 6** illustrates the distribution of property values across four categories. For geographic monitoring, properties were grouped into four classes based on housing features and Zillow public data: (i) mobile properties (homes valued below USD 10,000), (ii) ordinary properties (USD 10,000–USD 200,000), (iii) community properties, such as churches and Walmart Neighborhood Stores (USD 200,000–USD 1 million), and (iv) government or large commercial property, including Walmart Supercenters (above USD 1 million). This classification integrated value thresholds with representative land-use categories. Notably, correlations

Table 1. Correlation of emergency room visits and social vulnerability

Social vulnerability	SVI	T1 ^a	T2 ^b	T3 ^c	T4 ^d
2018 ER visit rate	−0.01	−0.41	0.32	−0.03	0.15
2019 ER visit rate	−0.50	−0.37	−0.15	−0.05	−0.43
2020 ER visit rate	−0.61	−0.58	0.12	−0.58	−0.45
2021 ER visit rate	−0.21	−0.26	−0.40	−0.02	0.11

Notes: ^aSocioeconomic; ^bHousehold composition/disability; ^cMinority/language; ^dHousing/transportation.

Abbreviations: ER: Emergency room; SVI: Social vulnerability index.

between ER visit rates and property values were stronger in the Black Belt region than at the statewide level.

3.2.2. Physical and neighborhood features

With advances in the accuracy and validity of remote sensing data, progress in measuring and addressing social vulnerability has accelerated. Our satellite-based machine learning approach provided a scalable method for estimating wealth and health conditions in rural areas. The results suggest that such measures could help identify areas with potential health-related problems and assess recovery potential across counties. As shown in Table 3, ResNet-18 achieved significantly better classification performance compared to other models. Nonetheless, the model's accuracy could be further improved with a larger set of county-level images to strengthen testing and validation.

3.2.3. Latent visual feature

To identify temporal patterns in ER visit rate changes across counties, we applied housing satellite image feature clustering⁹ to analyze the relationship between health outcomes and spatio-temporal factors. Socioeconomic status, widely recognized as strongly correlated with community health, serves as an important reference in this analysis. Housing satellite image features were extracted using VGG16, autoencoders, masked autoencoders,⁹ and segmentation networks. The segmentation approach focused on calculating the percentage of housing area in each satellite image to examine associations between opioid overdose rates and proportions of housing features. Figure 7 illustrates satellite images and the visual processing by three types of neural networks. We found that UNET segmentation recognized housing features, and road features were highlighted using the Saliency Map with VGG16 feature extraction. All extracted features were clustered into four classes, as shown in Figure 8. After obtaining cluster counts, we used Pearson's correlation coefficient to measure the strength of association between

ER visit rates and cluster ratios. The strongest correlation was observed for features derived from the autoencoder model ($r = -0.53$), as shown in Table 4. Different models, AutoEncoder, Masked_AutoEncoder, and VGG16, were used to extract visual features from our collected satellite images. We then used a clustering algorithm to obtain four clusters of features extracted from satellite images. We also used segmentation to estimate the percentage of extracted housing features across the entire satellite dataset and analyzed the association between opioid overdose ER visit

Table 2. Correlation of emergency room visits and property value over time

Property value class/ER visit rate	2018	2019	2020	2021
C1_bb	0.01	-0.08	-0.20	-0.16
C2_bb	-0.34	0.31	0.20	0.28
C3_bb	0.04	-0.05	-0.01	-0.11
C4_bb	-0.12	0.24	0.60	0.00
C1	-0.09	0.14	-0.03	0.03
C2	-0.03	-0.10	-0.08	-0.07
C3	-0.01	-0.12	-0.15	-0.16
C4	-0.02	0.05	0.04	-0.12

Notes: C1: Property value<10,000 USD; C2: 10,000 USD<property value<200,000 USD; C3: 200,000<property value<1 million USD; C4: Property value>1 million USD. Abbreviation: ER: Emergency room.

Table 3. Accuracy of different satellite imagery-based artificial intelligence models

Artificial intelligence model	Accuracy	Val_accuracy
Convolutional neural network	0.6156	0.7234
ResNet-18	0.9671	0.9331
ResNet-50	0.6656	0.7708
External attention transformer	0.6189	0.6314

Abbreviation: Val_accuracy: Accuracy of another sample dataset.

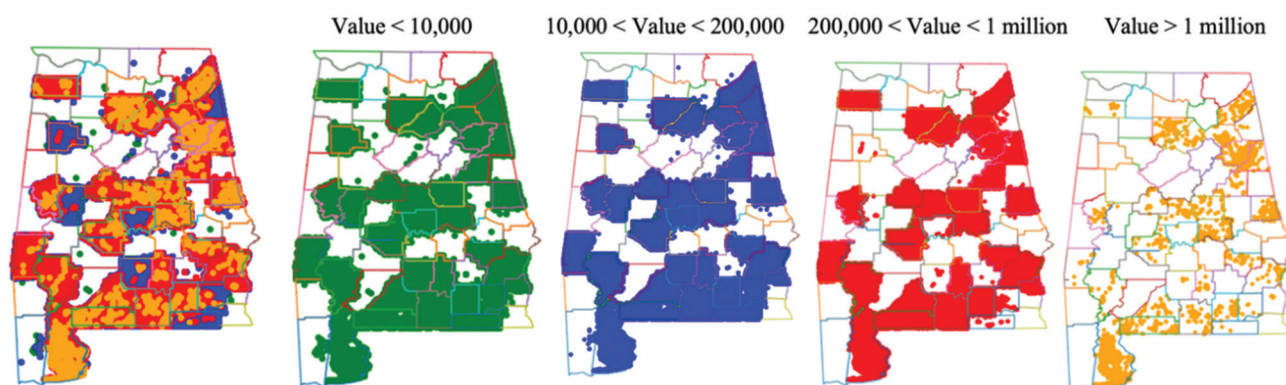


Figure 6. Alabama property value distribution (in USD)

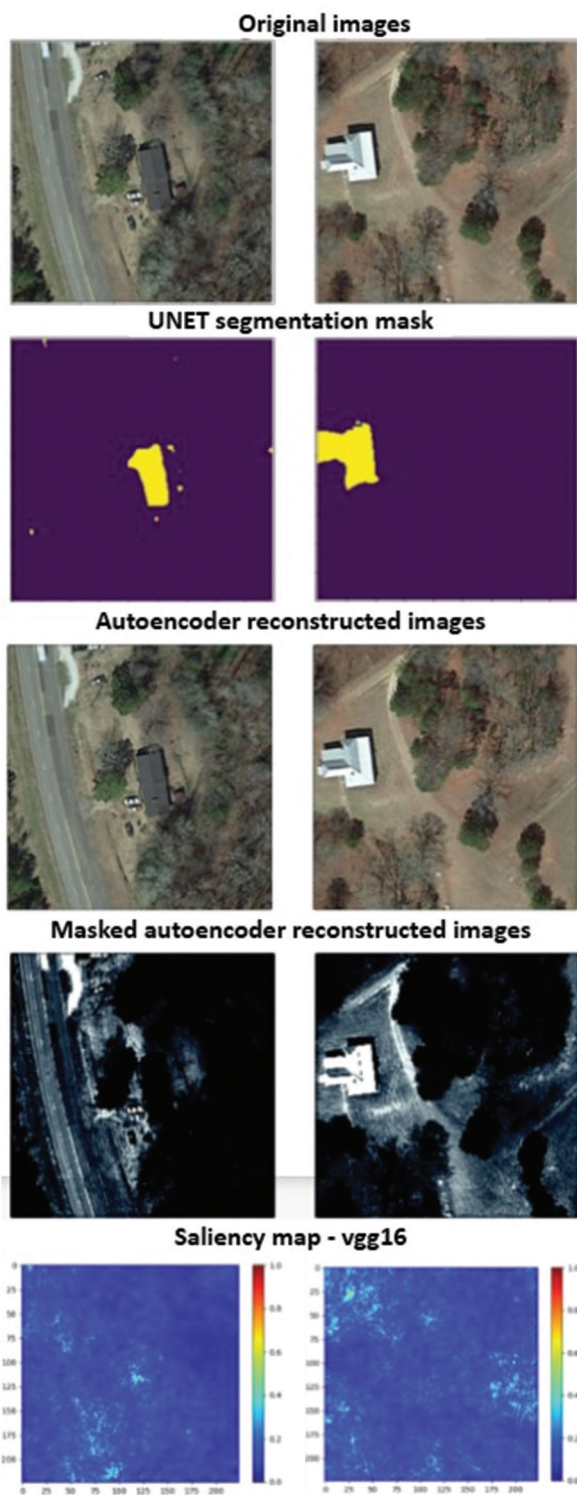


Figure 7. An illustration of satellite images and the visual processing by three types of neural networks

rates and the extracted housing feature percentage. Four different clusters' percentages were then correlated with

Table 4. Correlation of opioid overdose emergency room visits and clustering with four models over time

Models	AutoEncoder	Masked AutoEncoder	VGG16	Segment
2018_class_0	0.05	-0.01	-0.26	0.054
2018_class_1	-0.01	0.09	-0.01	-0.22
2018_class_2	0.01	0.15	0.09	0.14
2018_class_3	-0.03	-0.12	0.02	-0.25
2019_class_0	0.09	-0.48	0.16	0.17
2019_class_1	0.02	-0.10	-0.16	0.16
2019_class_2	-0.07	-0.44	-0.15	-0.19
2019_class_3	-0.05	0.3	0.23	0.12
2020_class_0	-0.53	0	0.13	0.43
2020_class_1	-0.28	-0.04	0.02	-0.18
2020_class_2	-0.18	-0.05	-0.17	-0.054
2020_class_3	0.52	0.05	0.13	-0.36
2021_class_0	-0.05	-0.14	0.09	-0.19
2021_class_1	0.24	0.02	-0.03	-0.25
2021_class_2	0	-0.28	0.02	0.26
2021_class_3	-0.06	0.1	-0.05	-0.2

Notes: Classes 0–3 represent four satellite image feature clusters obtained by applying K-means clustering to image embeddings extracted using AutoEncoder.

opioid overdose ER visit rates (2018–2021) with Pearson's correlation coefficient. We found several moderate to strong correlations between opioid overdose ER visit rates and extracted visual feature clusters. The illustrated visual patterns in the physical environment were associated with higher/lower opioid overdose ER visit rates, and there were predictive environmental indicators from satellite imagery, which encoded social vulnerability and health outcomes. To further explore the data, we applied PacMap for dimensionality reduction and visualized the four clusters (Figure 9). Representative examples, including the centroid satellite images and the four closest images to each centroid, are presented in Figure 10.

3.3. Geographic information monitoring

We used the open-source Python library for exploratory spatial data analysis. Spatial autocorrelation measures captured the degree of similarity between neighboring areas, providing both global and LISA for Alabama.

3.3.1. Global indicator of spatial association

Moran's I index results show limited similarity between counties and their neighbors in ER visit rates from 2018 to 2021. Positive values of Moran's I (2019 and 2021) indicated weak positive global autocorrelation, whereas negative values (2018 and 2020) indicated weak negative

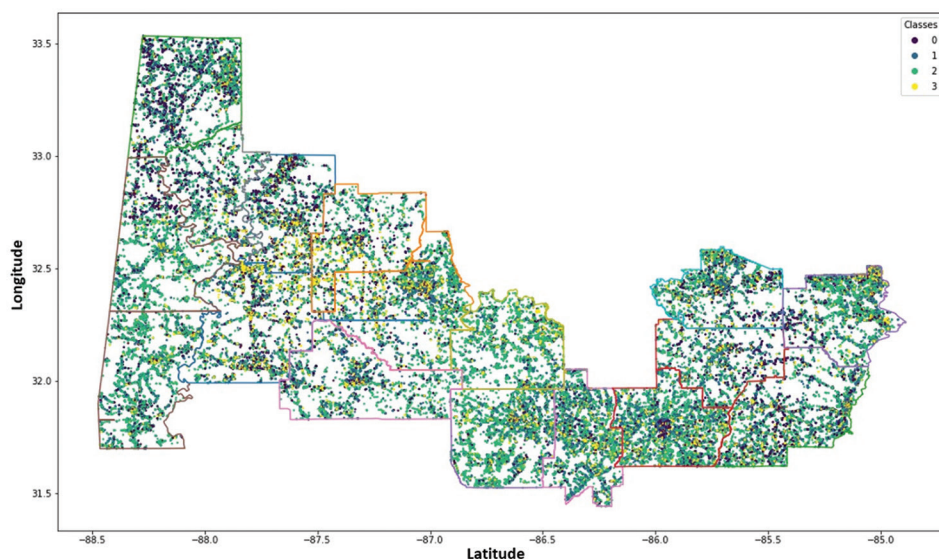


Figure 8. Black Belt county housing clustering

Notes: Classes 0–3 represent four satellite image feature clusters obtained by applying K-means clustering to image embeddings extracted using VGG16.

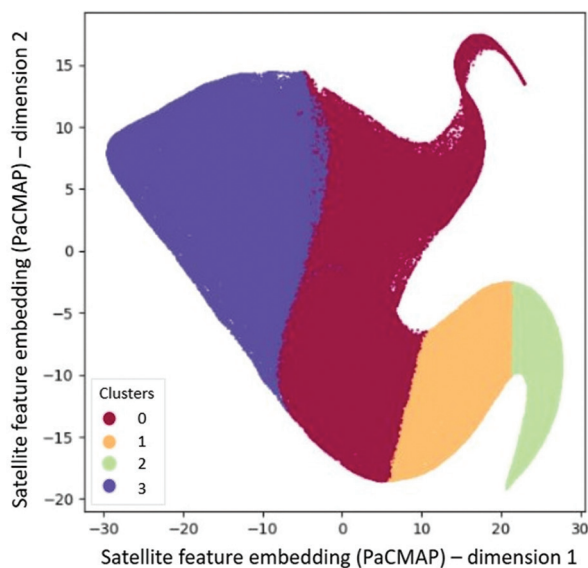


Figure 9. AutoEncoder clustering PaCMAP

Notes: Classes 0–3 represent four satellite image feature clusters obtained by applying K-means clustering to image embeddings extracted using AutoEncoder.

autocorrelation. The strongest association was observed in 2018 (Moran's $I = -0.024$). As shown in Table 5, the overall values across all 4 years were close to zero, suggesting uneven spatial patterns and large differences in ER visit rates between adjacent counties in Alabama.

3.3.2. Local indicator of spatial association

We applied LISA to precisely capture spatial variation, identifying specific areas that required targeted risk

Table 5. Global Moran's I index from 2018 to 2021

Year	Moran's I index
2018	-0.024
2019	0.018
2020	-0.004
2021	0.017

reduction. LISA provided two key advantages: it extended global measures to capture local variation and allowed for straightforward mapping of high- and low-risk areas. From the third map in Figure 11, the 2018 LISA analysis identified five distinct groups, represented in the map with different colors: red (high-high), pink (high-low), blue (low-low), light blue (low-high), and gray (outliers). Hotspots (red) and coldspots (blue) were prominent, while outliers (gray) were not significantly represented compared to their neighbors. LISA thus provided an effective tool for visualizing and interpreting local spatial patterns, with the sum of all LISA values proportional to the global Moran's I .⁶

Figure 11 shows that urban areas exhibited higher opioid-related death rates, while the LISA analysis of county-level ER visit rates highlighted several rural counties with significant spatial clustering of similar values. Given the global autocorrelation indicating a non-homogeneous spatial pattern, rural areas tended to exhibit consistently higher ER visit rates compared to urban areas. Identified hotspots and coldspots—counties with similarly high or low ER visit rates—warrant closer attention for targeted intervention.

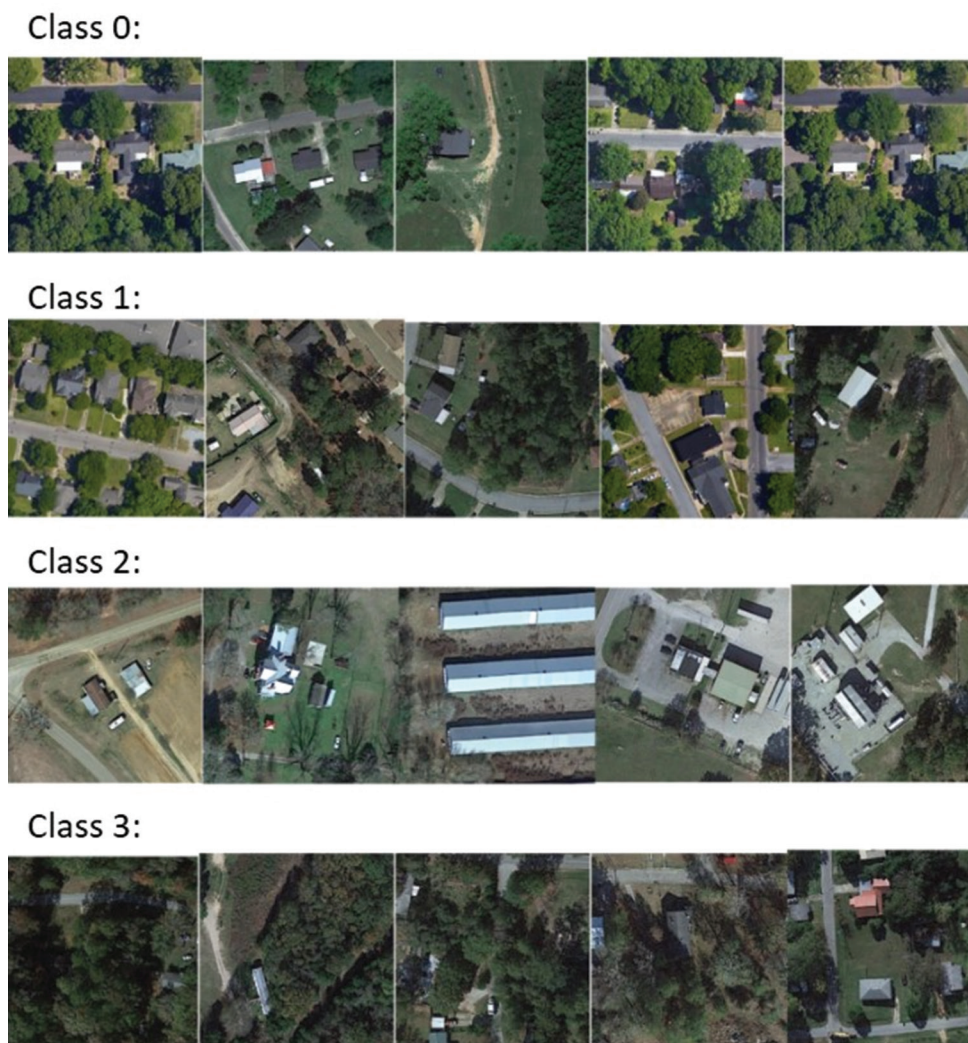


Figure 10. An example of housing data points close to the cluster centroids learned by the AutoEncoder

Notes: Classes 0–3 represent four satellite image feature clusters obtained by applying K-means clustering to image embeddings extracted using AutoEncoder.

Property values in both hotspot and coldspot counties changed over time. In 2018, most hotspot counties were concentrated in Class 0 and Class 1, while coldspot counties included properties in Class 0, Class 1, and Class 2.

4. Discussion

Our study provided a novel approach to integrate DL, statistical modeling, and geographic information to analyze spatio-temporal opioid overdose ER visit patterns in Alabama. There were three findings for this study: (i) ER visit rates varied significantly across Alabama counties, with urban counties (Jefferson, Mobile, and Madison) showing higher visit rates than numerous rural Black Belt counties (Sumter, Hale, Butler, and Crenshaw). Consistent with statewide trends, ER visit rates increased over time in both urban and rural

regions, with pronounced spatial clustering: northern Alabama contained identifiable overdose hotspots, whereas southern and Black Belt counties represented coldspots. (ii) The variation of hotspot areas for ER visits over time is critical to address in healthcare and opioid control. This change correlated significantly with socioeconomic factors, housing features extracted from satellite images, and property value. (iii) Urban areas in Alabama showed a higher death rate than rural areas in Alabama, and rural counties had similar ER visit rates to urban areas. (iv) Moreover, opioid overdose ER visit rates were negatively related to the value of property. These provided policymakers and community workers with insights into the underlying factors for adaptation and adjustment. (v) In addition, geographic information provided valuable data for exploring health-related crises.

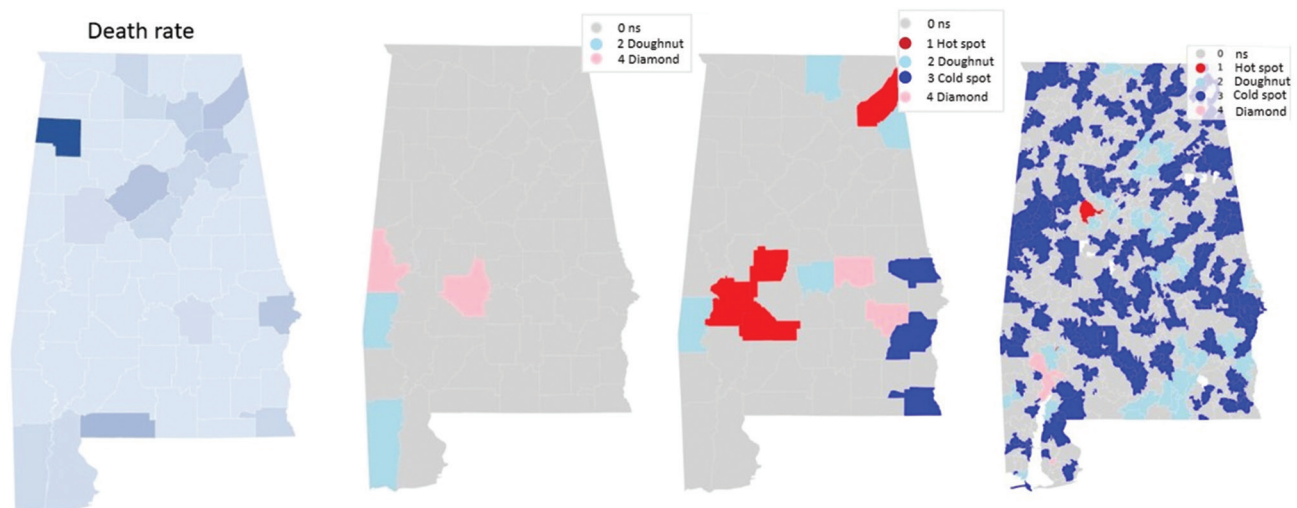


Figure 11. 2018 death rate, death rate LISA, county-level ER visit rates, and zip code-level ER visit rates

Notes: Hotspots, shown in red, represent counties with high opioid ER visit rates surrounded by neighboring counties with similarly high rates. Coldspots, shown in blue, indicate counties with low ER visit rates surrounded by other low-rate counties. Counties with high ER visit rates surrounded by low-rate neighbors are shown in pink (diamond), while those with low ER visit rates surrounded by high-rate neighbors are shown in light blue (doughnut). Potential outliers are displayed in gray, representing counties with no significant local autocorrelation.

Satellite-derived housing features revealed important patterns for analyzing opioid overdose behavior.

AI enabled these findings by providing scalable, automated extraction of built-environment features from satellite imagery. It captured environmental attributes, including housing density, land-use fragmentation, road connectivity, and indicators of structural disinvestment. By integrating these AI-derived features with temporal overdose data, the proposed framework provided a complete view of the physical and social conditions influencing opioid-related harm. The integration of DL with spatial statistics produced a multiscale spatio-temporal monitoring system, revealing fine-grained risk variations within counties that are often treated as homogeneous in public health research. These capabilities make AI particularly valuable for rural settings, where data and ground observations are limited. The correlations between AI-extracted satellite image features and social vulnerability also strengthened from 2018 to 2020, suggesting that built-environment deterioration and social stressors became increasingly aligned with overdose risk during this period. Moreover, AI helped identify emerging hotspots earlier than traditional indicators, demonstrating its potential as an early-warning tool for public health surveillance. These findings reinforce that overdose risk is shaped not only by socioeconomic status but also by environmental and infrastructural vulnerability.

From a smart-city and smart-community perspective, AI-enabled satellite monitoring offers a scalable and cost-effective approach to measuring environmental

conditions, detecting health-related risks, and supporting place-based decision-making. By adopting geospatial assessment principles similar to those used in livability and sustainability evaluations, rural regions can promote data-informed planning that strengthens both community resilience and public health outcomes. Ultimately, integrating environmental sustainability, livability principles, and AI-driven spatial analytics provides a pathway for policymakers and community leaders seeking equitable, context-sensitive strategies to mitigate opioid overdose risk and promote long-term community well-being.

As future studies, the time range and study areas can be broadened to design the spatio-temporal variation monitoring. Incorporating near-real-time or real-time satellite and healthcare data streams could further support smart-city-style early-warning systems for opioid overdose and other health crises. There are also privacy and ethical concerns to address when integrating satellite images into DL techniques and opioid information. The ethical concerns of satellite imagery usage are components that cannot be ignored in our research. Two major concerns in satellite data involve personal and private data. One concern is that although data from Google Earth and Google Maps are public, some countries remain frustrated by their use and are worried about how their data will be analyzed.⁴¹ Another concern is that some malicious groups may use this satellite imagery to advance their intentions in certain areas and among local populations.⁴¹ Satellite imagery at lower resolutions usually helps anonymity, and

blurring satellite imagery with a distance threshold⁴¹ will reduce privacy information leakage. There are numerous ethical implications when we use satellite imagery, including medium-resolution images that remain blurred when zoomed in. This distance threshold for blurring at lower spatial resolutions helps maintain anonymity. And the dataset we collected is from a public data source. For future model development and research progress, privacy concerns are always an important factor we should consider, even if the data usage is for humanitarian purposes.⁴¹

5. Conclusion

This article proposed a DL-based spatiotemporal framework to enable a comprehensive understanding of opioid overdose risk in rural Alabama. This work made several important contributions. First, it introduced an opioid overdose monitoring framework that fuses satellite imagery with social vulnerability and geographic data, enabling potentially cost-effective and transferable surveillance across other regions. Second, it advanced the application of satellite imagery in public health using AI techniques and improved the interpretability of DL approaches for monitoring opioid overdose-related ER visits. Third, the framework demonstrated practical utility by uncovering rural disparities and temporal trends in overdose ER visit rates in Alabama from 2018 to 2021, providing insights into spatial patterns that can inform targeted harm-reduction strategies.

Our results indicated that DL-derived features from satellite imagery captured meaningful environmental signals associated with social vulnerability and opioid overdose ER visit rates. Unsupervised clustering of satellite-based features provided interpretable representations of geographic conditions, offering insight into how relatively stable environmental attributes are associated with variations in opioid-related ER utilization over time.

For future work, we will extend this research by incorporating multi-temporal satellite imagery, expanding analyses to additional Alabama counties, and integrating complementary data sources such as United States Census data. Advances in multimodal and explainable AI may further enhance the interpretability and predictive capability of satellite-based public health monitoring.

In conclusion, this study demonstrated the integration of satellite imagery, social vulnerability, geographic data, and community-level data to support timely monitoring of opioid overdose risk. It provides a scalable and transferable foundation for rural health surveillance and offers a promising direction for leveraging AI-derived geospatial analytics to address opioid overdose and other health challenges in underserved communities.

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Jiaqi Gong, Xue Wu

Formal analysis: Xue Wu, Shengting Cao

Investigation: All authors

Methodology: All authors

Writing – original draft: Xue Wu

Writing – review & editing: All authors

Ethics approval and consent to participate

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Consent for publication

Not applicable.

Availability of data

Data are available upon request through xwu33@crimson.ua.edu.

References

1. Weiner SG, Ibrahimi SE, Hendricks MA, *et al.* Factors associated with opioid overdose after an initial opioid prescription. *JAMA Network Open*. 2022;5(1):e2145691. doi: 10.1001/jamanetworkopen.2021.45691
2. Florence C, Luo F, Rice K. The economic burden of opioid use disorder and fatal opioid overdose in the United States, 2017. *Drug Alcohol Depend*. 2020;218:108350. doi: 10.1016/j.drugalcdep.2020.108350
3. Ibragimov U, Young AM, Cooper HLF. Understanding rural risk environments for drug-related harms: Progress, challenges, and steps forward. *Int J Drug Policy*. 2020;85:102926. doi: 10.1016/j.drugpo.2020.102926
4. *Drug Overdose Deaths in the U.S. Top 100,000 Annually*. NCHS Pressroom. Available from: <https://www.cdc.gov/nchs/pressroom/releases/20211117.html> [Last accessed on 2023 Sep 08].
5. Alkhelaiwi M, Boulila W, Ahmad J, Koubaa A, Driss M. An efficient approach based on privacy-preserving deep learning for satellite image classification. *Remote Sens*. 2021;13(11):2221.

- doi: 10.3390/rs13112221
6. Acharya A, Izquierdo AM, Gonçalves SF, *et al.* Exploring county-level spatio-temporal patterns in opioid overdose related emergency department visits. *PLoS One*. 2022;17(12):e0269509.
doi: 10.1371/journal.pone.0269509
7. Crawford ND, Haardörfer R, Cooper H, *et al.* Characterizing the rural opioid use environment in Kentucky using Google Earth: Virtual audit. *J Med Internet Res*. 2019;21(10):e14923.
doi: 10.2196/14923
8. Jean N, Burke M, Xie M, Davis WM, Lobell DB, Ermon S. Combining satellite imagery and machine learning to predict poverty. *Science*. 2016;353(6301):790-794.
doi: 10.1126/science.aaf7894
9. Wu X, Cao S, Lee HY, Gong J. Let Every Voice Be Heard: Developing a Cost-Effective Community Sampling Frame in Rural Alabama to Combat COVID-19 (Poster). In: 2022 *IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)*. IEEE; 2022.
10. Tumpa PP, Islam MS. Lightweight parallel convolutional neural network with SVM classifier for satellite imagery classification. *IEEE Trans Artif Intell*. 2024;5(11):5676-5688.
doi: 10.1109/tai.2024.3423813
11. Yeh C, Perez A, Driscoll A, *et al.* Using publicly available satellite imagery and deep learning to understand economic well-being in Africa. *Nat Commun*. 2020;11(1):2583.
doi: 10.1038/s41467-020-16185-w
12. Li Z, Jia Y, Liu H, Hou J. *Learning from Sample Stability for Deep Clustering*. In: *Proceedings of the 42nd International Conference on Machine Learning*. 2025:34904-34919.
13. Jean N, Wang S, Samar A, Azzari G, Lobell D, Ermon S. Tile2Vec: Unsupervised representation learning for spatially distributed data. *arXiv*. Preprint posted online 2018.
doi: 10.48550/arXiv.1805.02855
14. Okaidat A, Melhem S, Alenezi H, Duwairi R. Using Convolutional Neural Networks on Satellite Images to Predict Poverty. In: *2021 12th International Conference on Information and Communication Systems (ICICS)*; 2021. p. 164-170.
doi: 10.1109/icics52457.2021.9464598
15. Shi J, Wu T, Qin AK, Lei Y, Jeon G. Self-guided autoencoders for unsupervised change detection in heterogeneous remote sensing images. *IEEE Trans Artif Intell*. 2024;5(6):2458-2471.
doi: 10.1109/tai.2024.3357667
16. Gong J, Wu X. Advancing Data Quality for Healthcare AI: Integrating Google Earth and Community Data in Opioid Crisis Mitigation. In: *Proceedings of the ACM/IEEE International Conference on Connected Health: Applications, Systems and Engineering Technologies*; 2025:329-334.
doi: 10.1145/3721201.3725436
17. Bianco S. Meta-XAI for explaining the explainer: Unveiling image features driving deep learning decisions. *IEEE Trans Artif Intell*. 2025;6(7):1859-1869.
doi: 10.1109/tai.2025.3529397
18. Wurm M, Stark T, Zhu XX, Weigand M, Taubenböck H. Semantic segmentation of slums in satellite images using transfer learning on fully convolutional neural networks. *ISPRS J Photogram Remote Sens*. 2019;150:59-69.
doi: 10.1016/j.isprsjprs.2019.02.006
19. Mak HWL. From COVID-19 Pandemic of Five Selected East Asian Cities to Assessment of Data Openness and Integration for Future City Development. *Joint Lab on Future Cities (JLFC) Report No. 2*. 2021. Available from: https://jlfc.hku.hk/wp-content/uploads/2025/10/JLFC-Report-2_Final.pdf [Last accessed on 2025 Nov 12].
20. Stokes EK, Pickens CM, Wilt G, Liu S, David F. County-level social vulnerability and nonfatal drug overdose emergency department visits and hospitalizations, January 2018-December 2020. *Drug Alcohol Depend*. 2023;247:109889.
doi: 10.1016/j.drugalcdep.2023.109889
21. Han S, Jeong Y, Lee K, In J. Environmental sustainability in health care: An empirical investigation of US hospitals. *Bus Strategy Environ*. 2024;33(6):6045-6065.
doi: 10.1002/bse.3790
22. Bedi C, Kansal A, Mukheibir P. A conceptual framework for the assessment of and the transition to liveable, sustainable and equitable cities. *Environ Sci Policy*. 2022;140:134-145.
doi: 10.1016/j.envsci.2022.11.018
23. Badanta B, Sierra AP, Fernández ST, *et al.* Advancing environmental sustainability in healthcare: Review on perspectives from health institutions. *Environments*. 2025;12(1):9.
doi: 10.3390/environments12010009
24. Chi Y, Mak H. From comparative and statistical assessments of liveability and health conditions of districts in hong kong towards future city development. *Sustainability*. 2021;13(16):8781.
doi: 10.3390/su13168781
25. Chichester K, Drawve G, Giménez-Santana A, *et al.* Pharmacies and features of the built environment associated with opioid overdose: A geospatial comparison of rural and urban regions in Alabama, USA. *Int J Drug Policy*. 2020;79:102736.
doi: 10.1016/j.drugpo.2020.102736
26. Lee HY, Wang K, Choi E, Gajos JM, Won CR. Opioid literacy

- among African Americans living in rural Alabama: Findings from a social determinants of health (SDH) framework. *J Drug Issues*. 2022;53(1):3-17.
doi: 10.1177/00220426221093610
27. Monnat SM, Peters DJ, Berg MT, Hochstetler A. Using census data to understand County-Level differences in overall drug mortality and opioid-related mortality by opioid type. *Am J Public Health*. 2019;109(8):1084-1091.
doi: 10.2105/ajph.2019.305136
28. Rigg KK, Monnat SM, Chavez MN. Opioid-related mortality in rural America: Geographic heterogeneity and intervention strategies. *Int J Drug Policy*. 2018;57:119-129.
doi: 10.1016/j.drugpo.2018.04.011
29. Mpofu E, Athanasou J, Craig A, Heasley S. Disability and vocational rehabilitation in rural and remote Australasia. In: *Disability and Vocational Rehabilitation in Rural Settings: Challenges to Service Delivery*. Berlin: Springer; 2017. p. 335-352.
doi: 10.1007/978-3-319-64786-9_18
30. Brodie ML. Understanding Data Science: An Emerging Discipline for Data Intensive Discovery. *DAMDID/RCDL*. 2015;238-245.
31. Jenkins RA, Hagan H. What is a rural opioid risk and policy environment? *Int J Drug Policy*. 2019;85:102606.
doi: 10.1016/j.drugpo.2019.11.014
32. Flanagan BE, Gregory EW, Hallisey EJ, Heitgerd JL, Lewis B. A social vulnerability Index for disaster management. *J Homeland Security Emerg Manag*. 2011;8(1):4-6.
doi: 10.2202/1547-7355.1792
33. *Client Challenge*. Available from: <https://www.scribd.com/document/786906346/svi-poster-07032014-final> [Last accessed on 2022 Jan 18].
34. Gaynor TS, Wilson ME. Social vulnerability and equity: the disproportionate impact of COVID-19. *Public Administ Rev*. 2020;80(5):832-838.
doi: 10.1111/puar.13264
35. Watmough GR, Marcinko CLJ, Sullivan C, et al. Socioecologically informed use of remote sensing data to predict rural household poverty. *Proc Natl Acad Sci U S A*. 2019;116(4):1213-1218.
doi: 10.1073/pnas.1812969116
36. *Find a satellite image photo of your home*. Available from: <https://www.satsig.net/maps/satellite-photo-image-viewer.htm> [Last accessed on 2022 Jan 10].
37. Pritt M, Chern G. Satellite image classification with deep learning. In: *2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*; 2017. p. 1-7.
doi: 10.1109/aipr.2017.8457969
38. Rivera AJ, Pérez-Godoy MD, Elizondo D, Deka L, Del Jesus MJ. Analysis of clustering methods for crop type mapping using satellite imagery. *Neurocomputing*. 2022;492:91-106.
doi: 10.1016/j.neucom.2022.04.002
39. Arabmakki E, Kantardzic M, Sethi TS. Ensemble Classifier for Imbalanced Streaming Data Using Partial Labeling. In: *2016 IEEE 17th International Conference on Information Reuse and Integration (IRI)*. IEEE; 2016:257-260.
doi: 10.1109/iri.2016.40
40. Simonyan K, Zisserman A. Very Deep Convolutional Networks for Large-Scale Image Recognition. *arXiv*. Preprint posted online 2014.
doi: 10.48550/arXiv.1409.1556
41. Briggs M. SatDash: An Interactive Dashboard for Assessing Land Damage in Nigeria and Mali. In: *Proceedings of the 4th ACM SIGCAS Conference on Computing and Sustainable Societies*; 2021:100-114
doi: 10.1145/3460112.3471949