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THE ROLE OF GEOSPATIAL ANALYTICS IN MITIGATING SOCIOECONOMIC DISPARITIES IN INFECTIOUS DISEASE OUTCOMES ACROSS THE UNITED STATES: A NARRATIVE REVIEW

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ABSTRACT
Despite ongoing advancements in prevention and treatment strategies, socioeconomic disparities in infectious diseases remain widespread across the United States and continue to disproportionately affect vulnerable communities. The COVID-19 pandemic brought attention to these issues of place-specific structural predisposition related to poverty, density of housing, inadequate medical care, and digital divides, which determine both disease exposure and mortality. The present narrative literature review aggregates knowledge from geospatial analytics (GA) solutions aimed at understanding and remediating these issues. Drawing from spatial epidemiology, geographic information systems (GIS), geospatial statistics techniques, ML-GIS hybrids, and GA optimization models, this review highlights how geospatial tools can be utilized to define infectious disease burden clustering in geographically stratified areas and to visualize disease burden gradients from rural to urban areas. Infectious disease burden data, coupled with advancements from remote sensing imagery and high-resolution ML models, have led to distinct increases in accuracy to accurately target infectious disease burden areas related to vaccination and rural preparedness planning; these areas can be utilized to prevent unacceptable infectious disease burden risks for anyone. Despite these advancements and ongoing research efforts, issues persist regarding data deserts, privacy issues related to geoprofiling techniques, heterogeneity in geospatial data models, and techniques related to infectious disease burden research study experiments in rural public health organizations across areas related to geospatial data storage requirements. A geospatial analytics solution inclusive and oriented towards equity can be transformative in enabling precision public health approaches directed towards disrupting infectious disease burden inequity rather than perpetuating issues of inequity.
KEYWORDS: *Geospatial Analytics, Infectious Disease Disparities, Social Determinants of Health*

1. INTRODUCTION
The distribution and outcomes of infectious diseases (IDs) are stratified based on socioeconomic status (SES), races, and ethnic groups in the United States (Hollis et al., 2021). The COVID-19 outbreak presented insurmountable proof of continuity of this challenge by clearly showing how existing social inequalities directly result in inequities associated with health outcomes (Marmot et al., 2020). Studies have shown that individuals belonging to racially/ethnically diverse populations and uninsured patients experienced higher risks of being confirmed COVID-19 positive, admitted to intensive care units, or died from infections (Cyrus et al., 2020), since these patients are largely congregated geographically within areas experiencing layered vulnerabilities (Kim & Bostwick, 2020). The concentration of negative health outcomes is inherently related to systemic socioeconomic realities (Baumer et al., 2020). In terms of COVID-19 death statistics, areas proportional to their percentage of African American residents demonstrated to be statistically associated with higher percentages of social vulnerability calculated by the Social Vulnerability Index (SVI) and death rates (Kim & Bostwick, 2020). Beyond the acute factors of infection, this pattern highlights a broader syndemic health burden where comorbidities, exacerbated by low socioeconomic status, high housing density, high crime rates, and poor access to healthy foods, intersect with unequal social determinants of health (Paul et al., 2021; Yancy, 2020). The COVID-19 pandemic served as a moment of crisis ethics to highlight pandemic prevention policies haunted by significant socioeconomic and racist injustices, and to realize effective measures against infectious diseases (Yancy, 2020).

Geospatial analysis techniques have played an integral role in identifying the dynamic and diverging trends of outcomes for infectious diseases between urban and rural areas, especially during the COVID-19 pandemic outbreak (J. A. Kang et al., 2025a; Wheeler et al., 2022). At the start of 2020, densely populated urban areas saw higher numbers of cases and death rates because of high transmission rates associated with high population density (Kang et al., 2024). Notably, however, the spatio-temporal landscape of vulnerabilities to infectious diseases saw a drastic change in 2021 (Kang et al., 2024). Later in the pandemic, from 2021 to 2022, rural regions have reported growing numbers of cases proportional to their population and steadily increasing death rates, besides having higher rates of case fatality ratios than urban areas (Ahrens et al., 2024; Kang et al., 2024). An examination of these geographic trends implies that while disparity between urban and initial cases was mainly because of exposure and population density, the chronic crisis among rural regions resulted from deep-rooted vulnerabilities of their structural foundations (Kang et al., 2024).

The crucial disparity metric for rural areas is not simply the number of infections but rather their treatment capabilities and response time for serious cases (Jiang et al., 2024). Research conducted to determine why such differences exist between urban and rural areas showed that at-risk populations within rural areas were adversely affected because of inadequate regional hospital resources for serious cases, especially referring to a lack of intensive care beds, ventilators, and staff (Galvani et al., 2022; Sharma et al., 2021). This structural failure is indicative of poor geospatial modeling coupled solely with transmission rates like population density, inherently failing to account for overall mortality risk to adequately address high-SVI rural areas within its modeling schema (Kang et al., 2024). The geographic context or place is now clearly recognized as being central to the mediation of health status because it serves as a proxy for SDOH (Kim & Bostwick, 2020; Paul et al., 2021). Geospatial analysis facilitates the shift from focusing on risk factors at one level to considering inequities based on place at another level, for example, ZIP code or census tract (Kim & Bostwick, 2020).

Spatial analysis reveals distinct drivers of diseases, depending on context (Paul et al., 2021). In urban settings, for example, higher death rates from COVID-19 were linked to population density and particular environmental risk factors, such as asthma rates (Hassaan et al., 2021). But for rural settings, death rates were most strongly linked to system-level determinants like poverty and unemployment (Paul et al., 2021). This context-specificity shows that localized modelling is required because general measures against health threats do not factor in these socioeconomic determinants for geographic areas (Mennis et al., 2022). The correlation between high chronic illness rates and high infectious illness rates mapped geographically shows clearly how big the syndemic is, because health is being influenced by local socioeconomic inequalities at the neighborhood level (Marmot et al., 2020; Paul et al., 2021).

The need to understand and analyze complex health-related risks distributed through geographical spaces is behind the quick adoption of Geospatial Analytics among contemporary epidemiology disciplines. Geospatial Analytics is composed of geographic information systems (GIS) analysis and new geospatial information from satellite images and Global Navigation Satellite Systems technology (Saran et al., 2020). GIS is widely regarded as the operational starting point for Spatial Data Infrastructure development to support effective disease surveillance and data sharing (Gyang et al., 2024; Samany et al., 2022). Additionally, spatial statistics can help to extract meaningful information about significant clusters and areas of high autocorrelation of social vulnerabilities (Goulding et al., 2021; Kim & Bostwick, 2020).

Big data analytics techniques have greatly transformed this area to cope with geospatial information flows now containing dynamic data inputs such as human mobility data, which have shown strong correlations to infectious disease transmission, especially respiratory infections such as COVID-19 or Influenza (Lessani et al., 2024). This information is combined with environmental attributes to create complex modeling for predictive analysis and digital contact tracing for infectious diseases (Lessani et al., 2024). To properly manage these high-velocity, high-volume, and multi-source data flows, the role of Artificial Intelligence (AI) and Machine Learning (ML) is integral to the paradigm. ML-GIS hybrids have shown the capability to discern intricate spatio-temporal relationships to thereby facilitate high-resolution risk projections beyond the capabilities of standard epidemiologic modeling techniques (Alkhanbouli et al., 2025). This synergy lends itself to having the right quantitative toolkit to examine geographic health inequities and social vulnerabilities to an uncharted level of geographical and temporal granularity (Alkhanbouli et al., 2025). Notwithstanding advances achieved by technology in the area of surveillance, such as the use of GA techniques, large socioeconomic inequities remain unaltered for infectious outcomes in the United States (Akinwumiju et al., 2022; Sheikhattari et al., 2023). Conventional planning conducted for addressing place-based socioeconomic inequities associated with infectious outcomes had remained ineffective in response to infectious events such as COVID-19 (Kohneh et al., 2023). There is still a large gap in the overall standardized integration of multi-source geospatial information, such as mobility data, satellite data, and environmental data, for just and effective modeling of various infectious diseases (Folkmann et al., 2024). While the application of big data has been substantial for COVID-19, it is of very limited use for any case of infectious diseases, and overall standardizations have not been developed nationwide for methodological use to determine the influence of geospatial information. The current literature suggests the overall need for geospatial modeling to focus on equality for all cases of infectious diseases. This narrative review explores the evolving role of geospatial analytics, encompassing GIS, spatial statistics, machine learning, and optimization models, in identifying, quantifying, and mitigating socioeconomic disparities in infectious disease outcomes across the United States.

2. LITERATURE REVIEW

2.1 *Spatial Epidemiology of Infectious Diseases and Socioeconomic Inequities*

Spatial epidemiology studies conducted within the US have consistently illustrated that infectious disease burdens do not have random geographical distributions but tend to occur among groups of individuals whose neighborhoods are economically poor and structurally disadvantaged, based on issues of racism or segregation (Zhang & Schwartz, 2020). While these geographical distributions have become highly apparent within the context of COVID-19 infections, similar distributions also tend to occur for respiratory infections like influenza or have been prevalent for many years for infections like tuberculosis, among others (Bilal et al., 2021). These patterns unfold across multiple spatial scales from census tracts and ZIP codes within large metropolitan areas to county- and state-level gradients underscoring that 'place' is a key determinant of infectious disease risk (Schnake-Mahl et al., 2025).

2.2 *Clustering of disease burden in poorer and socially vulnerable areas*

Initial studies conducted at the early stages of the COVID-19 outbreak, county-level data analysis utilizing the Social Vulnerability Index (SVI) developed by the CDC identified higher rates of infections and higher death rates for counties that were found to be more socially vulnerable (Islam et al., 2021). Nayak et al., demonstrated that SVI, especially measures of socioeconomic status and being from a minority group, was positively linked to initial COVID-19 incidence and death rates at the county level (Nayak et al., 2020). This study was further extended longitudinally by Neelon et al. (2021), where higher incidence and death rates were found to continue for counties belonging to the highest SVI quartile for 2020 than for less vulnerable counties after adjusting for urbanicity and state policies (Neelon et al., 2021). At a smaller geographic scale, it is observed from the analysis of census tracts and neighborhoods that Biggs et al. (2021) demonstrated using SVI for Louisiana at the tract level that neighborhoods with higher vulnerabilities experienced higher cumulative cases of COVID-19 than others within the same metropolitan area (Biggs et al., 2021). Lin et al., used spatial regression to identify concentrated longitudinal-impact counties where high COVID-19 mortality intersected with high concentrations of Black or Hispanic residents and multiple adverse social determinants, including income inequality, limited health care access, and housing problems (Lin et al., 2022a). Taken together, these studies indicate that socioeconomic inequalities are more than just background features, as they have geographic patterning and are very strongly associated with where the infectious disease burden is located. These associations are not specific to COVID-19. Tuberculosis (TB) incidence in California between 2012 and 2016 was highly associated with areas of lower levels of education, higher levels of crowd density, and higher percentages of poverty and was higher than threefold for areas of lowest socioeconomic status compared to areas of highest socioeconomic status (Bakhsh et al., 2023a). In terms of seasonal influenza cases, Adams et al., reported for adults hospitalized for lab-confirmed influenza cases located in high-SVI tracts where influenza infections tend to have higher prevalences of receiving invasive ventilation or extracorporeal membrane oxygenation support compared to those located in less-vulnerable tracts (Adams et al., 2024a). These multi-disease observations suggest a geographic unity of risk for socially and economically marginalized populations.

2.3 *ZIP-code and neighborhood-level disparities: urban spatial segregation*

Within major U.S. cities, ZIP code-level analysis has played a key role in uncovering local inequities of both exposure and testing access. Cordes and Castro analyzed ZIP code-level data for New York City to detect local clusters for high positivity rates and low testing access using Moran's Index and Spatial Scan statistics. Results showed areas of high Black and Hispanic population composition, high poverty levels, and high population overcrowding showed high positivity rates and low testing access at the initial stages of the outbreak, while areas of high affluence showed high testing and low positivity rates (Cordes & Castro, 2020). Comparable geospatial studies conducted in other states, for example, Wisconsin and Illinois have shown associations between geospatial areas where high concentrations of COVID-19 cases exist and local geodemographic profiles of those areas (Grubesic et al., 2022). Such intra-neighborhood inequities are indicative of interrelated social determinants of health: dense housing conducive to intra-household transmission, reliance on public transportation, aggregation among front-line or essential workers, and poor primary care and testing facility access. A study conducted by Lin et al., demonstrated that areas lacking easy access to the internet, having high rates of avoidable hospitalizations for preventable conditions, and experiencing socioeconomic deprivation were associated with higher COVID-19 death rates, especially in urban, suburban, and rural areas to different extents (Lin et al., 2022a). These structural features are place-based and geographically situated features mapped to racially segregated boundaries, confirming that inequities within infectious outcomes are generated by place-based infrastructures rather than behavioral outcomes alone.

2.4 *Rural under-reporting, data sparsity, and shifting urban-rural gradients*

Urban neighborhoods were early epicenters of COVID-19 in 2020 but gradually transitioned to rural areas of America. Studies conducted through systematic reviews and county-level analysis have demonstrated that by the Delta-Omicron wave, many rural counties reported higher rates of cases and mortalities than highly urban counties (Jones et al., 2023). According to Kang et al., there was strong evidence of initial higher rates of cases and hospitalizations among urban neighborhoods for 2020 but transitioned to higher rates among rural areas for 2021 and beyond because of inadequate immunizations and co-morbidities among residents (Kang et al., 2025b). This rural disadvantage was measured by Jones et al., to have resulted in as much as 51% higher rates of death from COVID-19 for the most rural counties than for urban counties during the Delta-Omicron wave of the pandemic, after adjusting for age composition and health status (Jones et al., 2023). These findings of differences are very likely representing only part of the actual geographical gradient. Rural health care infrastructure is also likely to have underdeveloped testing capabilities and reporting capacities for infections, as well as deaths (Grome et al., 2022; Pro et al., 2020). Some studies have already cited inconsistencies reported from some rural areas and reported lagged entry of data regarding higher percentages of death categories from these areas as factors capable of suppressing any actual geographical distribution of infectious diseases (Ackley et al., 2022; Stokes et al., 2021). Conversely, poor geographical accessibility to and from vital care facilities may also exist at least for some rural areas. For instance, analysis conducted by Kang et al., employing an advanced two-step Floating Catchment Area technique demonstrated high geographical inequality for hospital beds for COVID-19 patients within Illinois State in regions prone to poor accessibility for both rural and unserved areas (Kang et al., 2020).

2.5 *Spatial autocorrelation of social vulnerability and infectious disease outcomes*

A consistent methodological finding across this literature is the existence of strong autocorrelation for social vulnerabilities and cases of infectious diseases. Numerous studies have reported high values of Moran's Index for COVID-19 cases, deaths, and social vulnerability index scores, signifying that high-risk counties and geographic areas are prone to being grouped or located together rather than being randomly distributed (Ali et al., 2022). For instance, Islam et al. (2021) demonstrated significant associations between counties within the top SVI quartile and increased proportions of racial/ethnic minorities and higher COVID-19 incidence and death rates, which showed strong geographic concentrations of high risk in the Southern and Western regions (Islam et al., 2021). A Bayesian hierarchical negative binomial model accounting for the spatial dependence structure was adopted by Neelon et al., to demonstrate its importance for properly estimating the association between Social Vulnerability Index (SVI) and COVID-19 outcomes (Neelon et al., 2021). Results at the state level continue to emphasize the role of geographic patterning of vulnerability. Using measures of social vulnerability and social capital for all 50 states, Borges et al. (2025) reported a moderate correlation between social vulnerability and death rates from COVID-19 of approximately 0.52, with death rates higher in areas of higher social vulnerability scores (Borges et al., 2025). Such trends also exist among other infectious diseases. Cases of TB among Californians are grouped around low SES areas and demonstrate steady associations for both poverty and education levels (Bakhsh et al., 2023b). Positive outcomes for influenza and influenza vaccine coverage also have geographic gradients: County influenza vaccine rates decreased as SVI increased, as demonstrated by (Strully & Yang, 2022). Also, Adams et al., reported that patients from high SVI areas tend to have a higher need for advanced respiratory care once hospitalized for influenza infections (Adams et al., 2024b). These outcomes indicate that processes for concentration of COVID-19 burden through segregation, poverty, and lack of access to care also determine vulnerabilities to other pathogens.

2.6 *Social determinants, structural racism, and the spatialization of inequity*

Spatial epidemiology makes visible how structural racism and socioeconomic marginalization become literally mapped onto the landscape. This is because Lin et al., showed how county-level death rates from COVID-19 could be predicted by combined measures of social determinants of health, simultaneously defining lack of socioeconomic advantage, lack of mobility, and immigrant cohesion (Lin et al., 2022a). These findings align with broader evidence that racial and ethnic disparities in COVID-19 outcomes reflect structural inequities in employment, housing, transportation, and health care access, not biological susceptibility. Many analyses of mortality rates for COVID-19 between 2020-2023 demonstrate higher age-adjusted death rates for Non-Hispanic Blacks, Hispanics, American Indians/Alaska Natives, and Native Hawaiians/Pacific Islanders than Non-Hispanic Whites, with strong geographic concentration in the Southern and Western areas (Abidin et al., 2025). Spatial epidemiology offers the means to measure and visualize these structurally driven processes and link them to neighborhoods or counties that can benefit from targeted intervention strategies.

3. MACHINE LEARNING PLUS GEOSPATIAL ANALYTICS FOR HIGH-RESOLUTION RISK PREDICTION

The last few years have seen significant advances in remote sensing and observational technologies, computational capabilities, and ML methodologies, making possible a new generation of high-resolution spatial predictions of disease risk, those with spatial units of analysis sufficiently small, such as census tracts, zip codes, and grid cells, and with objectives of anticipation and surveillance, rather than explanation, of disease events, and focusing on mobility and environmental drivers of disease spread (Ajulo et al., 2025). From the perspective of inequities, hybrid ML-GIS systems hold promise in identifying high-risk geographical units before disease events, thereby enabling the formulation of targeted and equitable interventions. This topic will review the development of hybrid ML systems, their empirical performance superiority over traditional models of disease spread, and fair aspects of ML applications (Bobashev et al., 2020).

3.1 *ML-GIS Hybrid Models: Enhancing Predictive Surveillance Accuracy*

The need for advanced analysis methods arises from the recent massive growth of big data in public health. Machine Learning and AI are found to be crucially applicable to deal with complex spatial and temporal characteristics of big data regarding disease surveillance, prognosis, and diagnosis (Idahor et al., 2025). Such predictions and analyses are not feasible with traditional epidemiological analysis, which is based on census and survey data with long update cycles, making them inadequate for immediate responses and actions

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(Ekundayo, 2024). The application of predictive analytics to historic data, population dynamics, and biotic variables has been particularly successful in capturing diseases transmitted in multifactorial ways dynamics such as influenza and Zika (Cuadros et al., 2023). The automation of anomaly detection of AI increases data processing speed and enables integration of disparate data sets, thus improving forecasting capabilities for infectious disease outbreaks. Figure 1 shows a conceptual framework of epidemiology data analysis presented by (Forkuo et al., 2025) on how epidemiological data typically follows a structured workflow from initial collection to processing, analysis, and interpretation, which forms the foundation upon which ML-GIS hybrid models build.

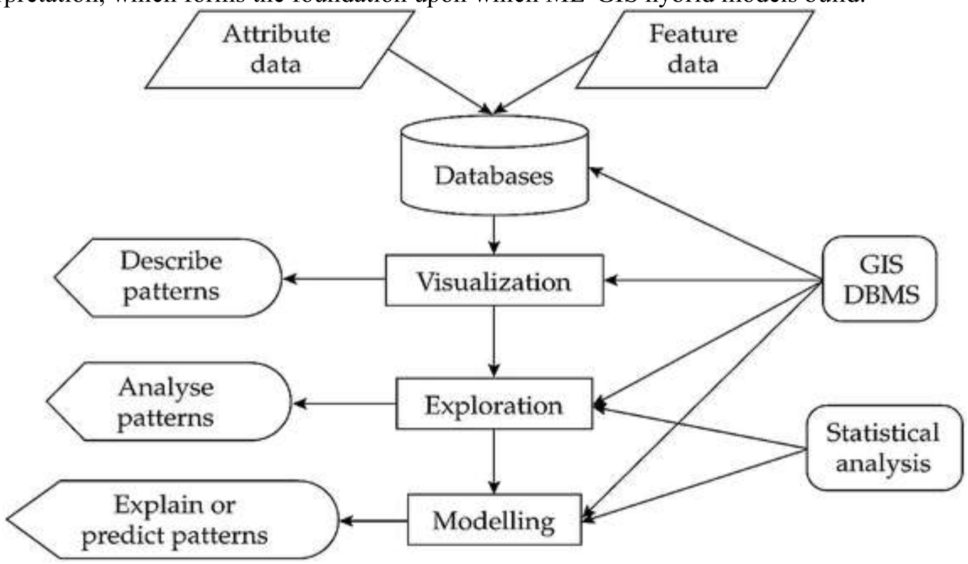

Figure 1: Conceptual Framework of Epidemiology Data Analysis (Forkuo et al., 2025).

ML-GIS hybrid models combine geographical context and spatial statistics into learning algorithms, thereby producing high-resolution and localized predictions. The various data streams flowing into ML-GIS models include satellite image layers, environmental sensing, and digital phenotyping feeds such as human mobility patterns (Ajulo et al., 2025). Research confirms a correlation between human mobility and contagious disease spread, specifically with respect to high-contagion diseases such as COVID-19 and Influenza, making human mobility a strong and dynamic spatial predictor variable (Lessani et al., 2024).

3.2 *Case Studies in Precision Public Health: Leveraging Big Data*

The integration of big data into geographical analysis has seen an extraordinary rise in COVID-19 management. But there is still an information gap concerning the application of holistic and multi-source data integration in managing different contagious diseases such as COVID-19 (Amusa et al., 2023). Geographical integration is paramount, as it offers assurance regarding predictive modeling focusing not only on medical risks but also on geographical disparities, providing success in creating tailored public health responses (Smith & Mennis, 2020).

Precision public health utilizes such risk maps to go from general population advice to proactive interventions. Though initial AI applications in prognostics involved small datasets (Jiang et al., 2024), the benefits of ML-GIS approaches regarding surveillance and outbreak prediction can no longer be ignored (Bekemeier et al., 2019a).

4. MAPPING HEALTHCARE DESERTS AND PLANNING TARGETED TESTING

Healthcare deserts in geospatial literature are defined as regions experiencing serious spatial inequities in healthcare facilities, personnel, and services (Ponce et al., 2025). To measure healthcare deserts in more quantitative terms, rather than qualitative approaches, new research indicates that healthcare deserts can be determined by geographical measures, such as the Gini coefficient, used to measure inequities in healthcare resource allocation per capita over administrative boundaries (Hsu et al., 2016).

Using models such as Location-Allocation algorithms, along with coverage modeling, analyses can be conducted to simulate present coverage and locate sectors with severe coverage deficits. Analysis often reveals a pronounced central concentration and peripheral scarcity phenomenon, characterized by high availability of services and infrastructure at the center, and serious deficits at the periphery and smaller, presumably lower-socioeconomic status, urban places (Hegland et al., 2022). Geospatial analytics, therefore, offers research justification for infrastructure allocation with spatial equity as its end-goal. Although literature remains limited, Geospatial analytics-related ideas have already been explored in various vaccination programs worldwide, including the Democratic Republic of Congo's georeferenced micro-plans that included spatial data such as settlements, facilities, and road networks, which were used to target remaining populations not recently vaccinated (Ngo-Bebe et al., 2025).

4.1 ***Optimizing Vaccine Distribution Networks***

Immunization rollouts can, however, widen inequities if allocation and rollout are solely based on size, without considering spatial vulnerability (Persad et al., 2020). Various research works have revealed that the usage of geospatial approaches and optimization methodologies can help make allocations and rollouts more equitable by incorporating parameters such as social vulnerability, mobility, and accessibility. Spatial Optimization to Improve COVID-19 Vaccine Allocation, for instance, used a spatial optimization algorithm in Missouri and found that if allocations were done based on mobility, distance traveled, and vulnerable populations, then nearly 8% of infections and healthcare expenses could be prevented, as opposed to equal allocation based solely on size (Scroggins et al., 2022). Similarly, A Data-Driven Spatially Specific Vaccine Allocation Framework for COVID-19 proposed an approach that uses a neural network classifier of risk and disease models and allocation optimization, and while specifically addressing the Chinese context, its applicability can be extracted and applied to U.S. scenarios (Hong et al., 2024). Furthermore, The Use of GIS Technology to optimize COVID-19 Vaccine Site Placement revealed that the application of GIS spatial analysis increased the effectiveness of COVID-19 vaccine site location (Krzysztofowicz & Osińska-Skotak, 2021).

Taken together, these findings suggest that, to achieve equity in vaccine allocation, there must be integration with geospatial considerations such as social vulnerability, travel time, and supply chain limitations to better target underserved populations and avoid exacerbating inequities through allocation methodology.

4.2 ***Enhancing Rural Disease Surveillance and Infrastructure Investment***

Rural and remote parts of the United States have long suffered from infrastructure issues that make it difficult to adequately monitor infectious diseases, such as closed hospitals, inadequacies in public health infrastructure, broadband connectivity gaps, and underreported surveillance data. Such deficits and others lead to surveillance blind spots, making it difficult to detect early warnings of emerging disease outbreaks (Chillag & Lee, 2020; Slonim et al., 2020). Geospatial analyses enable public health organizations to visualize concentrations of such gaps by layering broadband connectivity, electronic healthcare capability, and travel distances to healthcare facilities with maps of social vulnerability (Loccoh et al., 2022). Rural broadband inequities, thus, not only relate to digital justice, but disease surveillance capacity itself is heavily dependent upon broadband inequities in rural America (Cummins et al., 2025). Operationally, approaches to micro-planning incorporating satellite imagery, road networks, and settlements mapping have been effective in reaching remote settlements (Higgins et al., 2019). While implementations in the U.S. are few, transferability of its methodological application lies in its ability to demarcate catchment area boundaries, curvatures of services, and population groups, thus allowing those in rural, previously unmapped high-resolution analyses to be included in national maps outlining preparedness plans against contagious disease threats.

4.3 ***Implications, Best Practices, and Barriers to Implementation***

The application of geospatial technology in equitable interventions demands thoughtful design. The most effective designs, which emerged from recent literature, included leveraging multi-layered geographical variables, including social determinants of health, travel times, mobility trends, and service accessibility measures, which provide significant improvement in target accuracy performance (Lin et al., 2022b). Incorporating equity weights into spatial allocation models research modeling optimal COVID-19 vaccine allocation demonstrated that including equity weights, such as allocating vaccinations to high-SVI census tracts, led to better health outcomes than allocation proportional to population size (Scroggins et al., 2022). Despite this potential, there are evident barriers that impede its application. Gaps in data persist, and these are most pronounced in rural and poor communities, causing instability in spatial estimates (Crouch et al., 2025). Local health agencies may not possess geo-analytic skills, particularly if staff and funding are inadequately addressed by local health organizations (Bekemeier et al., 2019a). Furthermore, incongruous scales of analysis, such as analyzing by county when disparities are present at the census-tract level, may yield biased incongruous outcomes and set biased research priorities (Lin et al., 2022b). Failure to address such aspects may propagate disparities by favoring well-coded urban tracts over rural and high-risk ones, which may provide small amounts of, or even fail to provide, meaningful data.

5. ***Data Gaps in Low-Income and Rural Communities***

A fundamental barrier is varied data distributions over social and geographical lines. Rural, low-income, and racially minoritised communities frequently generate sparse or low-quality data, limiting the reliability of high-resolution spatial models (Bekemeier et al., 2019b). For instance, Svynarenko et al., employed gradient boosting machines and geographically weighted regression and found that 262 variables of social determinants of health in ~1,900 counties in the US had marked data distributions and spatial associations, particularly in rural regions and those with unexpanded Medicaid (Svynarenko et al., 2025). Likewise, digital health and broadband coverage mapping have identified systematic digital divides, which impact the efficiency of spatial and mobility approaches in surveillance in underserved regions (Cuadros, Moreno, Miller, et al., 2023). Such inadequacies created data deserts, which can be defined as regions with poor coverage in spatial models and may yield unreliable predictions, larger confidence intervals, and biased models towards better-funded urban regions.

5.1 *Privacy, Surveillance, and Ethical Considerations*
High-resolution geospatial tools often rely on mobility data, smartphone location traces, sensor networks, or fine-scale health-record linkages. This creates questions about individual geo-profiling, with vulnerable areas becoming not only selectively differentiated but also stigmatized. This is explored with reference to dependencies and trade-offs concerning high-resolution public health analysis and individual privacy, by (Harris & Delcher, 2024). Additionally, mapping vulnerable communities and then publicizing them can create inadvertent harm if, for example, a region is identified as a “hot spot”. The mosaic effect, by aggregating various data sources, may then further undermine privacy rights, particularly in vulnerable or small geographical populations (de Jong et al., 2019; Kamel Boulos et al., 2022). Ethical frameworks regarding geospatial approaches to public health ethics are rudimentary; as demonstrated by Iyer et al., there may be a need to make explicit normative judgments regarding efficiency, such as maximising cases prevented, and equity, such as not leaving behind those least served (Iyer et al., 2020). Hence, geospatial analytics must be paired with transparent governance, community engagement, fairness auditing, and guardrails against the misuse of location-based information.

In summary, challenges and risks that accompany the application of spatial analytics, in dealing with infectious disease inequity from issues of data deserts and algorithm bias, those privacy, infrastructure, and governance. Addressing these is essential if the potential of spatial analytics must be realized and if inequities with respect to infectious disease can be addressed, rather than exacerbated.

6. *Future Directions and Research Gaps*
Large gaps exist in terms of using geospatial analytics effectively to address inequalities in infectious disease outcomes in the United States. One of the most important areas is the development of real-time, multi-source geospatial surveillance to identify nascent patterns in marginalized areas. Broadband gaps, fragmented reporting systems, and capacity within public health agencies continue to cloud disease patterns in non-urban and disadvantaged areas. Future surveillance framework needs to combine syndromic surveillance, human mobility data, environmental factors sensed remotely, and community-produced data so that high-risk but poorly represented neighborhoods are no longer ‘blind spots’ within national risk estimation systems.

Another pressing requirement is attention to the integration of Social Determinants of Health variables in machine-learning GIS models. While indices, including Social Vulnerability Index, work well to uncover large-scale disadvantages, other factors, including housing quality, transport inaccessibility, environmental hazards, and connectivity, are insufficiently harnessed within machine-learning models despite their well-observed connections to adverse outcomes (Lin et al., 2022b). Future ML-GIS frameworks ought to utilize fairness-checked and transparent machine-learning strategies to ensure that predictions point to structural variables amenable to change for meeting disadvantaged needs rather than clinging to demographic patterns.

It is also important to bridge gaps in technology capabilities for jurisdictions that are either in, or include, lower-income areas, as well as rural areas. This is where many local county health agencies either do not have, or cannot afford, access to broadband or geospatial technologies, or qualified GIS experts to perform advanced spatial analyses on complex data problems using computation-intensive algorithms for advanced spatial analyses.

Furthermore, equity-oriented guidance for spatial models has emerged as an urgent requirement. Various studies have shown how biased algorithms, murky model development, or unconscious geographical discrimination in public-health AI can occur (Abràmoff et al., 2023). It has also become important to develop national standards for equity assessment, data governance, and geographical transparency for spatial models.

Finally, the United States lacks standardized protocols for its geographic public-health data. Inconsistent reporting, incompatible data formats, and variation in Social Determinant of Health data availability hinder cross-state comparisons and limit model scalability (Chandran & Roy, 2024) (Chandran et al., 2024). It is important to acknowledge that future studies must analyze whether data-driven interventions mapped out for geographic purposes, such as equity-adjusted vaccinations or testing, can diminish disparities in actual intervention contexts.

7. CONCLUSION
Geospatial analytics has emerged as an essential toolkit for analyzing and mitigating socioeconomic inequities that drive infectious disease patterns in the United States. By exposing how infectious disease burden is distributed in lower socioeconomic neighborhoods

and segregated communities, spatial analysis sheds light on patterns obscured by traditional disease surveillance efforts. However, new capabilities in geographic information system technologies, spatial statistics, machine learning, and mathematical modeling finally provide the means to create fine-scale risk mapping, model outbreak predictions for at-risk but functionally marginalized neighborhoods, and optimize location-specific interventions for vaccinations, mobile testing, or other interventions. Yet, significant data gaps in quality, availability, and analytics expertise, existing in large parts of neighborhoods most at risk, weaken the benefits derived from geographical analytics for infectious diseases. Moreover, broader ethical issues are raised for equitable geographic analytics in infectious public health.

With evolving threats to infectious diseases, the path forward requires integrating social determinants of health directly into spatial models, strengthening rural and underserved surveillance systems, and establishing equity-centered guidelines for geospatial public-health analytics. It will take investment in digital infrastructure, transparency, and interdisciplinary collaboration to ensure that the approaches to geographic analysis can do more than identify areas where inequities exist but also work to reduce inequities. Finally, geospatial analytics, when developed and governed with equity at their core offers a powerful means of advancing precision public health and ensuring that the benefits of early detection, targeted intervention, and informed planning reach all communities, not only those with the most resources.

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