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An Environmental Equity Assessment Using a Social Vulnerability Index during the SARS-CoV-2 Pandemic for Siting of Wastewater-Based Epidemiology Locations in the United States

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Abstract: Research has shown that there has consistently been a lack of equity and accessibility to SARS-CoV-2 testing in underserved and disadvantaged areas in the United States. This study examines the distribution of Wastewater-Based Epidemiology (WBE) testing placement across the United States (US), particularly within the context of underserved communities, and explores an environmental equity approach to address the impact of WBE on future pandemics. The methods combined the Centers for Disease Control Social Vulnerability Index (CDC-SVI) data set at the county level in a geospatial analysis utilizing ArcGIS and multilinear regression analysis as independent variables to investigate disparities in WBE coverage in the US. The findings show that disparities exist between counties in the use of WBE nationwide. The results show that WBE is distributed inequitably on national and state levels. Considering the nationwide adoption of WBE and funding availability through the CDC National Wastewater Surveillance System, these findings underscore the importance of equitable WBE coverage for effective COVID-19 monitoring. These findings offer data to support that a focus on expanding WBE coverage to underserved communities ensures a proactive and inclusive strategy against future pandemics.

Keywords: wastewater surveillance; CDC Social Vulnerability Index; geospatial analysis; GIS; COVID-19; early detection

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1. Introduction

Early in the COVID-19 pandemic, statistical methods were used to predict the beginning of an outbreak as a decision-making tool for stakeholders to direct resources in preparation for a surge in cases [1]. This approach was created using positive individual test results published by the World Health Organization (WHO) online dashboard, a method that was limited to short-term predictions and could not provide results over long periods of time [1]. There was a general acknowledgment in many publications that the number of positive cases and deaths attributed to SARS-CoV-2 was underreported [2]. A universal standard of population surveillance outside of the boundaries of a clinical lab would be crucial to quantifying the burden of the virus and mitigating community transmission [2]. Wastewater-Based Epidemiology (WBE) was identified as a possible solution to conduct pooled sampling and surveillance without a need for individual testing, but would need to be implemented on a national scale because incomplete gaps in geographical data would suffer from the same poor-quality data issues associated with only tracking clinically administered SARS-CoV-2 tests that have a positive test result [3].

This study addresses the problem of a lack of equity and access to consistent testing for SARS-CoV-2 for vulnerable populations in disadvantaged areas in the United States [4–6]. The vast majority of SARS-CoV-2 testing has been performed within populations consisting of voluntary subjects (e.g., those purposefully seeking test results in a clinical or hospital setting) or those required to submit to testing for various reasons such as work or educational requirements [6]. In contrast, the underserved minority population has generally been known to have adverse personal experiences with the healthcare system in combination with poor social determinants of health and a lack of need-based justice [7]. While the United States offered free at-home SARS-CoV-2 testing delivered via the United States Postal Service, the efforts of any Public Health Agency to identify SARS-CoV-2 outbreaks were missing a significant amount of formal testing data as at-home test results were not mandated to be reported by at-home private citizens to the CDC [8]. This also limited the ability of the United States (US) healthcare system to mount a timely response to stop the spread of SARS-CoV-2 once hospitalizations and deaths increased as they were limited to reactive strategic responses instead of preventative or proactive responses [9].

The proposed solution to this problem was to use a WBE approach to detect SARS-CoV-2 in small communities, rural areas, and compartmentalized populations such as prisons or nursing homes. Among other communicable diseases, WBE can predict SARS-CoV-2 outbreaks 4 to 10 days in advance both in symptomatic and asymptomatic populations [10]. This allowed a study of community infection dynamics and low-income areas that had inefficient disease monitoring systems.

To research the effects of socioeconomic and other community determining factors on equitable access to consistent SARS-CoV-2 testing, this study combined two spatial data sets: all known WBE sites and their proliferation across the US and census data related to social vulnerability taken from the 2020 CDC-SVI (CDC Social Vulnerability Index). To identify the locations of WBE sites across the US, raw data were compiled from the "COVIDPoops19" global dashboard of wastewater monitoring for SARS-CoV-2 as provided by the University of California Merced [5]. The data were used in both geospatial and statistical analyses to determine the possible effects of determinants of social vulnerability such as socioeconomic status, population density, lack of equitable income, minority status, and other variables on the placement of WBE sites and offer potential strategies regarding the selection of future sites.

The purpose of the study is to identify potential inequities in the placement of WBE site placement and to demonstrate how combining CDC-SVI data with WBE is a useful resource for various stakeholders that are involved with policies such as healthcare providers, local government, public health agencies, and emergency response services. This also includes an intent to explain the spatial perspective in reference to the sites utilizing WBE and the economic level surrounding it.

Wastewater-Based Epidemiology Proliferation, Costs, Utilization, Testing and Strategy

In the early stages of the SARS-CoV-2 pandemic, surveillance wastewater treatment facilities, various universities, public health departments, and private labs sought to develop a multidisciplinary approach to alternative methods for tracking the prevalence of the SARS-CoV-2 virus as close to in-real-time as possible [5]. To meet this need, these facilities adopted and refined a pre-existing viral detection process known as WBE which can quantify fragmented viral gene copies found in raw wastewater or sludge utilizing sampling methods applicable at any wastewater treatment facility or sewer system [5]. Defined as the use of wastewater to inform the health of a population within a contributing sewershed [11], WBE was repurposed initially to detect the potential re-emergence of poliovirus in the late 1990s [12]. WBE is a wastewater sampling, testing, and reporting process that can be utilized at wastewater treatment plants, systems, or water bodies which then send samples to clinical laboratories for the detection of targeted surveillance for pathogens or other substances as they occur in regional sewersheds [12].

WBE has numerous advantages over traditional testing methods including significantly diminished costs in comparison to PCR and serological testing methods [3], improved outbreak detection times, continuous population monitoring, and the ability to target local communities. The startup costs for a single WBE program are estimated to be between five to twenty thousand dollars (USD) per wastewater site depending on the sample testing method used by an existing lab [13]. With consistent population surveillance, WBE can predict SARS-CoV-2 outbreaks as well as other communicable diseases 4 to 10 days in advance, effectively serving as an early warning system [10]. The ability to continuously monitor populations could prevent a revisiting of the early Public Health policies that broadcasted stay-at-home orders [3]. While typical placement of WBE testing facilities occurs in large-scale regions, a WBE approach to detect SARS-CoV-2 can also be used in small communities, rural areas, and compartmentalized populations such as prisons or nursing homes [14]. This could in turn promote more accurate real-time specific outbreak data.

With funding provided by Loma Linda University (LLU) through the central administration, the LLU School of Public Health began collecting and refining WBE methods on campus near the end of 2020 [10]. These samples were collected and processed utilizing cost-effective methods within reasonable proximity to collection sites [10]. This group provided their WBE results to the University of California Merced (UCM); a UCM team of researchers processed this data and utilizing Geographic Information System (GIS) software (ArcGIS Pro 3.0.2), geolocated their WBE efforts as an addition to their worldwide dashboard entitled "COVIDPoops19", which is based on "combined standard literature review, direct submissions, and daily social media keyword searches" [5]. The GIS dashboard is a summary of global SARS-CoV-2 wastewater monitoring efforts data collected and quantified by UC Merced researchers and sourced from wastewater locations using WBE as shown in Figure 1 [5].

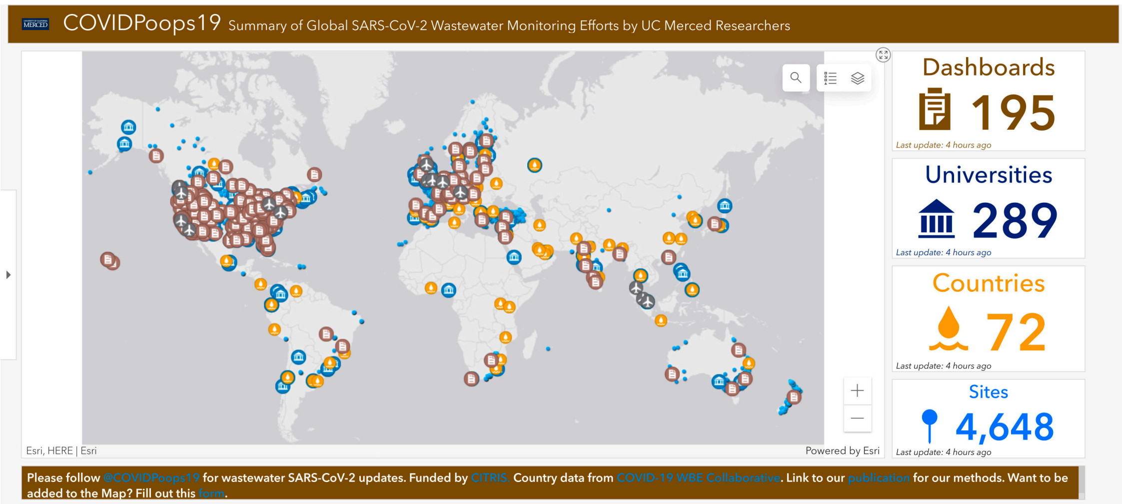

Figure 1. The COVIDPoops19 dashboard with geospatial rendering of global wastewater monitoring sites. Taken from Naughton et al., 2021 [5] with permission.

During the collaboration between LLU and UCM, researchers identified a gap in access to WBE in rural and low-income communities in California [4]. Based on the combined LLU/UCM research as well as the identified gap in WBE access, it was hypothesized that underserved areas may be last to benefit from WBE surveillance. Conversely, urban underserved areas are also locations where outbreaks spread faster than in other areas [15]. Also, some rural agricultural areas in California experienced rapid disease spread and proliferation during the first year of the pandemic, mostly due to poor infrastructure, the presence of essential workers with poor benefits, and poor healthcare infrastructure among underserved populations [4].

2. Materials and Methods

2.1. Hypotheses

Early geospatial analyses suggested that WBE testing locations are uniquely positioned in affluent communities and may not yet provide important surveillance data for disadvantaged areas [4,5]. After reviewing data on California's distribution of WBE [16], an additional focus on health equity motivated this research to further investigate the placement of WBE throughout the USA. The assessment evaluates the U.S. CDC's Social Vulnerability Index compared to a database of sites using WBE during the pandemic. The hypothesis assessed geospatial relationships between the 2020 CDC-SVI categories and their distribution on a map of WBE sites, testing if areas of lower SVI had less access to WBE.

The research sought to explore environmental equity within the scope of WBE to establish if WBE access was equitably distributed as visualized in Figure 2. The CDC-SVI (SVI) data set measures for the socioeconomic status of the United States population in terms of vulnerability through the quantification of various determinants such as the ability to earn an income, poverty status, level of employment, and educational attainment, and is indexed based on geographical location [17]. Data from the SVI data set, specifically the variable entitled "RPL_THEME1" (*RPL*), which indicates counties at highest risk for socioeconomic difficulty when compared to other counties by rank [18], were used in a geospatial analysis for the purposes of mapping and extraction of numeric county data to measure access to WBE in areas identified as being at the highest risk. In the early stages of research, Figure 2 below was generated utilizing GIS software (ArcGIS Pro 3.0.2) developed by the Environmental Systems Research Institute (ESRI) to combine WBE locations from the COVIDPoops19 dashboard with colorized county-level polygons whose color corresponds to the severity of social vulnerability based on the CDC-SVI ranking of each county. These combined data were then graphically rendered into a geovisualization view [19] utilizing ArcGIS to visually reflect ranked SVI *RPL* variable data [20].

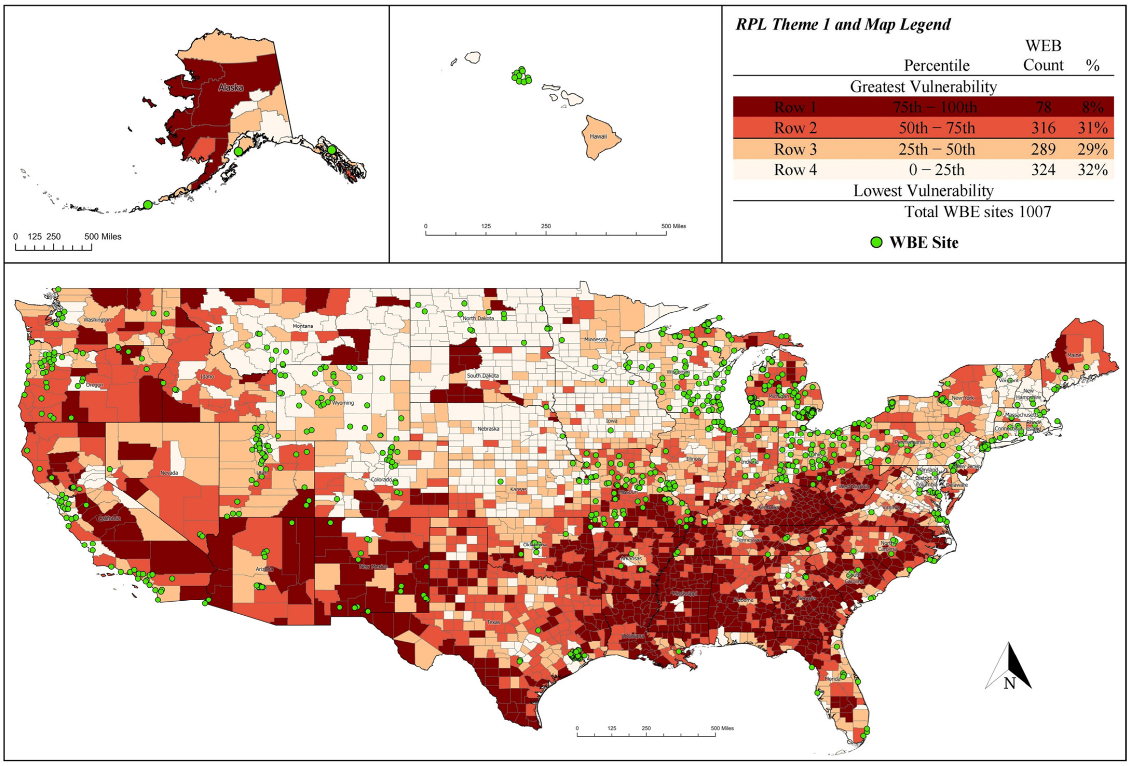

Figure 2. Geospatial heatmap generated utilizing GIS depicting united states WBE locations and counties of greatest SVI vulnerability. *Note:* Compiled from data taken from the "SVI Index" of the Centers for Disease Control and Prevention, 2022 (WBE site locations) [20] and Naughton et al., 2023 (heatmap) [5], with permission.

2.2. Measures and Data Collection

This study combined data from two separate sources: WBE site locations across the US provided by researchers who collected their data from 2020 to 2023 [5] and data from the 2020 CDC-SVI [17].

Data from the "COVIDPoops19" global dashboard of wastewater monitoring for SARS-CoV-2 were provided by the Environmental Systems Graduate Group at the University of California Merced [5] in November 2021. Data originally consisted of geospatial coordinates of each known WBE location in the US. These data were converted into city and state locations utilizing the United States NGS Coordinate Conversion and Transformation Tool (NCAT), made publicly available by the National Geodetic Survey, and utilizing Microsoft Excel 2019 pivot tables, were transformed into a quantifiable WBE site count by US county and state. These data were used as the dependent variable for the purposes of statistical analyses.

Data from the publicly available 2020 CDC-SVI database were used [17]. Variables included within the database that were extracted included those related to poverty and race as well as variables to link with the WBE dataset and are included in Table 1 [17]. These datasets correspond to the values as seen in Table 1 below and were designated as independent variables for the purposes of statistical analyses.

Table 1. The 2020 CDC-SVI dataset codes, shortened names, and corresponding descriptors.

Variable Name	Short Name	2020 Description
STATE	*state*	State name
COUNTY	*county*	County name
RPL_THEME1	*RPL*	Percentile ranking for Socioeconomic Status theme summary (overall summary ranking variable, state-to-state/county-to-county) [a]
E_TOTPOP	*population*	Population estimate, 2016–2020 ACS
E_POV150	*poverty*	Persons below 150% poverty estimate, 2016–2020 ACS
E_NOHSDP	*diploma*	Persons (age 25+) with no high school diploma estimate, 2016–2020 ACS
E_LIMENG	*English*	Persons (age 5+) who speak English "less than well" estimate, 2016–2020 ACS
E_MINRTY	*minority*	Minority (Hispanic or Latino (of any race); Black and African American, Not Hispanic or Latino; American Indian and Alaska Native, Not Hispanic or Latino; Asian, Not Hispanic or Latino; Native Hawaiian and Other Pacific Islander, Not Hispanic or Latino; Two or More Races, Not Hispanic or Latino; Other Races, Not Hispanic or Latino) estimate, 2016–2020 ACS
E_MUNIT	*density*	Housing in structures with 10 or more units estimate, 2016–2020 ACS
E_CROWD	*crowd*	At household level (occupied housing units), more people than rooms estimate, 2016–2020 ACS

Taken from the "CDC/ATSDR SVI 2020 documentation tables", CDC, 2022 [17]. [a] RPL_THEME1 is a calculated theme-specific percentile ranking of socioeconomic vulnerability status which ranks all counties across the US and was generated by the CDC [17].

The variables in Table 1 were selected from the wider set of variables found in the CDC SVI data set based on their identified potential to impact social equity and the subsequent effects on access to healthcare and testing; for instance, housing stability, access to education, perceived minority status and the associated potential for racial bias, poverty and income inequality, and high-density housing and overcrowding have been identified as sources of social inequity [21] and, as such, were considered to be of greatest significance when attempting to ascertain the potential impact of socioeconomic equity on WBE location placement as well as infectious disease monitoring.

2.3. Data Linkage and Analyses

2.3.1. Geospatial Analysis

Utilizing ArcGIS Pro 3.0.2 (ArcGIS), a national map was generated which placed polygonal borders based on known county lines within the U.S. This was then linked with SVI data from the variable *RPL*, which is a percentile ranking of socioeconomic status of all counties in the US and calculated by the CDC [17]; these data were chosen for the purposes of geospatial analysis because the ranked percentile nature presented an accurate, normalized single source of comparison between counties. These linked data were then used in ArcGIS to generate a colorized heatmap within the county polygons with percentile rank of social vulnerability severity per RPL data. ArcGIS was then used to combine the previously generated heatmap, which was subsequently overlaid with WBE geographical location data. The combined data were graphically rendered into a final geovisualization view in order to visually compare ranked *RPL* and WBE distribution data in the US at the county level and census tract.

2.3.2. Statistical Analysis

A univariate analysis was conducted to assess the distribution of WBE sites across counties and subsequent states across the US, along with a distribution of the SVI variables within counties and states. To assess the potential relationship between the independent SVI data and the number of WBE testing sites, a multilinear regression analysis was used. The number of WBE sites in a given county would be set as the dependent variable while the SVI variables were assessed as independent variables. It was determined that the formula for the multilinear regression is as follows:

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon \quad (1)$$

where $\hat{Y}$ is the number of WBE sites (dependent variable) and $\beta_1 X_1$ et al. are subsequent SVI predictor (independent) variables such as *population*, *English*, and *density*. The variable *RPL* is not included in the regression model because it is a statistically calculated comparative metric of the other variables used and not based upon raw data. The full formula can be written as follows:

$$\hat{Y} = \beta_0 + \textit{population}\ (X_1) + \textit{housing}\ (X_2) + \textit{population}\ (X_3) + \textit{diploma}\ (X_4) + \textit{English}\ (X_5) + \textit{minority}\ (X_6) + \textit{density}\ (X_7) + \textit{crowd}\ (X_8) + \varepsilon \quad (2)$$

In order to determine the proper order input sequencing of variables in the multilinear regression analysis, each independent variable was first analyzed in separate single linear regression models to determine the R-value of the relationship between each dependent variable and the individual SVI variables. After determining the individual R-values of the SVI variables, the SVI variables were ranked from greatest effect on the dependent variable to least and input into the multiple linear regression analysis. In conjunction with the multilinear regression analysis, various linear regression statistics including model fit, part and partial correlations, collinearity and residual casewise diagnostics for outliers outside two standard deviations from the mean, regression coefficient estimates, and 95% confidence interval regression coefficients with Bonferroni *p*-value correction were also calculated. To address the potential for collinearity among the variables, collinearity statistics including tolerance, VIF, and diagnostics were calculated, but no two variance proportion values showed significant collinearity. All statistical analyses and modeling were conducted utilizing SPSS 26.

3. Results

3.1. Geospatial Analysis

A total of 1,007 WBE site locations were identified for this study and shown on the map in Figure 2. Most of these sites were within the state of Michigan (n = 270), followed by Montana (n = 83) and Wisconsin (n = 64). The counties without or with less WBE are also those sites that have the highest vulnerability according to the U.S. CDC-SVI (Figure 2). Counties that ranked in the lowest two percentile quarters of vulnerability ($RPL \leq 0.499$) contained the majority of WBE testing sites (n = 613), while counties ranked in the greatest vulnerability range ($RPL \geq 0.750$) held only 8% (n = 78) of the total identified WBE testing sites. Of all counties in the United States, the counties of Kalawao, Hawaii, and Sargent, North Dakota (n_{RPL} = 0.000, 0.0003), ranked least vulnerable while Humphreys, Mississippi, and Macon, Georgia (n_{RPL} = 0.9994, 0.9997), ranked most vulnerable.

3.2. Regression Analysis

To analyze the hypotheses, a multiple linear regression analysis is shown in Table 2 below. The model showed statistical significance among all predictors (df = 7, $p < 0.001$, $R^2 = 0.306$). The analysis shows an overall $R^2 = 0.306$ indicating that 31% of the prediction in number of WBE site location is based upon the variables in the model.

Table 2. Multilinear regression model summary, wastewater based epidemiology site count by United States county (n = 1007).

R	R^2	Adj R^2	ΔR^2	S_e	ΔF	df1	df2	Sig. FΔ
0.553	0.306	0.304	0.306	0.857	178.628	7	2837	0.000

Note. Predictors = crowd, density, population, English, poverty, minority, diploma.

Of all predictor variables assessed in the multiple regression model as seen in Table 3, the variables *diploma* (β = −1.609, t = −8.393, $p < 0.001$) and *poverty* (β = 1.160, t = 9.879, $p < 0.001$) had the greatest significance and suggest that areas with lower amounts of high school diplomas or areas with more people above the federal poverty line tend to see less instances of WBE. This was followed by the variable *population* (β = 0.851, t = 10.484, $p < 0.001$), suggesting that there may be higher instances of WBE placement in areas in which there was an overall larger population density; the variable *minority* (β = −0.442, t = −3.543, $p < 0.001$), indicating that areas with fewer minorities have more access to WBE testing; and *English* (β = 0.402, t = 4.314, $p < 0.001$) suggesting that more WBE testing occurs in areas in which the population speaks English with greater ability. Although the variables *crowd* and *density* had the least impact on the model, they were both significant. The number of people in the household variable, *crowd*, suggests that areas with crowded housing may have lower WBE coverage (*crowd*, β = 0.248, t = 2.946, $p < 0.001$). Similarly, the variable d*ensity* suggests that areas with high-density housing had lower WBE coverage (*density*, β = −0.124, t = −3.193, $p < 0.001$).

Table 3. Multilinear regression analysis: coefficient table.

Predictor	B	SE B	B	*p*
population	2.53×10^{-6}	0.000	0.851	0.000
poverty	1.57×10^{-5}	0.000	1.160	0.000
diploma	-3.44×10^{-5}	0.000	−1.609	0.000
English	1.29×10^{-5}	0.000	0.402	0.000
minority	-2.07×10^{-6}	0.000	−0.442	0.000
density	-3.56×10^{-6}	0.000	−0.124	0.001
crowd	2.85×10^{-5}	0.000	0.248	0.004

Note. Dependent variable = WBECOUNT, upper/lower bound at 95% confidence level ($\alpha/n = 0.007$).

As can be seen in Table 3, the results of the statistical analysis support the hypotheses and suggest that there is evidence that socioeconomic vulnerability factors do play a role on average in the placement of WBE sites.

4. Discussion

The results from geospatial and statistical analyses included correlation of socioeconomic vulnerability factors on the known placement of WBE sites. According to the results of this study, in United States regions by county with statistically significant higher occurrences of lack of education, counties with greater concentrations of individuals who self-identify as minorities, or counties with higher rates of high-density housing per the CDC definition tend to experience lower placement rates of WBE sites. Conversely, an increase within a county of individuals over the 150% poverty threshold, counties with higher overall populations, populations in which individuals express a limited ability to speak English, and populations in which individuals live in conditions where the reported number of individuals living within a dwelling is at or above capacity, tend to see an increase in prevalence of WBE placement in their counties. This information suggests there are positively correlated and negatively correlated socioeconomic equity factors related to the placement of WBE sites across the nation. On one hand, WBE sites seem to be placed in higher concentrations based on higher population and lower poverty level; on the other, there appear to be fewer WBE sites in places with statistically lower education levels and higher populations of minorities. This information could be extrapolated to create both constructive, proactive and socioeconomically equitable WBE site placement strategies in the future as well as a method to develop SARS-CoV-2-related WBE Public Health campaigns targeted towards regions of greater need.

The theoretical approach combining geospatial analysis of WBE locations and CDC-SVI data sought to expose a gap in environmental equity which is defined as a fair dissemination of environmental risks with a special focus on accessing technologies [22]. The higher instances of lead poisoning among underserved minority communities [23] are an example of environmental inequity. This example mirrors the higher instances of poor health outcomes and higher SARS-CoV-2 death rates among similarly underserved communities [24]. Both studies share the same solution: a call for better surveillance in areas that are known to suffer from socioeconomic inequities and the public health issue at hand [23]. The results of this study could be used by decision-makers to bridge the gap between communities of high and low socioeconomic status to improve vaccine equity for regions with elevated positive SARS-CoV-2 rates from WBE [5]. Through equitable access to WBE as a tool to assess community infection dynamics, stakeholders and healthcare providers could focus resources on low-income areas with inefficient disease monitoring systems.

4.1. Limitations

Several limitations should be addressed regarding the research in the study. First, while reviewing and comparing data for homogeneity it was discovered that there were several areas that needed to be addressed by the researchers in which the dataset required modification to maintain robustness and minimize outliers. WBE location data were missing for the states of Alabama and Mississippi due to lack of availability of data to the researchers [4]. It was also discovered that due to confounding factors such as large-scale Federal funding caused by early participation over the course of the COVID-19 pandemic, the state of Michigan had a disproportionate number of WBE sites [25]. The prevalence of WBE collection sites in Michigan was disproportionate in comparison to other states [4]. As such, Alabama, Mississippi, and Michigan were excluded from both datasets and subsequent statistical analyses. Further, in relation to WBE data, previous researchers stated that it had been difficult to obtain data from government agencies and that this may have affected their location results [25]; however, the researchers noted that since initial data collection, government agency transparency and data availability has become more widespread [25]. Second, while the dataset *RPL* was a fit model for geospatial analysis, it was ascertained that it was not a fit dataset for statistical analysis and yielded inconsistent results. This was inferred to be due to the percentile ranking feature of the data in RPL. According to the supporting documentation provided by the CDC, the *RPL* dataset is a theme-specific percentile ranking derived by summing of the sums of categorical themes (categories of datasets) and then calculated to obtain percentile rankings in which counties are ranked against counties and states are ranked against states [17]. As provided, *RPL* was weighted, ranked data and, while suitable for the geospatial analysis portion of this study, for the purposes of statistical analysis and regression modeling it was determined that other non-ranked data available in the CDC SVI index would be significantly more suitable. Worth noting, the categories used for regression analysis were rather robust in nature and were composed of many thousands of data points taken from across the United States [17] Third, it was noted by the UC Merced researchers that data collection related to the COVIDPoops19 dashboard faced difficulties. They stated that their data collection method and model relied on only publicly available data as well as data self-reported by WBE agencies [5]. Furthermore, they acknowledge that some data points were missing from the data set which would impact further analyses [5] and more sites came online after this analysis. However, COVIDPoops19 had the most complete dataset of monitoring locations and regardless of the perceived errors, the statistical models utilized in the research project remain valid and statistically significant.

4.2. Areas for Further Research

Environmental justice demands equal access to a further-reaching WBE response to every level of SVI especially those that are known to be at the highest percentile of vulnerability [4], people who have a disproportionate need to be protected. The results of this analysis have the potential to be applied on a national level to allocate funds into continuing to protect public health through the standardization of WBE as well as WBE testing particularly in vulnerable areas. Locally, the results of this study should motivate policy makers to close the disparity gap in specific areas when examining new locations for WBE programs.

It is important to note that, as seen in Table 2 above, this research was only able to account for approximately 30% of the relationship between the variables. After using multiple datasets, 70% of the relationship is unexplained by the model. There is a need for further research to provide a clear framework in providing equitable WBE location placement strategies on a national level; clearly, the data exist in the form of publicly available CDC-SVI tables and simply need to be properly utilized to create a proactive, sustainable public health campaign in the future.

As noted in earlier references, many providers had to withhold their data from public use, a practice that sets up roadblocks in many areas including the demand for equitable access to WBE testing [5]. More research needs to be directed at data collection from wastewater sites and ease of access to WBE data. A public health campaign could be generated from this data and further research to emphasize the need to share data for the community's health. When comparing the overall cost of WBE against other testing methods, WBE has substantial cost benefits and stands to be used much more in the United States.

Understanding the broader landscape of environmental justice regarding WBE-based surveillance calls for further research. Unequal distribution of resources, including federal and local funding, regional economic disparities, and political influences, can heavily impact the placement of WBE surveillance and wastewater infrastructure [26]. These factors disproportionately burden marginalized communities. However, emerging trends in Europe and parts of the United States towards decentralized wastewater treatment offer promising avenues for expanding WBE surveillance reach and potentially mitigating exposure disparities [27]. To achieve this, further research is needed to explore: (1) the specific impacts of WBE placement on vulnerable communities, (2) the funding mechanisms and political dynamics shaping facility locations, and (3) the potential of decentralized approaches to address existing environmental inequities. By investigating these areas, it is possible to extend the reach of WBE surveillance systems that safeguard the health of all communities.

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