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ANALYSIS OF SPATIAL DISPARITY OF PHARMACIES IN VIRGINIA, U.S.A.

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Abstract: Many scholars have studied spatial equity issues of urban service delivery facilities in the past, including the pharmacy accessibility and pharmacy deserts. However, the analysis of spatial disparity of pharmacies in Virginia is lacking. To fill this research gap, we employed both statistical and geospatial methods to examine the pharmacy disparity and desert issues in Virginia. These methods include correlation, stepwise regression, average nearest neighbor analysis, network analysis, and geographically weighted regression (GWR). We examined five vulnerable populations and their accessibility to pharmacies. These subpopulations include racial minorities (defined as non-white population in this study), persons with income below the poverty level, older adults (age 65+), persons with disability, and households without vehicles. We found that spatial inequity of pharmacies exists in Virginia. At the statewide macro level, the spatial distribution of older adults is, largely, correlated with that of pharmacies. However, as revealed by GWR at local levels, the spatial pattern of pharmacy distribution is much more complicated, exhibiting both spatial inequity and social inequity (especially racial inequity, which is ubiquitous in Virginia). Pharmacies may be adequate for certain groups of people, but simultaneously inadequate for others.

Keywords:

spatial disparity;
accessibility;
geospatial analysis;
pharmacy;
Virginia

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Introduction

Spatial disparity or inequity of essential human services is a universal phenomenon that is intriguing to geographers, planners, spatial scholars, and others across the world. They probe into this issue from different perspectives, using different methods, and focusing on different subjects.

Pharmacy is an important urban service delivery outlet related to public health. Everyone needs to access pharmacies now and then to fill medical prescriptions, to consult with pharmacists about prescribed and over-the-counter drugs, or to receive vaccinations like the most recent COVID-19 vaccination, etc. Due to these reasons, in 2021 alone, 4.69 billion prescriptions were filled at pharmacies across the United States, and it is expected that this trend will continue unabated in the years to come (Statista 2022).

Virginia is a state with a diverse population of close to 9 million and a complex physical environment (mountains, plains, and coastal areas). The distribution of pharmacies is very uneven in Virginia resulting in pharmacy deserts (Abell et al. 2011) or the lack of accessibility to pharmacies. The adverse effects of pharmacy deserts and spatial inequity must be examined and understood in order to propose better public health solutions and policy recommendations on improving racial equity and promoting social justice in this area.

However, there is a scant attention paid to the spatial equity issues of pharmacies in Virginia. In particular, no rigorous statistical analysis has been performed at the macro- and micro-level on the relationship between the pharmacy locations and county-level socioeconomic characteristics. This paper intends to fill this research gap by conducting and reporting the results of correlational analysis, stepwise regression analysis, clustering analysis, such as the average nearest neighbour analysis, network analysis, and geographically weighted regression analysis.

Pharmacy Types and Distributions

There are different types of pharmacies. According to Barber et al. (2019), nearly 40% of pharmacies in the United States are chain pharmacies, like CVS, Walgreens, etc. Approximately 3% are within hospitals and clinics, 11% are inside mass retailers, such as Walmart and Costco, and 10% are in grocery stores. The rest of the pharmacies – about 35% – are independent, or privately owned, either established in a single store or a group of several stores. Different pharmacies have different characteristics in terms of their prescribed medications, licensed pharmacist profiles, business hours, and operation models, etc. In addition to their diverse characteristics, the pharmacy locations are also unevenly distributed in space across the United States. For example, in 2021, California had 6,081 pharmacies, the most of any state. California, Texas, New

York, Florida, and Pennsylvania round out the top five states for pharmacy locations. In contrast, Alaska had only 111 pharmacies in the same year (IQVIA 2022).

Spatial Equity

As an evolving concept, spatial equity is variously defined and the issue of how to measure spatial equity is somewhat nebulous and often difficult. According to Truelove (1993), spatial equity could be measured by such methods as: mapping areas beyond the range of service, service-to-needs ratio, correlation analysis, etc. Nevertheless, it is generally believed that the analysis of spatial equity is concerned with comparing the locational distribution of facilities or services to that of different socioeconomic groups, usually referring to different residents having an equal access to certain services (Talen and Anselin 1998, Tsou et al. 2005, Omer 2006, Chang and Liao 2011, Mashrur and Meher 2015).

With the elapse of time, the definition of spatial equity was expanded from spatial dimensions to include social dimensions, such as class, ethnic groups (Wen et al. 2013), income, and age (Comber et al. 2008). For example, Yao et al. (2014) revealed spatial and social inequities in HIV testing utilization in rural Mozambique. All these studies suggest that spatial equity research should take into account both spatial dimensions and social characteristics.

Just like African American and other minority ethnic groups in the U.S., the Roma communities in Romania and Central/East Europe have been discriminated and marginalized due to historical (e.g., slavery and nomadic history), cultural (e.g., self-exclusion), economic (e.g., low-income) and other reasons (large family, low education, social discrimination by the mainstream society). In terms of spatial inequity, in some Roma quarters, households must travel relatively long distances for shopping, since Roma rarely run retailing businesses in their communities (Creţan and Turnock 2008, Creţan et al. 2020). In Romania, evictions and invisibilisations create a heightened vulnerability to displaced people (Vesalon and Crețan 2012, Alexandrescu et al. 2021). Their destinations normally lack access or could have long distance access to basic social services, including pharmacies (Méreiné Berki et al. 2021). The miserable situation of Roma also exists in other European countries and regions, for example in Szeged, Hungary, where current efforts which strive for the desegregation and integration of urban Roma will be difficult to implement (Crețan et al. 2020, Méreiné Berki et al. 2021).

Accessibility

Accessibility is a measure used to evaluate whether spatial equity has been achieved (Talen and Anselin 1998). Among the different metrics measuring spatial equity, the accessibility-based approaches (e.g., the gravitational potential model, the two-step floating catchment method, etc.), and their corresponding improved models (Talen and

Anselin 1998, Shen and Sanchez 2005, Luo and Qi 2009, Chang and Liao 2011, Mao and Nekorchuk 2013, Hu et al. 2019, Zhao et al. 2020), are relatively popular methods for measuring spatial equity. For example, based on the gravity model, Chang and Liao (2011) developed a spatial equity index to explore the spatial equities of urban parks in Tainan City, Taiwan, from both accessibility and mobility perspectives. Talen and Anselin (1998) evaluated the spatial equity of public playgrounds by a gravity potential in the case of Tulsa, Oklahoma.

It is noted that, more recently, there was a trend to integrate travel modes into traditional accessibility models. For example, in order to explore the influence of travel modes on the spatial equity of healthcare facilities, Mao and Nekorchuk (2013) proposed a Two-Step Floating Catchment Area Method (2SFCAM), and they integrated bus and car travel modes into this model. Shen and Sanchez (2005) considered the impact of walking and driving on spatial equity, and they integrated those travel modes into a potential model. Hu et al. (2019) integrated the competition and attraction factors into the spatial equity model in the case of accessing the Changchun urban nursing homes in China. Zhao et al. (2020) used an Enhanced Two-Step Floating Catchment Area Method (E2SFCAM), based on a Gaussian function proposed by Luo and Qi (2009), to measure the accessibility to tertiary and secondary hospitals in Beijing.

Pharmacy Desert

It is noteworthy that the spatial equity research thus far has identified the existence of the so-called "pharmacy desert" phenomenon (modeling after the term "food desert") in the low-income and minority-dominant communities. The term "pharmacy desert" refers to certain communities with a lack of pharmacy access or pharmaceutically underserved areas (Bonner 2015, Pednekar and Peterson 2018). According to the research results of Di Novi et al. (2020), the difficulty in accessing drugs because of "pharmacy desert" negatively influences the patients' adherence to drug regimens, which requires that the prescription to be obtained promptly and the drug to be taken as prescribed in terms of dose, dosing interval, duration of treatment, and any additional special instructions.

Qato et al. (2014) found that "pharmacy deserts" are prevalent in Chicago's predominantly minority communities. In 2012, there were disproportionately more pharmacy deserts in Chicago's segregated black communities, as well as in low-income communities and federally designated Medically Underserved Areas.

Based on their visits to 408 pharmacies located in 168 socio-economically diverse communities, Amstislavski et al. (2012) found that geographic access to a neighborhood pharmacy, the type of pharmacy, and availability of commonly prescribed medications varies significantly across communities. Pharmacies in poor communities had significantly higher odds of medications being out of stock.

In the paper of Wisseh et al. (2021), pharmacy deserts were identified as census tracts where the nearest community pharmacy was 1 mile or more away from a census tract's centroid. K-means clustering was applied to group pharmacy deserts based on their composition of social determinants of health indicators (SDOH), such as poverty level, household ownership, vehicle ownership, education attainment, health insurance status, and language spoken at home.

In general, the people living in pharmacy deserted areas receive lower quality pharmaceutical services and they have less access to such services, creating disparities in pharmaceutical care (Oliveira et al. 2021). For example, research shows that an overall low quality and a limited availability of care contributes to lower medication adherence rates (Akinbosoye et al. 2016). Furthermore, a person in an underserved community may not receive the same in-depth explanation of their drug treatment plan as a person in a well-served community, increasing the likelihood of premature termination of drug treatment (Davis et al. 2017). Furthermore, people living in the low-income neighbourhoods may pay higher prices for their prescription medication than people in the middle- and high-income neighbourhoods, contributing to even further lower medication adherence rates and social equity issues (Qato et al. 2017).

The research and studies reviewed above have provided us with the framework to identify the needed research about spatial disparity of pharmacies in Virginia. In specific, we have identified the following research gaps which we intend to focus our study on and gain further insights:

1. First, the studies related to spatial disparity of pharmacies are lacking for Virginia;
2. Second, the geospatial analysis is insufficient. So far, the Geographic Information System (GIS) has primarily been used as a mapping tool in most of the prior studies. No extensive statistical analysis has been performed to examine the relationship between pharmacy locations and socioeconomic characteristics;
3. Third, a more fine-grained micro level analysis of pharmacy locational variation across space was also inadequate in Virginia.

Given these research gaps, we take a more comprehensive approach to investigate the relationship between vulnerable populations and their accessibility to pharmacies in Virginia. While there are various vulnerable populations under different contexts in the literature (Waisel 2013, Shi and Stevens 2021), we focused on the subpopulations who we believe are likely to experience inadequate access to pharmacies. They include racial minorities (defined as non-white population in this study), persons with income below the poverty level, older adults, persons with disability, and households without vehicles.

Methodology

Our study utilized SPSS to carry out traditional statistical analyses as well as ArcGIS to perform various geospatial analyses. We started with a correlation analysis to examine the relationships between variables followed by a stepwise regression to identify the key independent variables that would be retained in the regression model. We then carried out a series of geospatial analyses beginning with the Average Nearest Neighbour analysis to study the spatial distribution pattern of pharmacies. We also conducted a network analysis to measure the access to pharmacies by travel time based on the network distance. Lastly, we used the Geographically Weighted Regression (GWR) to examine accessibility to pharmacies of different vulnerable populations.

Data Sources

Pharmacy Locations

We downloaded the pharmacy locations in Virginia from the SafeGraph Company. According to SafeGraph, there were 1,668 pharmacies in Virginia in 2021. The dataset includes the latitude and longitude coordinates of all pharmacy locations. The pharmacy locations in Virginia are geocoded as shown in Figure 1.

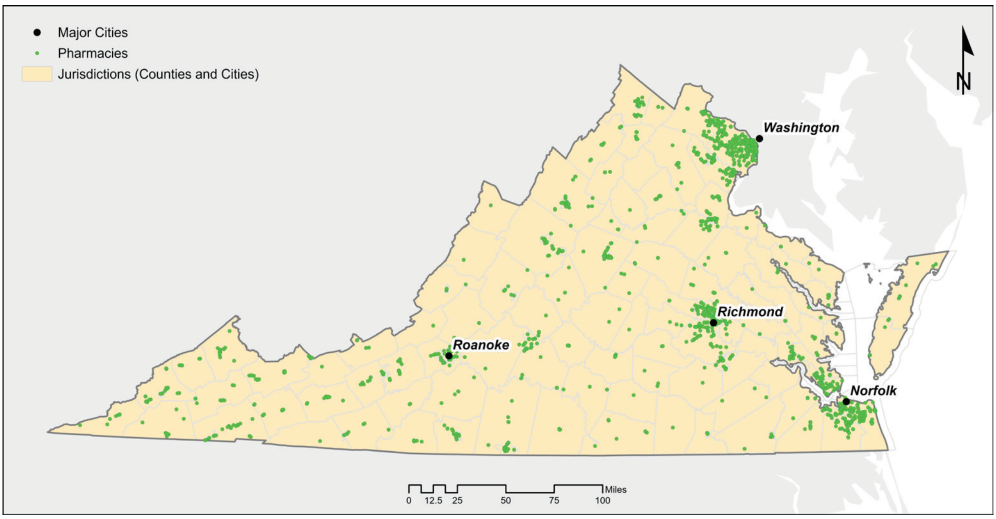


Figure 1. Pharmacies in Virginia

Vulnerable Populations

We obtained the data of vulnerable populations from the 2019 American Community Survey (ACS) – 5-Year Estimates Detailed Tables. In specific, the following tables were obtained to extract the respective vulnerable populations:

- B02001 Race: racial minorities (defined as non-white population in this study);
- B17001 Poverty Status by Sex by Age: persons with income below the poverty level;
- B01001 Sex by Age: older adults;
- B18101 Sex by Age by Disability Status: persons with disability; and,
- B08201 Household Size by Vehicles Available: households without vehicles.

Geographic Unit of Analysis

The above vulnerable populations data were collected at the local jurisdictions level (a total of 133 counties and cities) and then joined to the jurisdictional geographic features. Because the ACS data were estimated from samples, larger sample sizes would yield better estimated results. In contrast, many census tracts have no pharmacies located in them even though there may be pharmacies in their neighbouring tracts, which would lead to erroneous and invalid results. These are the two reasons why we decided to use local jurisdictions as geographic units of analysis in this study.

Network

The data source of the street network originally came from the Virginia Geographic Information Network (VGIN), which is the GIS Clearinghouse with a repository of geospatial data produced and used by state agencies in Virginia.

Pharmacy Visit

To gauge the realized access to pharmacies, the number of pharmacy visits during the period of June 27 (2022) to July 4 (2022) was downloaded from the SafeGraph website. In that period, there were a total of 54,133 pharmacy visits in Virginia.

Description and Normalization of Variables

Given that there were 1,668 pharmacies distributed among 133 local jurisdictions in Virginia, the number of pharmacies in each jurisdiction was determined and normalized by its area in square miles. It serves as the dependent variable of our study, i.e., number of pharmacies per square mile (denoted as Pharmacy_D hereafter). When it comes to the independent variables, we also normalized five vulnerable populations (the descriptive statistics are shown in Table 1) by their associated jurisdiction area on a per square mile basis. They are denoted as:

- Non_White_D – number of non-white persons (per square mile)
- Below_Poverty_D – number of persons with income below the poverty level (per square mile)
- A65_or_Older_D – number of persons aged 65 or older (per square mile)
- Disability_Pop_D – number of persons with disability (per square mile)
- No_Vehicle_HH_D – number of households without vehicles (per square mile)

Table 1. Descriptive statistics of variables (N = 133)

	Minimum	Maximum	Mean	Std. Dev.	Skewness	Kurtosis
Pharmacy_D	0.000	3.910	0.239	0.517	4.020	21.293
Non_White_D	0.040	3,881.080	272.486	572.467	3.427	14.728
Below_Poverty_D	0.530	1,049.000	107.392	198.669	2.654	7.875
A65_or_Older_D	1.800	1,156.980	112.859	192.413	2.823	9.726
Disability_Pop_D	1.020	714.010	90.248	142.742	2.068	4.216
No_Vehicle_HH_D	0.080	539.430	28.015	69.429	4.988	30.374

Results

Correlation Analysis

We examined the correlation coefficients between the dependent and independent variables to gain an understanding of their relationships. All independent variables exhibit a positive relationship with the dependent variable Pharmacy_D (Table 2). However, the strengths of the relationship vary among the independent variables. In specific, A65_or_Older_D has the strongest relationship (r=.865) followed by Disability_Pop_D (r=.737), No_Vehicle_HH_D (r=.662), Non_White_D (r=.654), then Below_Poverty_D (r=.633).

Table 2. Correlation coefficients between variables (N = 133)

Variables	*Pharmacy_D*	*Non _White_D*	*Below _Poverty_D*	*A65_or _Older_D*	*Disability _Pop_D*
Non_White_D	.654**				
Below_Poverty_D	.633**	.826**			
A65_or_Older_D	.865**	.906**	.836**		
Disability_Pop_D	.737**	.902**	.908**	.937**	
No_Vehicle_HH_D	.662**	.856**	.810**	.865**	.812**

*** The correlation is significant at the 0.01 level (2-tailed)*

Regression Analysis

Given the correlational relationships identified above, we subsequently ran a stepwise regression to derive a model of selected independent variables which made a statistically significant contribution to the R^2. The stepwise regression went through four iterations and it settled on the following four independent variables in the order of the increment to the R^2 in each iteration: A65_or_Older_D, Non_White_D, Disability_Pop_D, and No_Vehicle_HH_D. It should be noted that Below_Poverty_D was excluded because it did not make a statistically significant contribution to the R^2

after the above four independent variables were included in the regression model. The resulting multiple regression model is thus expressed as:

*Pharmacy_D (predicted) = bo + b1*A65_or_Older_D + b2*Non_White_D + b3*Disability_Pop_D + b4*No_Vehicle_HH_D*

This regression model (Table 3) showed a strong relationship between the independent variables and the dependent variable (Multiple R = .929). The independent variables also explained over 85 percent of the variance in the dependent variable (Adjusted R^2 = .858). When it comes to the influence of independent variables on the dependent variable, the standardized coefficients or beta weights revealed that A65_or_Older_D has the strongest influence (beta = 1.869) followed by Non_White_D (beta = -.537), Disability_Pop_D (beta = -.377), then No_Vehicle_HH_D (beta = -.190). It is worth noting that, when all selected independent variables are entered, A65_or_Older_D is the only independent variable that has a positive beta weight in the regression model while the other independent variables are negatively associated with the dependent variable. In other words, jurisdictions with higher standardized Non_White_D, Disability_Pop_D, or No_Vehicle_HH_D tend to associate with lower standardized Pharmacy_D. This finding of negative beta weights provided insights of potential pharmacy deserts in relation to different independent variables.

Table 3. Final regression model derived from the stepwise regression analysis

						Collinearity Statistics	
Independent Variables	**Coefficient**	**Std. Error**	**beta**	**t**	**Sig.**	**Tolerance**	**VIF**
Constant	-0.033	0.020		-1.601	0.112		
A65_or_Older_D	0.005	0.000	1.869	16.717	< 0.001	0.086	11.643
Non_White_D	0.000	0.000	-0.537	-6.051	< 0.001	0.137	7.325
Disability_Pop_D	-0.001	0.000	-0.377	-3.713	< 0.001	0.104	9.597
No_Vehicle_HH_D	-0.001	0.001	-0.190	-2.708	0.008	0.219	4.571

Dependent Variable: *Pharmacy_D*: number of pharmacies per square mile

Independent Variables: *A65_or_Older_D*: number of persons age 65 or older (per square mile)

Non_White_D: number of non-white persons (per square mile)

Disability_Pop_D: number of persons with disability (per square mile)

No_Vehicle_HH_D: number of households without vehicles (per square mile)

Multiple R = 0.929 R^2 = 0.863 Adjusted R^2 = 0.858 F = 200.940 ($p < 0.001$)

We also conducted a collinearity diagnostic test, yielding the results shown in Table 4. Since the condition indices for all dimensions are below 10, we believe that the potential multicollinearity among the independent variables is not a serious issue for our multiple regression model.

Table 4. Collinearity diagnostics (dependent variable: Pharmacy_D)

Dimension	Eigen value	Condition Index	Variance Proportions				
			(Constant)	*A65_or_Older_D*	*Non_White_D*	*Disability_Pop_D*	*No_Vehicle_HH_D*
1	3.984	1.000	0.010	0.000	0.010	0.000	0.010
2	0.733	2.331	0.810	0.000	0.010	0.000	0.020
3	0.161	4.981	0.110	0.020	0.020	0.110	0.780
4	0.081	6.994	0.060	0.140	0.940	0.100	0.030
5	0.040	9.943	0.000	0.840	0.020	0.790	0.150

Average Nearest Neighbour Analysis

We then shifted our focus to the spatial distribution of pharmacies in Virginia. Based on the geocoded results, it is visually evident that pharmacies are clustered in the urban areas, especially in Northern Virginia, Central Virginia, and the Hampton Roads urban areas. To quantitatively investigate the cluster pattern further, we performed an Average Nearest Neighbour analysis (Figure 2) which affirms that the spatial distribution of pharmacies is highly clustered, with a z-score of -61.6993 ($p < 0.001$). It is also worth noting that the resulting Nearest Neighbour Ratio of 0.2103 indicates that the observed average distance is much shorter than the expected average distance of pharmacies under random distribution.

Network Analysis

Given that pharmacies are highly clustered spatially, it is obvious that pharmacy-abundant places have better access to pharmacies in Virginia than places where pharmacies are sparse. To gain a better understanding of the accessibility to pharmacies, we conducted a network analysis using ArcGIS to delineate pharmacy service areas based on street network distance that can be reached from pharmacies in three specified travel times by car: less than 10 minutes, 10-20 minutes, and 20-30 minutes. It should be noted that the specified travel times were arbitrarily defined in this study to help the delineation and comparison of accessibility to pharmacies. The underlying rationale is that places which are closer to pharmacies would require less travel time to reach them, hence better accessibility. The resulting service area polygons are shown in Figure 3, which clearly indicate that the pharmacy deserts, i.e., places with poor access to pharmacies, are primarily located outside of the urban areas in the western and southern parts of Virginia.

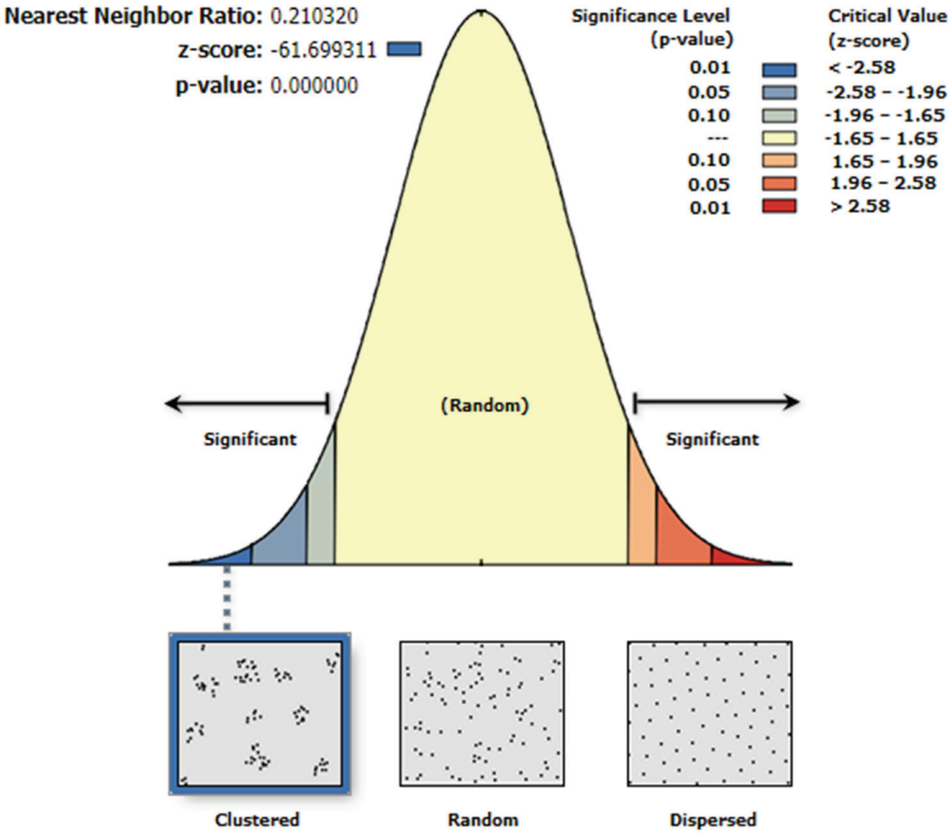


Figure 2. Average Nearest Neighbour analysis

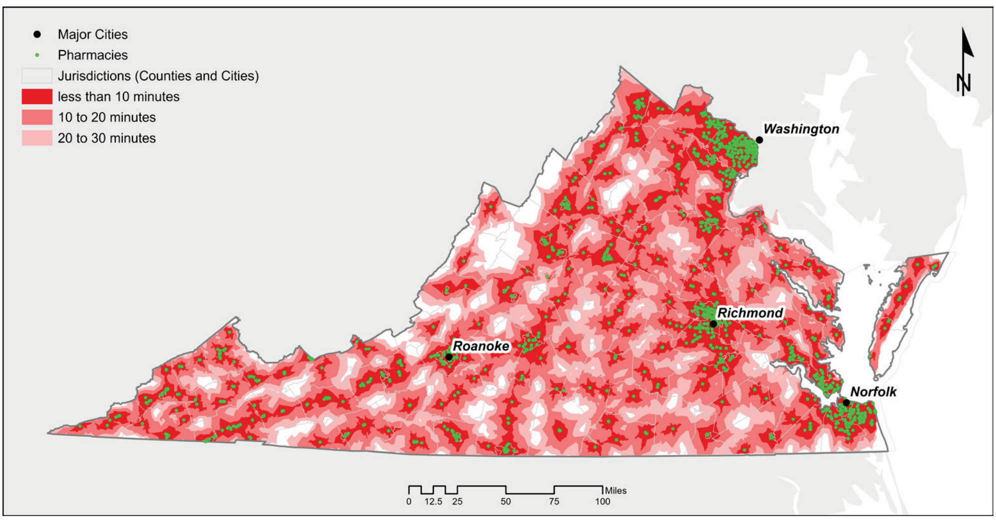


Figure 3. Access to pharmacies measured by travel time based on the street network distance

In addition to the accessibility measured by travel time based on the network distance, we also examined the number of visits to pharmacies as a proxy for the realized access. We obtained the number of pharmacy visits during the period of June 27 (2022) to July 4 (2022) from the SafeGraph website. They were aggregated to the jurisdiction level so that each local jurisdiction has a combined total of visits to pharmacies located within that jurisdiction. The visit volume is proportionally symbolized in relation to the access to pharmacies (Figure 4). It can be observed that urban areas are generally associated with a greater number of visits. However, it is worth noting that there are places in Virginia with better access to pharmacies but with a low visit volume.

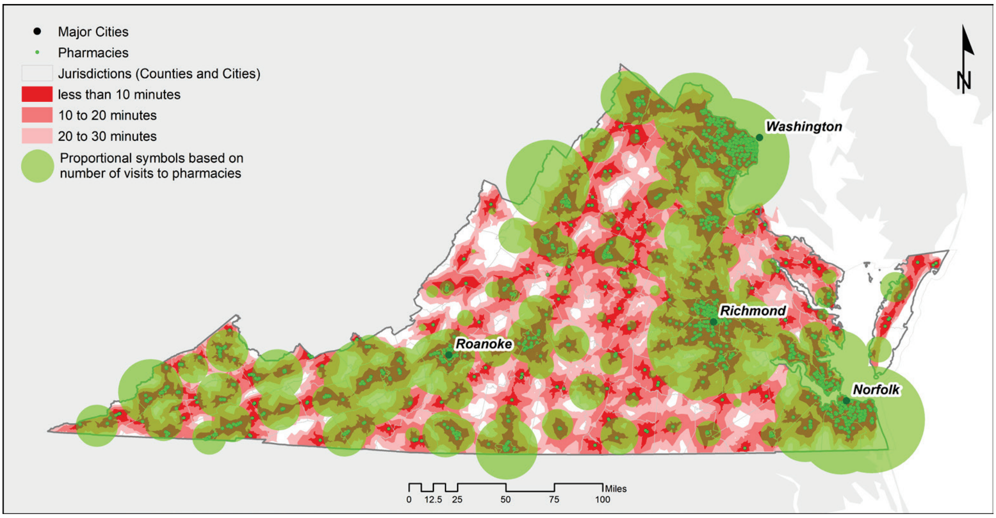


Figure 4. Number of visits to pharmacies in relation to the access to pharmacies

Geographically Weighted Regression (GWR) Analysis

While the network analysis painted a clear picture of accessibility to pharmacies based on the street network distance and travel time, it does not consider the vulnerable populations and their accessibility to pharmacies. Furthermore, the traditional linear regression model merely provided an overall picture of the relationships between the distributions of pharmacies and the vulnerable populations at macro level, as it still lacks the ability to capture local variations of such relationships. According to Chakravorty (1996), the spatial disparity may imply significant differences between neighbouring geographic features even when similar attribute values are spatially clustered.

To overcome these shortcomings, we used ArcGIS and we carried out a Geographically Weighted Regression (GWR) analysis to examine the relationships, which takes into account the pharmacy location information. The advantage of GWR over traditional linear regression is that GWR can model changing relationships spatially at a local geographic level than the entire study area as a whole (Fotheringham 2002, Mitchell and Griffin 2021). GWR has found many other applications as well, such as in studying accessibility to primary health care (Bagheri et al. 2009), spatial epidemiology of infectious disease (Liu et al. 2011), and the spatially varying predictors of population health (Shoff and Yang 2012).

We constructed our GWR model based on the same model specification derived from the stepwise regression where Pharmacy_D is the dependent variable; and the independent variables are A65_or_Older_D, Non_White_D, Disability_Pop_D, and No_Vehicle_HH_D. Figure 5 shows the spatial distribution of independent variables.

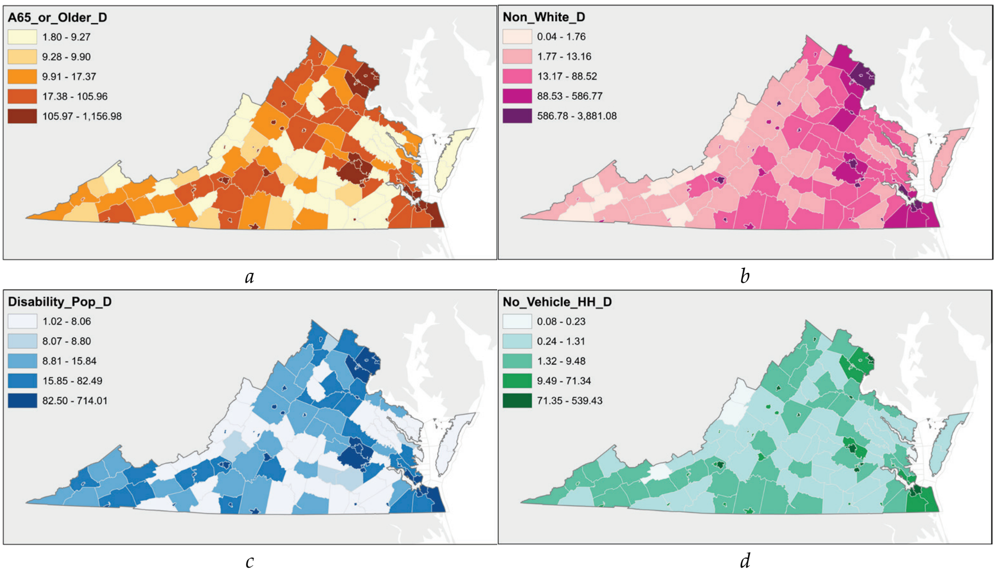
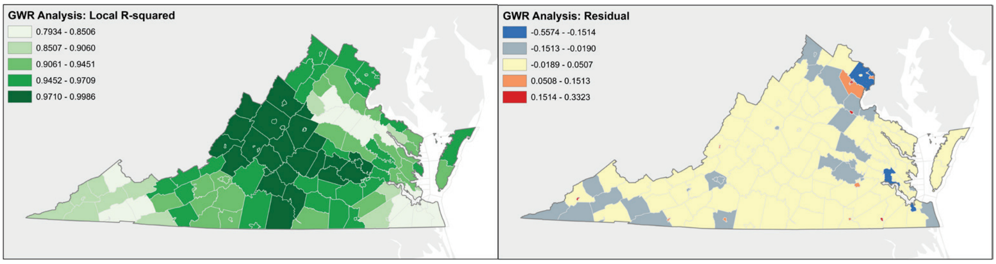


Figure 5. Spatial distribution of independent variables
(a) A65_or_Older_D, number of persons aged 65 or older per square mile; (b) Non_White_D, number of non-white persons per square mile; (c) Disability_Pop_D, number of persons with disability per square mile; and (d) No_Vehicle_HH_D, number of households without vehicles per square mile.

We specified the adaptive kernel and a bandwidth of 30 neighbours to solve the local regression analyses. GWR delivered an Adjusted R^2 of .960, and an improvement over .858 derived from the stepwise regression (Table 5). The spatial distribution of GWR outputs is illustrated in Figure 6.

Table 5. Geographically Weighted Regression

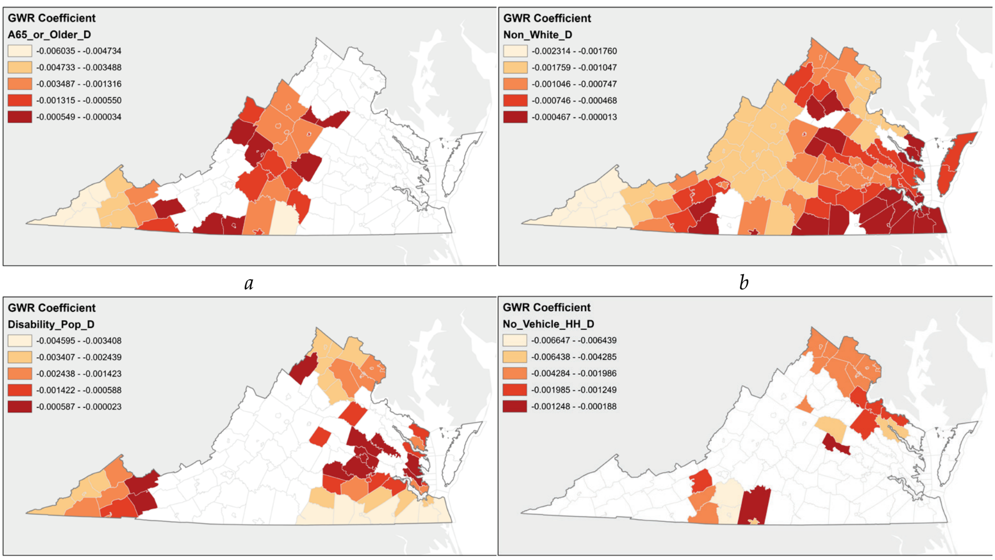
Dependent Variable:	*Pharmacy_D*: number of pharmacies per square mile		
Independent Variables:	*A65_or_Older_D*: number of persons age 65 or older (per square mile)		
	Non_White_D: number of non-white persons (per square mile)		
	Disability_Pop_D: number of persons with disability (per square mile)		
	No_Vehicle_HH_D: number of households without vehicles (per square mile)		
Neighbours = 30	**AICc** = -102.615	**R²** = 0.973	**Adjusted R²** = 0.960



a *b*

Figure 6. Spatial distribution of GWR outputs: (a) local R-squared; (b) residuals

A key characteristic of GWR is its ability to compute local regression coefficients associated with independent variables for each local jurisdiction. The local coefficients can be used to examine the varying relationships between the independent variables and the dependent variable Pharmacy_D. In the context of pharmacy deserts, we focused on the negative coefficients of each independent variable derived at the local jurisdictional level. This helps to highlight the inverse relationship between a given independent variable and the Pharmacy_D. When the vulnerable populations are all considered, local jurisdictions might have adequate pharmacies for certain populations but inadequate for others, relatively speaking (Figure 7).



c *d*

Figure 7. Spatial distribution of negative GWR coefficients associated with independent variables: (a) A65_or_Older_D, number of persons aged 65 or older per square mile; (b) Non_White_D, number of non-white persons per square mile; (c) Disability_Pop_D, number of persons with disability per square mile; (d) No_Vehicle_HH_D, number of households without vehicles per square mile

Even though A65_or_Older_D is the only independent variable with a positive beta weight in the stepwise regression indicating an overall positive relationship with Pharmacy_D, GWR revealed that the relationship varies over space among different jurisdictions. Figure 7(a) symbolizes the jurisdictions with negative local coefficients showing places where pharmacies are inadequate for people aged 65 or older.

Among the independent variables, the Non_White_D is the only one that has negative local coefficients across most jurisdictions. This means that pharmacies are inadequate to various extent in relation to non-white persons in Virginia overall. Figure 7(b) shows the variation of local coefficients, where the inadequacy of pharmacies is more severe in the jurisdictions coloured in red than the ones in yellow.

When it comes to Disability_Pop_D, pharmacies are relatively inadequate mainly in northern, southern, and western Virginia – Figure 7(c). As to No_Vehicle_HH_D, a few jurisdictions in north-eastern and south-central Virginia, shown in Figure 7(d), do not have adequate pharmacies in relation to households without vehicles.

Discussion

This pilot study is our first attempt to examine the pharmacy desert and disparity issues in the Commonwealth of Virginia. The most important findings are threefold. First, the pharmacy locations are unevenly distributed in Virginia. They are primarily clustered in three major urban areas: Northern Virginia, Central Virginia, and the Hampton Roads urban areas, which leave the pharmacy deserts to be more present in rural areas in the western and southern parts of the Commonwealth. Second, of the five vulnerable populations examined in this study, the concentration and distribution of senior citizens (aged 65 or older) are most significantly associated with the pharmacy locations at state-wide macro level.

Third, at the more fine-grained local levels, however, the GWR analysis has exhibited very complex spatial patterns along different social dimensions: local jurisdictions might have adequate pharmacies for certain populations but inadequate for others, demonstrating the existence of social inequity besides spatial equity. For example, in the western and southwestern parts of Virginia, pharmacies are inadequate for people aged 65 or older. Pharmacies are inadequate to various extent in relation to non-white persons overall revealing that racial inequity of access to pharmacies is ubiquitous in Virginia. The minority social groups are still more or less marginalized in American society due to historical, economic, social, and other reasons, which bear resemblance to those in the Roma communities in Eastern Europe. Racial inequity issues persist in the U.S. When it comes to people with disabilities, pharmacies are relatively inadequate mainly in northern, southern, and western Virginia. As to households without vehicles, inadequate pharmacies are observed in a few jurisdictions in north-eastern and south-central Virginia.

Based on the above findings, this paper makes the following policy recommendations for Virginian governments: governments should encourage the opening of more pharmacies in the rural parts of Virginia, such as the western and southwestern parts of the state, by providing more tax breaks and other incentives in these pharmacy deserted areas. Governments should invest more money in public transit and alternative transportation modes so that those households without vehicles, people with disabilities, and minority transit captive riders can also access the local pharmacies. Governments should be more sensitive to the social inequity and spatial inequity issues existing in pharmacy locations and their service delivery.

Despite the above preliminary findings and recommendations, we recognize a major limitation of the study in terms of pharmacy service capacity such as pharmacy types, service hours, number of pharmacists, number of prescription medications filled, etc. In addition, conducting a comparative study on the spatial disparity of pharmacies between urban and rural areas would offer more in-depth findings which can be based upon to devise effective policies to address issues related to the spatial disparity of pharmacies in Virginia.

Conclusions

The spatial disparity of social services such as pharmacies is a complicated phenomenon with many dimensions. Along the spatial dimension, pharmacy locations are simply unevenly distributed across space, which can be measured by many spatial statistical or geospatial tools, such as the average nearest neighbour analysis and network analysis. Though this case study presents the unique Virginian case, its methodology can be applicable to other countries as well.

Along the social dimension, the factors are much more complicated. For example, due to racial discrimination, gentrification, redlining and housing eviction, minority ethnic populations, especially African Americans, are more likely to be displaced to live in the cheap and dilapidated areas where no pharmacies exist nearby. These poor people are typically the transit captive riders with lower vehicle ownership. Except for the largest metropolitan areas such as New York, most areas in the U.S. do not have developed transit networks, which make disadvantaged people worse off in accessibility. To dig into more details of social issues requires more relevant data to be collected in the future.

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