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Research Article

Older Adult Mortality From COVID-19: Food Access as a Determinant Within a Socio-ecological Framework

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Abstract

Background and Objectives: Low access to food can have an adverse impact on health yet there is limited research on how it is related to coronavirus disease 2019 (COVID-19). The objective of this study was to (a) better understand how inadequate food access was associated with older adult mortality from COVID-19 and (b) determine the spatial distribution of mortality from low food access utilizing a socio-ecological framework.

Research Design and Methods: This study area was the larger Midwest, a region of the United States, which included the following states: Minnesota, Wisconsin, Iowa, Illinois, Indiana, Michigan, Ohio, and Pennsylvania. Data were aggregated from multiple sources at the county-level. Because the spatial data used in this study violated several assumptions of the global regression framework, geographically weighted regression (GWR) was employed.

Results: Results from GWR revealed low access to food was positively associated with mortality from COVID-19 for older adults but the association varied in (a) magnitude and (b) significance across the larger Midwest. More specifically, the socio-ecological framework suggested low access to food, female-headed households, and percentage Hispanic played a meaningful role in explaining older adult mortality for the western region of the larger Midwest. This was not as evident for the eastern portion.

Discussion and Implications: Such a finding calls attention to the importance of capturing the local context when devising policies to reduce mortality for older adults from COVID-19. Regional policymakers can collaborate with public health professionals when applying these results to formulate local action plans that recognize variations across geographic space.

Keywords: Coronavirus, Healthy aging, Pandemic, Population health

Low access to food remains a concern in the United States with an estimated 55 million (or nearly 18%) of the U.S. population being affected at some period during 2015 (Economic Research Service [ERS], U.S. Department of Agriculture [USDA], 2020). Low access is defined as a region where a significant number of people reside greater than one mile from the nearest supermarket or large grocery store for an urban area and greater than 10 miles for a rural area (ERS, USDA, 2021). Low access to food can be a factor leading to poor health (Gundersen & Ziliak, 2018). For example, it can contribute to diabetes, chronic diseases, and a lower quality of life (Dubowitz et al., 2015; Michimi & Wimberly, 2010; Miller & Thomas, 2020; Suresh & Schauder, 2020). Several studies have also found an association when examining the food environment with all-cause mortality (Sun, Liu et al., 2020; Tani et al., 2018; Wang et al., 2014). This is important to note because low-access areas tend to have fewer supermarkets and grocery stores, which often results in a reduced intake of fruits, vegetables, whole grains, and nutritionally dense foods (Torrence et al., 2018). Additionally, low-access areas mainly consist of convenience and corner stores that typically allocate less than five feet of shelf space for quality foods but nearly 300 feet of shelf space for beverages and snack foods (Caspi et al., 2017). In summary, residing in a low-access area can have an adverse impact on health, and such areas can position one to be at higher risk for mortality from the coronavirus. On-going research has advanced our understanding of the causes and consequences for low access to food and scholars and practitioners recognize social, economic, and ecological factors play a key role. However, the association between low access to food and mortality from severe acute respiratory syndrome coronavirus 2 (i.e., coronavirus disease 2019 [COVID-19]) for older adults has not been examined. The present study aims to fill this gap. By recognizing how inadequate access to food, along with other socio-ecological factors, is associated with older adult mortality at the local level, policymakers and public health professionals can work collaboratively to formulate action plans to alleviate a condition that has resulted in significant loss of life both in the United States and globally during the COVID-19 pandemic (Centers for Disease Control and Prevention [CDC], 2021; Gallo & Wilber, 2021).

Coronavirus Disease 2019

The importance of understanding the covariance of low access to food and mortality with its correlates can provide greater insight into which population groups are most vulnerable and what initiatives can be formulated to reduce mortality. COVID-19 is highly contagious and can spread before an individual shows any symptoms (Kuiken et al., 2003; Schmidt, 2019). COVID-19 also presents a threat to population health due to the disposition of the coronavirus genome to mutate. As such, continued research is needed to better understand which groups are at risk and what types of interventions may improve the health and well-being of older adults (Koyama et al., 2020). And if older adults with low access to food experience greater mortality from COVID-19, then policymakers and health professionals should examine food and nutrition interventions as larger public health efforts as tools against future epidemics and pandemics.

Conceptual Framework

This study applied the socio-ecological framework to examine low access to food prevalence with mortality from COVID-19 (Carter et al., 2014; Deller et al., 2017; Rivera et al., 2018). The framework consists of various levels: the individual (the innermost level), then the interpersonal level (e.g., friends, family), followed by the organizational level (e.g., employer, health system), then the community level, and finally the policy level (Bronfenbrenner, 1992; Goldberg & Mawn, 2015; Shoff et al., 2014). For the present study, the focus was on social and ecological factors as associated county-level structures in explaining the association between low access to food and mortality. Such an approach has been applied in other studies examining COVID-19 infection and mortality (Abedi et al., 2021; Mahajan & Larkins-Pettigrew, 2020; Sun, Matthews et al., 2020). Utilizing a similar framework, this study advanced our present understanding by constructing a spatial regression model with geographic weights using restricted mortality data at the county-level from January 2020 to December 2020.

Equation 1 represented the overall framework:

1. Mortality = f (social; ecological attributes) examined at the county-level with low access to food for older adults as the main variable of interest. This study examined the association between the spatial distribution of low access to food and older adult mortality with the following hypothesis:

H_A: Mortality from COVID-19 differed by county for varying levels of low access to food for older adults across the larger Midwest.

Method

Study Setting

The study area was the larger Midwest, a region of the United States, which included the following states: Minnesota, Wisconsin, Iowa, Illinois, Indiana, Michigan, Ohio, and Pennsylvania (Figure 1). According to the 2019 Census, the total population for these states estimated at 68.5 million or approximately 21% of the entire U.S. population (U.S. Census Bureau, 2019). In terms of older adults, approximately 23% of the population was aged 60 and older. As such, this region encompassed a large geographic area and represented a significant older adult population. Equally important, this area contained a sizeable percentage of older adults experiencing low access to food. Estimates from the Food Environment Atlas show several counties where at least 5% of the population aged 65 and older lived in an area with low access to food (ERS, USDA, 2021). In terms of individual states, approximately 5% of older adults experienced low access for Iowa and Illinois, close to 7% for Indiana and Michigan, 6% for Minnesota and Ohio, and 5% for Pennsylvania and Wisconsin. A closer examination revealed nearly 15% of the counties in Iowa approached 10% for low access and this approximated 10% of the counties for Illinois, 10% for Indiana and Michigan, 20% for Minnesota, and roughly 12% for Pennsylvania and Wisconsin. As explained below, this geographic area was also selected because it contained the most complete data record for mortality from COVID-19.

Data Sources and Measures

Main variables

For this observational study, data were aggregated from multiple sources. The main independent variable corresponded to the percentage of older adults with low access to food at

Figure 1. Study area.

the county-level. This measure was obtained from the USDA Food Atlas for 2019. It represented the percentage of adults aged 65 and older who resided more than one mile from the nearest supermarket or large grocery store for an urban area and greater than 10 miles for a rural area (ERS, USDA, 2021). The dependent variable corresponded to mortality from COVID-19 for adults at least 60 years of age. Specifically, the number of deaths attributed to the coronavirus was based on laboratory confirmation. This measure was calculated per 100,000 persons and then converted to a percentage to simplify interpretation with several of the regression coefficients, which were also measured as percentages. Data on mortality were collected by the CDC, and this study utilized restricted data that consisted of 2,193 counties (n = 173,325 individual observations for the older adult sample) with a start date of January 2020 and an end date of December 2020. While serving as a valuable resource, this data set contained a large percentage of incomplete records for various states (e.g., Arizona, Florida, Georgia, Missouri, and Texas). Due to this, the initial concept of a national-level framework was not possible, and preliminary analysis of the data revealed that the larger Midwest contained a more complete data profile, which reflected an analytic sample of 663 counties (n = 46,368).

Other variables

The social and demographic variables (e.g., percentage Black population, percentage Hispanic population, percentage aged 65 and older living alone, and percentage homeowners) were obtained from the U.S. Census for 2019. Health-related variables corresponded to adult smoking, obesity, and adult diabetes and were obtained from the 2018 Behavioral Risk Factor Surveillance System (see Supplementary Material for variable definitions). Recent work has found these variables to be significant determinants of COVID-19 infection and mortality (Abedi et al., 2021; Hamidi et al., 2020). Data for the ecological variables were obtained from various national programs. For example, $PM_{2.5}$ measured ambient air quality and it was collected for the 2016 period by the Environmental Protection Agency (US Environmental Protection Agency, 2020). This variable was selected because several research reports have found a positive association between poor air quality and mortality from the coronavirus (Brandt et al., 2020). The number of rural health clinics, available beds, primary care provider, nurse provider, and mental health provider ratios were obtained from the Area Health Resource Files for 2017, while the percentage of population with no leisure-time physical activity was obtained from the Diabetes Surveillance System for 2017. All these variables were reported at the county-level and were selected based on the aforementioned comprehensive reviews and research reports (Baltrus et al., 2021; Carter et al., 2014; Gundersen & Ziliak, 2018; Harris et al., 2014; Heid et al., 2021; Wu et al., 2020). That is, current research has found these socio-ecological factors explicate mortality for the coronavirus (Bundy et al., 2021; Chiou and Tucker, 2020; Figueroa et al., 2020, 2021; Lu et al., 2021; Russette et al., 2021; Wang et al., 2020; Williamson et al., 2020; see Supplementary Material for additional clarification about variables).

Analyses: Geographically Weighted Regression

Global ordinary least squares (OLS or global OLS regression) can be utilized to model older adult mortality from COVID-19. However, the spatial data used in this study violated several assumptions of the global regression framework (Fotheringham et al., 2003; Paez et al., 2011). First, global OLS regression assumes the observations are independent. In many cases, this does not occur with spatial data due to clustering (i.e., a pattern where high/low values are adjacent to other high/low values). Second, global OLS regression assumes spatial stationarity between the dependent and independent variables (i.e., coefficients will be constant across the geographic area). However, the social and ecological context of an area can influence the magnitude and direction of the relationship (Cressie, 2015). As a result, global OLS regression estimates may not be representative of the study area. Geographically weighted regression (GWR) relaxes these assumptions by creating local models (i.e., one for each county).

After conducting the preliminary step of spatial exploration and finding evidence of clustering, the next step was to employ GWR. In terms of an equation, GWR can be written as:

$$2.\quad y_i = \beta_{0i}(u_i, v_i) + \sum_{n=1}^{k} \beta_{ni}(u_i, v_i)\, x_{ni} + \varepsilon_i$$

where y_i was the measure of older adult mortality for county i and (u_i, v_i) denoted the centroid for each county with ε_i as the random error term. β_{0i} was the intercept while β_{ni} was the estimated parameter for variable n with respect to county i. These analyses were conducted using Stata V15, and the mapping exploration was performed using QGIS (StataCorp., 2015; QGIS Development Team, 2019).

GWR Formulation

The next steps were to formulate the GWR model by selecting the weighting function, which required the following: (a) considering the type of kernel (i.e., Gaussian or bi-square), (b) determining whether the kernel would be adaptive or fixed, and (c) applying a selection method to determine the distance bandwidth for the kernel. Because the distribution of observations varied across space, the bi-square weighting function with an adaptive kernel was employed. Stated differently, counties were smaller and closer together in Iowa and Indiana relative to Minnesota and Wisconsin. Due to this unequal distribution, the use of an adaptive kernel allowed adjustments to be made so counties closer to i would exert more influence on the estimation of $\beta_{ni}(u_i, v_i)$ than ones with a greater distance. Finally, a process that minimized the corrected Akaike Information Criteria (AICc) was used to determine the bandwidth (i.e., optimal kernel size). This was accomplished by using an iterative process that successively narrowed the range of values inside the bandwidth by searching and comparing the lowest obtained AICc scores.

Results

Descriptive Analyses

Older adult mortality from COVID-19 at the county-level ranged from less than 1% to 32% and exhibited spatial autocorrelation (Moran's $I = 0.23$ and $p < .01$; Table 1). Mortality was clustered in the central western and central southern counties of Iowa, southern counties of Illinois, southeastern counties of Pennsylvania, and northeastern counties of Wisconsin. As for older adults with low access to food at the county-level, it ranged from less than 1% to 17% and exhibited spatial autocorrelation (Moran's $I = 0.19$ and $p < .01$). Inadequate access to food for older adults was clustered throughout the northern and central western counties of Minnesota and the northeastern counties of Wisconsin. In terms of social variables, the mean for population Black was 3% with low percentages in northern Wisconsin, northern Michigan, and northern Minnesota and high percentages (i.e., near 40%) for counties that encompassed cities such as Chicago, Cleveland, and Detroit. Meanwhile, the Hispanic population was widely distributed throughout northern Illinois, northern Indiana, various parts of Iowa, central Michigan, and southeastern Pennsylvania. Overall, adult smoking was 17% with higher values in Indiana and Ohio, adult diabetes was 11% with higher percentages in central Michigan, central Indiana, and throughout Ohio, and obesity approximated 33% with greater values in central Michigan and southern Ohio. As for ecological variables, $PM_{2.5}$ was consistent throughout most of the region with a mean of 8.0 with slightly higher values in Ohio. In contrast, a wide range applied to the ratio of the population with primary care providers, ratio of the population with mental health care professionals, and percentage of households with access to parks for each state with higher values in urban areas and lower values in rural areas.

Regression Analyses

Global OLS regression results suggested older adult mortality from COVID-19 was positively associated with low access to food for older adults with an estimate of 0.08 with $p < .05$ (Table 2). As for social variables, percentage Hispanic and female-headed households were also positively associated with mortality from COVID-19. Percentage Black and percentage aged 65 and older and living alone were insignificant. An insignificant finding also applied to adult obesity and diabetes. Meanwhile, an increase in the percentage of population with physical inactivity was associated with greater mortality from COVID-19. As for the ecological variables, an increase in the percentage of households without internet access reflected greater mortality from COVID-19. Lastly, percentage of households with access to parks was negatively associated with mortality from COVID-19.

If one were to rely only on the global OLS model, then the local context would not be explicated. That is, socioecological differences at the county-level would not be captured when understanding how older adult mortality from COVID-19 was associated with low access to food. This was evident with the bivariate map, which revealed that the association of low access to food with older adult mortality from COVID-19 was notable in the western region and less so near the eastern portion (Figure 2). While two separate maps (i.e., one for the estimates and one for significance levels) can be presented, the bivariate map depicted both characteristics in one map. This map revealed a strong association between low access and older

Table 1. Descriptive Statistics for Social/Demographic, Health, and Ecological Attributes by State

	IL (n = 99)	IN (n = 87)	IA (n = 95)	MI (n = 73)	MN (n = 84)	OH (n = 88)	PA (n = 65)	WI (n = 72)	Total (N = 663)		
Variable	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Min.	Max.
Mortality (%)	9 (5)	5 (3)	8 (6)	4 (3)	6 (4)	4 (4)	5 (4)	5 (4)	6 (5)	0	32
Social/demographic											
Low access to food (%)	4 (2)	5 (2)	5 (3)	5 (2)	5 (3)	6 (3)	4 (2)	5 (3)	5 (2)	0	17
Non-Hispanic Black (%)	5 (7)	3 (5)	2 (2)	4 (6)	2 (2)	4 (6)	5 (6)	2 (3)	3 (5)	0	41
Hispanic (%)	5 (6)	4 (4)	5 (5)	4 (3)	5 (4)	3 (2)	5 (5)	4 (3)	4 (4)	1	32
Per capita income (US$)	28,187 (4,401)	26,948 (4,164)	29,509 (2,844)	27,224 (4,427)	30,757 (4,095)	27,505 (4,593)	28,942 (5,441)	29,772 (4,253)	28,589 (4,438)	15,360	48,225
Aged 65 living alone (%)	14 (2)	11 (2)	14 (2)	13 (3)	13 (2)	12 (2)	13 (2)	12 (2)	13 (2)	6	24
Female-headed households (%)	10 (2)	10 (2)	8 (2)	10 (2)	8 (2)	11 (2)	10 (2)	8 (3)	10 (3)	4	29
Homeowners (%)	75 (6)	74 (6)	75 (5)	77 (6)	77 (5)	72 (6)	73 (5)	74 (6)	74 (6)	49	90
Health attributes											
Physically inactive (%)	26 (4)	28 (4)	26 (4)	25 (4)	24 (4)	29 (4)	25 (4)	23 (4)	26 (4)	14	41
Adult smokers (%)	16 (1)	20 (2)	16 (1)	17 (2)	15 (2)	19 (2)	18 (2)	16 (3)	17 (2)	11	34
Adult obesity (%)	30 (4)	34 (4)	34 (4)	34 (4)	32 (4)	34 (4)	33 (4)	33 (4)	33 (4)	22	45
Diabetes (%)	11 (4)	13 (3)	10 (3)	12 (3)	10 (2)	13 (2)	12 (2)	10 (3)	11 (3)	3	26
Ecological											
Ratio of population (primary care)	1,870 (1,237)	2,022 (1,531)	1,506 (773)	1,455 (832)	1,900 (1,617)	2,186 (2,029)	1,231 (746)	1,929 (2,060)	1,782 (1,468)	64	15,042
Ratio of population (mental health)	1,294 (1,380)	1,772 (1,851)	2,447 (2,558)	799 (752)	1,537 (1,588)	944 (937)	1,058 (932)	1,176 (1,235)	1,416 (1,631)	142	14,011
Ratio of population (nurses)	2,164 (1,616)	2,054 (1,669)	2,299 (2,117)	2,328 (1,639)	2,527 (1,980)	2,035 (1,277)	2,184 (1,502)	2,488 (2,429)	2,253 (1,806)	194	15,434
Ratio of population (beds)	593 (489)	692 (407)	549 (633)	760 (773)	637 (632)	765 (871)	523 (719)	768 (591)	658 (651)	24	7,483
Rural health clinics	2.37 (2.43)	0.82 (1.43)	2.05 (1.73)	2.41 (2.64)	1.14 (1.56)	0.6 (1.55)	1.05 (1.79)	1.39 (1.95)	1.5 (2.03)	0	12
$PM_{2.5}$	8.71 (0.49)	8.87 (0.6)	7.63 (0.44)	7.4 (1.25)	6.34 (0.95)	8.92 (0.87)	9.18 (1.39)	7.05 (1.18)	8.03 (1.33)	3.1	12.7
Households with no internet (%)	21 (7)	21 (5)	20 (4)	20 (5)	18 (5)	20 (6)	20 (4)	19 (5)	20 (5)	5	50
Population with access to parks (%)	24 (19)	18 (12)	18 (14)	35 (19)	35 (21)	22 (15)	35 (17)	33 (17)	27 (18)	0	97

Note: IL = Illinois; IN = Indiana; IA = Iowa; MI = Michigan; MN = Minnesota; OH = Ohio; PA = Pennsylvania; WI = Wisconsin.

Table 2. Global OLS Regression Results for Older Adult Mortality From COVID-19

Variable	Est.	*SE*	*t* (Est./*SE*)	*p*
Intercept	0.00	0.04	0.00	1.00
Social/demographic				
Percentage low access to food**	0.08	0.04	2.09	.03
Percentage non-Hispanic Black	−0.07	0.05	−1.37	.17
Percentage Hispanic***	0.13	0.04	3.16	.00
Per capita income	0.06	0.07	0.82	.41
Percentage aged 65 living alone	0.08	0.05	1.55	.12
Percentage female-headed households***	0.29	0.06	4.47	.00
Percentage homeowners	−0.04	0.05	−0.79	.43
Health attributes				
Percentage physically inactive***	0.14	0.05	2.91	.00
Percentage adult smokers***	−0.37	0.07	−5.50	.00
Percentage adult obesity	−0.03	0.04	−0.75	.46
Percentage diabetes	−0.03	0.04	−0.64	.53
Ecological				
Ratio of population (primary care)	0.01	0.05	0.26	.80
Ratio of population (mental health)***	0.13	0.04	3.13	.00
Ratio of population (nurses)	−0.08	0.05	−1.58	.10
Ratio of population (beds)	0.00	0.04	0.06	.95
Rural health clinics	0.05	0.04	1.22	.22
$PM_{2.5}$	−0.01	0.04	−0.15	.88
Percentage of households (no internet)**	0.17	0.06	2.78	.01
Percentage of population with access to parks*	−0.08	0.05	−1.63	.09
Log-likelihood	−877.63			
AIC	1,797.27			
AICc	1,800.85			
R^2	0.17			
Adj. R^2	0.15			
N	663			

Note: OLS = ordinary least squares; AIC = Akaike information criteria; COVID-19 = coronavirus disease 2019.
***$p < .01$, **$p < .05$, *$p < .10$.

adult mortality from COVID-19 for Minnesota, Iowa, the northern counties of Illinois, and various southern counties in Michigan (i.e., darker shaded areas) and a weak association for many counties in eastern Indiana, Ohio, and Pennsylvania (i.e., lighter shaded areas). In terms of estimates, low access to food ranged from −0.03 to 0.26 with a median of 0.04 and mean of 0.06 while significance levels ranged from <0.01 to 0.10 (Table 3). As such, older adult mortality from COVID-19 differed for varying levels of low access to food for older adults across the larger Midwest. In formal terms, the GWR results suggested that a one percentage point increase in low access to food was associated with a 0.06 percentage point increase in older adult mortality. For the aforementioned areas in the western region of the Midwest, low access approximated much higher at 0.26 with significance at $p < .01$.

GWR analyses also suggested that social factors play a role when explaining older adult mortality from COVID-19. For example, as the percentage of households headed by females increased by one percentage point, older adult mortality from COVID-19 increased by 0.25 percentage points. A positive association was also found for percentage of the Hispanic population, which exhibited variation with a minimum estimate of 0.03, mean of 0.12, and maximum of 0.26. Percentage of adult smokers also revealed local nonstationarity with a minimum estimate of −0.50, mean of −0.24, and maximum of 0.22. Lastly, GWR analyses offered insight into ecological attributes. For example, a positive association was found for percentage of households without internet access with an estimate as high as 0.31, and a negative association was found for percentage of households with access to parks with an estimate as low as −0.21.

Specification Tests: Comparison of GWR and Global OLS Model Performance

To assess proper model specification, several tests were conducted: (a) comparison of GWR with global OLS, (b) check for nonstationarity of the regression coefficients, and (c) check for multicollinearity. When comparing GWR with global OLS regression, three measures were examined: (a) adjusted R^2, (b)

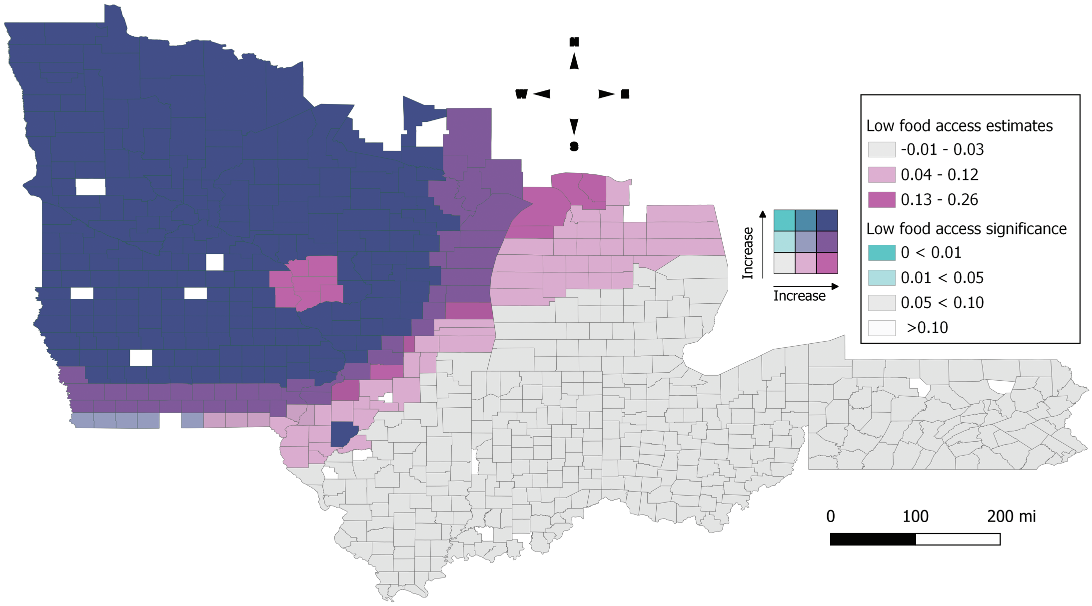

Figure 2. Bivariate representation of low access to food estimates and significance. *Note.* This map depicts both the estimates and significance for low access to food. As such, areas in purple correspond to higher values and greater significance.

residual sum of squares (RSS), and (c) the AICc. With a higher adjusted R^2 in the GWR model than in the global OLS model for the same set of variables (0.36 vs. 0.15, respectively), location played a role in explaining the variance of mortality from COVID-19. Second, the RSS in the GWR model estimated much lower than the global OLS model for the same set of variables (432.05 vs. 548.54, respectively), thereby supporting the use of a local model as better fitting the data. Finally, the AICc was used to measure goodness of fit. With a lower AICc score for GWR as compared to the global OLS model (1776.64 vs. 1800.85, respectively), the local model better represented the data.

The second specification check was to examine the nonstationarity of all the regression coefficients. This can be assessed by investigating both the direction and size of the local regression coefficients, where values that exhibit variation for the regression coefficients suggest nonstationarity. This would imply that the regression coefficients in the local GWR model changed across the counties in the study area. For example, the estimate for percentage Hispanic ranged from a value of 0.03 to 0.26, the estimate for adult smoking ranged from a negative value of −0.50 to a high of 0.22, and the estimate for percentage of population with access to parks ranged from a negative value of −0.21 to a positive value of 0.08. As such, the strength of the associations between mortality from COVID-19 for older adults and each of the explanatory variables varied based on the spatial location. A Monte Carlo randomization test also confirmed nonstationarity for the aforementioned variables. Stated differently, the determinants were not constant across the study area and were dependent on geographic location. Global OLS regression would fail to account for this.

The final specification check was to examine multicollinearity between the regression coefficients. Multicollinearity exists when one of the explanatory variables can be predicted from a linear combination of the other variables. That is, two or more variables exhibit a collinear relationship. When this occurs, the reliability of the individual variables will be reduced. In this study, the variance inflation factors (VIFs) test was utilized to examine multicollinearity between the physical inactivity, adult smoking, obesity, and adult diabetes variables. With a mean VIF of 1.36 and individual VIF values below 2, multicollinearity was not of concern because the values were below the problematic threshold of 10. This also applied for primary care provider ratio, mental health provider ratio, nurse provider ratio, bed ratio, and rural health clinics with a mean VIF of 1.43 and individual VIF values below 2.

Discussion and Concluding Remarks

Low access to food has been widely studied, and a well-established body of past and current research suggests that

Table 3. Local GWR Regression Results for Older Adult Mortality From COVID-19

Variable	Mean	SD	Minimum	Median	Maximum
Intercept	0.02	0.22	−0.35	0.04	0.46
Social/demographic					
Percentage low access to food	0.06	0.08	−0.03	0.04	0.26
Percentage non-Hispanic Black	−0.03	0.10	−0.18	−0.04	0.22
Percentage Hispanic	0.12	0.06	0.03	0.14	0.26
Per capita income	0.03	0.07	−0.15	0.04	0.20
Percentage aged 65 living alone	0.10	0.07	−0.03	0.11	0.24
Percentage female-headed households	0.25	0.08	0.09	0.26	0.43
Percentage homeowners	−0.01	0.06	−0.15	0.01	0.10
Health attributes					
Percentage physically inactive	0.13	0.07	0.03	0.13	0.27
Percentage adult smokers	−0.24	0.21	−0.50	−0.28	0.22
Percentage adult obesity	−0.03	0.06	−0.13	−0.03	0.09
Percentage diabetes	0.01	0.05	−0.09	0.02	0.08
Ecological					
Ratio of population (primary care)	−0.02	0.11	−0.25	−0.04	0.20
Ratio of population (mental health)	0.13	0.07	−0.04	0.16	0.22
Ratio of population (nurses)	−0.06	0.08	−0.18	−0.09	0.08
Ratio of population (beds)	−0.01	0.08	−0.21	0.03	0.08
Rural health clinics	0.01	0.06	−0.08	0.00	0.14
$PM_{2.5}$	−0.01	0.08	−0.16	−0.02	0.14
Percentage of households (no internet)	0.11	0.07	−0.08	0.10	0.31
Percentage of population with access to parks	−0.09	0.09	−0.21	−0.12	0.08
Log-likelihood	−795.60				
AIC	1,753.64				
AICc	1,776.64				
R^2	0.36				
Adj. R^2	0.27				
N	663				

Notes: GWR = geographically weighted regression; AIC = Akaike information criteria; COVID-19 = coronavirus disease 2019. Mean column denotes the average value for each estimated coefficient.

educational attainment, poverty level, physical barriers, social supports, unemployment, and urban/rural designation are associated with access to and availability of healthy foods (Burris et al., 2019; Larson et al., 2009; Tucher et al., 2020). The present study builds on this learning by examining the association between low access to food and older adult mortality from COVID-19. GWR results suggested a positive association between the percentage of the older adult population with low access to food and COVID-19 mortality for older adults for many counties along the western area of the larger Midwest (Figure 2). In terms of a geographic perspective, these counties comprise large parts of Minnesota, Wisconsin, Iowa, Illinois, and some areas in Michigan. The association between low access to food and mortality estimated the lowest in Ohio and Pennsylvania. For many counties in this region, low access to food was not as consequential and suggested a minimal impact on mortality. The local context was also a worthwhile consideration when examining other socio-ecological attributes: Hispanic and female-headed households. Although most counties with a greater percentage of the Hispanic population experienced higher levels of older adult mortality, this association varied in magnitude. More specifically, some areas (e.g., southeastern Indiana and western Ohio) exhibited a weak association with an estimate of 0.03 while other areas (e.g., eastern Iowa and western Illinois) exhibited a strong association with an estimate of 0.26. This finding provides additional insight into mortality differences by ethnicity. For this study, some counties with a greater percentage of the Hispanic population may have exhibited higher mortality due to employment in high-contact jobs, such as construction, and food processing (Williams et al., 2020). Some scholars found occupational exposures to be an important factor when explaining racial and ethnic disparities (Bochtis et al., 2020; Hawkins, 2020). In various parts of the larger Midwest, the Hispanic workforce is concentrated in counties with a long-standing and well-established agricultural base and this could lead to greater exposure to the coronavirus (Waltenburg et al., 2021).

Counties with a greater percentage of female-headed households also experienced higher levels of older adult mortality and this was notable throughout the larger Midwest with a consistent estimate of 0.25. This seems plausible because female-headed households are often located in census tracts with (a) greater poverty and (b) reduced access to health care (Carli, 2020; Khanijahani & Tomassoni, 2021). Additionally, persistently unhealthy counties have a higher percentage of female-headed households (James et al., 2020). In summary, regional associations may play an important role in explaining mortality by gender for many counties throughout the United States (Kindig & Cheng, 2013). While racial disparities have become a focal point, gender differences should also become part of the health disparities conversation. For example, the current five-year American Community Survey suggests nearly 12%–15% of the households were headed by women in the following counties: Mahnomen (Minnesota), Marion (Indiana), Menominee and Milwaukee (Wisconsin), and Wayne (Michigan). These counties could benefit from initiatives that continue to promote social distancing and require face coverings in public spaces.

Potential Policy Directions for Food Access

The on-going pandemic has exacerbated access to food due to regional and global supply shortages, shelter-in-place (SIP) orders, and labor disruptions in the retail, transportation, and food industries. Despite these challenges, policymakers can collaborate with local businesses, community leaders, and public health professionals to devise strategies that increase access to food for older adults. Because this study found variation in magnitude and significance for low access to food with older adult mortality from COVID-19 based on geographic location, a practical public health intervention may involve using the Food Abundance Index (FAI) to measure the level of food insecurity within a geographic region (Murrell & Jones, 2020). The FAI scorecard evaluates (a) access, (b) diversity, (c) quality, (d) density, and (e) affordability using a point system. The results can be used to rank a county or neighborhood into one of four categories: food desert, food gap, food cluster, or food bounty. For several areas in Iowa, Minnesota, and Wisconsin, the FAI can be utilized to facilitate a dialogue among the community as to what interventions may be undertaken to address low access to food.

Limitations

This study was limited in a few ways. For one, obtaining quality data has been difficult. States, as well as individual counties, have different reporting protocols. State health officials undertake the tedious task of gathering and then entering data, a process that can have multiple individuals involved at various time periods. Additionally, states and counties collect and synthesize data at time intervals that may or may not coincide with the time used by other states and counties. As such, obtaining data with uniformity and consistency can be challenging. Another limitation was the lack of availability of variables pertaining to initial exposure, doubling time, and trajectory (White et al., 2020). These types of variables were not included in the analyses. Having such measures would provide a richer understanding of how the local context influenced mortality because each state and county underwent different trajectories for virus transmission. Although the data used in this study covered a time frame of nearly one year (i.e., enough time for exposure), there may be cases where the onset or progression of the virus did not begin until the latter part of the year. This has the potential to underestimate mortality counts for a few areas. Third, this study did not account for shelter-in-place (SIP) ordinances. Including this variable would provide additional insight because shelter orders and business closures can limit the transmission of the virus. However, this may be a minor limitation. For example, recent work by Berry et al. (2021) examined a period where SIP policies were enacted and then lifted across the nation. After following 15–17 million smartphone devices at the county-level for several months, these scholars did not find a statistically significant outcome from SIP policies on coronavirus cases or deaths. Additionally, SIP policies affected mobility only during the short term and individuals returned to previous patterns of behavior. Fourth, the GWR regression and the estimated coefficients for a county were influenced by bordering counties. Because the distance of influence is a theoretic construct, a county may encompass too large of a geographic area. Although a county-level analysis can be useful for policy and planning purposes because administrative boundaries are recognized, an examination at a smaller geographic level may better capture local variation and offer greater insight into how community-level socio-ecological factors are associated with mortality. Fifth, this study utilized data that were collected prior to 2020 and this has the potential to yield slightly higher or lower estimates for some of the coefficients. While the values for ecological attributes are less likely to change substantially within the year, social/demographic attributes (e.g., per capita income, percentage aged 65 living alone) may vary due to family changes before and during the pandemic. Lastly, this study examined the association between low access to food for older adults with mortality from the coronavirus by accounting for regional/local variation in socio-ecological attributes. The analytical approach was not to establish a causal connection, and results should not be interpreted in such a manner. Rather, this study sought to contribute to the existing and steadily growing body of literature by providing geographic insights that can be utilized by regional policymakers to devise public health interventions for older adults.

Concluding Remarks

The major strength of this study was the use of GWR in the analyses of the spatial distribution of COVID-19 prevalence for the larger Midwest. Building on the research of numerous scholars who have studied the pandemic, this present study applied their recommendations and extended the present state of knowledge by examining micro-geographies (i.e., regional scope) of coronavirus mortality due to low access to food for older adults within a socio-ecological framework. The findings suggest low access to food exhibited a positive association with mortality and socio-ecological factors also played a significant role. Given the value of utilizing GWR to better identify regional influences, policymakers can use these results to formulate local action plans. More specifically, (a) recognizing the importance of nutrition and food access and (b) involving female-headed households as part of the larger discussion regarding health disparities. Given the likelihood of ongoing coronavirus mutations, the possibility of reduced vaccine efficacy, and the still unknown long-term health impact, the global community can benefit from multiple approaches and initiatives when combating a virus that resulted in significant loss of life and has lasted for over a year.

Supplementary Material

Supplementary data are available at *The Gerontologist* online.

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Conflict of Interest

None declared.

Clarification

The CDC does not take responsibility for the scientific validity or accuracy of methodology, results, statistical analyses, or conclusions presented.

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