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Food Insecurity, Social Vulnerability, and the Impact of COVID-19 on Population Dependent on Public Assistance / SNAP: A Case Study of South Carolina, USA

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Abstract Apart from clinical and epidemiological factors, a multitude of demographic, social, and economic factors also influence the extent of the coronavirus disease prevalence within a population. Consequently, there is ongoing discourse regarding the socio-economic predictors of COVID-19. This study explores the influence of several demographic and socio-economic variables on COVID-19 cases in all 46 counties of South Carolina, USA as of October 18, 2020. To understand the level of association between the demographic and socio-economic variables with the coronavirus disease outcome, we employed a spatial mapping technique in a geographic information system (GIS) to assess social vulnerabilities of populations dependent on public assistance income and spatially compared the distribution with COVID-19 cases across the 46 counties in South Carolina, USA. We find that dependence on food stamps showed a positive but weak correlation to COVID-19. For individual variables, Age and poverty were strongly associated with dependence on public assistance and were determined to be major predictors of COVID-19. Social vulnerability assessment showed an interesting spatial pattern of counties with high prevalence of COVID-19 cases also having high social vulnerabilities. The results complement knowledge about the COVID-19 pandemic beyond clinical and biological risk factors by assessing socio-economic perspectives and determinants. Findings from this study can inform policy decisions on poverty alleviation, public assistance, and food security programs.

Keywords: *food insecurity, COVID-19, social vulnerability, SNAP*

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1. COVID-19 Overview

Coronavirus disease 2019 (COVID-19), which was firstly discovered in Wuhan, China [1,2], swiftly circulated around the world [2,3,4,5], and was declared a pandemic by the world health organization (WHO) on March 11, 2020 [6]. As of February 11, 2020, over 43,000 cases of COVID-19 had been reported in 28 countries [2], with the number of cases increasing to over 3 million in 185 countries, with a mortality rate of greater than 200,000 as of April 28, 2020 [7,8]. As at October18, 2020, world COVID-19 daily case count had risen upwards of over 300,000 with cumulative cases at well over 39 million cases and about 1.2 million deaths had been recorded worldwide [9]. In the US, there had been over 8 million COVID-19 cases and about 218,000 deaths had been recorded. Specific to South Carolina state, over 163,000 COVID-19 cases and about 3,650 deaths have been recorded [10].

The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which is the causal agent of COVID-19 is a single stranded ribonucleic acid (RNA) virus which is similar to the Middle East respiratory syndrome coronavirus (MERS-CoV) and severe acute respiratory syndrome coronavirus (SARS-CoV) [7]. SARS-CoV-2 is commonly spread among humans via respiratory droplets or through direct contact [3,11,12,13]. Typically, some patients start showing symptoms of COVID-19 between 4-5 days but cases of symptoms taking up to 14 days before showing have been reported [14,15]. There have also been reported cases of asymptomatic carriers resulting in probable asymptomatic transmission of COVID-19 [2]. The most reported symptoms of COVID-19 include fever, cough, and fatigue [4,16], with other symptoms such as headache, shortness of breath, loss of smell, taste, and appetite also being reported [15]. Severe symptoms of COVID-19 include acute respiratory distress syndrome (ARDS), sepsis, acute pneumonia, respiratory failure and multiorgan dysfunction [4,17,18], patients with some of these symptoms sometimes require mechanical ventilation and are admitted into the intensive care unit (ICU) [19]. COVID-19 have been observed to affect more adult males with an approximate age of 50 years than females of the same age [16,20,21].

2. Food Insecurity and SNAP

Food insecurity refers to the unavailability or limited supply of nutritionally adequate food in a household, or the inability of a household or people to obtain quality foodstuffs in a socially acceptable way [22,23,24]. Food insecurity may exist alone or sometimes accompanied by moderate to severe hunger. Food insecurity accompanied by moderate hunger is usually characterized by a painful sensation caused by food deprivation, while food insecurity accompanied by severe hunger usually occurs due to children or adults experiencing a regular reduction in food intake or constant hunger [23,25]. Poor intake of protein, vitamins and minerals have been observed in food-insecure households as well as an increase in sugar and saturated fat intake [24,26].

In the United States, about 8% of households were observed to suffer from food insecurity alone, an extra 4% of households were observed to suffer food insecurity coupled with hunger [27]. Several federal food assistance programs have been implemented by the U.S. government to help alleviate food insecurity and to aid Americans earning a low income. One of the major programs implemented to tackle the issue of food insecurity in the U.S. is the supplemental nutrition assistance program (SNAP) formerly known as food stamps. Over the years, SNAP has proven to be successful not just in combating the issue of food insecurity and hunger in the U.S. but also in helping to reduce poverty [28,29]. In 2017, SNAP alone helped in lifting over 3 million people out of poverty [29]. A household without a person with disability or a senior (60 years and above) and earning a monthly income of less than or equal 130% of the poverty guideline is eligible for SNAP benefits [23].

The COVID-19 pandemic has emphasized the need for policies that would help in alleviating food insecurity in the U.S. The families first coronavirus act (FFCRA) which was signed into law on March 18, 2020 have been able to provide billions of dollars in relief or nutrition assistance to households already registered under SNAP whose children receive free or decreased price meals. This helped in tackling food insecurity among school children especially during periods when schools were shut down due to the COVID-19 pandemic [30]. A limitation of FFCRA is that it does not take into consideration families of undocumented immigrants who do not meet the requirements for SNAP or individuals being assisted by the child and adult care food program (CACFP) [30]. The coronavirus aid, relief, and economic security (CARES) act signed into law on March 27, 2020 allocated about $15 billion dollars and $8 billion dollars for SNAP and child nutrition programs, respectively [30,31,32]. The CARES act has been successful in providing relief and food security to family's dependent on it. The public charge rule implemented February 24, 2020, has discouraged a lot of immigrant families from receiving public assistance such as SNAP due to the rule providing grounds for inadmissibility to immigrants who receive one or more public benefits. This rule puts immigrant families at an increased risk for COVID-19 [30].

In this study, we mapped COVID-19 cases at the county scale alongside seven demographic and socio-economic variables that are closely associated with populations dependent on public assistance and food stamps. To examine for possible associations of selected vulnerability indices with COVID-19 cases, we performed a social vulnerability assessment to construct a social vulnerability index for the state of South Carolina, USA at the county scale. We also statistically tested the vulnerability indices against COVID-19 cases using correlation and regression statistics to investigate how those indices predict COVID-19 cases. Our methods and results are elaborated in the following sections.

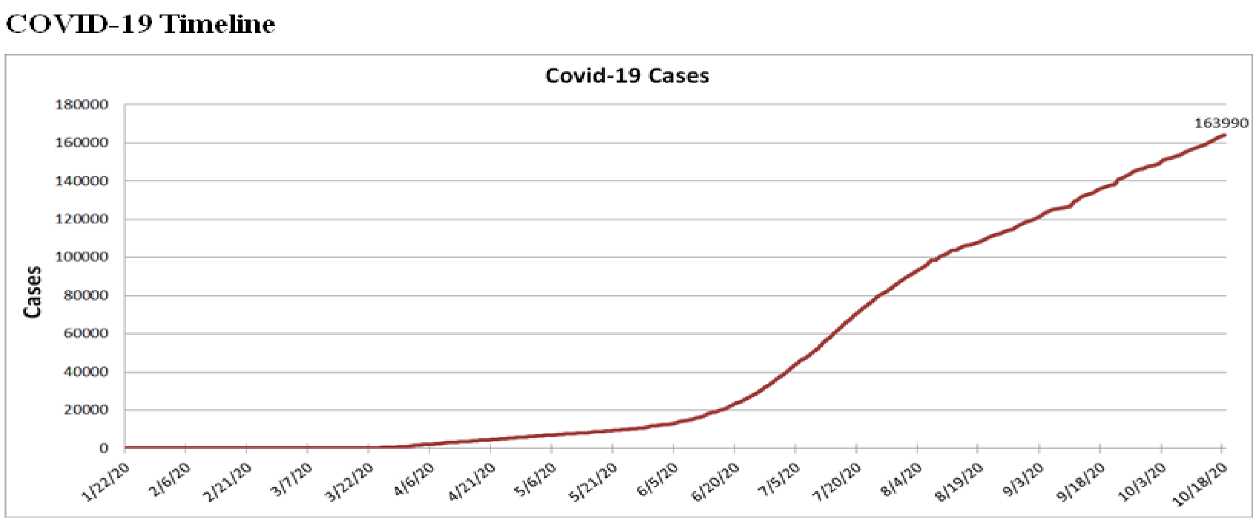

Figure 1. COVID-19 case timeline in South Carolina, USA

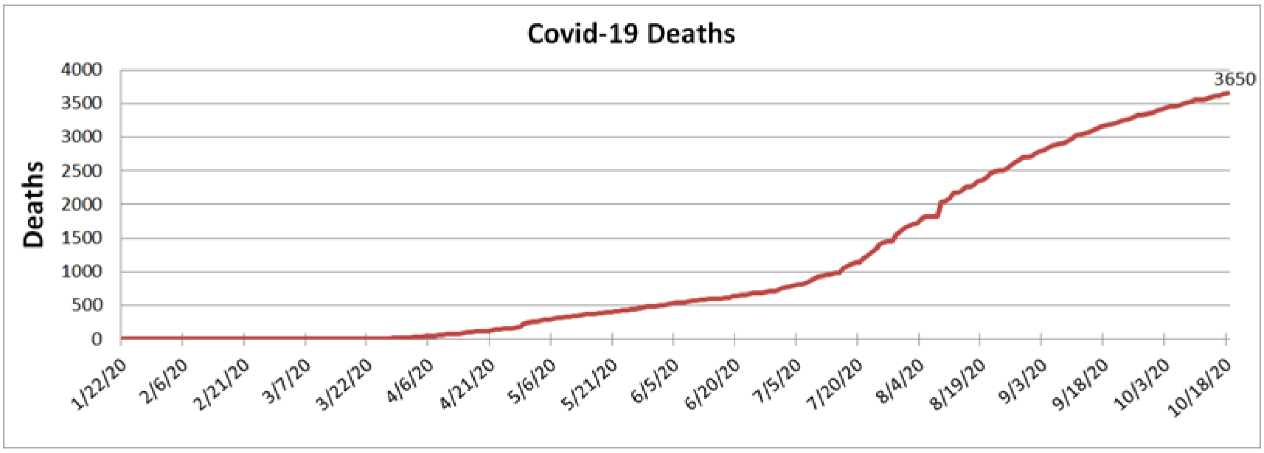

Figure 2. COVID-19 death timeline in South Carolina, USA

3. Data and Methods

Data used in this study was obtained from the US Census Bureau, specifically from the 2018 American Community Survey (ACS). Data obtained include the number of the population in South Carolina, USA that are dependent on public assistance income and/or on food stamps or SNAP. Data was obtained at the county scale for the 46 counties in South Carolina, USA. COVID-19 case data as of October 18, 2020, at the county scale for South Carolina, USA was also obtained from the Centers for Disease Control and Prevention (CDC). ArcGIS Pro, a Geographic Information System and analytical mapping software was used to map out these data to visualize the spatial distribution of the population dependent on public assistance compared with COVID-19 cases (Figure 3). Other factors such as unemployment, disability, absence of health or life insurance, poverty, older population, less educated population, which are closely related to populations dependent on public assistance and SNAP were derived from the US Census Bureau (ACS 2018) and mapped out as well (Figure 4 to Figure 9). To obtain a comprehensive map combining all these factors, Susan Cutters' model [33] was used to construct a social vulnerability index for South Carolina, USA. Specifically, all demographic and socio-economic factors were combined to derive a final social vulnerability index (SoVI) map and then compared with a map of COVID-19 case count (Figure 10a and 10b). Maps of the individual factors compared with COVID-19 cases are shown in the following section.

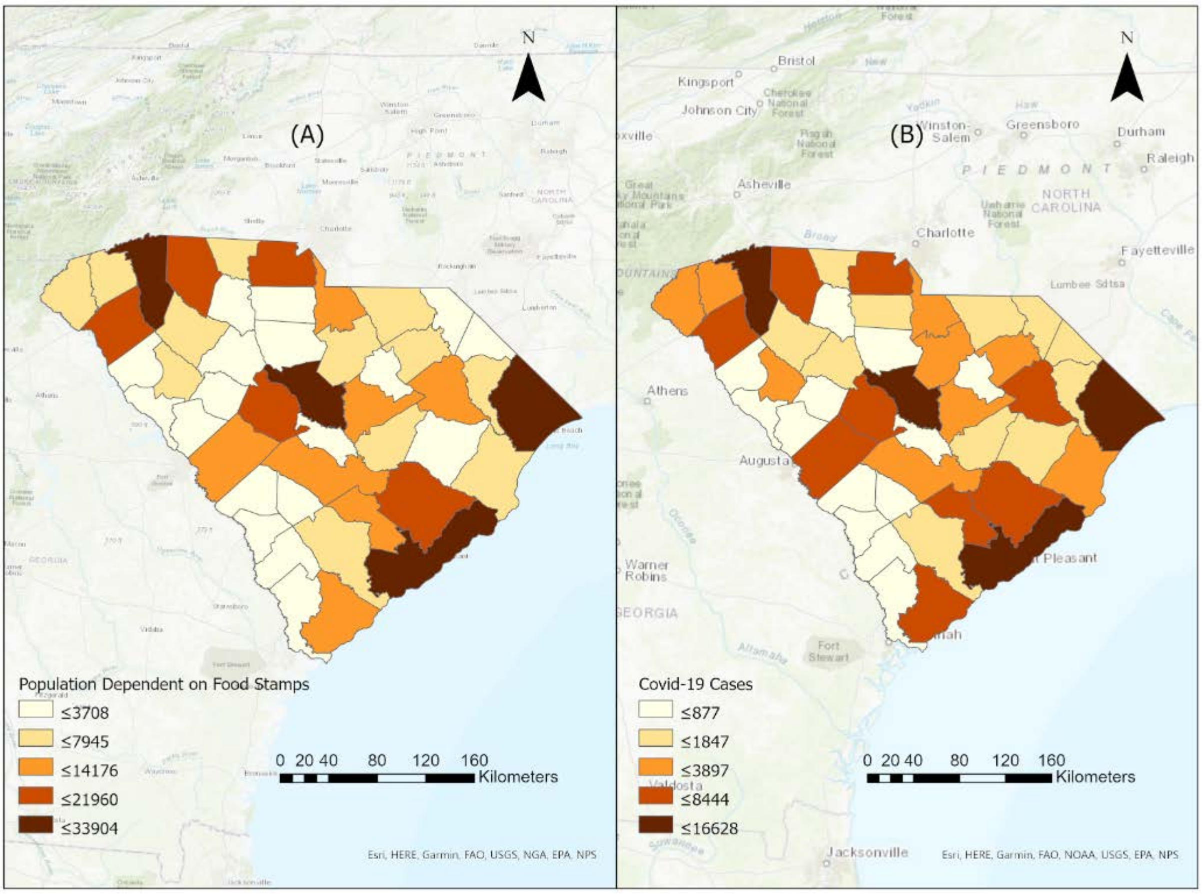

Figure 3. Population dependent on food stamps; distribution of COVID-19 cases

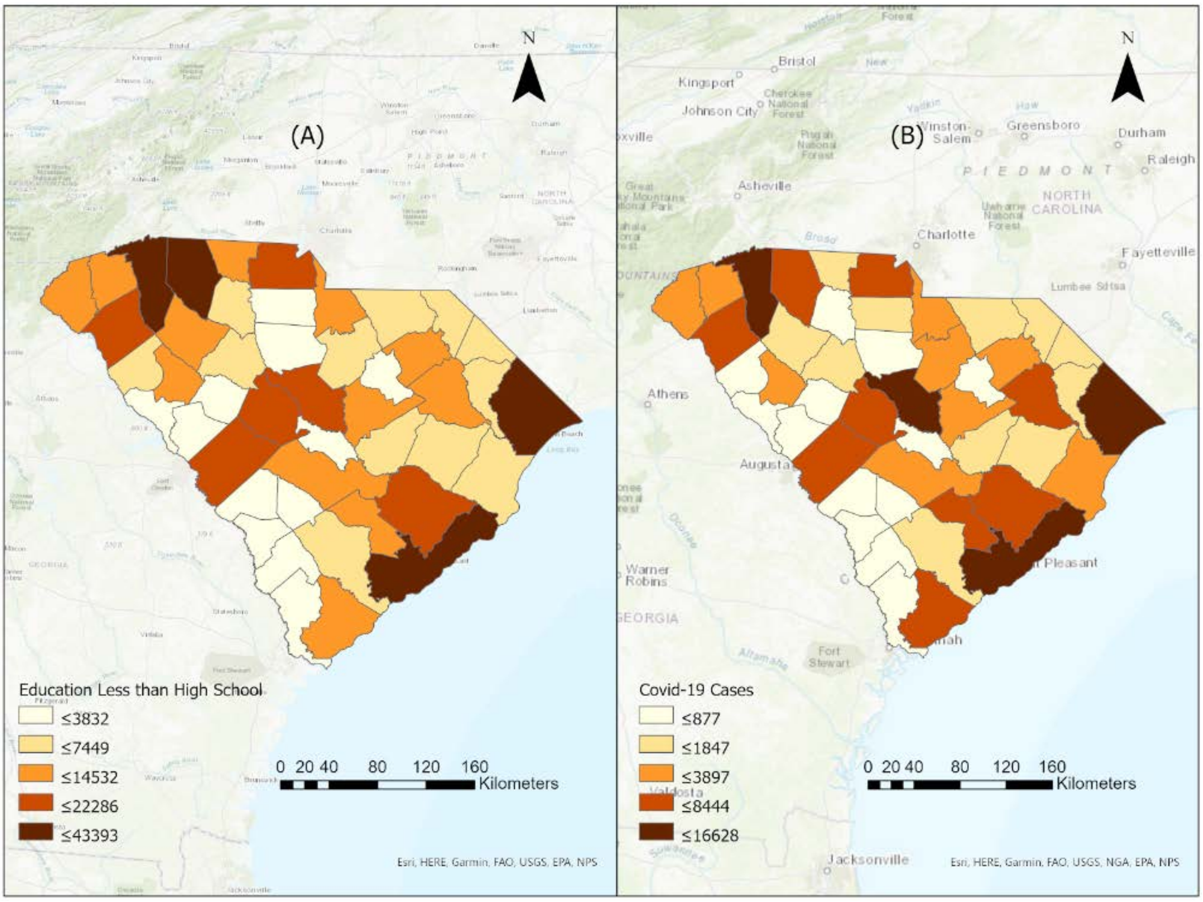

Figure 4. Population with education less than high school; distribution of COVID-19 cases

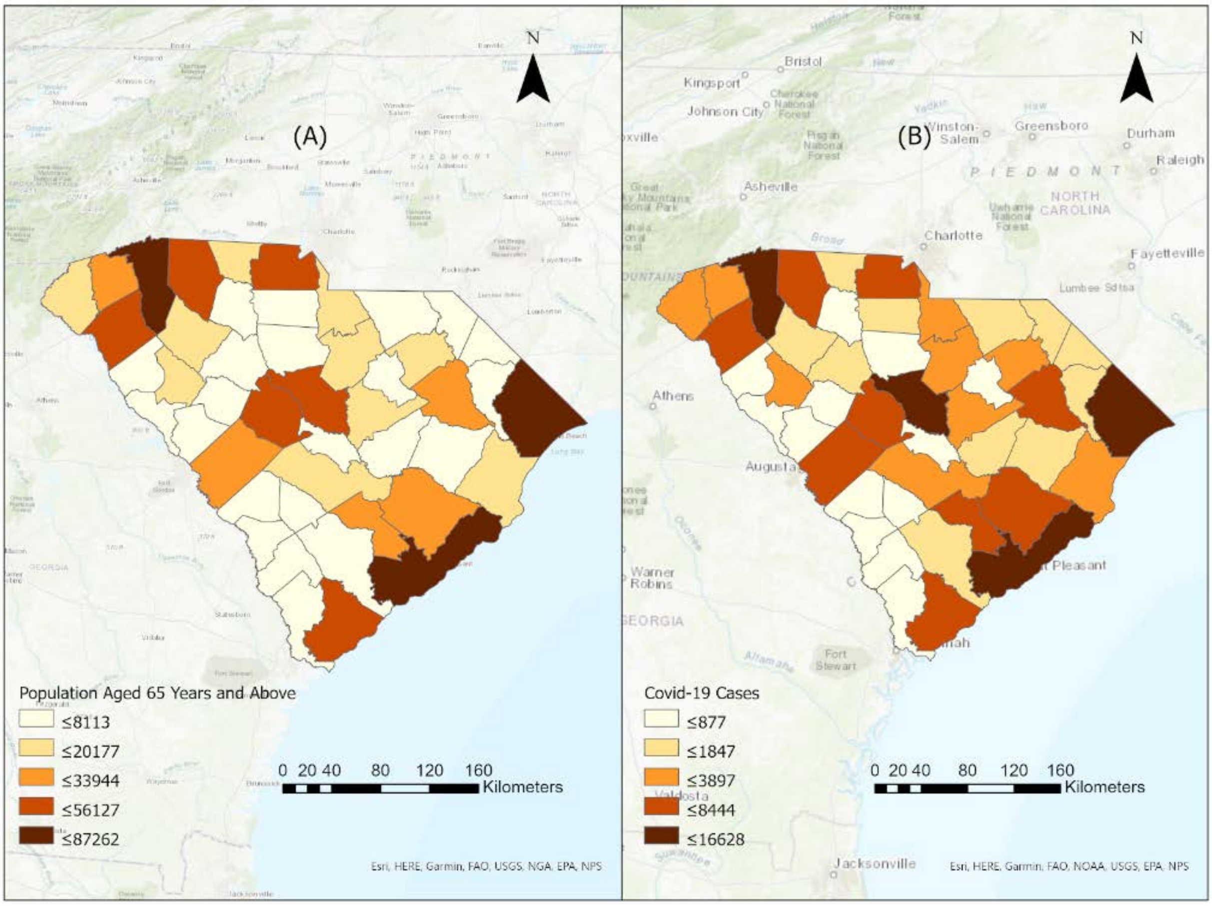

Figure 5. Population aged 65 years and above; distribution of COVID-19 cases

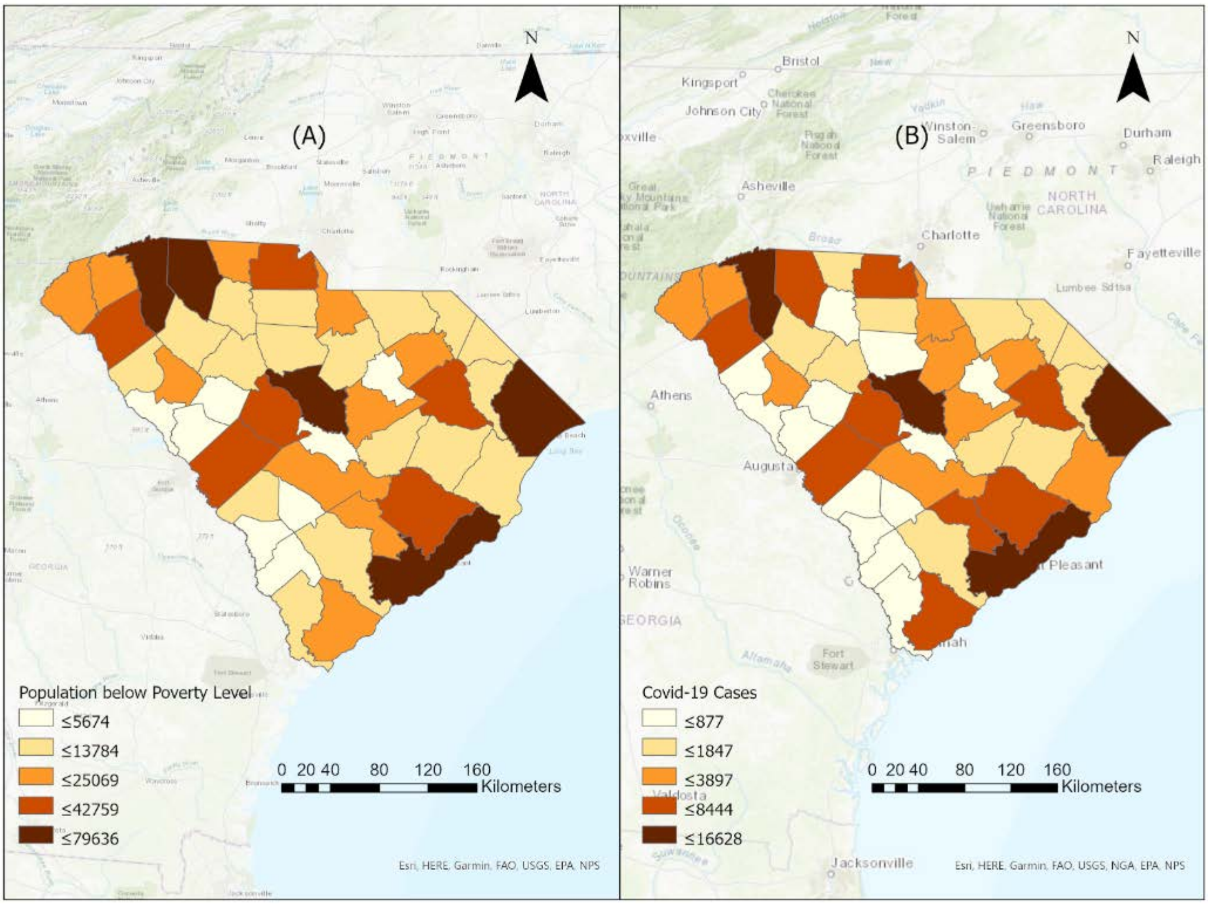

Figure 6. Population below poverty level; distribution of COVID-19 cases

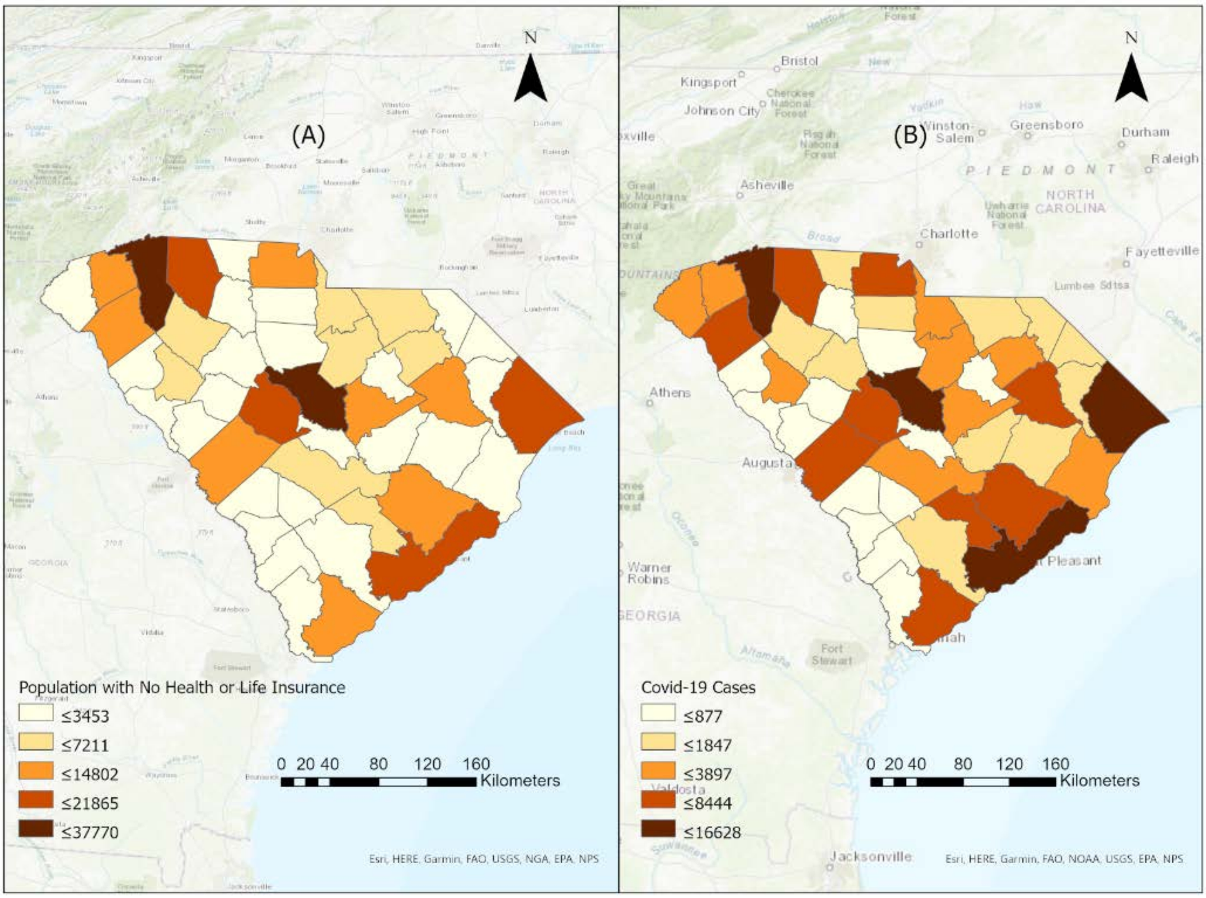

Figure 7. Population with no health or life insurance; distribution of COVID-19 cases

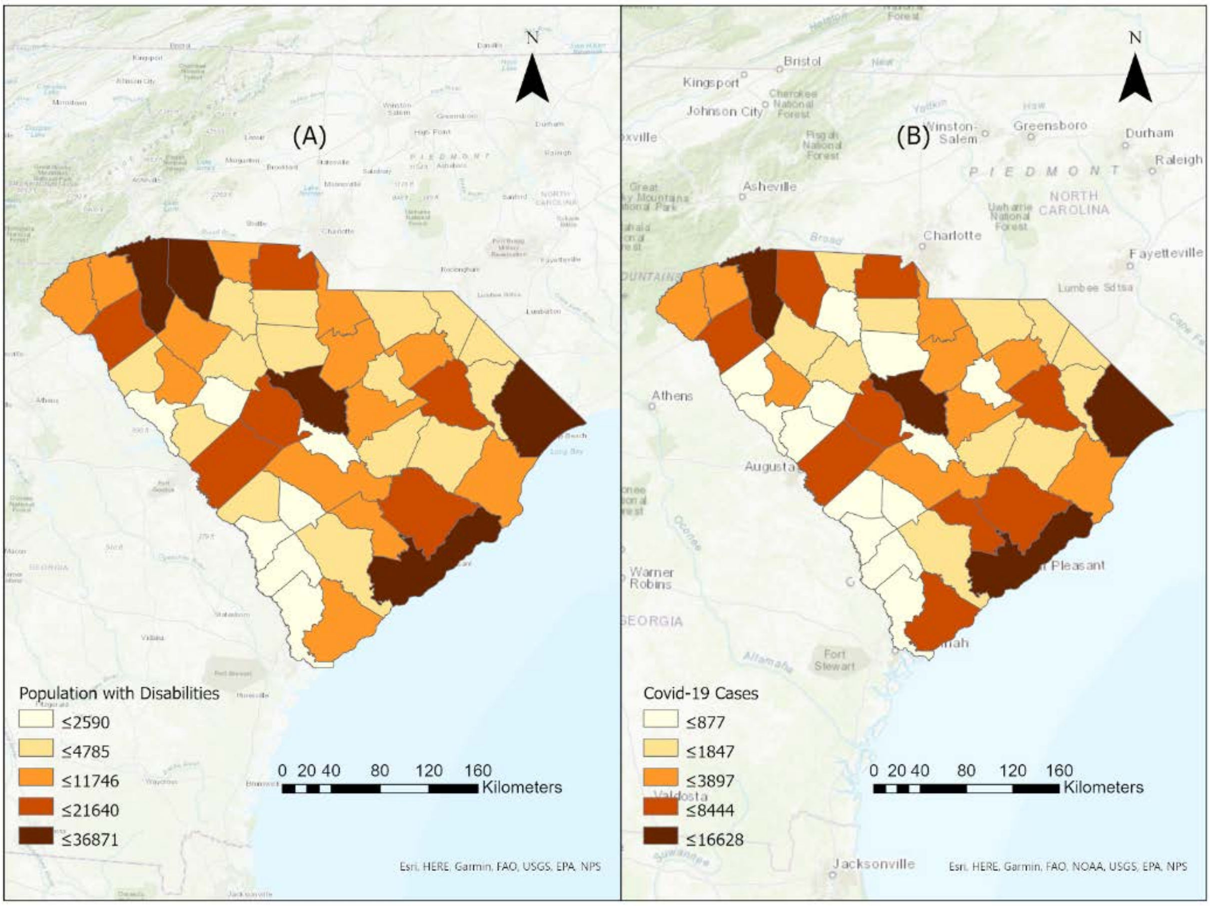

Figure 8. Population with disabilities; distribution of COVID-19 cases

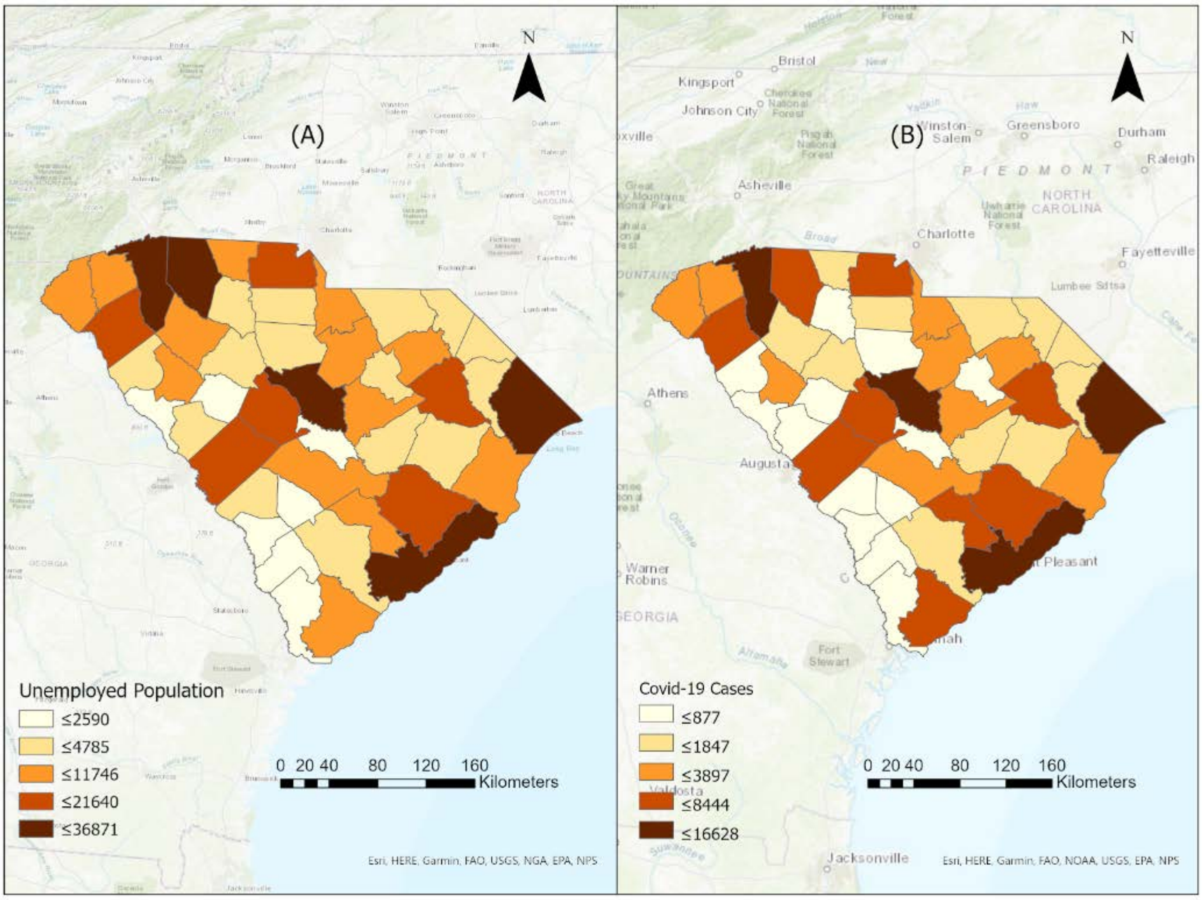

Figure 9. Unemployed population; distribution of COVID-19 cases

4. Results and Discussion

Calculating Social Vulnerability Index (SoVI)

SoVI is an additive model depicting individual factors being added together to derive an index. No weights were assigned to individual factors in our model as we assume that all factors used in this study are equally significant. The added factor scores were normalized using a min-max stretching formulae shown in equation one where $y\alpha$ is the summed value of a factor per county, $ymin$ is the minimum value in the range of a factor and $ymax$ is the maximum value in the range for a factor. Equation one is shown below:

$$x = y\alpha - y\min / y\max - y\min \tag{1}$$

Normalized SoVI scores range from 0 to 1 with 0 being the lowest possible score and 1 being the highest. The additive model equation used to calculate SoVI is shown in equation 2 below, x depicts individual factors added together to derive index s. By using this model, no weight was assigned as all factors were assumed to present equal relevance in the overall vulnerability model:

$$I = x_1 + x_2 + x_3 \;\ldots x_n / N \tag{2}$$

The SoVI map consisting of an addition of seven demographic and socio-economic variables is shown in the map below and compared with COVID-19 cases distribution (Figure 10).

We calculated a correlation matrix consisting of all the variables under study to analyze how they correlate with cases of COVID-19, and to each other. This informed how we set up the nested multiple linear regression model, to determine which variables will be combined into indices and which variables are excluded from the model. Table 1 below shows the correlation matrix of the variables. All the independent variables showed a strong positive correlation with a correlation coefficient 'r' greater than 0.5 meaning that they are significant at $\leq$ 0.05. Poverty showed the strongest positive correlation with COVID-19 cases followed by age, the higher the number of people aged 65 and above, the higher the risk of contracting COVID-19.

Variable 1 is the number of COVID-19 cases, which is the dependent variable determined by the demographic and socioeconomic attributes that we would later test in the linear regression models. Starting at variable 2, which are the independent variables comprising of people older than 65 years, no high school diploma, no insurance, poverty, unemployment, disability and dependence on public assistance and food stamps. The objective is to determine how these demographic and socioeconomic attributes predict COVID-19. It is important to note the strong positive relationship between the independent variables. As the number of unemployed people increases in each county, there is an increase in the percentage of poverty population which consequently leads to a higher percentage of population without insurance, and an increase in dependence on public assistance and food stamps, and vice versa.

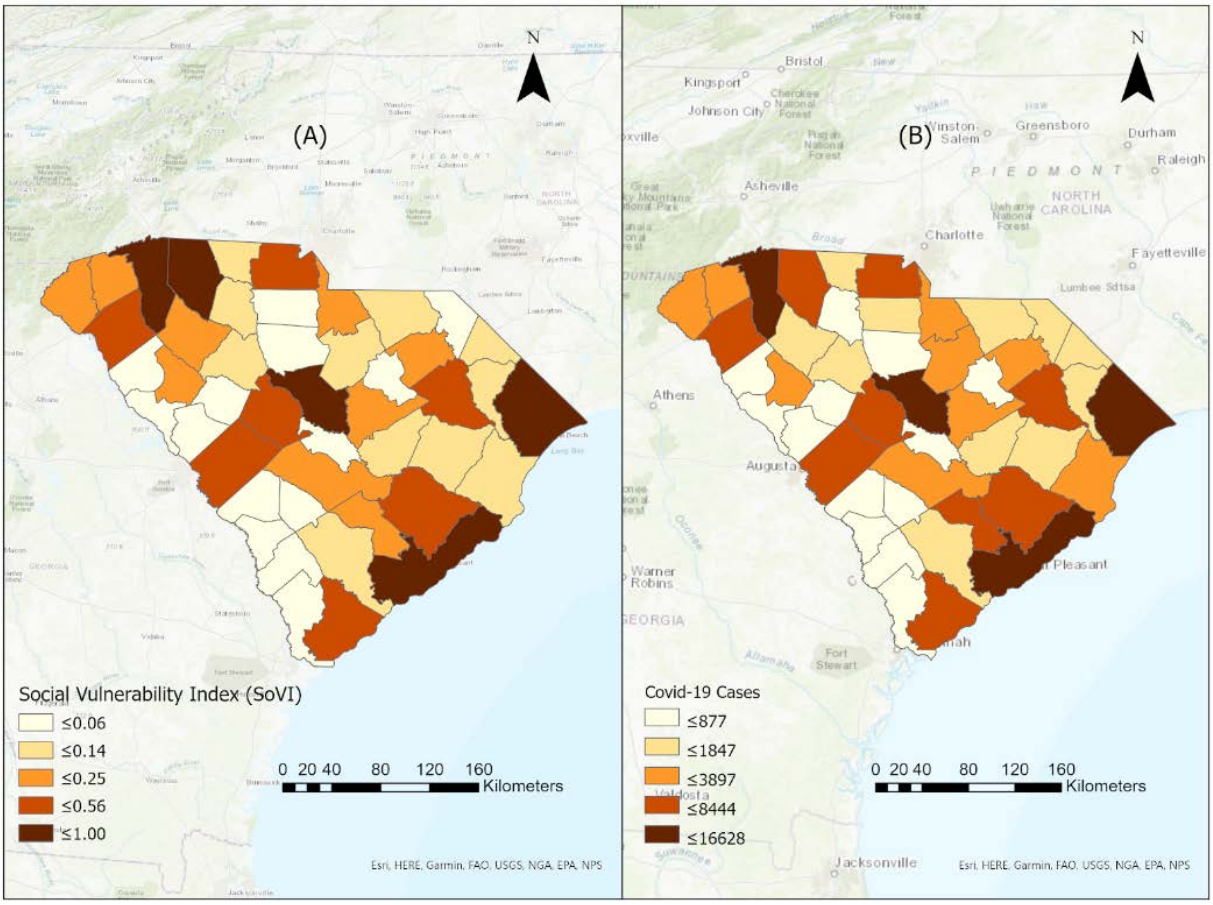

Figure 10. SoVI map; distribution of COVID-19 cases

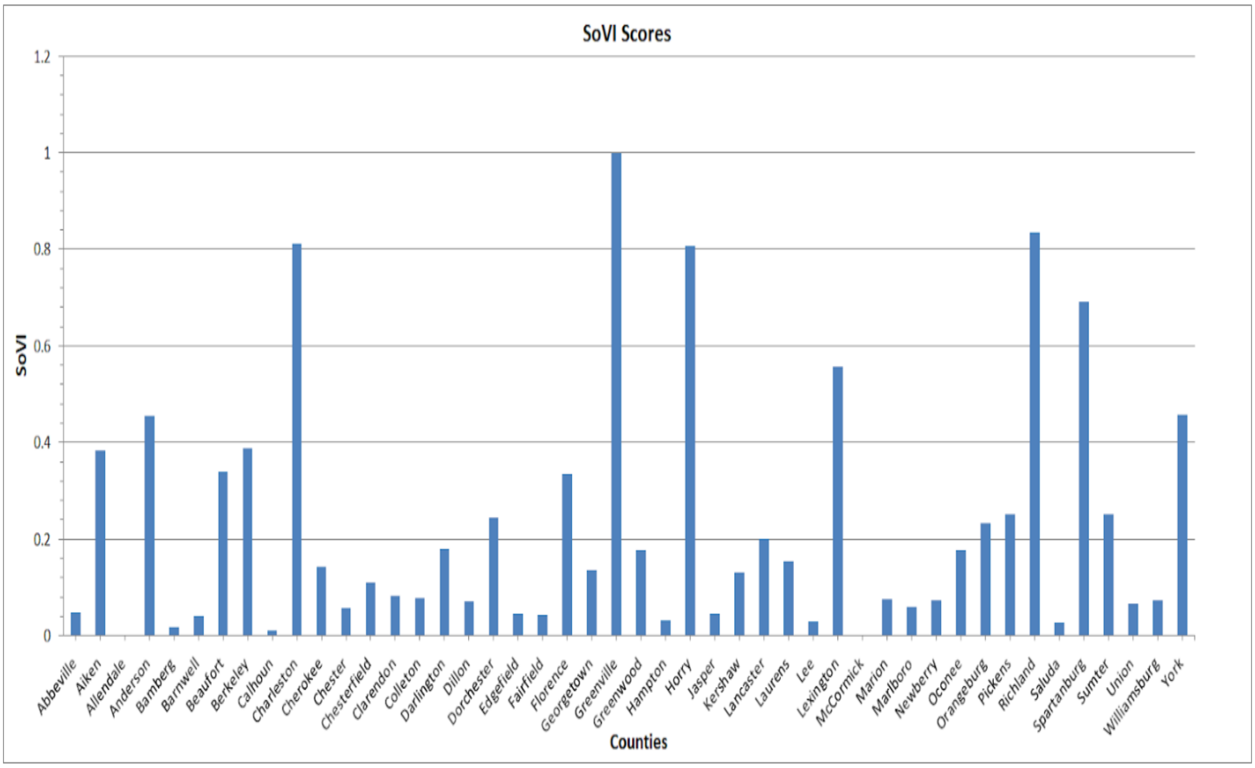

Figure 11. SoVI scores per county

Table 1. Correlation matrix of model variables with range, means, and standard deviations

	1	2	3	4	5	6	7	8
1 Cases								
2 Older than 65	0.94							
3 No High School Diploma	0.90	0.95						
4 No Insurance	0.96	0.90	0.91					
5 Unemployed	0.96	0.94	0.94	0.97				
6 Poverty	0.98	0.96	0.94	0.94	0.98			
7 Disability	0.96	0.94	0.94	0.97	1.00	0.98		
8 Public Assistance	0.96	0.96	0.96	0.95	0.99	0.98	0.99	
Min	259	1506	1441	611	1212	1558	1212	672
Mean	3565	19975	10216	7383	9317	20217	9317	8837
Max	16628	87262	43393	37770	36871	79636	36871	33904

all correlations > .3 are significant at the .05 level or better

The second method of analysis included three nested linear regression models, each with COVID-19 cases as the dependent variable. The independent variables were selected to conceptualize demographic and socioeconomic predictors of COVID-19. The first model consists of demographic information i.e. age (older than 65 years), and number of people in the county with less than a high school diploma. This model tests the level of association between age, educational attainment, and COVID-19. These variables explain a small amount of the variance in COVID-19 prevalence in the counties. Age (b = 0.18) is directly proportional to the rate of COVID-19 and it is significant at .001 level of significance. On the other hand, educational attainment has a very weak but positive relationship (b = 0.02) with the rate of COVID 19 and this relationship appears to be insignificant. Thus, educational attainment as not a major predictor of COVID-19 in South Carolina, USA.

Model 2 introduces socioeconomic attributes like employment status, poverty, and status of insurance. These variables are conceptualized as indicators of the economic status of individuals in the population. These variables, although not significantly affecting the outcome, increased the significance of the impact of educational attainment and the amount of variance explained by the model. No Diploma became significant at .001 level of significance. Employment status showed an inverse relationship that is not significant with COVID-19 (b = -0.08). On the other hand, poverty (b = .02) and insurance status (b = .04) were significant at .001 level of significance and showed a positive relationship with the dependent variable. The economic variables however did not improve the model fit as the adjusted R^2 value remained at 0.98.

Model 3 accounts for disability and dependence on public assistance. Dependence on public assistance has a weak positive relationship with the dependent variable (b

= 0.13) and it is insignificant. Disability on the other hand, does not add anything to the model and therefore it was excluded. Model 4 uses other independent variables to predict who was likely to be more dependent on public assistance. The unemployed showed a significantly strong relationship (b = 0.64) at p < .001 level of significance while age (b = 0.08) was significant at p < .01 level. It is therefore determined that the unemployed are more likely to be dependent on public assistance and food stamps. The overall model fit is 0.99 adjusted R^2.

Table 2. Demographic and Socio-Economic Predictors of COVID-19

	COVID-19		Public Assistance	
Model	**1**	**2**	**3**	**Full Model**
Variable				
Intercept	-174.80	-46.38	-51.90	43.40
	(348.04)	(152)	(150.32)	(266)
Older than 65 years	0.18 ***	0.06 ***	0.05 **	0.08 **
	(0.03)	(0.02)	(0.02) .	(0.03)
No Diploma	0.02	-0.20 ***	-0.21 ***	0.12 .
	(0.08)	(0.03)	(0.04)	(0.06)
Unemployed		-0.08	-0.16 .	0.64 ***
		(0.06)	(0.08)	(0.11)
Poverty		0.17 ***	0.17 ***	0.01
		(0.02)	(0.02)	(0.04)
No Insurance		0.24 ***	0.24 ***	-0.02
		0.04	(0.04)	(0.07)
Disability			-	-
Public Assistance			0.13	-
			(0.09)	
Adjusted R^2	0.98	0.98	0.98	0.99

*** p < .001; ** p < .01; * p < .05; p < .1

The key findings of the research: there are more cases of COVID-19 in counties with a higher number of people older than 65 years. Elderly people are at a high risk of developing serious complications when they contract COVID-19 and are therefore considered the vulnerable population. This high level of susceptibility is attributed to a weakened immune system [34]. Employment status and poverty were introduced into the model to examine how the socioeconomic status of the population predicted their susceptibility to COVID-19. While poverty level showed a weak positive relationship with COVID-19 cases, it is evident that the relationship is significant and thus explains the higher rate of COVID-19 cases in counties with higher numbers of the population below the poverty line. This result is supported by [35] who found that economically disadvantaged groups are more vulnerable to the novel coronavirus than their wealthier counterparts. Conversely, unemployment showed a negative relationship with COVID-19 cases.

5. Conclusion

This study mapped out factors that determined food insecurity, and social vulnerabilities among the population in South Carolina, USA using Susan Cutters SoVI [33,36]. The combined socio-economic factors compared with the COVID-19 case count map (as of October 18, 2020) revealed that most of the counties with a high rate of COVID-19 cases were also socially vulnerable. Age and poverty were strongly associated with dependence on public assistance and were determined to be major predictors of COVID-19. The results from this study can help inform agencies concerned for developing public assistance programs and providing relief assistance to counties that are most vulnerable socio-economically. These counties should be properly funded to alleviate acute dependencies on public assistance. In general, implementing additional public assistance programs and increasing access to already introduced relief programs would help in reducing food insecurity thereby making individuals less vulnerable to the COVID-19 pandemic.

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Authors Contribution

All authors performed substantial contributions to conception and design of the article and to acquisition, analysis, and interpretation of data. All authors reviewed the manuscript for important intellectual content and approved the final version for publication. All authors agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflicts of Interest

The authors have no conflicts of interest.

Acknowledgements

This article is dedicated to all medical personnel around the globe who are in the front line of the COVID-19 pandemic.

Abbreviations

SARS-CoV-2, severe acute respiratory syndrome coronavirus 2;
MERS-CoV, middle east respiratory syndrome coronavirus;
COVID-19, coronavirus disease 2019;
SNAP, supplemental nutrition assistance program;
FFCRA, families first coronavirus act;
CARES, coronavirus aid, relief, and economic security;
CACFP, child and adult care food program;
SoVI, social vulnerability index;

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