Structural Racism in the Covid-19 Pandemic

A Risk Analysis of the Contiguous United States | Grace Anderson, Introduction to GIS, ENV 107, Spring 2020

Background

The coronavirus pandemic has been the principle topic of conversation across the entire world since early 2020. Although the exact date that Covid-19 arrived in the United States is debated, the country has been vigorously reacting since at least early March. Covid-19 is an incredibly contagious and lethal coronavirus. The spread of which is exacerbated by asymptomatic carriers (Yu and Yang, 2020).

Covid-19 can cause numerous dangerous symptoms such as fever, shortness of breath, and dry cough. More serious cases can require hospitalization. The best way to avoid spreading or contracting Covid-19 is to socially distance, even when asymptomatic.

For these reasons I decided the most important variables for analysis would be proximity to hospitals, population density, a grade on social distancing measures, and current Covid-19 case numbers.

As of May 2nd, 2020 there were over a million coronavirus cases and over 60,000 deaths in the United States alone (CDC, 2020). Schools, stores, and restaurants have largely been shut down across the United States but are quickly reopening.

This project uses GIS to identify the counties in the contiguous United States that are most at risk for deadly outbreaks of Covid-19 based on spatial data analysis. I will compare the most at-risk counties to racial population statistics in the area. This will help determine if counties with higher percentages of people of color are at an increased risk for coronavirus.

Methodology

I used ArcMap version 10.7.1 to analyze risk. I defined the projection to be the North American Equidistant Conic for all layers because it preserves area.

I converted the hospitals layer to raster, used the Euclidean distance tool to analyze distance from hospitals, and reclassified with break values of 2, 10, 25, and 50 miles. 2 miles corresponds to a risk of 1, and all points over 50 miles correspond to a risk of 5 (Figure 1). Finally zonal statistics was used to calculate the mean distance from hospitals risk for each county (Figure 2).

Proximity to Hospitals Risk

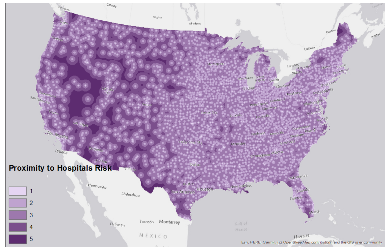

Figure 1: Proximity to Hospitals

Mean Hospital Proximity Risk by County

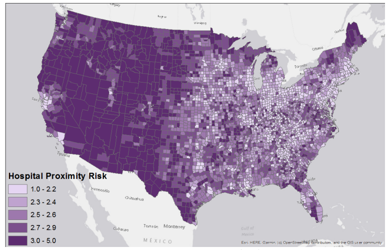

Figure 2: Proximity to Hospitals by County

A new field was created in the USA Counties layer for population density by county. It was given a new field for risk factor from 1-5 generated using quintiles (Figure 3). The same procedure was done for the Covid-19 cases and social distancing layers (Figures 4 and 5).

Comparative Population Density Risk

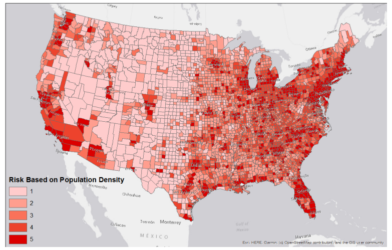

Figure 3: Population Density

Coronavirus Cases Per Capita Risk

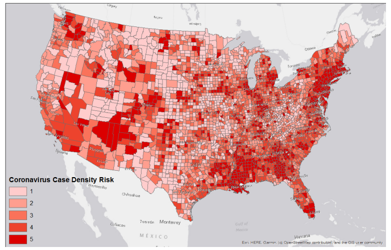

Figure 4: Coronavirus Cases Per Capita

Social Distancing Grade Risk

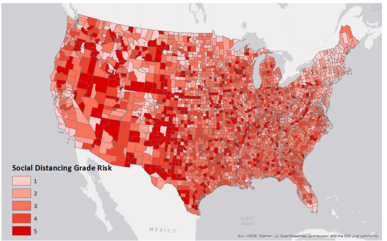

Figure 5: Social Distancing Grade

All layers were joined to USA Counties using FIPS codes. A field was created for mean total risk. The risk factors for each layer were averaged. Final Risk is depicted by quintile. (Figure 6).

The percent of the population that is people of color, and the percent that is Black was calculated for the 8 highest and lowest risk counties. The table to Excel tool exported the data. The AutoSum mean feature was used to calculate the mean percentage of people of color and Black people for the sixteen counties.

Results

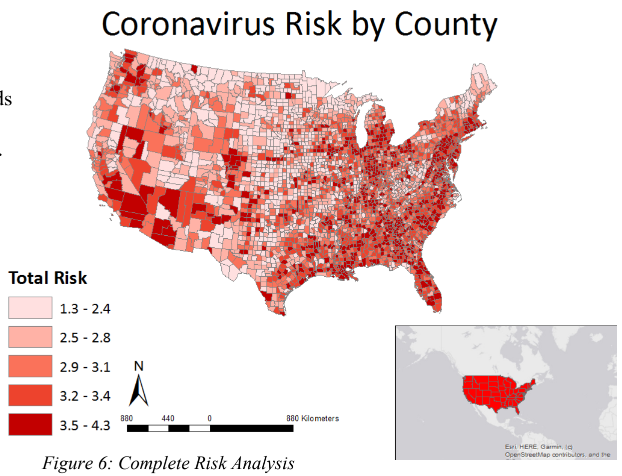

Figure 6: Complete Risk Analysis

The total risk analysis map shows that there is more risk near the coasts than in the middle of the country.

Analysis of the top 8 and bottom 8 counties at risk reveals a strong racial disparity. For the counties least at risk (Table 1) the mean percentage people of color is 5.5428% and the mean percentage of Black people is 0.8303%. The counties most at risk (Table 2) had 23.9113% and 13.9208% respectably.

Therefore high-risk counties average 4.3 times more people of color and 16.8 times more Black people.

Table 1: Lowest Risk Counties

Town, State	Risk	Percent POC	Percent Black
Lac qui Parle, MN	1.2899	2.3695%	0.2342%
Collingsworth, TX	1.3706	23.5198%	4.3834%
Ness, KS	1.3789	4.4416%	0.5793%
Boyd, NE	1.3955	3.0491%	0.0476%
Comanche, KS	1.3956	3.4902%	0.3173%
Kingsbury, SD	1.3978	1.9425%	0.1360%
Decatur, KS	1.4029	2.6342%	0.5741%
Perkins, NE	1.4031	2.8956%	0.3704%
	Mean:	5.5428%	0.8303%

Table 2: Highest Risk Counties

Town, State	Risk	Percent POC	Percent Black
Jackson, IN	4.1213	5.5031%	0.6655%
Harrisonburg, VA	4.1250	21.5542%	6.3622%
Hall, NE	4.1316	17.3938%	1.7455%
Sumter, FL	4.1398	13.4093%	9.6575%
Walker, TX	4.1404	32.9350%	22.4827%
Crittenden, AR	4.1515	53.9389%	51.1787%
Potter, TX	4.1833	30.1884%	10.2128%
Warren, KY	4.2637	16.3676%	9.0613%
	Mean:	23.9113%	13.9208%

Discussion

This risk analysis shows that there is a clear correlation between higher coronavirus risk and a higher percentage of people of color. This is not a surprise considering the long history of structural racism in the United States. One reason for such a strong correlation is that one of the main risk factors for exposure to coronavirus is a high population density Lower income neighborhoods tend to have higher population densities. People of color tend to be less wealthy than whites because of historical structural racism. These results are not surprising and seem to align with current media criticism that people of color at are much higher risk of dying of coronavirus.

In the short term these results would be useful for policy makers to see which counties are likely to be the most devastated by the pandemic. This way resources can be allocated to the areas that need them most. In the long term these results will be useful for identifying yet another important example of structural racism.

In the future I would like to build a more robust analysis that accounts for more variables. Some of these variables are discussed in the limitations section. I think an analysis by state could be useful as well. This could be used by policy makers to decide which states are at the lowest risk of coronavirus and could therefore reopen soonest.

Limitations

There are two main limitations to this analysis. The primary one is that the coronavirus case data changes constantly. This makes sense because the counties most at risk change every day based on how they handle the outbreak. The second limitation is that there are many factors that influence the spread of disease. Examples of some variables that were unaccounted for are access to clean water for hand washing, wealth to afford social distancing (more likely to be able to work from home, can hire others to do grocery shopping, more money to treat ailments, etc.), and distribution of immunocompromised individuals and the elderly. There are many other variables that dictate the spread of disease, and the knowledge of which variables are most important changes every day.

Data Sources and References:

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Covid-19 Cases V2, May 2, 2020, published by Johns Hopkins online link, accessed May 2, 2020.
County by County Grade for Social Distancing Explorer, April 2020, published by Unacast online link, accessed April 2020.
Definitive Healthcare: USA Hospital Beds, March 2020, published by Definitive Healthcare online link, accessed May 1, 2020.

Projection: North American Equidistant Conic