

## Mapping the ChristianaCare response to COVID-19:

### Clinical insights from the Value Institute's Geospatial Analytics Core

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#### Abstract

**Introduction:** COVID-19 exemplifies the spatial nature of infectious disease in both its mechanism of transmission and the community-level conditions that facilitate its spread. With a long history of use for infectious disease applications, maps and geographic information systems (GIS) have been widely used in recent months for surveillance and risk prediction mapping. The Value Institute's Geospatial Analytics Core applied spatial methodologies to inform ChristianaCare's pandemic response around telehealth, testing disparities, and test site prioritization. **Methods:** Descriptive data related to disparities in telehealth utilization were mapped to identify areas in which intervention is needed to increase telehealth access. Cluster detection methodology was used to identify "hot" and "cold" spots for COVID-19 testing by place and race across New Castle County, DE. A composite risk score was created to prioritize communities for testing sites. All analyses took place in Delaware from March-June 2020, with particular emphasis on New Castle County. **Results:** Parts of northeastern New Castle County and western Sussex County were highlighted for intervention to increase broadband internet access for telehealth utilization. "Cold" spots for COVID-19 testing were found in New Castle County, indicating neighborhoods in which testing levels were significantly lower than expected. Data for testing levels, disease positivity, and socioeconomic risk factors were used to identify communities in northeastern New Castle County that warranted new test sites to mitigate disease spread. **Public Health Implications:** Geospatial methodologies can be used to combine electronic health record data and population-level spatial data for pandemic response efforts. This allows health systems to confidently identify areas of need while mitigating disparities in resource allocation.

#### Background

COVID-19 exemplifies the spatial nature of infectious disease in both its mechanism of transmission and the community-level conditions that facilitate its spread. Among individuals, COVID-19 is transmitted via respiratory droplets spread in close contact to others and through aerosolized transport.<sup>1</sup> Across neighborhoods and counties, the disease has spread more rapidly where high residential density, large proportions of residents who work in essential service occupations, and low socioeconomic status (SES) undermine people's capacity to practice social distancing.<sup>2,3</sup> Data from across the U.S. show that Black and Hispanic/Latino/a populations have borne the brunt of the pandemic.<sup>4</sup> Although further research is needed to understand this disparity, the emerging evidence strongly points to structural inequalities that place these racial and ethnic groups at greater health, economic, and social risk than their White counterparts.<sup>5</sup> That is, longstanding racist and other discriminatory policies have contributed to inadequate health care access, poor housing and occupational conditions, and a general lack of financial safety nets for racial and ethnic minority groups,<sup>6-8</sup> which is today manifesting as higher rates of COVID-19 morbidity and mortality.<sup>9,10</sup>

The spatial nature of COVID-19 can be understood by utilizing geographic information systems (GIS) to create maps and inform tracking and response efforts. With a long history of use for infectious disease applications, GIS have been used in recent months for COVID-19 surveillance, risk prediction mapping, and analyses of mobility data to track social distancing.<sup>3,11</sup>

The Value Institute's Geospatial Analytics Core has applied spatial methodologies to inform ChristianaCare's response to the current pandemic. Established in 2017, the Geospatial Analytics Core uses GIS and inferential spatial statistics to not only create maps, but to 'go beyond the map' and estimate relationships between exposures that vary spatially and important health outcomes. Within health care, these methods can be used to segment patient populations by geography, measure proximity to health care providers, and study environmental determinants of health such as air quality or access to healthy food.

Before the pandemic, the Geospatial Analytics Core at ChristianaCare was developed primarily to study noncommunicable chronic conditions. However, during this "all hands on deck" moment, we quickly pivoted to apply spatial methodologies to three chief priorities during the early months of the COVID pandemic. First, as providers adopt telehealth to ensure continuation of care delivery while allowing patients to social distance, additional resources may be needed to serve areas with limited broadband internet access. Second, there was a need to examine potential spatial or racial disparities in testing by examining "cold spots," or areas where testing is significantly lower than expected, particularly in predominant minority neighborhoods. Finally, ChristianaCare and New Castle County (NCC) were tasked with identifying communities for immediate prioritization during an expanded COVID-19 testing effort that commenced in June 2020.

## **Methods**

### **Telehealth**

Descriptive data related to disparities in telehealth access were obtained for Delaware census tracts from the U.S. Census Bureau and the Centers for Disease Control and Prevention (CDC). These included the percentage of households lacking broadband internet access,<sup>12</sup> the percentage racial minority population,<sup>12</sup> and the CDC's socioeconomic vulnerability ranking. The socioeconomic vulnerability ranking is a domain within the CDC's Social Vulnerability Index that ranks census tracts within states for vulnerability based on poverty, unemployment, income, and education.<sup>13</sup> These three measures were depicted as choropleth maps using natural breaks classification, a method that minimizes variation within each class. The maps were compared side-by-side to identify geographic trends suggesting barriers to telehealth services.

### **Disparities in testing access**

We used cluster detection methodology to identify potential racial disparities in testing levels by census tract for New Castle County adults. Areas with testing levels significantly higher or lower than the rest of the county were considered "hot" and "cold" spots, respectively. A hot or cold spot, known as a cluster, is a set of contiguous geographic units in which their combined rates represent a large departure from the average across the map area. SaTScan<sup>TM</sup>, a common cluster detection software, was used to determine if testing was spread evenly across New Castle County after accounting for underlying population size.<sup>14</sup> These analyses were also adjusted for the race of tested individuals, meaning that any clusters were assessed relative to countywide testing

levels by race. SaTScan methodology assumes that test counts by race are distributed by census tract proportional to each tract's share of the county population by racial group. The program uses a likelihood ratio statistic to gauge the discrepancy between observed and expected test counts and generates a p-value using Monte Carlo simulations. We performed cluster detection to identify hot or cold spots for testing using a dataset of people who received COVID-19 testing from ChristianaCare between March 16<sup>th</sup>-April 16<sup>th</sup> ( $N=5421$ ).

### **Identifying areas for testing prioritization**

In order to consider multiple indicators of COVID-19 morbidity and mortality that reflect greater need for testing, we calculated a census tract-level prioritization score that incorporated (1) testing levels, (2) positivity rates, and (3) socioeconomic risk factors using data from ChristianaCare, the U.S. Census Bureau, and the CDC.

#### ***Testing levels***

We calculated the proportion of tested adults at the census tract level using a dataset of adult New Castle County, DE residents who received COVID-19 testing from ChristianaCare between March 16<sup>th</sup> and May 6<sup>th</sup> ( $N=9,111$ ). Duplicate records were removed so that unique patients were represented only once in the testing dataset. Records were geocoded according to their home address (i.e., represented as a point on a map) and aggregated to the census tracts in which they reside. Testing levels were calculated as the number of tests per 100,000 adult residents. The population denominator data were obtained from 2018 U.S. Census Bureau estimates.<sup>12</sup>

#### ***Positivity levels***

Positivity levels by census tract were calculated using the same dataset of adult New Castle County residents tested by ChristianaCare from March 16<sup>th</sup>-May 6<sup>th</sup>. Positivity levels were calculated as the percentage of positive test results among all tested adults for each census tract.

#### ***Socioeconomic risk factors***

A social risk composite score was calculated using demographic and socioeconomic variables to assess risk of rapid transmission. Our risk score components included percentage racial or ethnic minority population<sup>12</sup>; percentage of people employed in service occupations, such as health care support, protective services, and food preparation<sup>12</sup>; percentage of households with more than one person per room (a common measure of overcrowding)<sup>12</sup>; and the CDC's socioeconomic vulnerability ranking referenced above. The distributions of each variable were examined and used to assign a score of 2 (high risk), 1 (moderate risk), or 0 (low risk) based on census tracts' values for each. We weighted our score to reflect greater risk for census tracts that had both high racial/ethnic minority populations and socioeconomic vulnerability. The final social risk score ranged from 0-11, with higher scores indicating greater risk.

#### ***Prioritization criteria***

Census tracts were prioritized for testing by first flagging those with positivity rates >15% based on World Health Organization (WHO) guidance stating that positivity rates >10% suggest under-testing.<sup>15</sup> Next, these tracts were filtered to include only those with social risk scores  $\geq 5$  (above the median value). The final list of census tracts was rank-ordered from lowest to highest

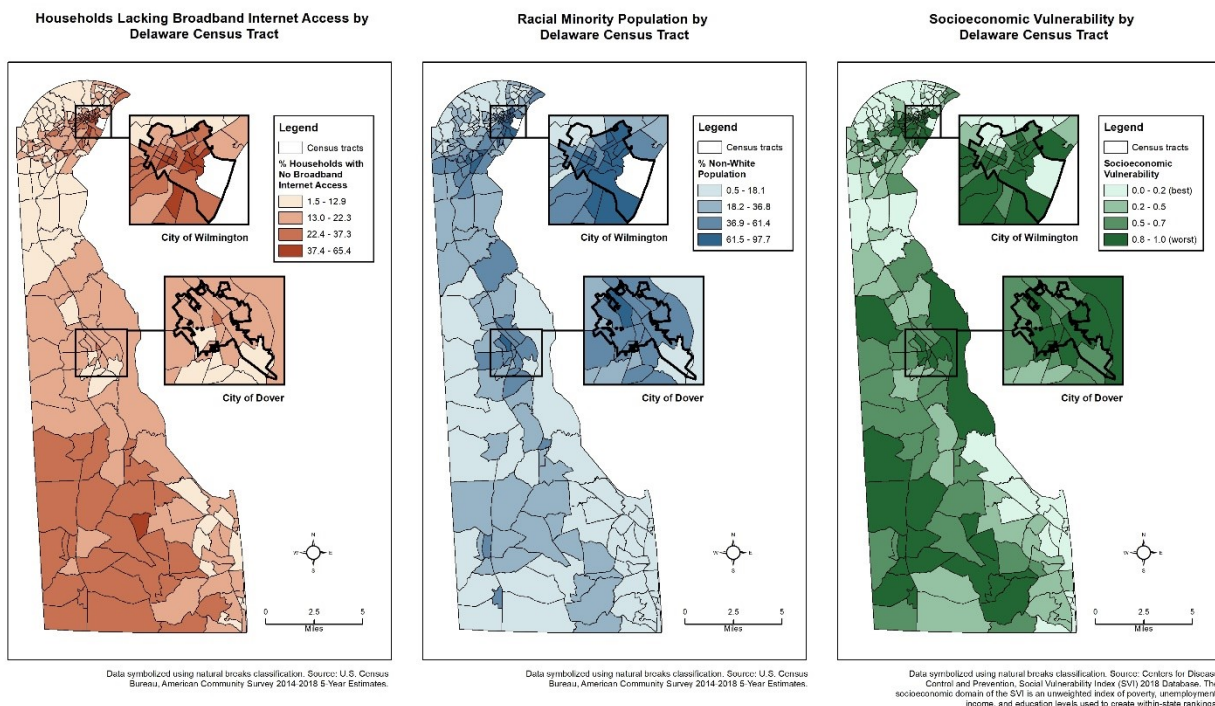
testing levels to identify the top 30 tracts for prioritization, based on the NCC capacity to conduct testing in June 2020.

## Results

### Telehealth

Figure 1 depicts choropleth maps of broadband internet access, racial minority populations, and socioeconomic vulnerability for New Castle County. The percentage of households lacking access to broadband internet was elevated in northeastern New Castle County, stretching from Claymont to southeastern Newark. In some eastern and south-central Wilmington neighborhoods, 37-65% of households lacked broadband access. Kent and Sussex counties had lower levels of broadband access compared to northwestern and southern New Castle County. Broadband access was relatively even across Kent County, but lack of broadband was more pronounced in southwestern Sussex County. These trends generally overlapped with data for racial minority populations and socioeconomic vulnerability, most prominently in northeastern New Castle County. This suggests inequities in telehealth access that could create and widen health disparities during the COVID-19 pandemic unless interventions are developed to increase access to broadband internet and technology.

Figure 1. Choropleth maps of broadband internet access, racial minority populations, and socioeconomic vulnerability for New Castle County.

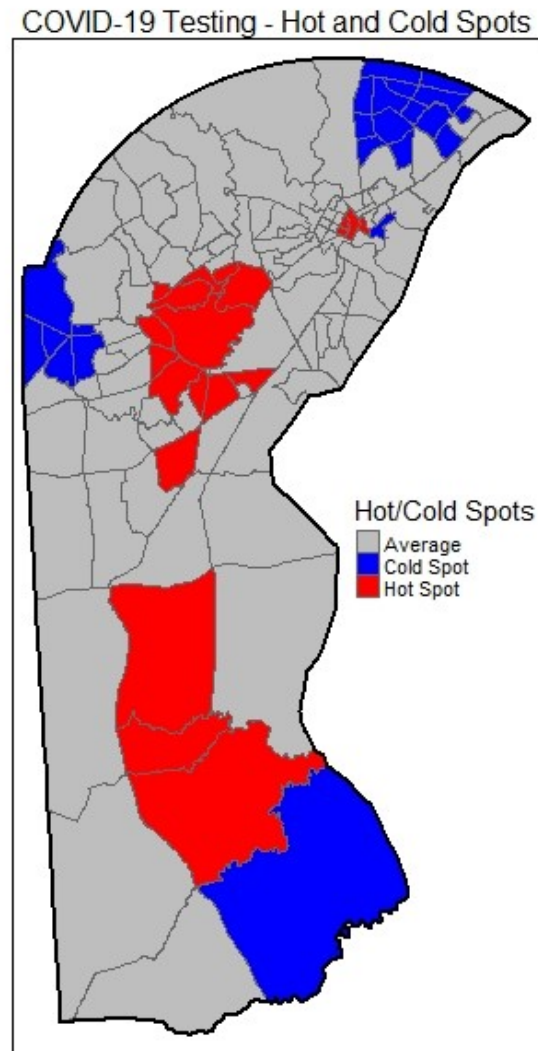


### Disparities in testing access

Using geocoded data for unique tested adults in New Castle County, 5,421 tests were conducted from March 16-April 16. Cluster detection found four statistically significant testing cold spots in southern Newark, north Wilmington/Claymont, east Wilmington's Riverside neighborhood,

and northeastern Smyrna (p-values <0.001) (see Figure 2). Special attention was paid to Riverside and northeast Smyrna because they have large minority communities. The adult populations of Riverside and northeast Smyrna are 70% and 44% African American, respectively.<sup>12</sup> Overall adult testing rates in Riverside and northeast Smyrna were 44% and 11%, respectively, of what would be expected if testing was distributed proportionally by population and adjusting for race. In Riverside, the overall testing levels were slightly more than half (7/1000 adults) of what were observed for New Castle County (12.5/1000 adults).

Figure 2. Testing Cold Spots

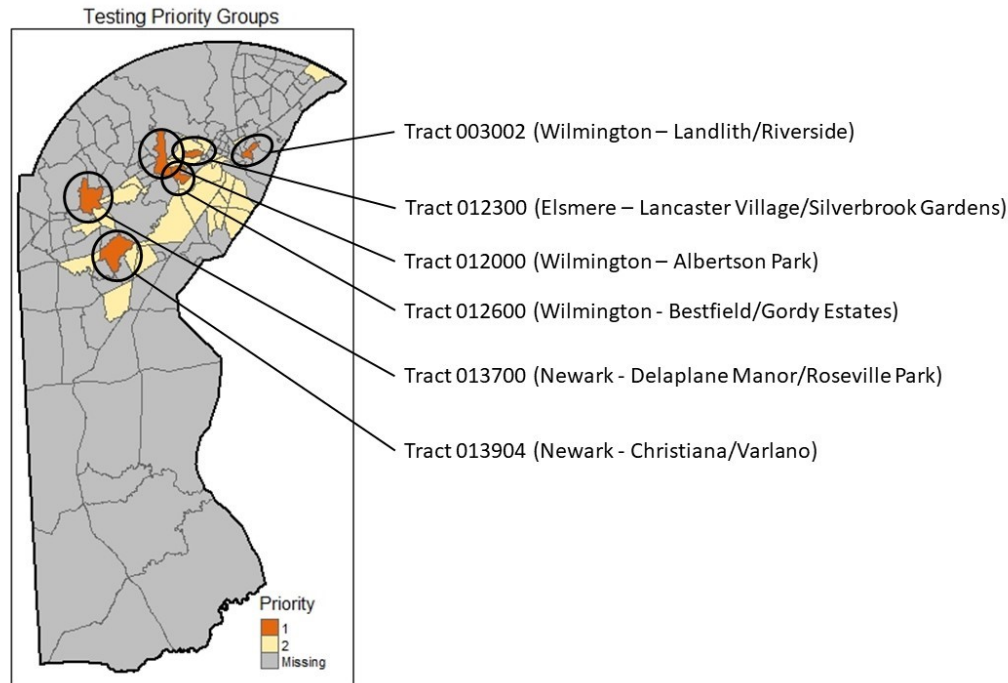


### Identifying areas for testing prioritization

We identified six census tracts for first priority testing in early June and another 24 for second priority testing in mid-June (Figure 3). The first priority group included neighborhoods in north-central New Castle County that ranged from southeastern Newark to northeast Wilmington. Three of the first priority census tracts were concentrated around Elsmere. The second priority census tracts covered the northeastern part of the county, primarily around southern Newark and the Route 9 corridor in New Castle. All three risk indicators used to prioritize testing – testing

levels, positivity rates, and social risk scores – were positively correlated with each other (testing and positivity,  $r=0.18$ ; testing and social risk,  $r=0.55$ ; positivity and social risk,  $r=0.24$ ; all  $p$ -values  $<0.05$ ).

Figure 3. Census Tracts for Priority Testing



## Discussion

These results demonstrate but only a few of the many possible ways GIS can be used to inform health system responses to the COVID-19 pandemic. First, public data sources were mapped to identify areas which may face barriers to telehealth access. These data were used in support of an application for a \$714,00 grant from the Federal Communications Commission (FCC), which ChristianaCare will use to expand its telehealth program by providing patients with broadband internet subscriptions and devices.<sup>16</sup> This has the potential to narrow geographic disparities in telehealth utilization during a prolonged period of social distancing,<sup>17</sup> which can be subsequently evaluated with GIS methods.

Next, the cluster detection and testing prioritization strategy show how different criteria can be used to examine testing levels over time and inform resource allocation. The March-April cluster detection results showed hot and cold spots in which testing levels significantly differed from the county average. While cold spots were detected in northeastern New Castle County and around Newark, these represent generally affluent and predominantly White communities, and neither were considered high-priority areas for testing in the ranking that incorporated positivity levels and social risk scores. In contrast, the Riverside cold spot was identified as a “priority 1” site for testing, which warrants additional concern. In response to these results, ChristianaCare began offering COVID screening appointments at Riverside’s Kingswood Community Center in late April.<sup>18</sup>

The Riverside and Smyrna cold spots were each comprised of single census tracts adjacent to testing hot spots. The existence of these small cold spots in larger areas which had adequate or

high levels of testing suggests unique barriers for their residents in accessing testing. Riverside is a geographically isolated neighborhood, bordered by Route 13, the Brandywine creek, and the Amtrak railroad. Northeast Smyrna is more rural and located at the bottom of New Castle County. Its close proximity to the county border suggests that its residents may have had more spatially accessible testing from Kent County providers. The cluster detection analyses will be repeated at a later date to determine if increased provision of testing reduced or eliminated New Castle County cold spots.

The strategy of prioritizing communities for testing provides an example of how health systems can make informed decisions using patient-level electronic health record data as well as population data from public sources like the Census Bureau. This allowed ChristianaCare to more confidently triangulate high-risk areas for COVID transmission and make recommendations for effective and equitable use of testing resources by placing them where the need is greatest. The correlations between testing levels, positivity rates, and social risk scores suggests that our prioritization criteria identified similar areas of need while providing unique information.

These analyses must be considered in light of a few key limitations. The telehealth maps relied on publicly available data that do not include individual-level indicators of telehealth usage. Investigators should avoid making inferences about an individual's access to telehealth services based solely on where they live. The cluster detection analyses used testing data from only one health care provider over a one-month period and do not reflect testing conducted by other providers, which may spatially differ from those administered by ChristianaCare. Similarly, only ChristianaCare data were used in determining areas in which to prioritize additional testing, and may fail to identify areas in which other providers have delivered sufficient levels of testing. The consideration of positivity levels reflects only those who have been tested, and the social risk score may not account for all variables associated with rapid spread of COVID-19. Despite these limitations, the use of multiple spatial methodologies allows us to identify broad trends in access to care that can mitigate the transmission and negative sequelae of COVID-19.

Together, these findings demonstrate the value of spatial methodologies not only for traditional disease surveillance, but also to inform resource allocation and narrow racial and economic health disparities by ensuring equitable access to care.

## **Public Health Implications**

Geospatial methodologies can be used to combine electronic health record data and population-level spatial data for pandemic response efforts. This allows health systems to more confidently identify areas of need while mitigating disparities in resource allocation.

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