# Identifying Priority Areas for Expanding Mental Health Facilities with Mixed Integer Linear Programming

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**Abstract**

This research attempts to estimate the unmet mental health services demand at a census tract level and identify new mental health facility locations in Ohio to maximize the number of new individuals with serious mental illness (SMI) who receive treatment. We find that among the 765,304 individuals with SMI in Ohio, 469,549 (61.4%) perceive an unmet need for mental health services due to the lack of geographic access and limited service capacity. Using estimates of the capacity of existing facilities, unmet demand in each census tract, and the distance between each census tract center, we modeled a mixed integer linear program to maximize coverage of newly opened facilities. The model suggests 10 new potential mental health facilities could provide geographic access to 418,228 new patients, comprising 89.1% of the total SMI population that currently has unmet mental health services demand in Ohio. The findings of this research could make recommendations for identifying hot spots for individuals with SMI and priority areas for expanding mental health facilities.

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# 1 Introduction

In contemporary society due to various risk factors including "psychiatric illness, previous suicide attempts, substance misuse, acute interpersonal stressors, partner-relationship disruption, and history of sexual abuse" (Yuodelis-Flores and Ries, 2015), people are becoming increasingly vulnerable to developing psychological disorders and mental illness. Serious mental illness (SMI) is defined as a diagnosable mental, behavioral, or emotional disorder that causes serious functional impairment that substantially interferes with or limits one or more major life activities (Evans et al., 2016). About 14.2 million people (5.6% of the US population) were diagnosed to have SMI among adults aged 18 or older in 2020. Within the diagnosed population, 9.1 million (64.5% of the diagnosed population) have received mental health services, while an estimated 7 million (49.7% of the diagnosed population) perceived an unmet demand for mental health services (Substance Abuse and Mental Health Services Administration, 2021a). While some patients may have received limited treatment or counseling services, they were not satisfied due to various factors including unaffordable service costs and geographic limitations. SMI is an important issue to study because of the burdens on families and stigma on patients themselves. The effects of stigma include perceived, experienced, anticipated, and self-stigma; the consequences of these stigmas include low quality of life, suicide risk, life dissatisfaction, and non-effective personal recovery (Dubreucq, Plasse, and Franck, 2021). Additionally, it is suggested that individuals with SMI are both more likely to cause criminal offenses and to be arrested for displaying psychiatric symptoms (Junginger et al., 2006).

The most frequent diagnoses of SMI includes schizophrenia, bipolar disorder, major depression, and other non-affective psychosis and affective disorders (Walsan et al., 2019). Among all SMI diagnoses, mental health treatments are typically a combination of therapy and prescriptions. Most people with schizophrenia are treated by community mental health teams that provide day-to-day support and treatment while ensuring patients' independence as much as possible (National Health Service, 2022). For people with bipolar disorder, seasonal affective disorders, or major depression, most treatments are a combination of different medications like mood stabilizers, treatment for the major symptoms of depression and mania, psychological treatment, and lifestyle advice.

Access to mental health facilities is essential for individuals with SMI to attain treatment services. More research on the accessibility of mental health facilities in various areas has been conducted over the past ten years. A previous study evaluated the accessibility of health services in southwest Montreal (Ngui and Vanasse, 2012). Ngui and Vanasse marked the postal code of psychiatric hospitals, psychiatric clinics, and community mental health facilities, measured the travel distance between these places, and provided insight into the spatial accessibility to healthcare. The accessibility to mental health facilities in Florida has also been evaluated based on different age groups (Ghorbanzadeh et al., 2020). They stated that most of the rural areas in Florida have poor access to mental health facilities, and this is because opening facilities in urban areas are always profitable and accessible, but it ignores the geographic accessibility in rural areas. The Department of Health and Human Services State Standards for Access to Care in Medicaid Managed Care published the standards for distance and travel time for urban and rural areas. According to these standards, the commute distance to primary care providers should be limited to 30 miles (Department of Health and Human Services, 2014). Meanwhile, a previous study also evaluated the access differences between higher-income areas and lower-income areas in the city of Toronto (Wang and Ariwi, 2021) and found there are more mental health facilities located in lower-income neighborhoods. While telehealth care can offer inexpensive SMI treatment to patients, more investigation is needed to establish whether the benefits outweigh the drawbacks such as lower patient satisfaction compared to in-clinic treatment (Lawes-Wickwar, McBain, Mulligan, et al., 2018; Langarizadeh et al., 2017; Pratt et al., 2013).

Previous studies have used mathematical models to examine geographic access to treatment providers. The geospatial buffering model was used by Langabeer et al. (2020) to estimate the treatment access for buprenorphine providers nationally. Rosenblum et al. (2011) investigated the commuting patterns among 23,141 patients enrolling in 84 opioid treatment programs (OTPs) in the US and predicted the distance traveled to the treatment program by individuals by using linear mixed model analysis. OTPs are specialized clinics that provide medication-assisted treatment for opioid addiction. Bonifonte & Garcia (2022) studied opioid overdoses by adapting optimization models that maximize the new clients served and minimize the travel distance for existing clients. This research adapts these methods to find the optimal locations for mental health facilities that maximize the geographic coverage of serious mental illness patients. Since opening new facilities is normally costly and depends on local policies, the results from this research could be regarded as a recommendation for facility location planning and an example of building models to optimize the geographic locations of facilities.

This research aims to identify priority areas for expanding mental health facilities to maximize the number of SMI patients who can be provided geographic access. In Section 2, we describe the methods adopted for cleaning data, estimating facility capacity, unmet demand, the distance between census tracts, and building the optimization model for new potential facilities. The optimization model maximizes the number of new individuals with SMI that can be covered. In Section 3, we describe the data sources that are used, including the geographic information of existing facilities, census tract data, the number of people diagnosed with SMI and received treatment, and the radius that is used for limiting commuting distances. In Section 4, we present descriptive results including visualizations and modeling output. Finally, in Section 5, we discuss the implications and limitations of this research.

## 2 Data Collection

Existing outpatient mental health facilities that provide services for patients with SMI were identified from the National Substance Use and Mental Health Services Survey (N-SUMHSS) 2021 directory conducted by the SAMHSA (Substance Abuse and Mental Health Services Administration, 2022a). The longitude and latitude of each address were geocoded using the data from Open Street Map. For those addresses that cannot be found using the geocoder, they were located and collected using Google Maps.

Census tract data including the geographic information and population was gathered from the Bureau (2018). The 2019 American Community Survey 1-Year Estimates was used for the population. Census tract centers were defined as the mean center of the population within each tract based on the 2010 census.

The total number of people with SMI for each census tract is obtained by multiplying the total number of people of each census tract and the average percentages of people with SMI in different substate regions. The substate estimates are collected from National Survey on Drug Use and Health (NSDUH) 2018 - 2020 directory conducted by the SAMHSA (Substance Abuse and Mental Health Services Administration, 2022b). Ohio's 88 counties are distributed into 21 substate regions, allowing for more granular estimates than whole state.

The total number of people with SMI who have received treatment in the United States was acquired from the National Mental Health Services Survey (N-MHSS) 2020 directory conducted by the SAMHSA (Substance Abuse and Mental Health Services Administration, 2021b). Both the nationwide estimate and state estimates are used in this study, and the estimates are cumulative over the year.

The threshold that patients are considered to be having access to the services in this research is set at $r = 30$ miles. This is based on the Department of Health and Human Services State Standards for Access to Care in Medicaid Managed Care (Department of Health and Human Services, 2014). These standards are set to ensure access to care within a reasonable distance. While the guidelines vary from state to state, and only 32 states limit the travel distance, the average longest drive distance to primary care in urban areas is 30 miles. It is assumed that those individuals with SMI beyond a 30 miles radius of a mental health facility cannot be served because it would be time-consuming to travel a long distance to acquire services, especially since those mental health services are normally counseling services and it always takes hours for a complete service.

# 3 Methods

## 3.1 Facility capacity

In this work, we restrict our focus to outpatient treatment facilities. We assume that individuals with SMI have geographic access to mental health facilities if the centers of their residence census tracts are within a specified radius $r$ of facilities with treatment capacity. To estimate the capacity of the facilities, we first record the number of diagnosed SMI population in Ohio. Then, we obtain the number of people with SMI that have received treatment by multiplying by a nationwide percentage of who received treatment. We make this proportionality assumption because there is no state-specific data on SMI treatment populations. Finally, we divided this estimated population by the number of existing facilities in Ohio to estimate average facility capacity.

## 3.2 Estimating unmet demand

**Raw Data**

| Facility | Tract | Tract Population | Distance |
|---|---|---|---|
| Facility 1 | Tract 1 | $A$ | $d_1$ |
| Facility 1 | Tract 2 | $B$ | $d_2$ |
| Facility 2 | Tract 3 | $C$ | $d_3$ |
| Facility 2 | Tract 4 | $D$ | $d_4$ |

**Step 1**

| Facility | Total Population |
|---|---|
| Facility 1 | $T_1$ |
| Facility 2 | $T_2$ |
| Facility 3 | $T_3$ |
| Facility 4 | $T_4$ |

**Step 2**

| Facility | Tract | Tract Population | Distance | Total Population | Capacity | Average Demand |
|---|---|---|---|---|---|---|
| Facility 1 | Tract 1 | $A$ | $d_1$ | $T_1$ | $c$ | $\frac{A}{T_1}c$ |
| Facility 1 | Tract 2 | $B$ | $d_2$ | $T_1$ | $c$ | $\frac{B}{T_1}c$ |
| Facility 2 | Tract 3 | $C$ | $d_3$ | $T_2$ | $c$ | $\frac{C}{T_2}c$ |
| Facility 2 | Tract 4 | $D$ | $d_4$ | $T_2$ | $c$ | $\frac{D}{T_2}c$ |

**Step 3**

| Tract | Demand Served |
|---|---|
| Tract 1 | $\frac{A}{T_1}c+\frac{B}{T_1}c$ |
| Tract 2 | $\frac{C}{T_2}c+\frac{D}{T_2}c$ |

**Step 4**

| Tract | # Diagnosed | Demand Served | Demand Unserved |
|---|---|---|---|
| Tract 1 | $x$ | $\frac{A}{T_1}c+\frac{B}{T_1}c$ | $x-(\frac{A}{T_1}c+\frac{B}{T_1}c)$ |
| Tract 2 | $y$ | $\frac{C}{T_2}c+\frac{D}{T_2}c$ | $y-(\frac{C}{T_2}c+\frac{D}{T_2}c)$ |

Figure 1: Procedure of estimating unmet demand

Figure 1 summarizes the procedure for obtaining the unmet demand estimates. To estimate the unmet demand for mental health services, we first identified and filtered out those census tracts that are not within the radius by calculating the Euclidean distances between facilities and the center of each census tract. The geographic information of facilities including latitude and longitude are geocoded using the data from Open Street Map. We then aggregated the number of census tracts covered by each facility and assigned each census tract with demand served based on the percentage of the tract population. We noted some tracts might be covered by multiple different facilities. We then aggregated the census tracts and summed up the demand served for each tract. Based on the SMI percentage estimate by substate regions, we obtained the number of people diagnosed with SMI by multiplying it with the population of each census tract. Subtracting the demand served from the total number of diagnosed people generates the unmet demand, which represents the number of people with SMI that are currently not receiving any mental health treatment. We assume that every individual diagnosed with SMI needs mental health services, ignoring it will have tremendous negative consequences for the individual and communities.

### 3.3 Estimating the distance between each census tract

In this research, we used the Euclidean distance between census tract centers to define the set of underserved individuals with SMI and help optimize the number of newly covered people with SMI. For computational tractibility, we assume that facilities are opened in the geographic center of tracts.

### 3.4 Prescriptive Model

| **Parameters** | |
|---|---|
| **U** | The set of census tracts with currently unmet demand (demand $> c$ or distance to nearest facility $> r$) |
| **N** | The set of potential new facilities |
| $k$ | Number of new facilities to open |
| $u_i$ | Currently unsatisfied demand of tracts; $i \in U$ |
| $d_{ij}$ | Distance from tract $i$ to facility $j$; $i \in T, j \in A$ |
| $r$ | The distance used as a threshold, set to be 30 miles (48.3 km) |
| **Variables** | |
| $y_{ij}$ | Newly served SMI people from tract $i$ served by facility $j$; $i \in U, j \in N$ |
| $z_j$ | 1 if we open facility$j$, or 0 otherwise; $j \in N$ |

Table 1: Notation and Decision Variables

Table 1 shows the notation used in this study. The parameter $k$ is a self-determined value that indicates the number of new facilities to open, and the values for other parameters are collected from various sources as mentioned in the earlier section. There are two types of decision variables that are included in the optimization model. First, $y_{ij}$ is a continuous variable that represents the number of clients with unmet demand from census tract $i$ that is served by potential new facility $j$. Second, $z_j$ is a binary variable representing whether to open facility $j$. By our assumption of existing facility capacities saturated by existing demand, all underserved clients can only be served by new potential facilities.

One modeling challenge is if we were to limit the capacity of newly opened facilities, the optimization model would place these facilities only in populous cities because of their large unmet demand, even for large $k$ values. In this situation, we would not open any new facilities in rural areas despite their unmet demand. Furthermore, there would exist multiple optimal solutions, namely to open a facility in any area with more unmet demand than new facility capacity. To avoid this outcome, we allow for infinite capacity of newly opened facilities to identify areas that could provide geographic access with respect to their radii of coverage.

The optimization model is given by:

$$\max \quad \sum_{i \in U} \sum_{j \in N} y_{ij} \tag{1}$$

$$\text{subject to} \quad \sum_{j \in N} y_{ij} \leqslant u_i \quad \forall i \in U \tag{2}$$

$$\sum_{i \in U} y_{ij} \leqslant M z_j \quad \forall j \in N \tag{3}$$

$$\sum_{j \in N} z_j \leqslant k \tag{4}$$

$$y_{ij} = 0 \quad \forall i \in U, j \in N : d_{ij} > r \tag{5}$$

$$y_{ij} \geqslant 0, \quad z_j \in \{0, 1\} \tag{6}$$

The objective function (1) maximizes the number of individuals that currently lack geographic access to mental health facilities that can be covered with newly opened facilities. Constraint (2) enforces that the number of newly met demand cannot surpass the unsatisfied demand. Constraint (3) ensures that demand can only be served by newly opened mental health facilities; when $z_j = 1$, the unmet demand can be served up to an arbitrary large number M; when $z_j = 0$, no demand can be served at facility $j$. Constraint (4) limits the number of new facilities that may be opened to the specific parameter $k$. Constraint (5) indicates that the newly covered SMI people can only attend the facilities within the radius $r$ of them. Lastly, (6) includes nonnegativity and binary constraints.

# 4 Results

According to our estimates, the capacity of each existing facility is 1,837 over one year based on the cumulative estimates of the population that have received treatment. In Ohio, there are about 765,304 people diagnosed with serious mental illness, which is about 6.55% of the total population in Ohio. These individuals account for about 5.4% of the total nationwide population that has been diagnosed with SMI (14.2 million), while the population of Ohio is only 3.54% of the whole population of the United States. Among the 765,304 people with SMI in Ohio, 469,549 (61.4%) are unable to access mental health treatment due to the lack of geographic access or facility capacity, while among the 14.2 million people nationwide with SMI, it is reported that 49.7% (about 7 million people) have unmet demand for mental health services.

## 4.1 The distribution of the existing facilities and the number of diagnosed SMI patients

For our preliminary step, we plot the distribution of the existing facility locations and the SMI patient population. Figure 2 shows the map of facility locations and the number of people diagnosed with SMI at the census tract level. Each gray dot indicates one existing facility, and the color of the census tract indicates the SMI population. According to the map, the majority of the facilities concentrate in populous cities including Columbus, Cleveland, Cincinnati, Dayton, and Toledo, while the others are scattered evenly over the east part of Ohio, and the distribution of the number of individuals with SMI is fairly evenly spread in rural areas. The facilities have covered most of the state; however, the capacities restrict them from sufficiently serving all the diagnosed individuals with SMI. In contrast to Eastern Ohio, note the sparsity of facilities in the West, especially around Findlay, which has as much demand as other areas. Based on our preliminary findings, we expected to see more facilities open outside of the major cities, especially the areas around Findlay.

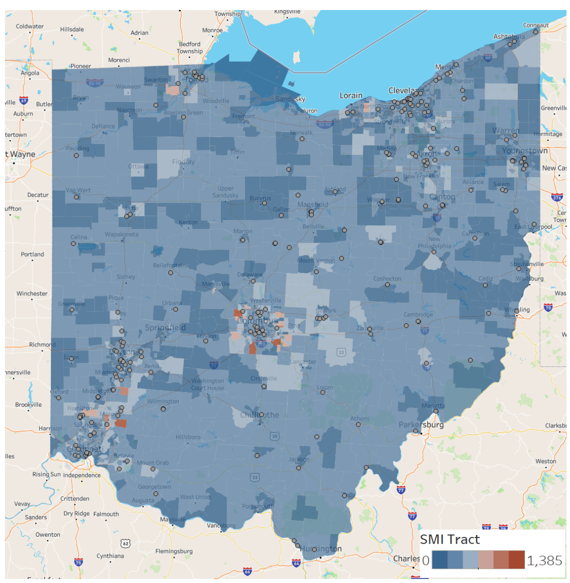


Figure 2: Existing facilities and the heat map of diagnosed SMI population for each tract

## 4.2 Estimated Unmet Demand

Figure 3 compares the demand for mental health services that has been served by existing facilities and the unmet demand. In comparison with Figure 2, the heat map of demand served appears to be similar because most of the served demand concentrates at major cities like Cleveland, Columbus, Cincinnati, Dayton, and Toledo. This pattern perfectly corresponds to the distribution of the existing facilities. On the other hand, we see similar patterns in the unmet demand map because of urban density and facility capacities. Intuitively, both Figures 2 and 3 show correlates with the overall population, that urban centers are hot spots and rural areas are cold regions. This could be fairly interpreted to mean that new facilities should simply be located in urban centers to serve the most people. Therefore, even though those populous cities have a large number of existing facilities and have already served a huge amount of the SMI population, there still exists a fair amount of unmet demand in these areas. However, this is unfortunate because it assumes that impractical, expensive high-throughput facilities would have to be established. Whereas, it can still be seen from Figure 3 that rural areas have unmet demand and may be in need of additional facilities to address the demand there. Thus, an alternative strategy could be for practical, cheaper, low-throughput centers to be opened across rural areas, and many more of such facilities could be afforded.

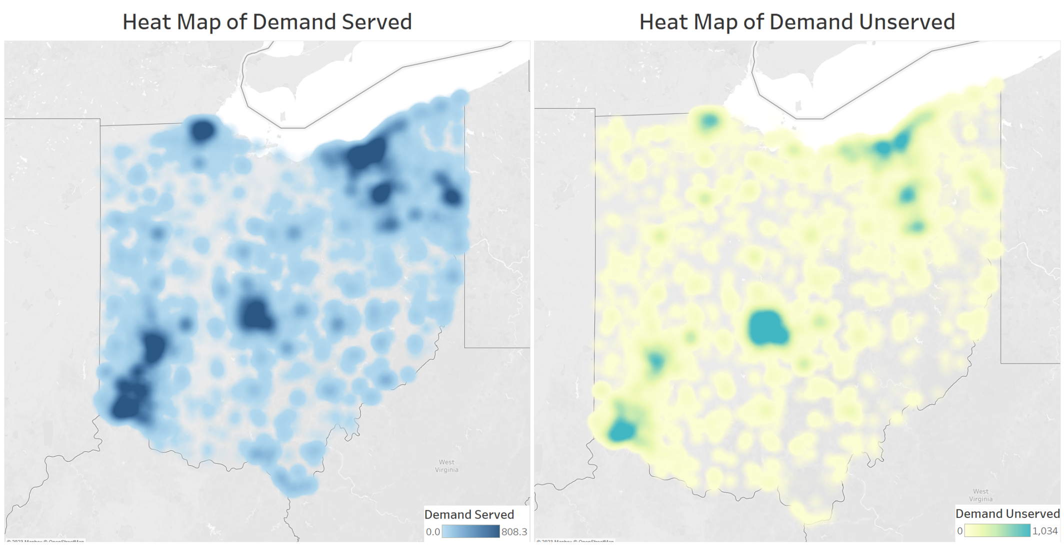


Figure 3: The demand served by existing facilities and unmet demand

## 4.3 New patients served

As discussed in Section 3.4, we assume infinite capacity of newly opened facilities to focus our results on the geography of unmet demand. For values $k \in \{1, 2, ..., 12\}$, the MILP model is solved independently. Figure 4 summarizes the characteristics of the optimal solution for each k value. As $k$ increases, we observe decreasing marginal returns in the number of patients covered by each facility with more facilities opened. With 10 new facilities opened, a total of 418,228 patients may be covered, representing 89.1% of the total SMI population that are perceived with an unmet demand for mental health services.

Table 2 displays the number of new individuals with SMI served and the geographic region of the newly opened facilities with $k = 10$ in Ohio. The results for 10 new facilities are conveyed

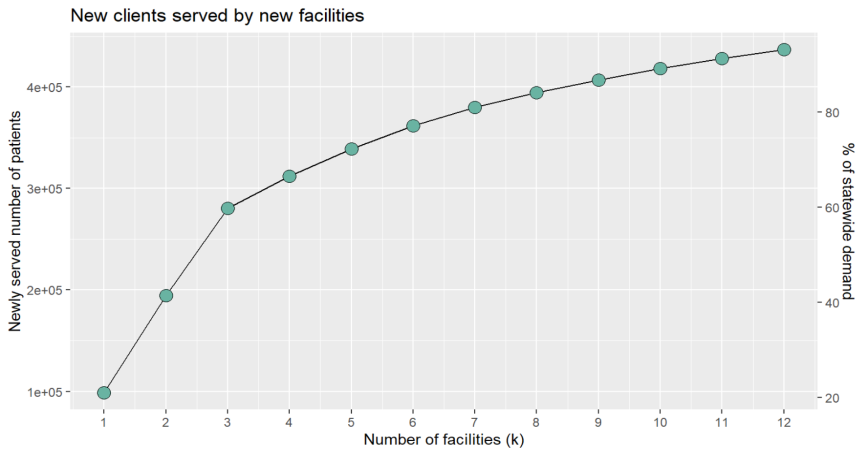


Figure 4: Number of new patients served with different $k$ values

in the table because computing detailed results for more facilities is extremely time-consuming: it takes two hours for $k = 10$, six and a half hours for $k = 11$, and over twelve hours for $k = 12$. The results presented assume the apriori choice of $k = 10$ facilities are opened. If fewer than 10 facilities were opened, the optimal locations may be different from those in the solution with $k = 10$ because a greedy approach by myopically opening additional facilities would not necessarily result in systemwide optimality. As discussed in Section 4.2, it is important to note that our optimization model does not limit the capacity of newly opened facilities. Therefore, these results demonstrate the geographic coverage and corresponding demand of newly opened facilities rather than the demand that could be served by one new facility. While we are not proposing the exact facility locations, these new potential facility locations can be used to address the patient demand identified in surrounding areas.

| **Facility** | **Region Served** | **New patients covered** |
|---|---|---|
| 1 | Delaware | 92,016 |
| 2 | Mason | 78,329 |
| 3 | Cleveland | 75,949 |
| 4 | Warren | 36,046 |
| 5 | Troy | 30,143 |
| 6 | Bowling Green | 29,287 |
| 7 | Berlin | 25,206 |
| 8 | Willard | 20,421 |
| 9 | New Lexington | 18,047 |
| 10 | Washington Court House | 12,783 |

Table 2: New patients served when $k = 10$

### 4.4 Facility Locations

Figure 5 shows the 10 new potential mental health facilities in Ohio suggested by the optimization model. As we expected, the new facilities suggested by the model cover (the circles with solid outline) most of the hot spots (shaded with green). Rather than opening facilities in the city centers of Columbus, Cincinnati, and Akron, the model suggests to open them in the suburban areas nearby. The reason behind this may involve greater coverages by skewing slightly off-center of major metropolitan areas to better capture dense suburbs. As suggested from Figure 5, Columbus (Facility 1) in central Ohio is the area most in need of additional treatment facilities, with over 90,000 individuals within 30 miles not receiving sufficient treatment. Cleveland and Cincinnati (Facilities 2 and 3, respectively) each have over 70,000 individuals nearby needing treatment. The other facilities on Figure 5 cover underserved individuals in suburban and rural areas, and ten new facilities cover a wide range of regions throughout Ohio, including both urban and rural areas. These new facilities could cover up to 418,228 individuals with SMI, which is about 89.1% of the total individuals with SMI that are perceived with an unmet demand for mental health services in Ohio. We note this is a planned $k = 10$ systemwide optimal solution, whereas a greedy solution may pick different locations for various $k$.

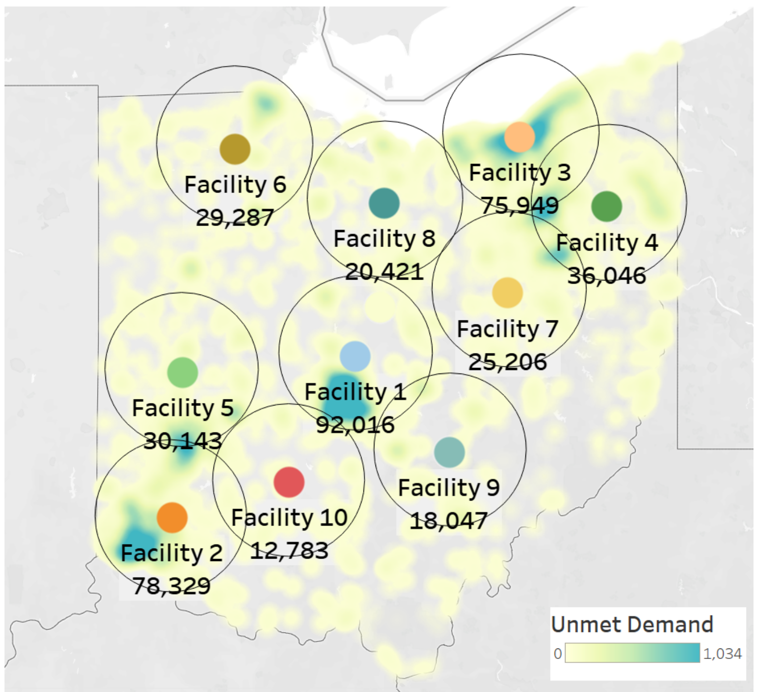


Figure 5: Optimal locations for mental health facilities

# 5 Discussion

One of the major objectives of this research is to estimate the number of SMI patients with unmet demand for mental health services. In Ohio, based on our estimates, there are about 765,304 people that have been diagnosed with serious mental illness, which is 6.55% of the total population in Ohio. The number of SMI patients in Ohio is about 5.4% of the total population that has been diagnosed with SMI in the US (14.2 million), while the population of Ohio is 3.54% of the whole population of the United States. Among the 765,304 people with SMI, 469,549 (61.4%) are estimated with an unmet demand for mental health treatment due to the lack of geographic access or facility capacity, while it is reported that in the US 49.7% (about 7 million) people were perceived unmet demand for mental health services among the 14.2 million people with SMI (Substance Abuse and Mental Health Services Administration, 2021a). These estimates emphasize the importance of this research due to the higher proportion of the SMI population and unmet demand for mental health services in Ohio and demonstrate the need for improving geographic accessibility to mental health facilities for serving as many new SMI patients as possible.

Another major objective of this research is to identify the optimal facility locations to maximize the number of new individuals with SMI that can be covered in Ohio. As expected, the recommended new potential mental health facilities are suggested to be in the regions that are most in need of the services, considering both geographic access and existing facility capacities. For example, many of the new potential facilities in Figure 5 are suggested to be in suburban or rural areas near major cities that have hot spots. These ten facilities could cover approximately 89.1% of unmet demand in Ohio.

While this work considers a system-wide perspective, in real-world implementation, facility construction would be done in a greedy consecutive way, as opening new facilities can be costly and time intensive. The facility locations change each time when solving for different $k$ values. As we increase the $k$ value, more facilities will be suggested to open in Columbus, Cincinnati, and Cleveland because of the hot spots there, and more facilities will also open in rural areas to address the unmet demand there. However, the computational time for large $k$ values can be limiting, taking two hours for $k = 10$, and six and a half hours for $k = 11$. And over twelve hours for larger values. In this research, we only focused on 10 new potential facility locations for computational reasons.

While opening new mental health facilities is largely based on local policies, especially for those public mental health service centers heavily relying on government funding, the approach and results of this research could be considered as the recommendation for future implementation of facility location problems. Since the large cities have many mental health facilities and serve diagnosed people in the surrounding census tracts, considering the geographic accessibility and estimating unmet demand in different regions would widen the service coverage.

## 5.1 Limitations

This research has limitations related to the input data and modeling assumptions. Firstly, for input data, we assumed that the distribution of demand served is the same as the population distribution of census tracts and not accounted for variability in facility capacities. This assumption could be relaxed if more detailed data on the distribution of the served population were available. Secondly, we assumed the maximum travel distance is 30 miles for all patients for modeling purposes, whereas we acknowledge there exists individual variability in willingness to travel. Additionally, for modeling assumptions, we have assumed that the new potential mental health facilities can only be opened at the center of census tracts. It reduces the computation difficulty because we do not need to consider all possible spots to be potential locations on the map. Finally, because of our objectives and approach, we have considered the capacity of existing facilities for distributing met demand but did not consider the capacity of newly opened facility as a decision variable.

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