DETECTION OF DISPARITIES IN VISION DIFFICULTY CARE THROUGH REGRESSION ANALYSIS

An Undergraduate Research Scholars Thesis

by

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ABSTRACT

Detection of Disparities in Vision Difficulty Care through Regression Analysis

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Due to the progressive nature of preventable vision loss, annual examinations are necessary to address early stages of diseases. While studies have focused on risk factors leading to preventable vision loss, little work has been done to understand prevalence of vision difficulty in regard to availability of services and factors such as age, health insurance, and poverty. This study demonstrates geographic trends in vision difficulty to broaden the understanding of disparities in vision care accessibility in the United States. American Community Survey 2014 5-Year Estimate disability data were analyzed alongside Urban Influence Codes and National Provider Identifier registry data for optometrists and ophthalmologists to investigate correlations between accessibility to eye care and prevalence of vision difficulties. Through ArcMap software, ordinary least squares analysis of county-level data of eye care providers and other factors produced the standard residuals for the model used to identify vision care disparities. Vision care disparities were detected in 107 total counties between all twelve Urban Influence Codes classifications using county-level data. This study focuses only on the first of three phases of addressing equal health care access and establishes necessary background material for the next two phases by geographically identifying the locations of vision care disparities.

ACKNOWLEDGEMENTS

I would like to thank Dr. Daniel Goldberg for his guidance and support throughout this research. From the beginning, he offered ideas and perspective that became invaluable to the development of this work.

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NOMENCLATURE

ACS	American Community Survey
UIC	Urban Influence Codes
Metro	Metropolitan
Micro	Micropolitan
NPI	National Provider Identifier

CHAPTER I

INTRODUCTION

Access to eye care services can only be considered fair and equal when use of such services is solely based upon the needs of an individual; not on sex, race, ethnicity, income, insurance, education, or any other identifying barrier.[1] While developing a targeted method of health promotion available to the public at healthcare highways like community health centers, general practitioner offices, hospital emergency services lobbies, and school nurses is an attractive concept, first the identification of high-need areas is crucial to understand how to best design and deploy materials. Because resources are limited, identifying potential areas where health disparities occur would lead to more effective use of resources. For further development of public health initiatives, the methodical, continued collection of data tracking health disparities is necessary to alleviate the burden of vision care disparities in the United States.[1]

The first step of addressing a health disparity is to detect where it exists. Next are developing an understanding and creating a plan for an intervention.[2] Because no work has been done to map vision care disparities in the United States, this research not only develops methodology for detecting vision care disparities, but also lays the groundwork for future studies on locations of disparities and understanding them. Within this study, conjecture over potential disparities is disregarded by systematically working to detect disparities based upon national data.

In this study, vision difficulty is defined as blindness or trouble seeing even with prescribed lenses.[3]

Objectives

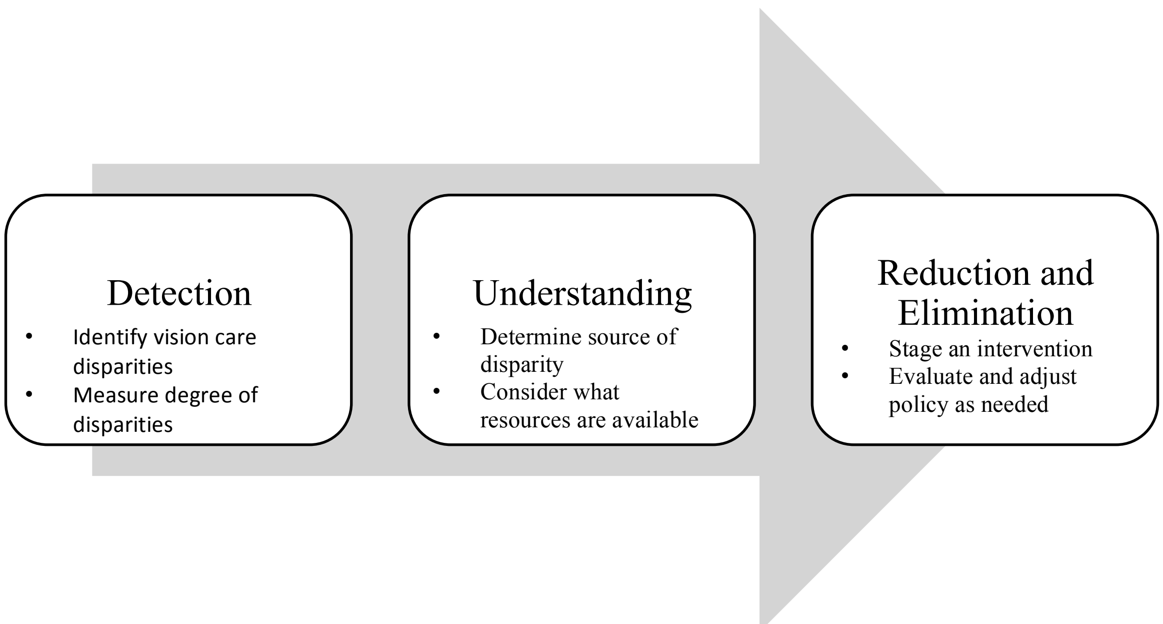
The objective of the work proposed is to evaluate different socioeconomic variables against measured accessibility to eye care providers in the context of prevalence of vision difficulty.

- Define which explanatory variables are related to high levels of vision difficulty in the United States
- Develop a model for identifying counties with vision care disparities in the United States
- Examine performance of model within the twelve Urban Influence Codes suggested as the classification system with which to observe health care disparities[4,5]
- Provide the foundation from which further studies may deepen the understanding of vision care disparity and identify appropriate methods of intervening health promotion

Related Work

This study uses the framework of three phases to approaching health disparity research developed by Kilbourne, Switzer, Hyman, Crowley-Matoka, and Fine as the guideline with which the methods and analyses were designed. The three phases- detection, understanding, and reduction- provide the context through which this work attains relevancy in the greater picture of health disparity reduction in the United States.[2] Aligning to the aforementioned standard, this study focuses on the detection phase in that it investigates potential disparities while studying the possible barrier of logistical accessibility as a correlation. The second phase depends on this work because regions must first be identified before the next step can be taken to understand why these regions are in disparity. Then, once an understanding is accomplished, effective intervention methods can be developed to reduce the disparity in the third phase. Because resources are limited, it is crucial to fully understand the spread of unequal access to vision care before they may be most efficiently deployed. Figure 1 summarizes the organization of the framework.

Figure 1. *Framework of the three phases used to study health disparities*



Prior work in vision care public health has identified risk factors for preventable causes of vision loss.[6,7,8] However, there is a need for future collection and integration of data tracking to provide a stronger foundation for understanding and reducing identified disparities.[6] The lack of geographic study of regions in disparity were the inspiration for the development of this study.

The work of Hall, Kaufman, and Ricketts thoroughly examines the different types of classifying counties as rural or urban depending on the focus of different studies. Since this study works to identify disparities, it was deemed best to follow the metropolitan, micropolitan, and noncore designations developed by the United States Department of Agriculture Economic Research Service.[5] These designations consider the effects of work commutes and proximity to metropolitan and micropolitan areas as well as economic growth, giving the study unique insight into the lifestyle of the people in each county in regard to their mobility and the use of transportation available to them.[4]

CHAPTER II

METHODS

American Community Survey 2014 5-Year Estimate (ACS) disability data were used to determine county-level prevalence of vision difficulty, which indicates a person is "blind or having serious difficulty seeing, even when wearing glasses."[3] Blindness indicates a severe amount of vision loss. Serious difficulty, even with glasses, indicates the need for a new prescription lens, which implies this person should seek a comprehensive eye exam. This county-level data was calculated as a percentage to demonstrate the proportion of people afflicted per county. Then, the average percentage per county was taken to calculate the standard deviation. The number of standard deviations away from the mean per county was calculated and rounded to an integer.

The classification of each county depending on proximity to metropolitan and micropolitan areas as well as level of economic integration through 2013 Urban Influence Codes (UIC) produced by the United States Department of Agriculture Economic Research Service was necessary to most effectively understand how accessible eye care providers across the county and neighboring counties was.[4,5]

National Plan and Provider Enumeration System National Provider Identifier records were used to identify optometrists and ophthalmologists with their addresses. The addresses were geocoded to provide coordinates. Ophthalmologists listed under the code for "Ophthalmic Plastic and Reconstructive Surgery" were omitted from the research due to the nature of the specialty and this study's desire to focus on services related to vision support and detection of potential risk factors for vision loss.[9]

In ArcMap, the coordinates for optometric and ophthalmologic services were mapped as points on the 2014 United States Census Bureau shapefile of United States counties. The count of optometrists and ophthalmologists per county was made by assigning individual counties as polygons. Then, points were joined to polygons. The attribute table for the polygon points listed the counts, which were then exported to calculate the number of providers per person per county. Due to lack of reliable geocoding results in Puerto Rico, Puerto Rican counties were discounted from the study. Hoonah-Angoon Census Area, Alaska and Petersburg Borough, Alaska were omitted as well due to lack of data acquired from these districts during the process of calculating eye care providers per county.

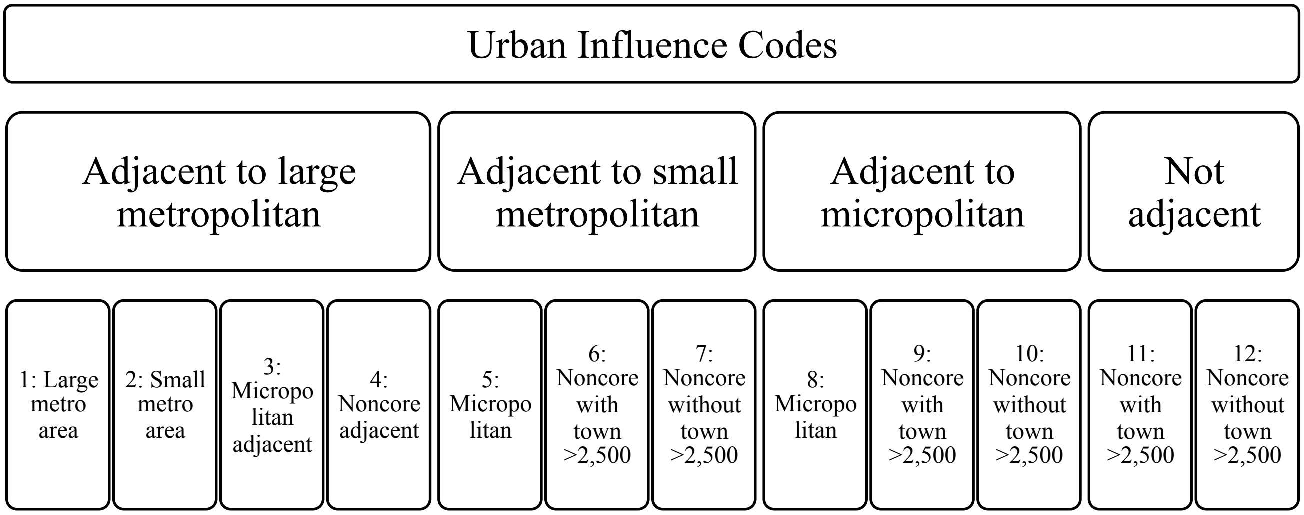
To find average time travelled to the nearest five eye care providers, the geometric county centroids were used as the starting points from which the time travelled was measured. Distances calculated as a negative value were determined to be null. Speed limits were taken into account for the time travelled data.

ACS data were used once more to determine health insurance status, poverty level, and proportion of senior citizens 65 and over. The regression was run through ordinary least squares with the percent of uninsured citizens, percent of citizens under the 1.38 ratio of the poverty threshold, percent of citizens 65 and over, square root of the optometrists and ophthalmologists per person, and the square root of the average distance travelled for the nearest five optometrists and five ophthalmologists. To simplify the UIC codes in the model produced in ArcMap with the ordinary least squares analysis, metro, micro, and noncore counties as determined by the UIC designations were assigned numbers 1, 2, and 3, respectively.

To determine regions of disparity in vision care, the standard residuals from the ordinary least squares were organized. Those less than -2 and greater than 2 were labeled as strong deviants due to their great variation from what the model predicted. Values between -0.5 and 0.5 were labeled as successes for the model, and those in between -2 and -0.5 and 0.5 and 2 were labeled moderate deviants. Strong deviants in the negative spectrum were the determined areas of realized vision care disparity due to having a stronger negative deviation from the mean value of vision difficulty. Strong deviants in the positive spectrum were the determined areas of potential vision difficulty growth in the future due to having a stronger positive deviation from the mean value of vision difficulty.

The Urban Influence Codes were then used to divide and analyze the labeled standard residuals to better understand which classifications of counties were modeled most effectively. Because the code designation of 1, 2, and 3 for metro, micro, and noncore counties produced insignificant results in the ordinary least squares analysis, for the purpose of displaying simplified results, the UIC codes were distributed into four overarching groups based upon relation to nearby counties. Figure 2 illustrates the how the UIC codes were divided for the purpose of analysis.

Figure 2. *Groupings of UIC codes for counties based upon the classification of neighboring regions*



CHAPTER III

RESULTS

Data and Figures

Table 1. *Number of counties per standard deviation from mean vision difficulty per person.*

Standard deviations from mean	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1
Number of counties	1	0	1	4	5	16	49	215	812	1788	249

The average county percentage of vision difficulty per person was 3.0005%. Table 1 shows the number of counties per rounded standard deviation away from the mean. Bedford City, VA was not counted due to lack of available data; therefore, Bedford City was omitted from the rest of the results and calculations as well as the analysis.

A total of 72,848 optometrist NPI designations were geocoded. The average optometrist per county resident in the United States is 0.000203, or approximately one optometrist per 5,000 residents. The rounded standard deviations from the mean are displayed in Table 2. Of the 3,108 counties with complete ACS datasets, 585 counties, or 18.85%, do not have optometry practices. In 174 counties, or 5.60%, people must drive at least 1 hour to access an optometry practice. In 3 counties, the combined 2,065,433 residents living in them must travel more than 3 hours to reach the closest optometrist's office. 301 counties have an average travel time of over 1 hour for the closest 5 practicing optometrists, which decreases the accessibility of residents to choose doctors based on personal preference as well as have their needs met by a specific specialist.

Figure 3 illustrates the distribution of the different counties and their values regarding prevalence of vision difficulty.

Table 2. *Number of counties per standard deviation from mean percentage of optometrists per person.*

Standard deviations from mean	-1	0	1	2	3	4	5	6	7
Number of counties	860	1617	549	71	26	8	5	3	1

Figure 3. *Standard deviations from mean county percentage of vision difficulty prevalence.*

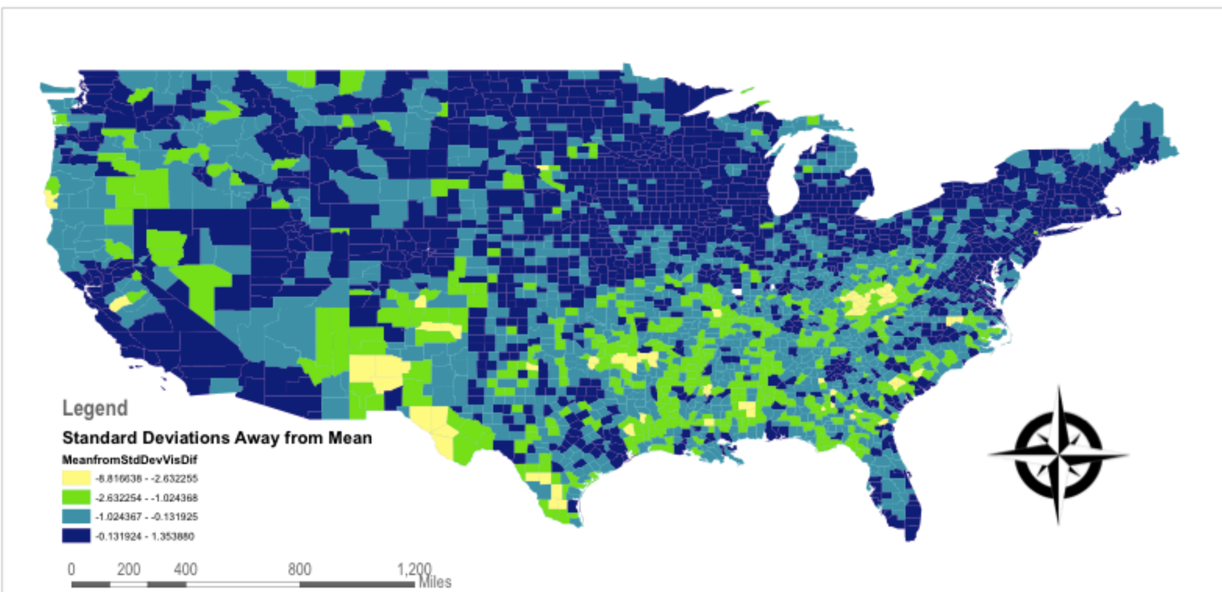
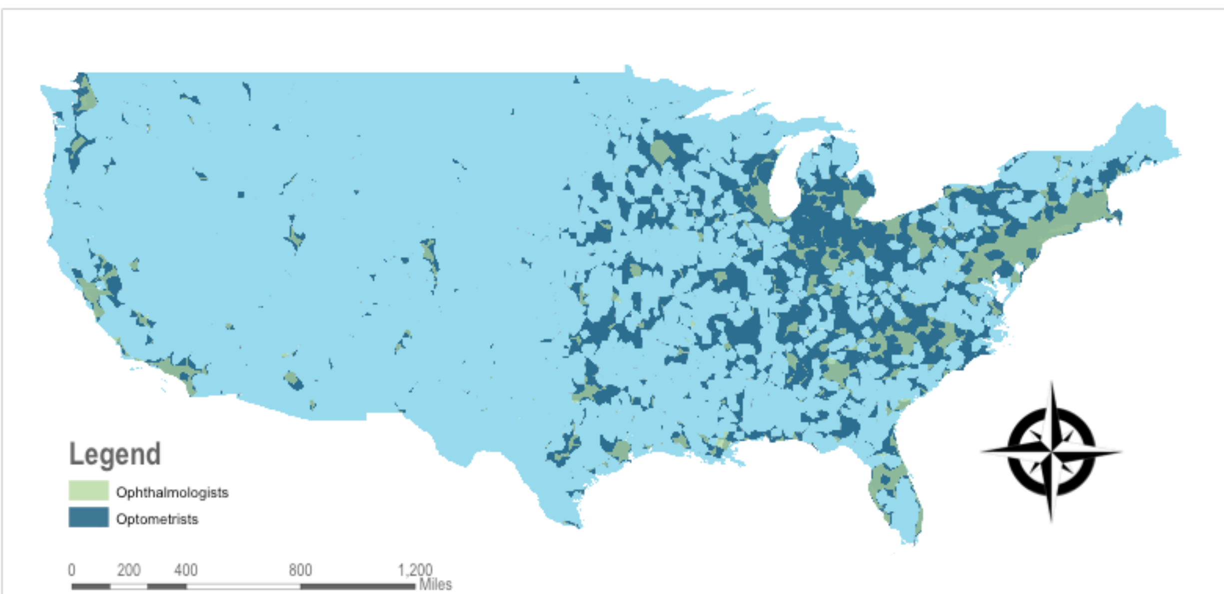


Table 3. *Number of counties per standard deviation from mean percentage of ophthalmologists per person.*

Standard deviations from mean	-1	0	1	2	3	4	5	6	8	9	11	23
Number of counties	1663	769	524	126	35	11	4	3	2	1	1	1

30,609 ophthalmologist National Provider Identifier numbers were analyzed, with an average of 0.000045 ophthalmologists per county resident in the United States, or approximately one ophthalmologist per 22,000 residents. The rounded standard deviations away from the mean are displayed in Table 3. Of the 3,108 counties, 1632, or 52.51% do not have ophthalmology practices. People in 2,550, or 82.05%, of counties have to travel at least 1 hour to reach the closest practice. 1,857,991 residents in 33 different counties have to drive more than 3 hours to reach the closest ophthalmologist. In 838 counties, residents have to travel over an hour to the closes 5 ophthalmologists, decreasing their ability to have a say in their medical professional treatment and accessibility to different specialties.

Figure 4. *Aggregation of geocoded optometrists and ophthalmologists within a 30-mile radius.*



107 counties were strong negative deviants and determined to have a vision disparity. Owsley County, Kentucky had the most negative standard residual with a value of -10.52. 545 counties were moderate negative deviants. 1,608 counties were model successes, comprising

51.7% of the 3,108 counties examined. 811 counties were moderate positive deviants. 37 were strong positive deviants. Corson County, South Dakota had the most positive standard residual with a value of 3.58.

The ordinary least squares results demonstrated that the percent county residents 65 years of age and over and percent county residents under 1.38 times the poverty threshold had an inverse relationship with the number of standard deviations away from the mean county percentage of vision difficulty. The coefficients were -4.0036 and -5.3758, respectively, with both having a p-value of 0.0000. The percent of citizens uninsured had a statistically significant, but low, coefficient of -0.0103 with a p-value of 0.0005. The square roots of optometrists per person and ophthalmologists per person both had a positive relationship. The coefficients and p-values were 6.1445 and 0.0020, and 11.0540 and 0.0002, respectively. The square roots of the average time traveled to the nearest eye care providers were not statistically significant. The assigned UIC data numbers were also not statistically significant, deeming the attempt to better the model by classifying the counties as metro, micro, and noncore with an assigned integer ineffective.

The specific values for the percentage of counties assigned to each UIC code are displayed in Table 4. Figure 5 illustrates the standard residual labels for every UIC designation. Figure 6 shows the same information with the categories assigned in Figure 2 to better summarize the data and demonstrate the effects of neighboring regions on a county's performance in the analysis.

Table 4. *UIC Data with analyzed standard residual labels in table form.*

UIC	Strong Negative	Moderate Negative	Success	Moderate Positive	Strong Positive
1 (Large Metro Area)	0.23%	11.60%	75.64%	12.53%	0.00%
2 (Small Metro Area)	2.05%	17.26%	60.41%	20.00%	0.27%
3 (Micro Area by Large Metro Area)	1.55%	12.40%	59.69%	25.58%	0.78%
4 (Noncore by Large Metro Area)	2.68%	16.11%	51.01%	28.19%	2.01%
5 (Micro by Small Metro Area)	1.24%	16.94%	52.07%	28.51%	1.24%
6 (Noncore by Small Metro Area with town with over 2,500 residents)	5.83%	23.03%	39.94%	30.32%	0.87%
7 (Noncore by Small Metro Area with no town with more than 2,500 residents)	4.97%	17.39%	38.51%	36.02%	3.11%
8 (Micro Area not by Metro Area)	3.38%	20.30%	47.74%	27.07%	1.50%
9 (Noncore by Micro Area and town with over 2,500)	4.89%	21.74%	40.76%	32.07%	0.54%
10 (Noncore by Micro Area with no town with more than 2,500 residents)	8.02%	16.58%	32.09%	39.04%	4.28%
11 (Noncore not adjacent to Metro or Micro with a town with more than 2,500 residents)	6.90%	21.55%	37.93%	33.62%	0.00%
12 (Noncore area not adjacent to Metro or Micro Area with no town with more than 2,500 residents)	7.65%	18.24%	33.53%	36.47%	4.12%

Figure 5. *UIC Data with analyzed standard residual labels in chart form.*

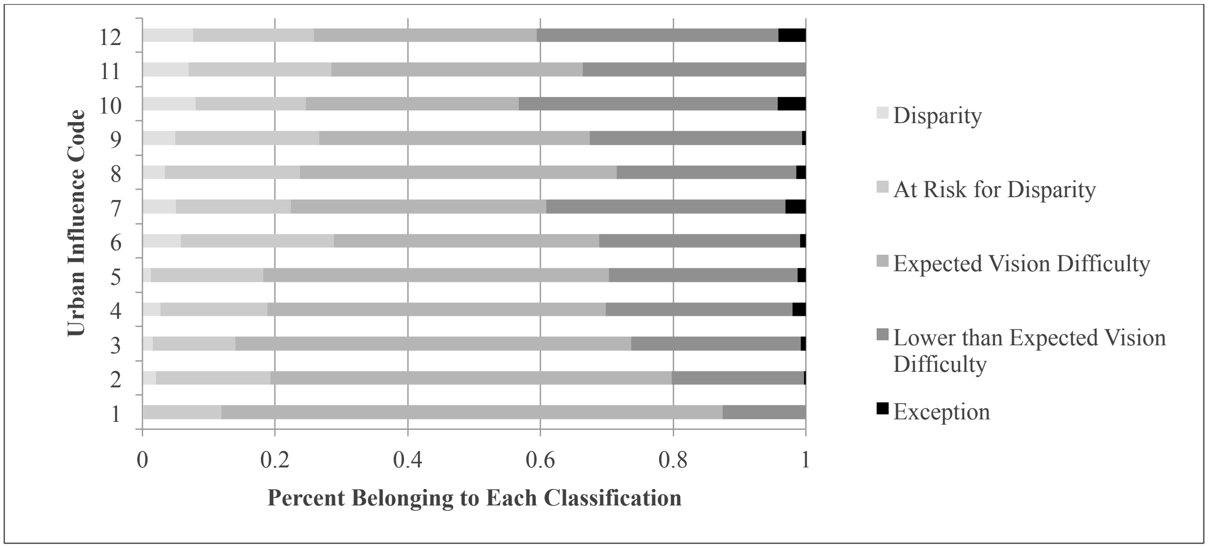
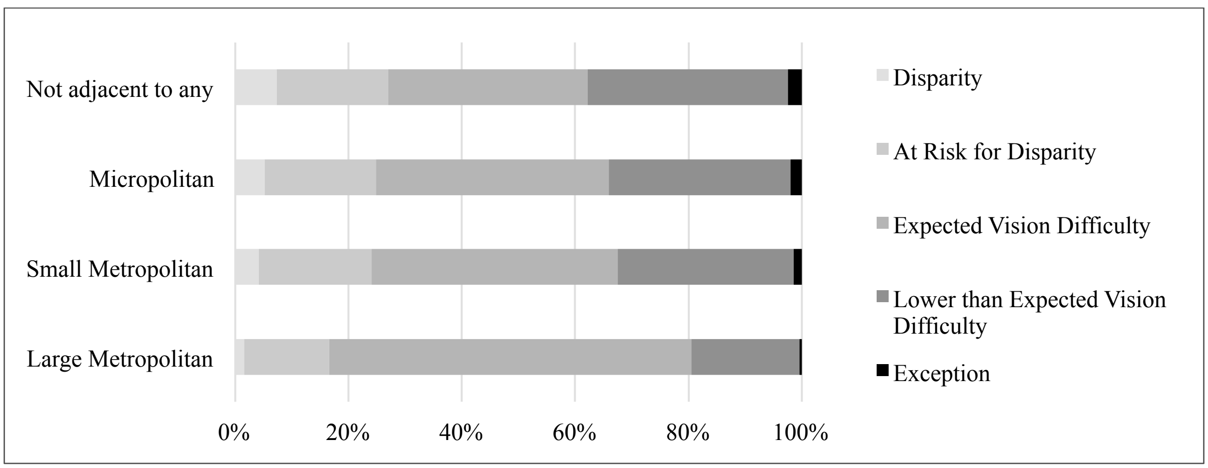


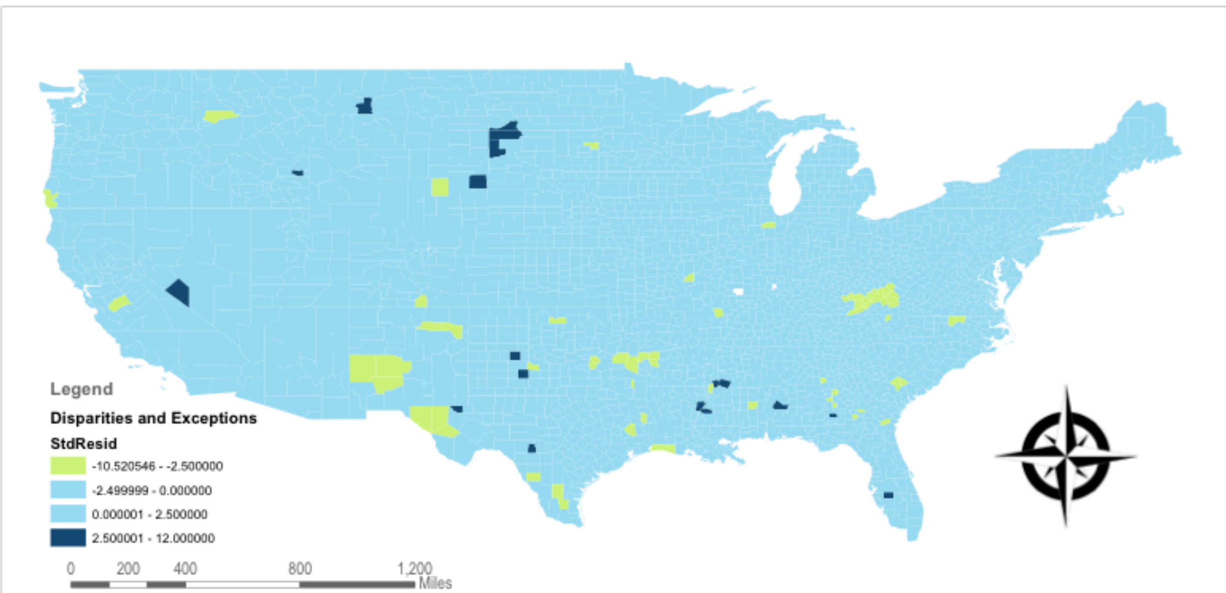
Figure 6. Percentage of counties in each standard residual label



The mapped standard residual labels were adjusted to only highlight the counties in disparity and the exceptional counties. These specific counties are the key to following up these results in the understanding phase of studying vision care accessibility. The 107 detected disparities and 37 detected exceptions fall outside the model and show where the prediction of vision difficulty based upon the explanatory variables does not line up with the actual vision difficulty. The lighter counties are those in disparity, and the darker counties are those that have exceptionally low presentation of vision difficulty.

Of the 2,964 counties not highlighted in Figure 7, 1,608 counties aligned with the model's prediction. In all, the model predicted the vision difficulty of 51.7% of counties based upon poverty level, presence of senior citizens, density of eye care, and insurance status in the county population.

Figure 7. Map of counties in disparity and counties classified as being an exception



Discussion

The relationships of the explanatory variables with the vision difficulty dependent variable in the regression analysis demonstrate interesting implications for the identified disparities. Senior residents were controls for age-related vision loss, while poverty, travel time, and number of doctors offered insight into accessibility.

The standard residuals provide a classification system for whether a disparity is present because the strong and moderate negatives demonstrate more vision difficulty exists than expected, while the strong and moderate positives show less vision difficulty than expected. The extremes were classified as the counties with disparities or with exceptionally low vision difficulty prevalence to detect the potential areas of study. The identification of the 107 counties with disparities and 37 counties with exceptionally low vision difficulty prevalence highlight the successful completion of the first attempt to detect vision health disparities in the United States.

Counties identified as having more vision difficulty than expected can be divided into two different causes of disparity. Just as there is potential access and realized access, disparities can be potential or realized, depending on the barriers. Potential access barriers relate to whether care is available. Realized access barriers are more complicated, with socioeconomic and environmental factors affecting the patient use of services and satisfaction.[10] Potential disparities would be those in which potential access is limited. Counties without optometrists or ophthalmologists, or those in which patients would have to drive over an hour, would fall under the classification of having a potential disparity. Counties optometrists or ophthalmologists available, yet still experience higher than expected prevalence of vision difficulty, would have a realized disparity.

Counties with a realized disparity are more complicated to address than those with a potential disparity. The care is available, maybe even in excess, but patients are not taking advantage of services. These counties require more focused study to determine the barriers.

10.58% of residents in Vance County, North Carolina are blind or cannot see with their corrective lenses; however there are 10 optometrists and 3 ophthalmologists serving the residents. A potential barrier could be racial in nature, considering the county is 42.5% White (not including Hispanics or Latinos) and 49.7% Black. Socorro County, New Mexico has 4 optometrists and 1 ophthalmologist, but a vision difficulty rate of 13.69%. The county is 49.0% Hispanic, 36.7% White, and 12.1% Native American. For both of these counties, identifying the racial and ethnic spreads and the locations of the vision care offices could provide insight into why so many residents are experiencing vision difficulty.[2]

Manasses Park, VA would offer interesting results as well. As the county with the lowest percentage of vision difficulty at 0.58% of the UIC 1 counties, it also maintains a diverse population that 40.0% White, 12.4% Black, and 34.0% Hispanic. A thorough analysis of this social ecosystem may demonstrate useful practices and distribution of healthcare that could be used as a model in the future. Because of the social and cultural nature of these barriers, the understanding phase of the framework for addressing health disparities designates this work as the step that will be a follow up from these detection phase results.[2]

Of the 12 UIC classifications used in this study, codes 6-12 reported lower than 50% success in predicting vision difficulty. Of these, five are noncore area codes, while one code is for micropolitan areas not adjacent to a metropolitan area. The variation exhibits a need for explanatory variables that improve the regression analysis accuracy for rural areas. The attempt to amend this issue by using 1, 2, and 3 as codes for metropolitan, micropolitan, and noncore counties as an explanatory variable failed. A more comprehensive method is called for; perhaps the use of census codes for rural and urban may prove more useful. The variation of these less urban results may indicate two things.

Firstly, a more effective system for classifying urban and rural for the purpose of studying health disparities may be needed. While, Hall, Kaufman, and Ricketts provided a guide for how to define urban and rural areas in epidemiology, their work did not examine whether a new system may be necessary.[5] Health disparity research has increased in popularity since the Office of Disease Prevention and Health Promotion has established *Health People 2010* and *Healthy People 2020*. With the subsequent demand for more resources available to disparity researchers, the development of a code system specific to classifying rural and urban communities is a beneficial possibility.

Secondly, the variation may be due to the rural nature of these counties. UIC 12 actually demonstrates a higher percentage of moderate positives than successful predictions unlike the other codes. UIC 12 also has the second highest percentage of counties with disparities. Because this classification represents noncore areas not adjacent to metro or micro areas without a town of over 2,500 residents, the lack of urban influence may be the root of the spread of the results. Phase two research is key to understanding whether the lack of urban influence is a sufficient explanation.

CHAPTER IV

CONCLUSION

Vision care disparities exist in 3.44% of United States counties. 17.5% are at risk for developing a vision care disparity. Further study is necessary to attempt to decrease the prevalence of vision care disparities, while future work will also provide a more effective analysis that will identify disparities with more accuracy. While this model accurately predicted over half of the 3,108 counties studied, and deviations from accurate predictions are the very definition of disparities and exceptions, there is much room for improvement. With only a handful of explanatory variables proven to be statistically significant, further investigation will identify more that can be confirmed as risk factors for vision care disparities once the second phase is completed. If the explanatory variables could be further developed, the creation of a more universally proven metric or equation for calculating whether a vision care disparity exists would greatly assist in county-level diagnostics for local public health professionals.

With the average rate of 1 optometrist per 5,000 residents in a county and 1 ophthalmologist per 22,000 residents, it is evident that these fields have a need for more eye care providers. The data from the regression analysis clearly shows a higher number of providers available correlates with lower prevalence of vision difficulties. A study of the counties with significantly lower vision difficulty than expected that demonstrates few barriers to potential access could provide a golden rule of vision care providers per county resident depending on the rural or urban designation. If this were to happen, the American Optometry Association and

American Academy of Ophthalmology would have the resources to develop a method for encouraging their doctors and physicians to offer services in identified areas of need.

Ultimately, future work beyond improving upon and adjusting the methods used in this study should focus on understanding the detected disparities. A comprehensive, local evaluation of the counties in the two extremes of the standard residual results could deliver the necessary context with which an intervention could be staged in phase three. For phase three, data regarding location of Community Health Centers and which have vision care services onsite will lay the foundation for possibly integrating this approach with Community Health Services and be a key component in the effort to reduce vision care disparities in the United States. Beyond just detection of disparities based upon vision difficulty, it would also be beneficial to evaluate awareness levels of the importance of vision care as well as utilization rates of vision care services relative to a county's population. While there are many opportunities for improvement and expansion on the research conducted, there is also potential for increasing its focus and analyzing state-level data to achieve a more specific system for vision care disparity detection.

This work succeeds most in its demonstration of the potential for use of a model to detect health care disparities. Depending upon the desired field of study, the dependent variable may be altered accordingly and analyzed alongside different explanatory variables in the regression analysis. Using the methods developed, any number of variables may be used in this universal model construction. Going forward, how public health interventions are organized and deployed would become more effective by targeting areas highly impacted by detected disparities. Then, analyses of potential and realized access would be further developed to understand effects of health care utilization nationwide and establish extensive methods on understanding and addressing disparities beyond the experimental detection methods created for this study.

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