Climate Risks and Opportunities in the Great Lakes Region

Leveraging Green Infrastructure as a Resilience Measure for Stormwater Infrastructure

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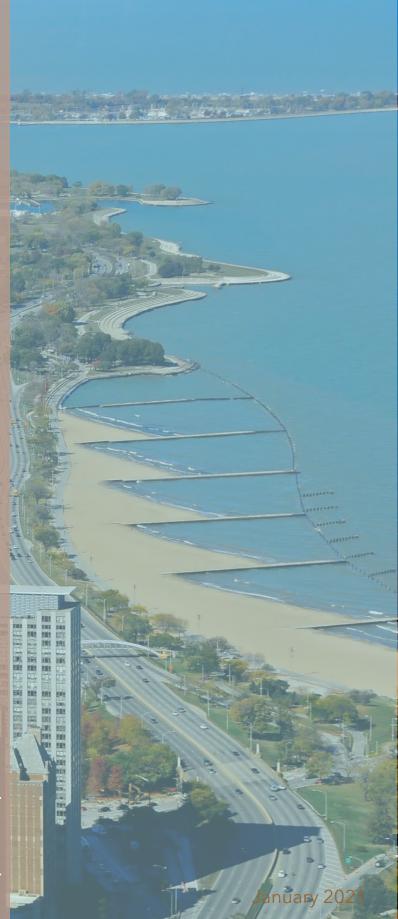
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1. Executive Summary

As climate change increasingly threatens the ecological, human, and social systems of our world, it is vital to understand the risks, resilience, and opportunities faced by different communities. This report examines several dimensions of how communities, municipalities, and states in the Great Lakes region can anticipate the risks posed by climate-change-worsened stormwater events, the vulnerabilities among their populations, and their workforce capacity to execute Green Stormwater Infrastructure (GSI) projects, and presents ways to strategically finance projects for maximum value and efficiency. This report pinpoints the locations that can most benefit from interventions related to a combination of climate risk, social vulnerability, workforce agility, and financial flexibility.

The report features narrative context and analysis of publicly available data pertaining to the 653 counties in the eight states that comprise the Great Lakes region in the United States. The introduction provides a high-level context of climate change, its equity impacts, and some of the municipal bureaucratic infrastructure on which policy and financing mechanisms rest. Next, research and analysis that evaluates and maps key metrics to determine the counties with the highest and lowest climate risk, social vulnerability, workforce agility, and financial flexibility is presented. Finally, these metrics are synthesized into a composite rating which ultimately provides a "priority list" of **counties best suited for intervention** due to being highly at climate risk, with highly vulnerable populations, with highly agile workforces, and strong financial capacity. Top twenty counties in the U.S. side of the Great Lakes basin and their composite scores are presented below in Table 1 and Figure 1.

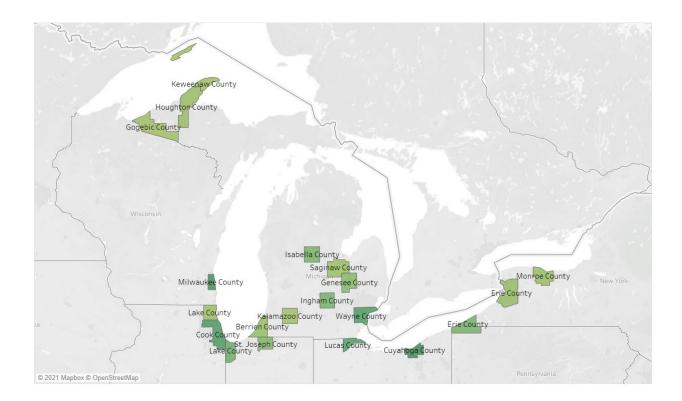
Table 1: Top 20 Best Fit Great Lakes Basin Counties for GSI Intervention and Planning

Rank	Great Lakes Basin County	Final Composite Score
1	Cuyahoga County, Ohio	70.10%
2	Milwaukee County, Wisconsin	69.09%
3	Cook County, Illinois	67.66%
4	Wayne County, Michigan	67.28%
5	Lucas County, Ohio	66.67%
6	Lake County, Indiana	62.86%
7	Ingham County, Michigan	61.61%
8	Erie County, Pennsylvania	61.54%
9	Isabella County, Michigan	61.33%
10	St. Joseph County, Indiana	60.53%

Rank	Great Lakes Basin County	Final Composite Score
11	Genesee County, Michigan	59.69%
12	Erie County, New York	58.45%
13	Berrien County, Michigan	57.98%
14	Houghton County, Michigan	57.80%
15	Monroe County, New York	57.76%
16	Saginaw County, Michigan	57.45%
17	Lake County, Illinois	57.40%
18	Gogebic County, Michigan	56.99%
19	Kalamazoo County, Michigan	56.99%
20	Keweenaw County, Michigan	56.67%

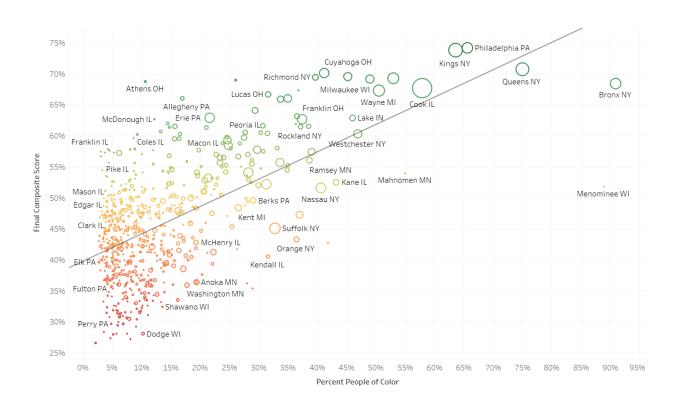
The conclusion summarizes research findings and elucidates key trends for prioritizing investing. Commonalities among the "best fit" counties include: a) large urban centers, b) worse inequality and concentrations of vulnerable populations, c) higher educational attainment, d) greater unemployment and job need, and e) being geographically situated in floodplains (including both urban impermeable surfaces and agriculturally tiled areas).

Figure 1: Top Twenty Great Lakes Basin County Composite Scores



Importantly, this work can serve as a resource for investing in underrepresented communities and communities of color in particular. As shown below in Figure 2, there is a strong correlation between a county's final composite score and its population percentage people of color. As sites of historical disinvestment and structural barriers to equitable economic growth, these counties may be poised to derive some of the greatest benefits from investment in Green Infrastructure guided with a justice-oriented approach.

Figure 2: Final Composite Scores versus Population Percent of People of Color



2. Introduction

Climate Change in the Great Lakes Basin

Climate change is altering the ecological underpinnings of the world, and the Great Lakes Basin is no exception. The Great Lakes Basin supports more than 34 million human residents, 3,400 species of plants, 170 species of fish, 350 species of migratory birds, and contains one fifth of the world's fresh surface water. The Great Lakes are home to one of the world's largest regional economies, comprised of a \$7 billion fishing industry, a \$16 billion tourism industry, and a \$15 billion agricultural sector (Appendix A). In the Great Lakes Basin, annual mean temperatures have warmed by 1.6°F from historic averages. Warming is occurring at a faster pace than the surrounding contiguous United States, whose average temperature has increased by 1.2°F. Despite the Great Lakes' capacity to create its own localized climate system, it is increasingly vulnerable to the pressures of climate change (Wuebbles et al., 2019). Rapid shifts are expected in both temperature and precipitation, which will significantly alter local ecosystems, communities, and economies.

Globally, anthropogenic emissions of greenhouse gases continue to increase, accelerating patterns of warming air and water temperatures, changing precipitation, and increasing variability and extremity of storms. The annual-average temperature globally has increased by 1.76°F (0.98°C). Nineteen of the twenty hottest years in recorded history have occurred since 1998. Carbon dioxide levels in May 2020 reached 414 ppm and are steadily climbing, alongside average global temperatures (NASA, 2020). The degree of warming the world will experience is determined primarily by the amount of greenhouse gases emitted. If significant reductions to emissions are achieved, annual temperature rise could remain under 3.6°F (2°C), thereby avoiding catastrophic climate conditions. With no alterations to current emissions, experts predict a global annual temperature rise of 9°F (5°C) or more by 2100 (USGCRP, 2017).

Equity

Climate change will not impact all residents of the Great Lakes Basin equally. Inhabitants of urban areas in the Great Lakes are more vulnerable to negative health and economic impacts associated with climate change than those in smaller, more rural communities. As urban temperatures continue to increase, poor air quality will frequently co-occur due to air stagnation, increasing particulate, concentrations and ozone action days. Urban areas will experience increased air pollution in summer and pose higher risks for heat-related illnesses, such as heatstroke and even death. Especially at risk are urban residents with pre-existing conditions such as asthma (Sharma et al., 2016). Careful placement and design of green infrastructure can provide heat wave relief to urban areas by reducing the urban heat island effect through its use of vegetation. When green infrastructure, such as green roofs, are sited in neighborhoods, which channel natural airflow patterns instead of blocking them, the cooling effect will not inhibit airflow (Sharma, n.d.).

Low income urban residents of the Great Lakes are disproportionately Black, Indigenous, and People of Color. These communities are at highest risk for negative impacts of climate change due to a combination of low property values with aging structures, communities built in flood-prone

areas, and aging and/or absent stormwater infrastructure. As summer temperatures continue to rise, people without access to air conditioning or proper shelter, as well as those who work outdoors, will be at higher risk for heat related illnesses. As precipitation and severe storms increase, low income communities will be especially vulnerable to floods and drinking water contamination, resulting in serious risks to public health.

Indigenous people are uniquely impacted by climate change in the Great Lakes Basin. Their livelihoods and economies are often tied closely with local ecology, including both water and land resources, all of which is changing due to climate change (Wuebbles, et al., 2019). The accelerated pace of climate change affects the success of traditional practices, with little time for adaptation. In recent years, the Dakota people of Minnesota reported unpredictable changes in the timing of Sugar Bush, or maple syruping season, as well as wild rice harvesting. Furthermore, moose, an important source of subsistence for the Dakota people, are decreasing in abundance due to disease-carrying parasites, which thrive in milder winters (Hilleary, 2017).

Green Stormwater Infrastructure

Green Stormwater Infrastructure (GSI) has rapidly emerged as a critical component of any effort to improve the climate resilience of the Great Lakes. Considered an effective method of combating stormwater runoff and meeting regulatory compliance needs, GSI relies upon green spaces, parks, and pervious surfaces to filter stormwater runoff and increase water retention in soil and groundwater (Environmental Law & Policy Center, 2019). A recent survey of key stakeholders, including respondents from sectors such as the government, nonprofits, builders, and other experts, shows that they understand that the benefits of GSI outweigh its costs.

Implementing a basin-wide GSI program could yield ecological benefits to the Great Lakes and help to address some of the significant nutrient loading challenges in the region. Unfortunately, between 1996-2010, Great Lakes coastal counties added more than 1,259 square miles of real estate development, an area larger than the cities of Chicago, Indianapolis, Detroit, Columbus, and Milwaukee combined (Great Lakes Regional Land Cover Change Report: 1996-2010). Much of this development utilized the same shortsighted design standards that currently impair Great Lakes water quality and overall ecological health. During this period, the same Land Cover Report indicated that the Great Lakes region also experienced a net loss of 1,735 square miles of forest cover and forest carbon storage. When combined with outdated hydrologic conveyance systems, these alterations to Great Lakes land cover, as well as continued changes in hydrologic patterns in the region, exacerbate the water quality impairments in all the Great Lakes urban areas.

As if that was not enough, climate-related meteorological changes are also now well-researched and documented. In the Midwest, between 1951 and 2017, University of Michigan-based Great Lakes Integrated Sciences & Assessments Center estimates that the level of precipitation falling in the most extreme storms has increased by 35 %. Another recent study in the journal *Science* (Sinha, Michalak, and Balaji, 2017) showed that increased rainfall in the coming decades will wash more

agricultural nutrients and fertilizers – including nitrogen, a primary cause of algae growth – into the waterways.

Large-scale adoption of distributed GSI is a practical, logical path forward, but how much benefit could one expect? The short answer is a lot. For example, Prince George's County has taken a green streets approach to achieving the retrofit of 2,000-acres of impervious areas. At the end of the first, three-year phase, the county has reduced stormwater runoff from 90 % of storm events by capturing the first one inch of runoff and achieved pollution reductions of up to 50 % of nitrogen, 40 % of phosphorus, and 80 % of sediment (U.S. Environmental Protection Agency [EPA], Prince George's County Maryland clean water partnership).

Economic benefits of GSI use are also well documented. Depending on the best practices used, GSI can cost less than conventional gray infrastructure, result in green jobs, and reduce municipal water usage and cooling costs. Within the Great Lakes, Milwaukee Metropolitan Sewerage District's 2035 vision plan to build GSI is expected to yield cost savings of over \$44 million, to create 500 green jobs, and to increase property values by \$667 million (Milwaukee Metropolitan Sewerage District, 2013). The Center for Neighborhood Technology recently completed a study with SB Friedman Development Advisors that found doubling the square footage of rain gardens, swales, planters, or pervious pavement near a home is associated with a 0.28% to 0.78% higher home sale value, on average (Center for Neighborhood Technology, 2020).

Nationally, while cities have historically relied upon grey infrastructure to manage stormwater, GSI has become popular. The Great Lakes region is no exception. Several Great Lakes communities have amended Clean Water Act consent decrees to include GSI as a strategy to come into compliance. A recent report indicated that the market size for private finance investment in GSI across the Great Lakes is substantial, and the states of Ohio, Wisconsin, Minnesota, Illinois, and Indiana can support more than a billion dollars of GSI (Sinha et al., 2017). Although integrating green infrastructure into grey infrastructure is a substantial challenge, important progress is being made.

3. Assessing Risks and Opportunities

For the purposes of this report, four key dimensions were determined by the project team to be researched and analyzed: Climate Risk, Social Vulnerability, Workforce Agility, and Financing Capacity. Within each of these dimensions, numerous metrics were researched, analyzed, and then ultimately synthesized into a composite rating. This process allows insight into both individual granular measures (e.g.: the total county average \$ amount of National Flood Insurance Program [NFIP] claims paid per capita between 1973-2019) as well as the bigger picture (when combined with the other climate metrics, the net stormwater related Climate Risk) for any given county in the database.

The various metrics selected to be included in the final analysis illuminate the complex dimensions of climate resilience and suitability for GSI. The analysis involved gradually removing inputs to eliminate redundancies or over-correlation wherever possible. However, many of the final metrics do share some correlation. The researchers' point of view is that this is not problematic for the analysis, but rather strong evidence of the intersectionality of these issues, and a strong case for interventions where many of these metrics do in fact line up.

Table 2 provides an overview of the metrics analyzed for each pillar alongside the insights derived from each and the data source. In the next section, each metric is reviewed in detail.

Table 2: Overview of metrics analyzed

Pillar	Metric	Insight	Source
Climate	Percent Impervious Ground Cover	Correlated with heat-island effect, watershed degradation, and flooding.	EPA Watershed Index Online
Climate	Total Heavy Rain and Flood Disaster Events	Historical flood records indicate baseline future risk.	National Oceanic and Atmospheric Administration [NOAA] National Center for Environmental Information
Climate	NFIP Claim Count	Historical flood severity indicates baseline future risk.	Federal Insurance and Mitigation Administration (FIMA) NFIP Redacted Claims Dataset
Climate	National Flood Insurance \$ Amounts	Historical flood severity indicates baseline future risk.	FIMA NFIP Redacted Claims Dataset
Social	Population >65 Years of Age	Vulnerability Index Component – Correlated with Vulnerability	Census: American Community Survey
Social	Population Living Alone	Vulnerability Index Component – Correlated with Vulnerability	Census: American Community Survey
Social	Population >65 Years and Living Alone	Vulnerability Index Component – Correlated with Vulnerability	Census: American Community Survey
Social	Diabetes Rate	Vulnerability Index Component -	HIP Investor Ratings

Pillar	Metric	Insight	Source
		Correlated with Vulnerability	
Social	Percent Land Cover without Vegetation	Vulnerability Index Component - Correlated with Vulnerability	EPA Watershed Index Online
Social	Percent of Households with Air Conditioning	Vulnerability Index Component – Correlated with Vulnerability	Census: American Housing Survey
Social	High School Graduation Rate	Vulnerability Index Component – Correlated with Vulnerability	Census: American Community Survey
Social	Percent People of Color	Vulnerability Index Component – Correlated with Vulnerability	RWJ Foundation: 2020 Community Health Rankings
Social	Percent of Population in Poverty	Vulnerability Index Component – Correlated with Vulnerability	Census: American Community Survey
Social	GINI Index	Measure of Wealth Inequality	Census: American Community Survey
Social	Percent of Population in Poor or Fair Health	Measure of Pre-Existing Health Issues	RWJ Foundation: 2020 Community Health Rankings
Social	Life Expectancy	Measure of Pre-Existing Health Issues	RWJ Foundation: 2020 Community Health Rankings
Social	Income Inequality by Gender	Measure of Social Inequality	HIP Investor Ratings
Workforce	Unemployment Rate	Measure of Population Potentially Able to be Employed by New Infrastructure Project	Census: American Community Survey
Workforce	Bachelor's Degree Rate	Measure of Skilled Labor Potentially Able to be Employed by New Infrastructure Project	Census: American Community Survey
Workforce	High School Graduation Rate	Measure of Skilled Labor Potentially Able to be Employed by New Infrastructure Project	Census: American Community Survey
Financing	Total Public Debt Outstanding	Measure of Pre-Existing Debt Burden that may Limit Future Spending Capacity	Census: Annual Survey of State and Local Government Finances
Financing	Has a Climate Action Plan or Mayoral Climate Pledge	Indicates Whether Municipality has Policy Infrastructure Supportive of Climate-Related Financings	CDP North America

4. Results

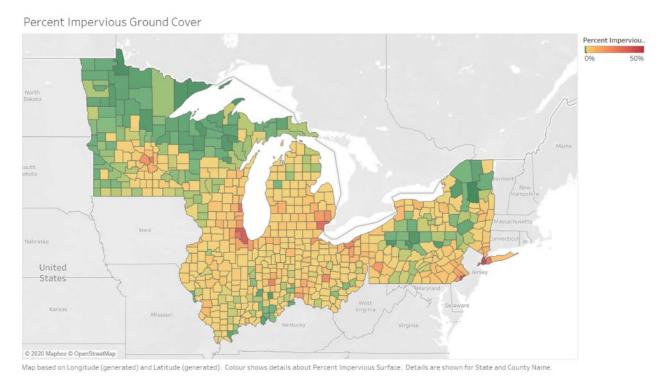
Impervious cover and climactic events/claims

Increasingly severe climate-related events and disasters are affecting all counties across the Midwest, and some more intensely than others. The following visualizations capture the impact that heavy rainfall and flooding have on Great Lakes counties.

Figure 3 shows the percentage of ground cover that is impervious in all Great Lakes counties using data from the EPA Watershed Index Online resource. The darkest green color represents counties with close to zero impervious ground cover, and the darkest red represents counties with the highest percentage of impervious ground cover. The median yellow is set at 10% due to research suggesting that above 10% imperviousness, watersheds begin to degrade (Booth, 1991; Booth and Reinelt, 1993). The counties with lowest percentage of impervious ground cover are Hamilton County, New York (.07%); Lake of the Woods County, Minnesota (0.13%); and Cook County, Minnesota (0.18%). The counties with the highest percentage of impervious ground cover are the New York City Counties (59.9% - 50.5%) followed by Philadelphia County, Pennsylvania (47.8%) and Cook County, Illinois (42.6%).

The clear trend is that impervious surfaces are associated with cities and urban centers. There is a visible pattern of urban sprawl radiating from the center points of major cities. For the purposes of climate-related impacts, impervious surfaces have <u>several significant impacts</u> including the heat island effect and habitat degradation. For the purposes of this report, the chief impact to analyze

Figure 3: Percent Impervious Ground Cover



is infiltration and retention capacity reduction. Infiltration refers to the ability of surfaces to absorb water. Whereas in many natural ecosystems, healthy soils containing vegetation and microbial activity demonstrate significant capacity to absorb and hold large volumes of water, impermeable surfaces like standard concrete and asphalt have little to no infiltration. These impermeable surfaces are susceptible to flooding.

Figure 4 maps heavy rain and flood events recorded by the National Weather Service's Storm Events Database between 2011 and 2020. Events included are those "having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce" (NOAA Storm Data Definitions, 2018). Flood events include flash floods, floods, and lakeshore floods. Heavy rain events include events in which damage or injury occurred due heavy rain-induced hazards such as sheet rain causing vehicles to hydroplane on roadways. Dark green indicates counties with fewer such events. Dark red indicates counties with a high number of events. 19 counties reported zero (0) heavy rain and/or flood events, including Florence County, Wisconsin; Cameron County, Pennsylvania; and Red Lake County, Minnesota. Counties with the greatest number of events included Allegheny County, Pennsylvania (357); Westmoreland County, Pennsylvania (190); Gibson County, Indiana (158); and Cook County, Illinois (145).

Due to the nature of the data (specifically, that in order for events to be counted, they must cause a loss of life, injury, property damage, or disruption to commerce) there is an inherent tilt towards more heavily populated counties, where there is greater potential for exposure to damage. Therefore, another way to look at this data may be events per population, as displayed in Figure 5.

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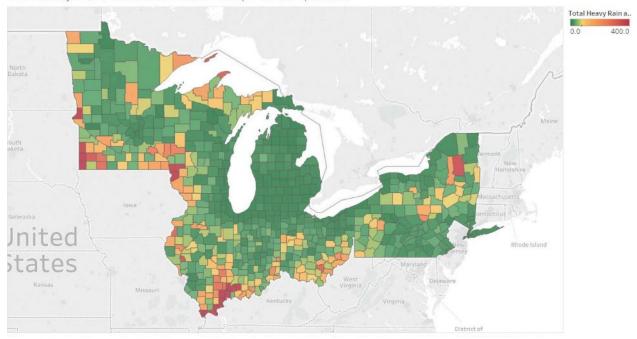
District of

Figure 4: Total Heavy Rain and Flood Events

Climate Risk, Resilience, and Opportunities in the Great Lakes Region Leveraging Green Infrastructure as a Resilience Measure for Stormwater Infrastructure

Figure 5: Total Heavy Rain and Flood Events per Population

Total Heavy Rain & Flood Events 2011-2020 per 100k Population



When standardized per population, more noticeable themes emerge. Specifically, a greater impact appears visible along geographic patterns. In Upstate New York, significant impacts are visible around the Adirondack Mountains, and Lake George Valley. In Pennsylvania, the Golden Triangle of the Allegheny, Monongahela, and Ohio Rivers join to subject Alleghany County to frequent flooding. On the southern borders of Ohio and Indiana, the foothills of the Appalachian Mountains, particularly weakened by strip mining, are susceptible to flood damage. And at the southern tip of Illinois, the confluence of the Ohio and Mississippi Rivers experiences the highest heavy rain and flood events per population of the entire Great Lakes region.

It is noteworthy that there are relatively few events in the database along Great Lakes shores – perhaps due to planning and construction accounting for sensitivity to flood potential, better local drainage of excess water into the lakes, or historical investment in flood prevention such as wetland protection and other stormwater interventions. However, local drainage into lakes may have negative consequences for local water quality; if communities are avoiding urban flooding or other storm impacts by relying on discharge points into the lake, that may unintentionally compromise water quality, creating a distinct need for intervention. Additionally, as observed by NASA, extreme rainfall events are becoming more frequent in this area. In general, much more property is at risk of flooding than previously anticipated. This flood damage potential has become increasingly clear in the past several years, as evidenced by the significant damage from flooding in the Midwest in 2019. FEMA and others are currently assessing lake levels and coastal threats due to historically high and sustained lake levels, as well as higher wave action during storm events contributing to significant coastal erosion.

Figure 6 demonstrates a similar concept of mapping food damage by utilizing the FIMA NFIP Redacted Claims Dataset. The NFIP provides affordable flood insurance for buildings in the Special Flood Hazard Area for participating communities. Green represents counties with fewer claims per population; red represents counties with more claims per population. Because a community must participate in the NFIP in order to be able to generate claims, this dataset is somewhat limited in its intra-county comparability. Additionally, the greatest concentration of NFIP enrollments is in the southeastern United States, making the Great Lakes region data potentially less reliable. Nonetheless, notable geographic patterns emerge, such as concentrated claims along the northwest border of Minnesota, home to low-population counties and the flood-prone Red River.

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Figure 6: National Flood Insurance Program Claim Count per Population

Social Vulnerabilities

Some counties are significantly more vulnerable than others due to a variety of social factors. These factors are summarized in a "vulnerability" rating, as well as several featured individually to highlight the complex ways in which exogenous shocks may interact with social structures and built environments.

Figure 7 presents a composite Vulnerability Index aimed at evaluating the impact of extreme weather events, primarily heat events, may have on Great Lakes counties. The index is a simple recreation of <u>Mapping Community Determinants of Heat Vulnerability</u> (Reid et. al, 2009). The study aggregates variables presented in Table 3.

Figure 7: Vulnerability Index

Vulnerability Index

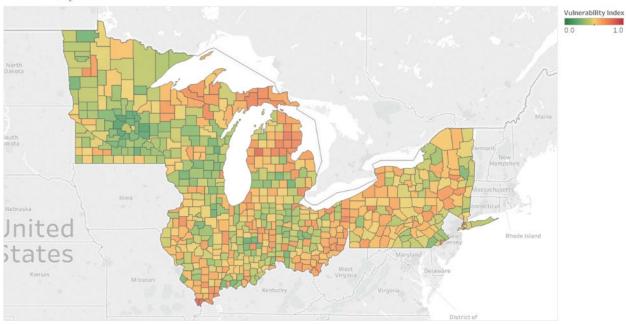


Table 3: Vulnerability Index Weighting

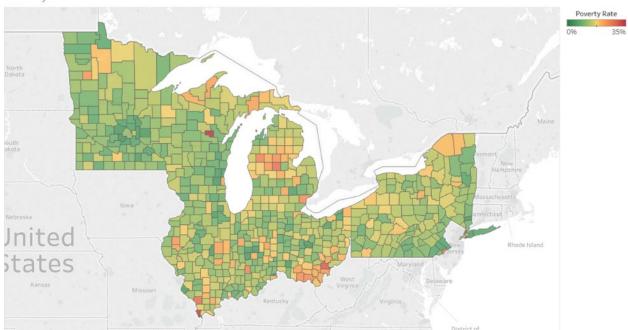
Metric	Weight
Diabetes Rate	11.1%
High School Graduation Rate	11.1%
Poverty Rate	11.1%
People of Color Rate	11.1%
65yrs + Rate	11.1%
Living Alone Rate	11.1%
65+ and Living Alone Rate	11.1%
Air Conditioning Rate	11.1%
Land Area without Vegetation Rate	11.1%
Total	100%

Green represents less vulnerable, and red represents more vulnerable. Although less clear distinctions emerge, generally, the northern parts of Michigan and the southeastern border of Indiana appear most vulnerable.

Figure 8 maps the percentage of county population with incomes below the Federal Poverty Threshold. Poverty is one significant dimension of vulnerability and a root basis of inequality in the United States. Green represents counties with lower poverty, and red represents counties with higher poverty. Highest poverty rate counties include Menominee County, Wisconsin, which contains the Menominee Indian Reservation (35.8%); Alexander County, Illinois (33.4%); and Athens County, Ohio (30.2%). Lowest poverty rate counties include Putnam County, New York (4.8%); St. Croix County, Wisconsin (4.8%); and Wright County, Minnesota (5.0%).

Figure 8: Poverty Rate

Poverty Rate



Population health, another important marker of social resilience and vulnerability, is shown in Figure 9 by the percent of county population identified as being in "poor" or "fair" health as reported by the RWJ Foundation. Green represents counties with the lowest percent of people in poor or fair health, and red represents the counties with the highest percent of people in poor or fair health. Strong visual patterns emerge showing poor health concentrated in southern Indiana and Ohio, as well as counties coterminous with Indian reservations further west (Mahnomen County, Minnesota, and Menominee County, Wisconsin). The healthiest states in general appear to be Minnesota and Wisconsin.

Figure 9: Population in Poor or Fair Health



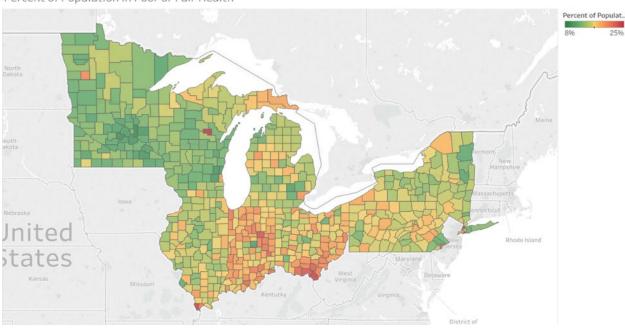


Figure 10 maps life expectancy across Great Lakes counties, with very similar results to Figure 9. Counties with the shortest life expectancy (red) include Mahnomen County, Minnesota (70.6 years); Menominee County, Wisconsin (70.6 years); and Scott County, Indiana (71.6 years). Counties with the longest life expectancy (green) include New York County, New York (84.9 years); Queens County, New York (84.8 years); and Red Lake County, Minnesota (84.6 years).

Figure 10: Life Expectancy

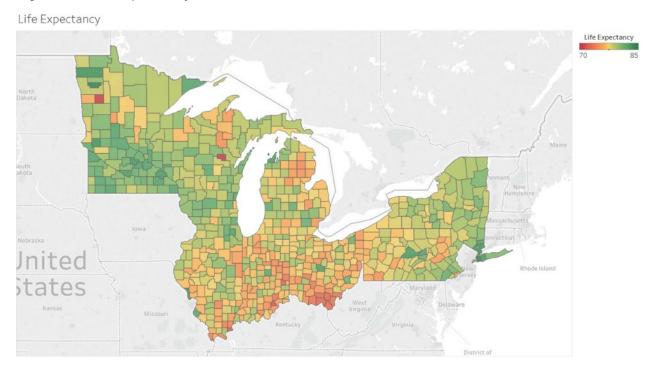


Figure 11 maps income equality by gender by calculating the distance between a county's average women's income and a county's average income for men and women combined (the greater the distance, the lower the rating). Green (areas like upstate New York) represents the most genderequal, and red (parts of southern Indiana and Michigan's upper peninsula) are the least genderequal. The most gender-equal county is Bronx County, New York (difference of 1.9%); and the least gender-equal county is Hardin County, Illinois (difference of 46.5%).

Figure 12 maps the racial diversity of Great Lakes counties measured as the percentage of county population who are non-white people of color (POC) as reported by the RWJ Foundation. Orange represents the least racially diverse counties, and blue represents the most racially diverse counties. Racial demographics are important indicators of vulnerability to climate change as within the United States, race remains <a href="https://district.night-ni

Figure 11: Income Equality by Gender

Income Equality by Gender (Women's Distance from Mean. Less Distance = More Equal)

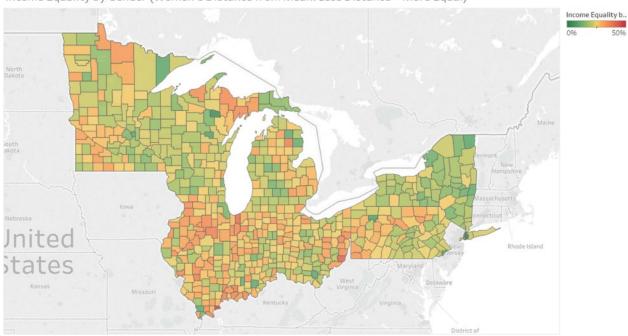


Figure 12: People of Color



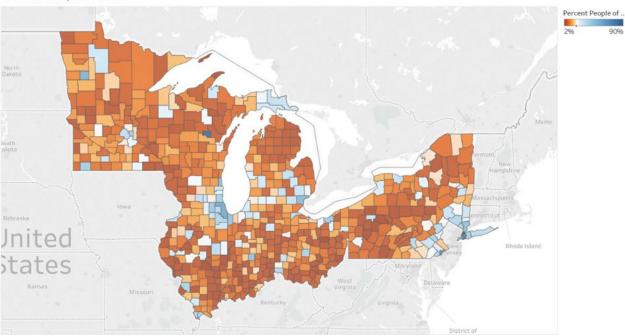


Figure 13 maps the GINI coefficient of Great Lakes counties. GINI coefficients are a mathematical measure of economic inequality, in which a 1 represents perfect inequality (one person has all the wealth) and a 0 represents perfect equality (where wealth is perfectly evenly distributed). Although it is not entirely clear what is a "good" GINI coefficient, the map portrays counties with lower GINI coefficient as green, and counties with higher GINI coefficients as red. The lowest GINI coefficient counties are Ohio County, Indiana (0.34); Lake of the Woods County, Minnesota (0.35); and Chisago County, Minnesota (0.36). The highest GINI coefficient counties are New York County, New York (0.60); Westchester County, New York (0.54); and Jackson County. Illinois (0.54). As shown in Figure 14, there appears to be a strong positive correlation between GINI coefficient and POC percentage, suggesting a racialized nature to inequality.

Figure 13: GINI Index



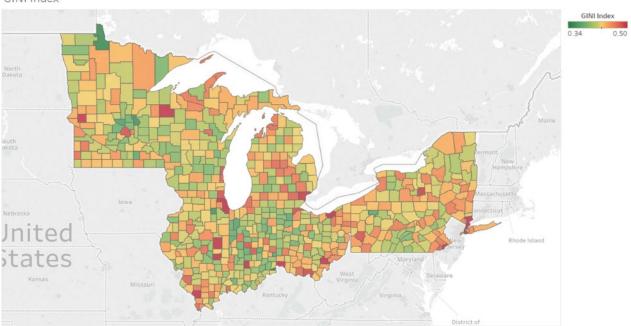




Figure 14: GINI Coefficient v. POC Population

Workforce Development

In the event that these counties are able to invest in climate resilience, workforce variables will play an important role in roll-out capacity and potential for public private partnerships (PPPs). Workforce may be considered in several capacities, such as worker volume, skill-level, and jobdemand.

Figure 15 maps the unemployment rate across Great Lakes counties according to data from the American Community Survey. The data is from 2019 U.S. Census American Community Survey, and does not include COVID-19 impacts. Counties with high unemployment may be desirable targets for GSI projects for two reasons: impact (serving a need for employment) and workforce availability (ensuring that there are workers available to fill jobs created by the GSI projects). Green represents counties with the lowest unemployment, and red represents counties with the highest unemployment. Counties with the lowest unemployment include Wilkin County, Minnesota (1.4%); Rock County, Minnesota (1.9%); and Chippewa County, Minnesota. Counties with the highest unemployment include Hardin County, Illinois (22.2%); Schoolcraft County, Michigan (13.9%); and Roscommon County, Michigan (13.0%).

Figure 15: Unemployment Rate

Unemployment Rate

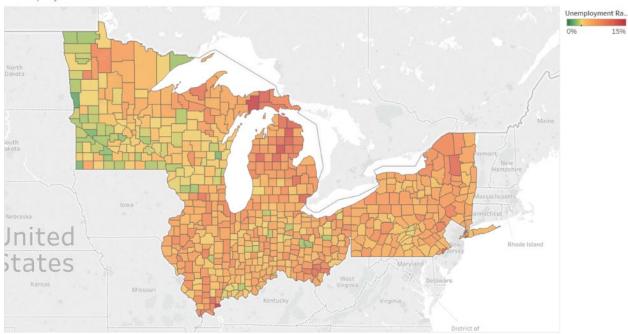
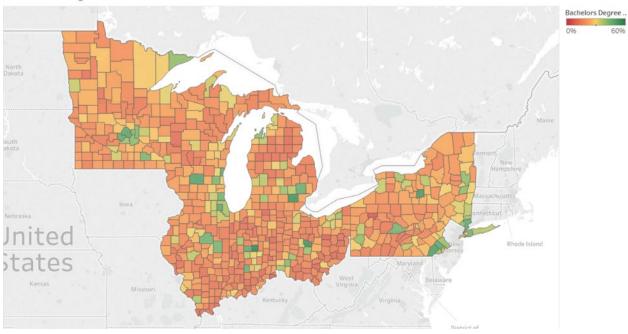


Figure 16 shows the percentage of county residents who have bachelor's degrees. Bachelor's degrees are one measure of the skilled workforce available to fill the skilled jobs that the project may create. Additional metrics for future study may include the availability apprenticeships,

Figure 16: Bachelor's Degree Rate





training programs, and experienced contractors. In Figure 16, green represents a higher percentage of residents having bachelor's degrees, and red represents a lower percentage of residents having bachelor's degrees. The data displays a clear visual trend in which bachelor's degree density appears concentrated around cities and dense urban areas. The counties with the lowest percentage of bachelor's degrees are Forest County, Pennsylvania (7.0%); Holmes County, Ohio (8.5%); and Switzerland County, Indiana (8.7%). The counties with the highest percentage of bachelor's degrees are New York County, New York (60.7%); Hamilton County, Indiana (57.5%); and Washtenaw County, Michigan (54.3%).

Figure 17 shows high school graduation rate for Great Lakes counties. Red represents counties with lower graduation rates, and green represents counties with higher graduation rates. In general, high school graduation rates are relatively high and evenly distributed throughout the counties. The counties with the lowest graduation rates are Holmes County, Ohio (58.2%); LaGrange County, Indiana (63.3%); and Bronx County, New York (71.5%). The counties with the

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Figure 17: High School Graduation Rate

highest graduation rates are Delaware County, Ohio (96.7%); Hamilton County, Indiana (96.2%); and Ozaukee County, Wisconsin (96.2%).

Figure 18 shows the relationship between vulnerability and unemployment. Not surprisingly, there is a strong positive correlation; counties indexed as more vulnerable (without utilizing unemployment as in input) also suffer the highest unemployment rates. One potential takeaway from this correlation is that many of the counties most in need of greater investment are also counties in which there is a large workforce looking for jobs - thus suggesting they may be a good location for investing in job-producing climate resilience initiatives.

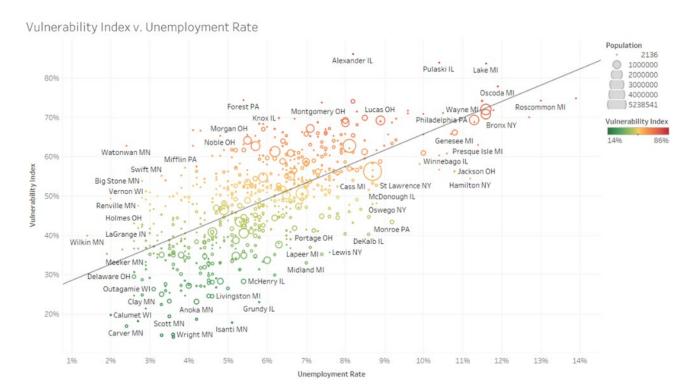


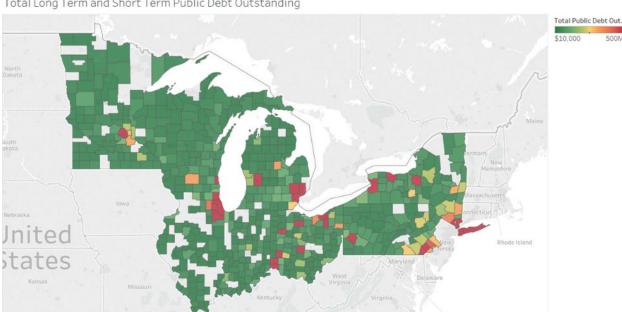
Figure 18: Vulnerability Index v. Unemployment Rate

Financing Capacity

These impacted counties have varying degrees of financial capacity to issue new debt to invest in climate-resilient infrastructure and programs due to pre-existing debt burdens - so more financing pathways are needed. Additionally, certain legislative and bureaucratic infrastructure such as Climate Action Plans and Mayoral Pledges exist to help provide mandates and structures for financing.

Figure 19 maps total outstanding public debt by county. Green represents counties with lower debt, red represents counties with higher debt and blanks represent counties with missing/insufficient data. The data is drawn from the 2017 U.S. Census, the most recently available comprehensive data set of municipal debt. Because the data represents a moment-in-time snapshot, it may not provide the most accurate representation of contemporary debt burdens. Nonetheless, a visual pattern emerges in which debt appears concentrated around major cities such as New York, Philadelphia, Pittsburg, Cleveland, Columbus, Cincinnati, Detroit, Grand Rapids, Chicago, Milwaukee, and Minneapolis. The counties with the highest outstanding debt are Nassau County, New York (\$4.0 billion); Suffolk County, New York (\$3.9 billion); and Franklin County, Ohio (\$3.5 billion). The counties with the lowest outstanding debt (notwithstanding counties with missing/insufficient data) are Scott County, Illinois (\$9,000); Edwards County, Illinois (\$12,000); and Menominee County, Michigan (\$32,000).

Figure 19: Total Long-Term and Short-Term Debt Outstanding



Total Long Term and Short Term Public Debt Outstanding

Figure 20 maps the same database of public debt, adjusted this time per capita. Green represents lower public debt per capita, red represents higher public debt per capita, and blanks represent missing/insufficient data. In this map, trends in debt distributions are less clear. Debt burden per capita likely provides a more precise estimation of a municipality's capacity for future spending than total debt burden (Figure 19) because per-capita adjustment accounts for expected future revenues from the resident population. The applicability of this ratio can vary by location due to differences in municipal financing structures and tax law, thus more research is required. Nonetheless, an interesting pattern emerges as shown in Figure 21; Counties with larger total debt burdens appear to often have higher debt burdens per capita. This may be due to urban municipal infrastructure (the higher total debt burdens) having some fundamental characteristics correlated greater spending per capita (such as distinct services like rapid transportation that rural communities may not possess).

Figure 20: Total Long-Term and Short-Term Public Debt Outstanding Per Capita

Total Long Term and Short Term Public Debt Outstanding (Per Capita) Total Public Debt .



Figure 21: Total Public Debt v. Total Public Debt per Population



Figure 22 shows the counties that either have a Climate Action Plan (CAP) registered with the CDP's 2020 dataset, are signatories to the Climate Mayors project, or are signatories to the Global Covenant of Mayors for Climate & Energy. The counties mapped include counties meeting these criteria, or counties that contain cities, towns, or places which meet these criteria. The visual trend appears to suggest that the more urban counties are more likely to have CAPs or be signatories to the mayoral climate pledges. The significance of this metric is that it indicates a first step for municipalities to address climate change, and thus may provide an approximation of how ready a county may be to engage in climate change adaption and resilience work. Although many other state or local level programs may exist pertaining to climate resilience, a formally adopted CAP is simply one standardized program. For a full list of Great Lakes states counties with CAPs for mayoral climate pledges, see Appendix B.

Taken together, Figures 21 and 22 provide additional insights. Figure 23 shows Total Public Debt v. Total Public Debt per Population ONLY for Counties who have a municipal CAP or Mayoral Climate Pledge. Within this chart, it is clear that there are municipalities of different sizes and debt loads who may be strong candidates for GSI projects due to having low debt per capita as well as the political infrastructure for financing.

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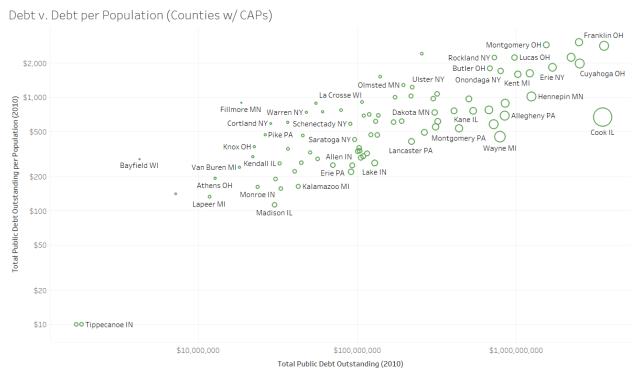
Noth
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Figure 22: Counties with Climate Action Plans or Mayoral Climate Pledges

Map based on Longitude (generated) and Latitude (generated). Colour shows details about County or Municipality within County has a CAP or Mayoral Pledge?. Details are shown for State and County Name.

Figure 23: Total Public Debt v. Total Public Debt per Population (Filtered for Counties with CAPs)



5. Climate Action Priority Framework: Composite Scores

After reviewing the individual metrics, we can now synthesize the metrics into a composite score that identifies the "priority" or "best fit" counties for intervention or new GSI projects. These counties are those that have the highest climate risk, the highest social vulnerability, the highest agile workforce, and the highest financial capacity to finance new infrastructure. The composite scores are created by generating 0-100 scores for each metric for each county, based on the county datapoint's distance from the metric mean (Table 4). The distance is scored as a percentile of a normal distribution of data. The metrics are directionally aligned (where 100 = most targetable, and 0 = least targetable), then evenly averaged together into a final 0-100 score. When data is unavailable for a certain metric for a certain county, the weight of that missing datapoint is evenly redistributed across the other metrics. When all metric data is available, the weighting of the metrics is as follows.

Table 4: Final Composite Metric Weights

Pillar	Metric	Weight
Climate	Impervious Ground Cover	10%
Climate	NFIP Claims \$ per Population	10%
Climate	Heavy Rain and Flood Damage Events per Population	10%
Social	Vulnerability Index	10%
Social	Population in Poor or Fair Health	10%
Social	GINI Coefficient	10%
Workforce	Unemployment Rate	10%
Workforce	Bachelors Degree Rate	10%
Workforce	High School Graduation Rate	10%
Financing	Debt Outstanding per Capita	10%
	Total	100%

Figure 24 displays the final composite scores generated using the process described above. The scores range from 25% (worst fit for municipal engagement) and 75% (best fit for municipal engagement). Visually, the map appears to combine the themes that emerges in many of the individual metrics shown above: urban areas are often "best fit" due to being generally the most socially vulnerable, containing more agile workforces, and being more likely to have the financing capacity (especially CAP infrastructure) to take on climate resilient watershed projects. Urban areas with environmentally risky floodplains are particularly of interest. However, there are also certainly counties that are a strong fit for intervention that are a smaller size by population. By examining Figures 25–29, we see a best fit county of any size can always be determined.

Figure 24 - Final Composite Scores on Climate Action Priorities

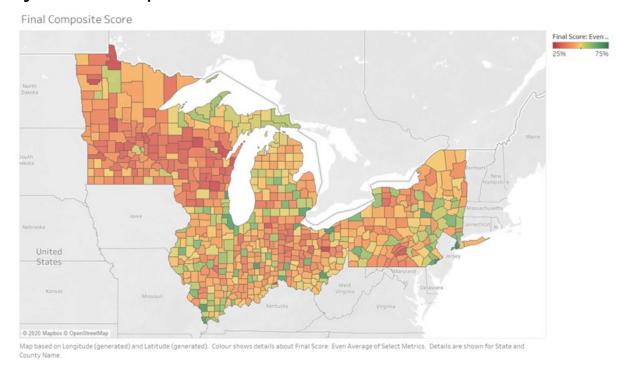


Figure 25: Final Composite Scores v. County Populations - Bigger Counties Are Better Fit for Green Stormwater Interventions

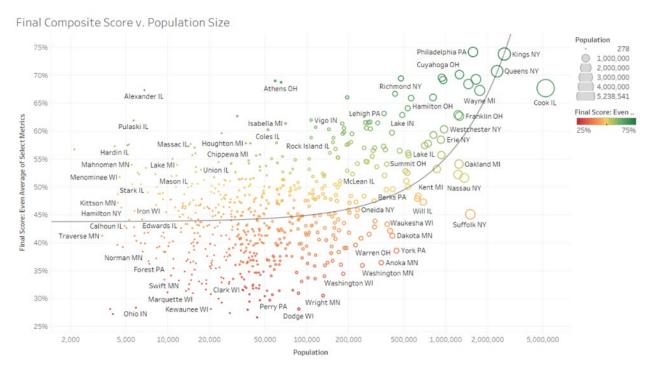


Figure 26: Final Composite Scores v. County Populations (250k - 1m Segment)

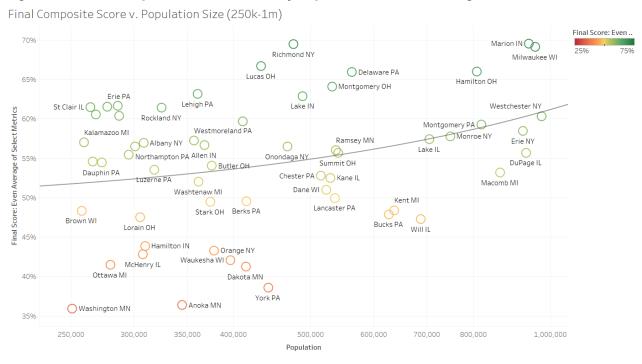


Figure 27: Final Composite Scores v. County Populations (100k - 250k Segment)

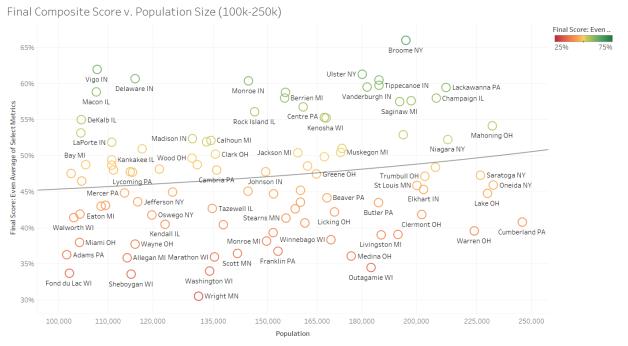


Figure 28: Final Composite Scores v. County Populations (50k - 100k Segment)

Final Composite Score v. Population Size (50k-100k))

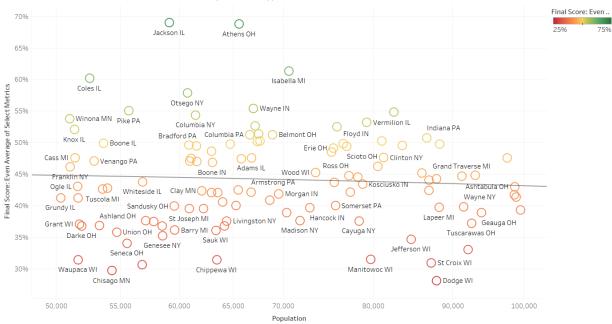
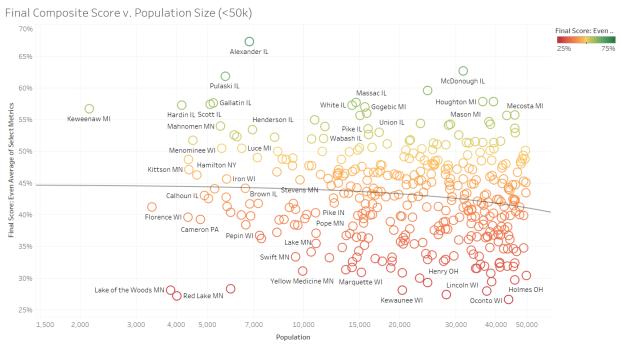


Figure 29: Final Composite Scores v. County Populations (50k - 100k Segment)



Lastly, Table 5 identifies the top 20 "best fit" scoring counties in the Great Lakes basin. A full table of counties, in all of the Great Lakes states, is provided in Appendix C.

Table 5: Top 20 Best Fit Great Lakes Basin Counties for GSI Intervention and Planning

Rank	County	Final Score
1	Cuyahoga County, Ohio	70.10%
2	Milwaukee County, Wisconsin	69.09%
3	Cook County, Illinois	67.66%
4	Wayne County, Michigan	67.28%
5	Lucas County, Ohio	66.67%
6	Lake County, Indiana	62.86%
7	Ingham County, Michigan	61.61%
8	Erie County, Pennsylvania	61.54%
9	Isabella County, Michigan	61.33%
10	St. Joseph County, Indiana	60.53%
11	Genesee County, Michigan	59.69%
12	Erie County, New York	58.45%
13	Berrien County, Michigan	57.98%
14	Houghton County, Michigan	57.80%
15	Monroe County, New York	57.76%
16	Saginaw County, Michigan	57.45%
17	Lake County, Illinois	57.40%
18	Gogebic County, Michigan	56.99%
19	Kalamazoo County, Michigan	56.99%
20	Keweenaw County, Michigan	56.67%

6. Conclusion

Large counties with urban centers provide strong opportunities for targeted GSI intervention due to several compounding factors. Urban centers are often at high risk of floods due to lack of permeable surfaces and concentrated development along rivers and in floodplains. Urban centers often contain high rates of vulnerability and poverty. Urban centers additionally often host highly agile workforces due to having larger pools of workers, mid-high unemployment rates leading to strong job demand, and a greater concentration of highly skilled and educated workers. Finally, urban centers appear more likely to have the financial capacities (larger budgets as well as higher prevalence of CAPs and mayoral climate pledges to facilitate climate resilience spending) to take on GSI projects. Of the top 20 best-fit counties by composite score, only 3 have populations less than 100,00 (Alexander County, Illinois; Jackson County, Illinois; and Athens County, Ohio). These 3 non-urban counties are outliers on several other metrics. Alexander County is extremely flood prone and highly socially vulnerable. Jackson County, home to Southern Illinois University, is relatively vulnerable, yet highly educated and employment agile. Athens County, home to Ohio University, is relatively vulnerable, highly educated and employment agile. It is also a member (City of Athens) of the Climate Mayors project.

However, counties of all sizes and types may be targeted for GSI interventions for outlier status on individual metrics (rather than composite), as well as based on additional on-the-ground information. Unique demographic, political, and social factors may create sufficient demand for GSI projects. Ultimately, the purpose of this report is to serve as a data guide to approaching municipal partnerships for GSI and climate resilience projects; human judgement, relationship buildings, and collaboration should be the final deciding factors.

Appendix A Climate Change in the Great Lakes

Air Temperature

In the Great Lakes region, climate change is increasing the incidence of hotter, drier summers. In the Great Lakes Basin, annual average temperatures are now 1.6°F warmer than historical averages. By 2070, the average annual air temperature of the northern Great Lakes Basin will be 5-6°F higher, while the southern region will experience a 4-5°F rise (GLISA, n.d.). Rising air temperatures in the Great Lakes are causing seasonal cues to change – spring is starting sooner, and winter is starting later (USGCRP, 2018). From 1951 to 2017, the frost-free season has increased by 16 days in the Great Lakes and may increase by an additional 50 days by 2100 (GLISA, 2019).

Extremely warm days (days above 90°F) will occur more frequently, especially in the southern region of the basin. By the end of the century, the Great Lakes Basin will experience 17 to 40 more extremely warm days per year, depending on location within the watershed. The number of extremely cold days (days below 32°F) is already decreasing and will continue to do so. The most significant decrease in extremely cold days will be in the northern region. By 2050, there will be between 21 and 25 fewer extremely cold days annually (Wuebbles et al., 2019).

In recent years, such as winter of 2014, the Great Lakes region experienced multiple "polar vortexes," where the jet stream carried Arctic climate conditions uncharacteristically southward. While research suggests that climate change is responsible for this extreme weather event, scientists predict that severe cold anomalies will become less extreme and less frequent in the coming century (Screen, et al 2015).

Precipitation and Flooding

In the Great Lakes Basin, total annual average precipitation is increasing due to climate change. As air temperature rises, its capacity to hold water vapor increases. With warmer air and surface water temperatures, higher rates of evaporation occur. This creates more significant cloud cover and increases the severity of precipitation events and storms (Dietz 2011). However, this overall rise in precipitation is not uniform amongst the basin nor throughout the seasons. Though precipitation varies lake-by-lake and region-by-region, the Great Lakes will generally experience a more pronounced dichotomy of wet season (winter and spring) and dry season (summer and fall). In the short term, dry season precipitation will continue to increase in variability, but it will stabilize towards the end of the century (Cherkauer and Sinha, 2010; Byun et al., 2018).

On average, precipitation specifically occurring over-lakes will decrease, while terrestrial precipitation will increase. Between the periods of 1954-1983 and 1984-2013, Lake Superior experienced the largest over-lake precipitation decreases at 7.9%, followed by 6.8% decrease over Lake Erie, and 2% decrease over Lake Huron and Lake Michigan. Over-lake precipitation increased for the eastern-most lake, Lake Ontario, at 3.5% (Wuebbles, 2019).

This contrasts with predicted and measured precipitation increases on surrounding land masses. Current models predict 7% greater average rainfall intensity per degree of surface warming in the Great Lakes region (d'Orgeville et al., 2014). With increased variability and intensity of precipitation,

intermittent periods of flooding and drought will become both more frequent and severe (Carpenter et al., 2017). In recent years, the central basin (Indiana, Illinois, and Michigan) experienced more frequent flood events due to greater annual precipitation (ECCC 2018). Urban centers are at high risk due to lack of infiltration capacity from aging infrastructure and high percentages of impervious surface (Carpenter et al., 2017).

In addition to changes in rainfall patterns, rising air temperatures are decreasing the annual number of snow cover days in the Great Lakes Basin. While precipitation will increase during the winter and spring, it will occur less frequently as snow, and more often as rain. Spring snowmelt will take place earlier in the season, and contribute less prominently to peak flow events, as total quantity of snow cover continues to decline (Cherkauer, et al., 2018). In the short-term, lake-effect snowfall is expected to increase. In the long-term, annual snowfall will decrease, while rainfall increases (Wuebbles et al., 2019). For larger watersheds, this will shift peak flow events earlier in the season. For smaller watersheds, the peak flow will occur later in the season (Cherkauer, et al., 2018). Winter and spring precipitation events, whether in the form of snowmelt or rainfall, will contribute to more severe spring flooding.

By the end of the century, Great Lakes ice cover will decline. However, in recent years, ice cover grew on average, due to the phenomenon of polar vortexes. In winter 2017-2018, every Great Lake saw near or above average concentrations of ice cover. Yet as annual average temperatures rise, ice cover will decrease, allowing for greater evaporation of lake water, and higher rates of winter precipitation (Mishra, et al., 2011).

Great Lakes Water Levels

In recent years, methodologies and models used to determine lake level patterns have shifted. Current research now predicts Great Lakes levels will experience "smaller drops on average and the possibility of a small rise in lake levels by the end of this century." Over the past few decades, Great Lakes water levels reached both record lows and highs, with Lakes Huron and Michigan most susceptible to water level shifts due to large basin size and drainage patterns (Wuebbles, et al., 2019). When averaged over the past hundred years, water levels in Lakes Superior, Michigan, and Huron showed no significant change, unlike Lakes Erie and Ontario, whose water levels rose (EPA, 2019).

Due to the complex hydrological influences on the Great Lakes, it is difficult to discern which incidences of lake level change are considered natural variation in the hydrological cycle versus impacts of climate change (EPA 2019). Predicting future and current lake levels is complicated by the altered patterns in Arctic ice and snow cover, which shape Great Lakes weather systems. However, scientists expect increased extremes in precipitation events, higher rates of evaporation, greater incidence of unusual climate events, and extreme variation in high and low Great Lakes levels, as already seen in recent decades (Gronewold, et al., 2019).

When lake levels drop to extreme lows, connectivity between aquatic habitats is reduced. Coastal estuaries and high-quality wetlands become hydrologically isolated from the larger watershed. Fish abundance and community composition suffer, as connectivity provides necessary access to habitat for nurseries, foraging, spawning, and reproduction. When lake levels reach extreme lows, predator-prey interactions may increase or change as spatially-separate species within the water column are subjected to sharing similar depths (Dietz 2011). With recent extreme rises in lake levels, coastal communities and terrestrial ecosystems are most at risk. Rising lake levels increase soil erosion, reduce quality and quantity of coastal habitat, displace coastal residents, damage coastal property, and delay spring planting of agricultural crops (Gronewold et al., 2019).

Understanding the current and future shifts in Great Lakes water levels is best explained by net basin supply (NBS). A given lake's NBS is calculated by the sum of precipitation and runoff minus evaporation. In recent years, Lake Superior's NBS decreased by 17.5%, while Lake Huron and Lake Michigan (which are hydrologically the same lake) experienced a 3% increase in NBS. Lake Ontario's NBS grew by 9.5%, and no significant change in NBS was found in Lake Erie (Wuebbles, 2019). New research supports that water management, such as human water consumption, is less at fault to extreme variability in Great Lakes water levels than the impacts of climate change. Additional research is needed to better understand the drivers of NBS and therefore improve the accuracy of lake level predictions in the Great Lakes (Gronewold and Rood, 2018).

Water Quality

Great Lakes water temperatures are increasing at a faster rate than the surrounding air. Extended duration of summer stratification is the main driver of warming waters, as it continues to occur earlier in spring and persist further into fall. When stratified, the lake's warmest waters rise to the surface. Changing seasonal air temperatures in the Great Lakes typically cause turnover to occur in spring and fall, in which a complete mixing of the water column occurs. During turnover, lakes experience near-homogenous water temperature and dissolved oxygen levels. Earlier onset of summer stratification brings warmer water to the surface earlier in the year, inhibiting further oxygenation of a lake's deepest, coolest waters. Longer duration of summer stratification is reinforced in a feedback loop; The epilimnion reaches a greater temperature differential from the hypolimnion, which further delays fall turnover.

As lake ice cover decreases towards the end of the century, the lower albedo of water contributes to the warming feedback loop (ice-albedo feedback) (Austin et al., 2007).

Additionally, warmer water increases rates of primary productivity (production of biomass by autotrophs). This creates summer hypoxic conditions, which will occur more frequently in the coming century (Nelson et al., 2009). Hypoxic conditions cause aquatic life die-off, particularly in invertebrate communities (Collingsworth et al., 2017).

Warmer water and higher rates of primary production support the formation of harmful algal blooms (HABs). HABs can include toxin-producing cyanobacteria, which toxifies drinking water

sometimes to the point of fatality in humans (EPA, 2019). Nutrient loading, stratification, and water temperature all influence the extremity and frequency of HABs. Already, there is evidence to support severe climate events' roles in the formation of HABs. Certain toxic algae, such as Cylindrospermopsis, which forms a toxic bloom, requires temperatures above 22°C to germinate (Dietz, 2011). Microcystis exhibits higher growth rates and incidences of toxicity in warmer temperatures (Cheung, et al., 2013). During HABs, water is no longer drinkable, as not even boiling water removes toxins (City of Toledo, n.d.).

Western Lake Erie is at the highest risk for increased incidence of HABs. 500,000 people in Toledo, Ohio lost access to safe drinking water for 72 hours in 2014 due to HABs (City of Toledo, n.d.). In addition to eliminating safe drinking water, HABs also contribute to conditions of hypoxia, causing mass die off events of aquatic life. The combination of extensive nearby agriculture operations and warm shallow water creates seasonal dead zones in Western Lake Erie (Wuebbles et al., 2019). When compounded with the success of invasive aquatic species, such as quagga and zebra mussels, HABs grow at even greater rates.

Nutrient loading is predicted to increase with the onset of climate change. Intensified precipitation events drive greater sediment and pollutant runoff, both in urban and agricultural settings. Cities with combined sewer systems are at high risk of overflow due to extreme weather events. Higher risk of flooding is correlated directly with decrease in water quality. In municipalities with combined sewer systems, climate change is predicted to increase the concentration of nutrients and harmful bacteria from human waste and sewage in Great Lakes water supply, posing both ecological and human health risks (Robertson, et al., 2011). From agriculture runoff, primarily nitrogen and phosphorous will accumulate in waterways in greater rates as precipitation events continue to intensify (EPA, 2019). Between 2071-2100 under high emissions scenarios, nitrogen loading in the Great Lakes is expected to increase by 21% (Sinha et al., 2017). Currently, Lake Superior has the healthiest levels of phosphorus of the five Great Lakes (EPA, 2019), and yet still experienced a rare algal bloom in spring of 2018 due to sediment runoff from a severe storm (ECCC, 2018).

Agriculture

Farmers are already seeing negative impacts of climate change in the Great Lakes Basin. Great Lakes Basin agriculture is predicted to increase its contribution to nutrient loading, run off, and soil erosion due to higher frequency of severe storms combined with large-scale livestock operations and heavy fertilizer use. Warmer average annual temperatures lengthen growing seasons, which has the potential to increase crop yield (Verma 2015).

However, the potential benefits of a longer growing season are negated if planting is delayed, due to risk of spring flooding and overly saturated soils. Uncertainty around shifting frost dates and new extreme precipitation events will increasingly make it difficult to determine when, or if, to plant crops. Delayed planting puts crops at higher risk for the new onset of summer droughts.

Therefore, climate change is predicted to increase irrigation needs, despite overall average annual increases in precipitation in the Great Lakes Basin (Bowling et al., 2018).

Growing degree days (GDD) is a calculation of daily temperature degrees that exceed 5 $^{\circ}$ C (41 $^{\circ}$ F), summed into an annual average, and used to describe the available season for crop growth. Climate change is causing GDDs to rise in the Great Lakes region. Southern Wisconsin and southern Michigan historically averaged between 2000–3000 GDD from 1980–2010. By the end of the century, this same region will experience 4000–5000 GDD (USFS, 2019).

Crop yield will decrease due to hotter temperatures' interference with crop pollination. Crop yield is expected to reduce by 10-30% by the end of the century, while irrigation will increase by 90% due to high consumptive-use coefficient. This will increase extraction of water from the Great Lakes Basin's groundwater stores. Corn and soybeans will experience the greatest decreases in yield, with fruit crops similarly vulnerable to extreme weather events. Agriculture in the southern Great Lakes is the most at risk to conditions of severe drought stress.

Necessary agricultural adaptations include shifting corn and soybean farming northward, irrigating more intensively, experimenting with more drought-tolerant crops, and incorporating ecological methods of agriculture. Some restorative or ecological agriculture approaches include cover cropping, double cropping, and improvements in soil health (Wuebbles et al., 2019). By increasing the quantity of organic matter in soils and growing cover crops in the off-season, the resiliency of intensive monoculture agriculture can greatly increase. Such methods improve water holding capacity of soils, reduce runoff, and retain soil nutrients and microbes (UCSUSA, 2019). Though options for adaption do exist for farmers, long term agricultural productivity in the Great Lakes region is expected to decrease (Baule et al., 2014).

Great Lakes Ecosystems & Wildlife

Both directly and indirectly, climate change is altering the quality and composition of ecosystems within the Great Lakes Basin. Wildlife must adapt to a myriad of environmental changes, including shifting temperature and precipitation patterns, habitat loss, fragmentation, increased competition from invasive species, higher rates of disease, and altered ecological processes (Hoving et al., 2013; Merila and Hendry, 2014, as cited in Wuebbles 2019). The climate is changing too quickly for natural selection to support genetic adaptation for most Great Lakes species. Therefore, reductions in species fitness, declining populations, and potential for extinction will occur for many Great Lakes species as climate change progresses (Dietz et al., 2011).

Range and distributions of native species are, in general, moving to cooler climates (typically northward). The Great Lakes Basin is relatively flat, therefore, range shifts to higher elevations are not reliable options for most at-risk species. Due to the rapid rate of climate change, species with the ability to move quickly over a human-altered landscape, such as birds, are more likely to "keep pace" with changes in climate, if no other variables are considered.

Tree species ranges in the Great Lakes are currently moving both northward and westward at a rate of 10-15 km per decade, with noted potential for range contraction particularly in eastern tree species (Woodall et al., 2009; Fei et al., 2017). Northern forest communities will be outcompeted by range-expanding oak/hickory and oak/pine forests. Boreal forest communities such as spruce/fir and white/red/jack pine will be pushed northward, while white/red/jack pine and spruce predicted to exit the Great Lakes region entirely (Baule et al., 2014). However, there is a high degree of uncertainty in determining how native species and ecosystems will be affected by the changing climate (Wuebbles et al., 2019).

Pressures of climate change put specialist species at higher risk for population decline and extinction. Obligate marsh-nesting birds, for instance, are predicted to decrease in population if Great Lakes water levels drop significantly due reduction of marsh habitat (Timmermans, et al., 2008). Similarly, Kirtland's warbler (Setophaga kirtlandii), a specialist of young jack pine barrens, is at risk due to competition of north-migrating southern tree species, competing with jack pines (Pinus banksiana) (Dietz et al., 2011). As community composition shifts in Great Lakes ecosystems, it is predicted that wildlife with greater body mass are more susceptible to population decline than animals with smaller bodies. Moose (Alces alces) will struggle to thermo-regulate when faced with changing precipitation and temperature patterns. This is compounded by changing availability of browsable plants and new tick-borne diseases, both results of climate change (Rempel et al., 2011). Northward-expanding white-tailed deer (Odocoileus virginianus) are expected to replace declining moose populations (Thompson et al., 1998).

In both terrestrial and aquatic ecosystems in the Great Lakes Basin, primary productivity will increase (Wuebbles et al., 2019). In aquatic ecosystems, eutrophic conditions and algal blooms will occur more frequently due to excessive nutrients in the epilimnion and shallow waters. Concurrently, deep waters will experience increased incidences of hypoxia, causing anoxia in aquatic wildlife. Due to earlier onset of summer stratification and reduced periods of turnover, fewer deep-water nutrients will mix into the epilimnion, causing nutrient deficits in both deep-water and open-water habitats (Hinderer et al., 2011).

Fish are additionally impacted by loss of and shift in spawning habitat due to climate change (EPA, 2019). Increased intensity and variability in precipitation events will negatively impact fish species sensitive to unexpected changes in water temperature. Some warm-water species of fish, such as largemouth bass (*Micropterus salmoides*) will increase recruitment and population size. However, cold-water species, such as yellow perch (*Perca flavescens*) and lake whitefish (*Coregonus clupeaformis*), will drop in population size. As the coldest and deepest lake, cold-water species will find climate refuge in Lake Superior. To varying degrees, Great Lakes fishes will experience changes in physiological state and performance as well as spatial arrangement within a system as a result of climate change (Wuebbles, et al., 2019).

Many species who rely on phenological cues to trigger life cycle events will likely experience phenological mismatch due to climate change (USGCRP, 2018). Increased occurrence of extreme

weather events, such as severe warm or cold spells, place many species at risk of physical damage or death. Newly leafed-out spring vegetation has been particularly vulnerable to recent late-season arctic cold blasts (Dietz et al., 2011). For many birds, phenological mismatch will misalign migration with earlier hatching times of insects that serve as a primary food source (USGCRP, 2018). Worldwide, spring phenology events are occurring an average of 5 days earlier each decade due to climate change (Root et al., 2003).

Climate change is both expanding the ranges of and increasing pressures from aggressive non-native (invasive) species in terrestrial and aquatic ecosystems in the Great Lakes Basin. As native ecosystems decline in habitat quality, competition from invasive species heighten the risk of population decline of native flora and fauna. Research shows that at least 30% of introduced aquatic species in the Great Lakes have significant impact on socioeconomics and the ecosystem health. The EPA rates the situation of invasive species as "deteriorating," with more than 185 aquatic non-native species currently established in the Great Lakes. This number continues to increase (EPA, 2019).

Invasive aquatic species such as quagga and zebra mussels (dreissenids) change both ecological community composition and nutrient cycling in the Great Lakes. As filter feeders, dreissenids decrease phytoplankton abundance while increasing water clarity. This action of filtering initially decreases primary production, until an onset of algal blooms occurs. Quagga mussels alone sequester two-thirds of the Great Lakes' phosphorus in their body tissues, creating a phosphorus deficit in off-shore, open-water environments. Invasive dreissenids contribute to harmful algal blooms by concentrating lake nutrients to shallower coastal regions (30-100 feet deep), and consuming selective algal that does not include most toxic bloom-forming species. (Hinderer et al., 2011).

Climate change is already increasing the incidence of numerous human and wildlife diseases. Increased extremity of precipitation events causes more frequent overflow of combined sewer systems and runoff from agriculture. Warming lake temperatures support growth of pathogenic bacteria, viruses, protozoa, and harmful algal blooms (Robertson, et al., 2011). Lake Erie and Ontario are at highest risk for degradation by nutrient enrichment and/or sedimentation (EPA 2019). Climate change is reducing the duration and occurrence of vertical mixing of the water column in the Great Lakes, which is necessary to replenish and redistribute oxygen and nutrients throughout each lake. Without vertical mixing, Lake Erie is particularly at risk, due to its shallow depth and substantial inputs of agricultural nutrient runoff (Wuebbles, et al., 2019).

Growing public health issues in the Great Lakes extend to increasing populations of Lyme disease (*Borrelia burgdorferi*)-carrying ticks. Northern range expansions for disease hosts are already occurring for the ticks' host, the white-footed mouse (*Peromyscus leucopus*) (Wuebbles et al., 2019). In addition, lower water levels and higher water temperatures encourage the spread of avian botulism (*Clostridium botulin*), decreasing survival of many wild bird populations (Culligan et al., 2002).

Recreation

The diversity of recreation activities in the Great Lakes not only creates unique regional character, but it also supports the region's economy significantly. Boating and fishing are the largest recreational activities in the United States. In 2019, boating and fishing contributed \$36.93 billion to the United States economy (Great Lakes Scuttlebutt, 2018). Temperature change is the biggest driver of recreational activities. More research is needed to understand the collective economic and social impacts of climate change on Great Lakes recreation industries (Wuebbles et al., 2019).

Climate change will negatively impact winter recreation activities more so than warm-season activities. Reduced snow fall, warmer temperatures, and decreased lake ice cover will limit Great Lakes winter recreation, including snowmobiling, skiing, and ice fishing. Decreasing duration and thickness of lake ice cover will limit the locations available to participate in ice-based activities. By the end of the century, under high emissions projections, lack of snowfall and conditions needed to create artificial snow will render all existing ski resorts obsolete in the Great Lakes Basin (Chin, et al., 2018).

Degraded water quality and shoreline conditions are likely to impact warm season water-based recreation. Harmful algal blooms create toxic, and potentially fatal, water conditions, prohibiting both beach and swimming activities. If all Lake Erie beaches were affected by harmful algal blooms, impacts of up to \$2 million per year could be lost. With growing instances of bacterial and pathogenic plumes like E. coli due to climate change, beaches and shorelines will close more often (Palm-Forster et al., 2015). Approximately \$2 per trip will be lost due to a single beach closure (Murray et al., 2001). Stronger storms will result in damaging coastal erosion and flooding. In fall of 2018, an unusually strong October storm over Lake Superior caused \$18.4 million of damage to shoreline parks and infrastructure in Duluth, MN. (The Associated Press, 2018). Such events are expected to become more frequent in the next century (ECCC, 2018).

As native cold-water fish populations drop in the coming century, fisherman will more frequently catch invasive fish, such as silver Asian Carp (*Hypophthalmichthys molitrix*). It is unclear if the popularity and culture of fishing will change due to climate change, regardless of alterations in fish species composition. Additionally, little is known about how climate change will impact wildlife viewing activities, such as birding. As native species diversity and populations decrease, oncereliable migratory patterns of birds will shift, potentially changing locations of key birding interest (Wuebbles et al., 2019). Waterfowl hunters will notice declines in desirable species of ducks, including American black ducks (*Anas rubripes*), scaups (*Aythya sp.*), and canvasbacks (*Aythya valisineria*). In the Northern Mississippi Flyway, a bird migration route in the Great Lakes, waterfowl breeding habitat will diminish in quantity and decrease in quality due to summer droughts. Wetlands will reduce in size and smaller streams will be at risk for seasonal drying (Ducks Unlimited, n.d.).

Water Infrastructure

Two thirds of the 38 million Great Lakes Basin residents reside in urban areas. Cities are uniquely vulnerable to climate change due to aging and outdated water infrastructure, as it fails to meet water capacity needs for intensified precipitation events. Primary reliance upon grey infrastructure in urban centers reduces the ability of water to infiltrate into soil, and therefore increases stormwater runoff. Flood risk heightens as impervious surface increases, and flood vulnerability continues to grow as annual average precipitation climbs.

Cities with combined sewer systems are especially susceptible to impaired water quality due to flooding. When a combined sewer system is overwhelmed, sewage is discharged into surrounding waterways, and water treatment plants frequently shut down (Baule et al., 2014). In 2019, the state of Michigan discharged a total of 2711.5 million gallons of untreated combined sewer overflow and 349.2 million gallons of partially treated combined sewer overflow into surrounding waterways (EGLE, 2020). As excess nutrients and bacteria accumulate in water resources, water treatment costs increase, as purification produces toxic byproducts.

Communities built in floodplains and low-lying areas are particularly susceptible to infrastructural damage and issues of water quality (Wilson et al. 2010). In the May 2020, the Tittabawassee River flooded in Midland County, Michigan, and three dams were breached. The flood amounted to \$190 million in damages to homes, buildings, and businesses, and \$55 million to public infrastructure (Jones, 2020). State and federal programs such as the Federal Emergency Management Agency (FEMA)'s 'Acquisition and Relocation of Floodprone Structures' offer avenues for converting at-risk construction and development into flood-resilient greenspace (FEMA, 2005).

A shift from gray to green infrastructure presents effective options for improving urban resilience to climate change. Green infrastructure includes landscape systems such as rain gardens, parks, bio swales, permeable paving, green roofs, street tree planting, and green street corridors, among many other design systems. Green infrastructure promotes onsite infiltration of water, which reduces risk of flooding, reduces runoff, improves water quality, and contributes to groundwater recharge. Typically, green infrastructure can withstand impacts of severe weather events more effectively than aging gray infrastructure (Wuebbles et al., 2019).

Vegetated green infrastructure decreases soil erosion, creates additional areas of green space, and can decrease the urban heat island effect (Hopton et al., 2015). Planting one young tree near a building can cool an interior environment at the equivalent rate of ten room-sized air conditioners operating 20 hours per day. Cooling abilities of infrastructure are necessary as climate change brings severe heat waves, threatening public health (EPA, n.p.). Additionally, vegetated green infrastructure improves air quality through the pollution filtration capacity of plants (Wuebbles et al., 2019). Green infrastructure can also enhance coastal resiliency. Research suggests that wave height can be reduced 95% after crossing 100 feet of marshes (EPA, n.p.).

Climate Risk, Resilience, and Opportunities in the Great Lakes Region
avaraging Graan Infractructura as a Rasilianca Maasura for Stormwater Infractructura

Appendix B Citations

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Appendix C Places with Climate Action Plans or Mayoral Climate Pledges

Municipality	Count of Places
State of Illinois	23
Cook County, Illinois	7
Chicago, Illinois	1
Evanston, Illinois	1
Hoffman Estates, Illinois	1
Park Forest, Illinois	1
Skokie, Illinois	1
South Barrington, Illinois	1
Wilmette, Illinois	1
Lake County, Illinois	3
Highland Park, Illinois	1
Lake Forest, Illinois	1
Waukegan, Illinois	1
Kane County, Illinois	3
Aurora, Illinois	1
Elburn, Illinois	1
Elgin, Illinois	1
McLean County, Illinois	2
Bloomington, Illinois	1
Normal, Illinois	1
Champaign County, Illinois	2
Champaign, Illinois	1
Urbana, Illinois	1
McHenry County, Illinois	1
Woodstock, Illinois	1
Carroll County, Illinois	1
Savanna, Illinois	1
Winnebago County, Illinois	1
Rockford, Illinois	1

Municipality	Count of Places
DeKalb County, Illinois	1
DeKalb, Illinois	1
Madison County, Illinois	1
Alton, Illinois	1
Kendall County, Illinois	1
Montgomery, Illinois	1
State of Indiana	8
Vanderburgh County, Indiana	1
Evansville, Indiana	1
St. Joseph County, Indiana	1
South Bend, Indiana	1
Monroe County, Indiana	1
Bloomington, Indiana	1
Hamilton County, Indiana	1
Carmel, Indiana	1
Tippecanoe County, Indiana	1
West Lafayette, Indiana	1
Lake County, Indiana	1
Gary, Indiana	1
Allen County, Indiana	1
Fort Wayne, Indiana	1
Marion County, Indiana	1
Indianapolis, Indiana	1
State of Michigan	24
Oakland County, Michigan	5
Ferndale, Michigan	1
Huntington Woods, Michigan	1
Pleasant Ridge, Michigan	1
Rochester Hills, Michigan	1

Municipality	Count of Places
Royal Oak, Michigan	1
Wayne County, Michigan	4
Detroit, Michigan	1
Hamtramck, Michigan	1
Rockwood, Michigan	1
Westland, Michigan	1
Ingham County, Michigan	2
East Lansing, Michigan	1
Lansing, Michigan	1
Washtenaw County, Michigan	2
Ann Arbor, Michigan	1
Ypsilanti, Michigan	1
Ottawa County, Michigan	1
Holland, Michigan	1
Muskegon County, Michigan	1
Muskegon, Michigan	1
Macomb County, Michigan	1
Sterling Heights, Michigan	1
Kalamazoo County, Michigan	1
Kalamazoo, Michigan	1
Genesee County, Michigan	1
Flint, Michigan	1
Van Buren County, Michigan	1
South Haven, Michigan	1
Jackson County, Michigan	1
Jackson, Michigan	1
Grand Traverse County, Michigan	1
Traverse City, Michigan	1
Berrien County, Michigan	1
Buchanan, Michigan	1

Municipality	Count of Places
Kent County, Michigan	1
Grand Rapids, Michigan	1
Lapeer County, Michigan	1
Lapeer, Michigan	1
State of Minnesota	13
Hennepin County, Minnesota	4
Bloomington, Minnesota	1
Eden Prairie, Minnesota	1
Edina, Minnesota	1
Minneapolis, Minnesota	1
Ramsey County, Minnesota	3
Falcon Heights, Minnesota	1
Maplewood, Minnesota	1
Saint Paul, Minnesota	1
St. Louis County, Minnesota	1
Duluth, Minnesota	1
Dakota County, Minnesota	1
Burnsville, Minnesota	1
Fillmore County, Minnesota	1
Lanesboro, Minnesota	1
Winona County, Minnesota	1
Winona, Minnesota	1
Carver County, Minnesota	1
Carver, Minnesota	1
Olmsted County, Minnesota	1
Rochester, Minnesota	1
State of New York	31
Westchester County, New York	9
Ardsley, New York	1

Municipality	Count of Places
Dobbs Ferry, New York	1
Hastings-on-Hudson, New York	1
Irvington, New York	1
Ossining, New York	1
Sleepy Hollow, New York	1
Tarrytown, New York	1
White Plains, New York	1
Yonkers, New York	1
Ulster County, New York	3
Kingston, New York	1
Marbletown, New York	1
New Paltz, New York	1
Broome County, New York	2
Binghamton, New York	1
Whitney Point, New York	1
Monroe County, New York	2
Brighton, New York	1
Rochester, New York	1
Otsego County, New York	1
Cooperstown, New York	1
Tompkins County, New York	1
Ithaca, New York	1
Saratoga County, New York	1
Saratoga Springs, New York	1
Dutchess County, New York	1
Beacon, New York	1
Warren County, New York	1
Lake George, New York	1
Erie County, New York	1
Buffalo, New York	1

Municipality	Count of Places
Rockland County, New York	1
Nyack, New York	1
Kings County, New York	1
New York, New York	1
Queens County, New York	1
New York City, New York	1
Bronx County, New York	1
New York City, New York	1
Richmond County, New York	1
New York City, New York	1
New York County, New York	1
New York City, New York	1
Schenectady County, New York	1
Schenectady, New York	1
Clinton County, New York	1
Plattsburgh, New York	1
Columbia County, New York	1
Hudson, New York	1
Albany County, New York	1
Albany, New York	1
Cortland County, New York	1
Cortland, New York	1
Onondaga County, New York	1
Syracuse, New York	1
Niagara County, New York	1
Niagara Falls, New York	1
State of Ohio	12
Cuyahoga County, Ohio	3
Cleveland, Ohio	1
Cuyahoga County, Ohio	1

Municipality	Count of Places
Lakewood, Ohio	1
Athens County, Ohio	2
Amesville, Ohio	1
Athens, Ohio	1
Franklin County, Ohio	2
Bexley, Ohio	1
Columbus, Ohio	1
Lucas County, Ohio	1
Toledo, Ohio	1
Butler County, Ohio	1
Oxford, Ohio	1
Montgomery County, Ohio	1
Dayton, Ohio	1
Hamilton County, Ohio	1
Cincinnati, Ohio	1
Knox County, Ohio	1
Gambier, Ohio	1
State of Pennsylvania	19
Montgomery County, Pennsylvania	3
Abington Township, Pennsylvania	1
Ambler, Pennsylvania	1
Conshohocken, Pennsylvania	1
Northampton County, Pennsylvania	2
Bethlehem, Pennsylvania	1
Easton, Pennsylvania	1
Chester County, Pennsylvania	2
Downingtown, Pennsylvania	1
West Chester, Pennsylvania	1
Allegheny County, Pennsylvania	2
Duquesne, Pennsylvania	1

Municipality	Count of Places
Pittsburgh, Pennsylvania	1
Philadelphia County, Pennsylvania	1
Philadelphia, Pennsylvania	1
Centre County, Pennsylvania	1
State College, Pennsylvania	1
Erie County, Pennsylvania	1
Erie, Pennsylvania	1
Lackawanna County, Pennsylvania	1
Scranton, Pennsylvania	1
Delaware County, Pennsylvania	1
Swarthmore, Pennsylvania	1
Westmoreland County, Pennsylvania	1
Monessen, Pennsylvania	1
Pike County, Pennsylvania	1
Milford, Pennsylvania	1
Lehigh County, Pennsylvania	1
Allentown, Pennsylvania	1
Monroe County, Pennsylvania	1
Mount Pocono, Pennsylvania	1
Lancaster County, Pennsylvania	1
Lancaster, Pennsylvania	1
State of Wisconsin	16
Dane County, Wisconsin	6
Dane County, Wisconsin	1
Dunn, Wisconsin	1
Madison, Wisconsin	1
Middleton, Wisconsin	1
Monona, Wisconsin	1
Verona, Wisconsin	1
Milwaukee County, Wisconsin	2

Municipality	Count of Places
Glendale, Wisconsin	1
Milwaukee, Wisconsin	1
Kenosha County, Wisconsin	1
Kenosha, Wisconsin	1
Bayfield County, Wisconsin	1
Bayfield, Wisconsin	1
Brown County, Wisconsin	1
Green Bay, Wisconsin	1
La Crosse County, Wisconsin	1
La Crosse, Wisconsin	1
Racine County, Wisconsin	1
Racine, Wisconsin	1
Wood County, Wisconsin	1
Wisconsin Rapids, Wisconsin	1
Ashland County, Wisconsin	1
Ashland, Wisconsin	1
Eau Claire County, Wisconsin	1
Eau Claire, Wisconsin	1
Grand Total (Places)	146

Appendix D Composite Score Ranking for All Counties in U.S. Great Lakes States

Rank	County	Final Composite Score
1	Philadelphia County, Pennsylvania	74.1%
2	Kings County, New York	73.7%
3	Queens County, New York	70.7%
4	Cuyahoga County, Ohio	70.1%
5	Marion County, Indiana	69.5%
6	Richmond County, New York	69.4%
7	New York County, New York	69.2%
8	Milwaukee County, Wisconsin	69.1%
9	Jackson County, Illinois	69.0%
10	Athens County, Ohio	68.7%
11	Bronx County, New York	68.4%
12	Cook County, Illinois	67.7%
13	Wayne County, Michigan	67.3%
14	Alexander County, Illinois	67.3%
15	Lucas County, Ohio	66.7%
16	Hamilton County, Ohio	66.0%
17	Broome County, New York	66.0%
18	Delaware County, Pennsylvania	65.9%
19	Montgomery County, Ohio	64.1%
20	Lehigh County, Pennsylvania	63.1%
21	Lake County, Indiana	62.9%
22	Allegheny County, Pennsylvania	62.9%
23	McDonough County, Illinois	62.6%
24	Franklin County, Ohio	62.6%
25	Vigo County, Indiana	61.9%
26	Pulaski County, Illinois	61.8%
27	Ingham County, Michigan	61.6%
28	Erie County, Pennsylvania	61.5%
29	St. Clair County, Illinois	61.5%

Rank	County	Final Composite Score
30	Rockland County, New York	61.4%
31	Isabella County, Michigan	61.3%
32	Ulster County, New York	61.3%
33	Delaware County, Indiana	60.6%
34	St. Joseph County, Indiana	60.5%
35	Peoria County, Illinois	60.5%
36	Winnebago County, Illinois	60.4%
37	Monroe County, Indiana	60.3%
38	Westchester County, New York	60.3%
39	Coles County, Illinois	60.2%
40	Tippecanoe County, Indiana	59.7%
41	Genesee County, Michigan	59.7%
42	Saline County, Illinois	59.6%
43	Vanderburgh County, Indiana	59.5%
44	Lackawanna County, Pennsylvania	59.4%
45	Montgomery County, Pennsylvania	59.2%
46	Macon County, Illinois	58.8%
47	Schenectady County, New York	58.8%
48	Erie County, New York	58.5%
49	Berrien County, Michigan	58.0%
50	Champaign County, Illinois	58.0%
51	Otsego County, New York	57.8%
52	Franklin County, Illinois	57.8%
53	Houghton County, Michigan	57.8%
54	Monroe County, New York	57.8%
55	Massac County, Illinois	57.7%
56	Sangamon County, Illinois	57.6%
57	Gallatin County, Illinois	57.6%
58	Saginaw County, Michigan	57.5%

Rank	County	Final Composite Score
59	Lake County, Illinois	57.4%
60	Scott County, Illinois	57.4%
61	White County, Illinois	57.3%
62	Hardin County, Illinois	57.3%
63	Westmoreland County, Pennsylvania	57.2%
64	Gogebic County, Michigan	57.0%
65	Kalamazoo County, Michigan	57.0%
66	Albany County, New York	56.9%
67	Centre County, Pennsylvania	56.7%
68	Keweenaw County, Michigan	56.7%
69	Allen County, Indiana	56.6%
70	Northampton County, Pennsylvania	56.5%
71	Onondaga County, New York	56.5%
72	Rock Island County, Illinois	56.0%
73	Ramsey County, Minnesota	56.0%
74	Ashland County, Wisconsin	56.0%
75	Stephenson County, Illinois	55.7%
76	DuPage County, Illinois	55.7%
77	Brown County, Indiana	55.7%
78	Summit County, Ohio	55.7%
79	Mecosta County, Michigan	55.6%
80	Dutchess County, New York	55.4%
81	Wayne County, Indiana	55.4%
82	Monroe County, Pennsylvania	55.2%
83	Kenosha County, Wisconsin	55.2%
84	Pike County, Pennsylvania	55.0%
85	Mackinac County, Michigan	55.0%
86	DeKalb County, Illinois	54.9%
87	Howard County, Indiana	54.8%

Rank	County	Final Composite Score
88	Chippewa County, Michigan	54.7%
89	Madison County, Illinois	54.5%
90	Dauphin County, Pennsylvania	54.4%
91	Meigs County, Ohio	54.4%
92	Columbia County, New York	54.3%
93	Mason County, Michigan	54.3%
94	Jefferson County, Illinois	54.2%
95	Mahoning County, Ohio	54.1%
96	Iroquois County, Illinois	54.1%
97	Butler County, Ohio	54.0%
98	Oakland County, Michigan	54.0%
99	Mahnomen County, Minnesota	54.0%
100	Lake County, Michigan	53.9%
101	Winona County, Minnesota	53.8%
102	Beltrami County, Minnesota	53.6%
103	Pike County, Illinois	53.5%
104	Luzerne County, Pennsylvania	53.5%
105	Henderson County, Illinois	53.4%
106	Vermilion County, Illinois	53.2%
107	Macomb County, Michigan	53.2%
108	Tompkins County, New York	53.1%
109	Union County, Illinois	53.0%
110	Delaware County, New York	52.9%
111	Racine County, Wisconsin	52.9%
112	Chester County, Pennsylvania	52.8%
113	Marquette County, Michigan	52.7%
114	Richland County, Illinois	52.6%
115	Ontonagon County, Michigan	52.6%
116	Clare County, Michigan	52.6%

Rank	County	Final Composite Score
117	Kane County, Illinois	52.5%
118	Sullivan County, New York	52.5%
119	Madison County, Indiana	52.4%
120	Sullivan County, Pennsylvania	52.3%
121	Niagara County, New York	52.2%
122	Hennepin County, Minnesota	52.2%
123	Schoolcraft County, Michigan	52.2%
124	Calhoun County, Michigan	52.1%
125	Knox County, Illinois	52.1%
126	Washtenaw County, Michigan	52.0%
127	Wabash County, Illinois	52.0%
128	Switzerland County, Indiana	51.9%
129	Fayette County, Pennsylvania	51.9%
130	LaPorte County, Indiana	51.8%
131	Leelanau County, Michigan	51.8%
132	Menominee County, Wisconsin	51.7%
133	Perry County, Illinois	51.6%
134	Gratiot County, Michigan	51.6%
135	Nassau County, New York	51.5%
136	Morgan County, Illinois	51.5%
137	Mower County, Minnesota	51.4%
138	Jefferson County, Indiana	51.4%
139	Williamson County, Illinois	51.4%
140	Delta County, Michigan	51.3%
141	Emmet County, Michigan	51.3%
142	Cheboygan County, Michigan	51.3%
143	Belmont County, Ohio	51.2%
144	Columbia County, Pennsylvania	51.2%
145	Hancock County, Illinois	51.2%

Rank	County	Final Composite Score
146	Charlevoix County, Michigan	51.1%
147	Adams County, Ohio	51.0%
148	McLean County, Illinois	51.0%
149	Dane County, Wisconsin	51.0%
150	La Crosse County, Wisconsin	50.9%
151	Indiana County, Pennsylvania	50.7%
152	Sawyer County, Wisconsin	50.6%
153	Bayfield County, Wisconsin	50.5%
154	Muskegon County, Michigan	50.5%
155	Luce County, Michigan	50.5%
156	Stark County, Illinois	50.4%
157	Fayette County, Indiana	50.4%
158	Jackson County, Michigan	50.4%
159	Guernsey County, Ohio	50.4%
160	Gladwin County, Michigan	50.3%
161	Bartholomew County, Indiana	50.2%
162	Grant County, Indiana	50.2%
163	Sullivan County, Indiana	50.2%
164	Clark County, Ohio	50.2%
165	Jefferson County, Ohio	50.2%
166	Morgan County, Ohio	50.2%
167	Marion County, Illinois	50.1%
168	Montgomery County, New York	50.1%
169	Oscoda County, Michigan	50.0%
170	Lancaster County, Pennsylvania	50.0%
171	Cottonwood County, Minnesota	49.9%
172	Mason County, Illinois	49.9%
173	Boone County, Illinois	49.9%
174	Porter County, Indiana	49.8%

Rank	County	Final Composite Score
175	Floyd County, Indiana	49.8%
176	Fulton County, Illinois	49.8%
177	Lawrence County, Pennsylvania	49.8%
178	Warren County, New York	49.7%
179	Jo Daviess County, Illinois	49.7%
180	Wood County, Ohio	49.7%
181	Washington County, Ohio	49.6%
182	Berks County, Pennsylvania	49.6%
183	Midland County, Michigan	49.5%
184	Bradford County, Pennsylvania	49.5%
185	Stark County, Ohio	49.5%
186	Kankakee County, Illinois	49.4%
187	Jackson County, Ohio	49.4%
188	Scioto County, Ohio	49.4%
189	Henry County, Indiana	49.3%
190	Antrim County, Michigan	49.2%
191	Erie County, Ohio	49.1%
192	Spencer County, Indiana	49.1%
193	Schuyler County, Illinois	49.0%
194	Alger County, Michigan	48.9%
195	Vilas County, Wisconsin	48.8%
196	Tioga County, New York	48.8%
197	Cortland County, New York	48.8%
198	Baraga County, Michigan	48.8%
199	Clearwater County, Minnesota	48.7%
200	Bay County, Michigan	48.7%
201	Chautauqua County, New York	48.7%
202	St. Lawrence County, New York	48.7%
203	Vinton County, Ohio	48.7%

Rank	County	Final Composite Score
204	Pope County, Illinois	48.7%
205	Herkimer County, New York	48.6%
206	Clarion County, Pennsylvania	48.6%
207	Roscommon County, Michigan	48.5%
208	Oceana County, Michigan	48.5%
209	Portage County, Ohio	48.5%
210	Lyon County, Minnesota	48.5%
211	Van Buren County, Michigan	48.5%
212	Miami County, Indiana	48.5%
213	Kent County, Michigan	48.4%
214	Washington County, Pennsylvania	48.4%
215	Greene County, New York	48.3%
216	Brown County, Wisconsin	48.3%
217	Richland County, Ohio	48.1%
218	Schoharie County, New York	48.1%
219	losco County, Michigan	48.1%
220	Newaygo County, Michigan	48.0%
221	Highland County, Ohio	48.0%
222	Cambria County, Pennsylvania	48.0%
223	LaSalle County, Illinois	48.0%
224	Posey County, Indiana	47.9%
225	Warren County, Illinois	47.9%
226	Bucks County, Pennsylvania	47.9%
227	Pike County, Ohio	47.8%
228	Manistee County, Michigan	47.8%
229	McKean County, Pennsylvania	47.8%
230	Edgar County, Illinois	47.8%
231	Dickinson County, Michigan	47.8%
232	Johnson County, Indiana	47.7%

Rank	County	Final Composite Score
233	Pipestone County, Minnesota	47.7%
234	Clark County, Indiana	47.7%
235	Alcona County, Michigan	47.7%
236	Lycoming County, Pennsylvania	47.7%
237	Crawford County, Indiana	47.7%
238	Clinton County, New York	47.6%
239	Arenac County, Michigan	47.6%
240	Cass County, Michigan	47.6%
241	Adams County, Illinois	47.5%
242	Steuben County, New York	47.5%
243	Lawrence County, Ohio	47.5%
244	Lorain County, Ohio	47.5%
245	Eau Claire County, Wisconsin	47.5%
246	Blue Earth County, Minnesota	47.4%
247	Greene County, Ohio	47.4%
248	Susquehanna County, Pennsylvania	47.3%
249	Wexford County, Michigan	47.3%
250	Saratoga County, New York	47.3%
251	Will County, Illinois	47.2%
252	Ripley County, Indiana	47.2%
253	Washington County, Indiana	47.2%
254	Gallia County, Ohio	47.2%
255	Trumbull County, Ohio	47.2%
256	Noble County, Ohio	47.1%
257	Kittson County, Minnesota	47.1%
258	Monroe County, Illinois	47.1%
259	Knox County, Ohio	47.1%
260	Cass County, Illinois	47.1%
261	Venango County, Pennsylvania	47.0%

Rank	County	Final Composite Score
262	Warrick County, Indiana	47.0%
263	Kalkaska County, Michigan	46.9%
264	Boone County, Indiana	46.8%
265	Monroe County, Ohio	46.8%
266	Osceola County, Michigan	46.8%
267	Hamilton County, Illinois	46.7%
268	Marshall County, Indiana	46.7%
269	Fountain County, Indiana	46.7%
270	Clark County, Illinois	46.7%
271	Johnson County, Illinois	46.6%
272	Parke County, Indiana	46.6%
273	Columbiana County, Ohio	46.5%
274	Ford County, Illinois	46.5%
275	Pulaski County, Indiana	46.4%
276	Yates County, New York	46.4%
277	Crawford County, Illinois	46.4%
278	Iron County, Michigan	46.3%
279	Wyoming County, Pennsylvania	46.3%
280	Hamilton County, New York	46.3%
281	Jersey County, Illinois	46.2%
282	Montour County, Pennsylvania	46.2%
283	Clearfield County, Pennsylvania	46.2%
284	Koochiching County, Minnesota	46.2%
285	Orange County, Indiana	46.2%
286	Woodford County, Illinois	46.2%
287	Franklin County, New York	46.1%
288	Carroll County, Indiana	46.1%
289	Greene County, Illinois	46.1%
290	Cass County, Indiana	46.0%

Rank	County	Final Composite Score
291	Oneida County, New York	45.9%
292	St. Louis County, Minnesota	45.9%
293	Marshall County, Illinois	45.7%
294	Cass County, Minnesota	45.7%
295	Ogemaw County, Michigan	45.6%
296	Iron County, Wisconsin	45.6%
297	Crawford County, Ohio	45.6%
298	Polk County, Minnesota	45.6%
299	Lee County, Illinois	45.5%
300	Harrison County, Indiana	45.5%
301	Stevens County, Minnesota	45.5%
302	Menominee County, Michigan	45.4%
303	Aitkin County, Minnesota	45.4%
304	Starke County, Indiana	45.3%
305	Elkhart County, Indiana	45.3%
306	Chenango County, New York	45.3%
307	Wood County, Wisconsin	45.3%
308	St. Clair County, Michigan	45.2%
309	Muskingum County, Ohio	45.1%
310	Randolph County, Indiana	45.1%
311	Hocking County, Ohio	45.1%
312	Schuylkill County, Pennsylvania	45.1%
313	Suffolk County, New York	45.0%
314	Dearborn County, Indiana	45.0%
315	Presque Isle County, Michigan	45.0%
316	Clinton County, Ohio	44.9%
317	Blair County, Pennsylvania	44.9%
318	Fayette County, Illinois	44.9%
319	Gibson County, Indiana	44.8%

Rank	County	Final Composite Score
320	Effingham County, Illinois	44.8%
321	Northumberland County, Pennsylvania	44.8%
322	Mercer County, Pennsylvania	44.8%
323	Ross County, Ohio	44.8%
324	Lake County, Ohio	44.7%
325	Union County, Pennsylvania	44.7%
326	Owen County, Indiana	44.7%
327	Macoupin County, Illinois	44.7%
328	Olmsted County, Minnesota	44.7%
329	Grand Traverse County, Michigan	44.7%
330	Otsego County, Michigan	44.6%
331	Alpena County, Michigan	44.6%
332	Blackford County, Indiana	44.6%
333	Vernon County, Wisconsin	44.5%
334	Cattaraugus County, New York	44.5%
335	Newton County, Indiana	44.5%
336	Brown County, Ohio	44.3%
337	Carroll County, Illinois	44.2%
338	Ozaukee County, Wisconsin	44.2%
339	Beaver County, Pennsylvania	44.1%
340	Edwards County, Illinois	44.1%
341	Wayne County, Illinois	44.1%
342	Cook County, Minnesota	44.0%
343	Chemung County, New York	44.0%
344	Fayette County, Ohio	44.0%
345	Jackson County, Indiana	44.0%
346	Jefferson County, Pennsylvania	43.9%
347	Hamilton County, Indiana	43.9%
348	Whiteside County, Illinois	43.7%

Rank	County	Final Composite Score
349	Hancock County, Ohio	43.7%
350	Mercer County, Illinois	43.7%
351	Potter County, Pennsylvania	43.6%
352	Benzie County, Michigan	43.6%
353	Jefferson County, New York	43.6%
354	Rensselaer County, New York	43.6%
355	Scott County, Indiana	43.5%
356	Butler County, Pennsylvania	43.5%
357	Henry County, Illinois	43.4%
358	Greene County, Indiana	43.4%
359	Kosciusko County, Indiana	43.4%
360	Crawford County, Michigan	43.4%
361	Clay County, Illinois	43.3%
362	Orange County, New York	43.3%
363	Greene County, Pennsylvania	43.2%
364	Crawford County, Wisconsin	43.2%
365	Douglas County, Illinois	43.2%
366	Wabash County, Indiana	43.2%
367	Ontario County, New York	43.1%
368	Rush County, Indiana	43.1%
369	Ogle County, Illinois	43.0%
370	Livingston County, Illinois	43.0%
371	Calhoun County, Illinois	43.0%
372	Perry County, Indiana	43.0%
373	Eaton County, Michigan	43.0%
374	Ashtabula County, Ohio	43.0%
375	Franklin County, Indiana	42.9%
376	Montgomery County, Illinois	42.8%
377	McHenry County, Illinois	42.8%

Rank	County	Final Composite Score
378	Schuyler County, New York	42.8%
379	Fulton County, New York	42.7%
380	Lincoln County, Minnesota	42.7%
381	Tazewell County, Illinois	42.7%
382	Nobles County, Minnesota	42.6%
383	Menard County, Illinois	42.6%
384	Hendricks County, Indiana	42.6%
385	Missaukee County, Michigan	42.6%
386	Tuscola County, Michigan	42.6%
387	Big Stone County, Minnesota	42.6%
388	Marion County, Ohio	42.5%
389	Itasca County, Minnesota	42.4%
390	Huron County, Michigan	42.4%
391	Ottawa County, Ohio	42.4%
392	Warren County, Pennsylvania	42.4%
393	Crawford County, Pennsylvania	42.4%
394	Huntingdon County, Pennsylvania	42.4%
395	Clay County, Minnesota	42.3%
396	Hillsdale County, Michigan	42.3%
397	Pine County, Minnesota	42.2%
398	Licking County, Ohio	42.2%
399	Armstrong County, Pennsylvania	42.1%
400	Adams County, Indiana	42.1%
401	Clinton County, Michigan	42.1%
402	Lawrence County, Indiana	42.1%
403	Waukesha County, Wisconsin	42.1%
404	Crow Wing County, Minnesota	42.0%
405	Montcalm County, Michigan	42.0%
406	Sanilac County, Michigan	42.0%

Rank	County	Final Composite Score
407	Knox County, Indiana	42.0%
408	Morgan County, Indiana	41.9%
409	Allen County, Ohio	41.9%
410	Pike County, Indiana	41.8%
411	Clermont County, Ohio	41.8%
412	Perry County, Ohio	41.8%
413	Oswego County, New York	41.8%
414	Union County, Indiana	41.8%
415	Montmorency County, Michigan	41.7%
416	Brown County, Illinois	41.7%
417	Lenawee County, Michigan	41.7%
418	Lawrence County, Illinois	41.7%
419	Washburn County, Wisconsin	41.7%
420	Ottawa County, Michigan	41.5%
421	Jay County, Indiana	41.5%
422	Coshocton County, Ohio	41.4%
423	Logan County, Ohio	41.4%
424	Clinton County, Indiana	41.4%
425	Walworth County, Wisconsin	41.4%
426	Carver County, Minnesota	41.4%
427	Stearns County, Minnesota	41.4%
428	Clay County, Indiana	41.3%
429	Dubois County, Indiana	41.3%
430	Putnam County, Illinois	41.2%
431	Wayne County, Pennsylvania	41.2%
432	Allegany County, New York	41.2%
433	Grundy County, Illinois	41.2%
434	Dakota County, Minnesota	41.2%
435	Traverse County, Minnesota	41.2%

Rank	County	Final Composite Score
436	White County, Indiana	41.2%
437	Bond County, Illinois	41.1%
438	Forest County, Wisconsin	41.1%
439	Hardin County, Ohio	41.1%
440	Rock County, Minnesota	40.9%
441	Becker County, Minnesota	40.8%
442	Shiawassee County, Michigan	40.8%
443	Cumberland County, Pennsylvania	40.7%
444	Randolph County, Illinois	40.7%
445	Bureau County, Illinois	40.7%
446	Rock County, Wisconsin	40.7%
447	Jennings County, Indiana	40.6%
448	Carbon County, Pennsylvania	40.6%
449	Daviess County, Indiana	40.6%
450	Vermillion County, Indiana	40.5%
451	Goodhue County, Minnesota	40.5%
452	Kendall County, Illinois	40.5%
453	Douglas County, Minnesota	40.4%
454	Lebanon County, Pennsylvania	40.4%
455	Grant County, Minnesota	40.3%
456	Cumberland County, Illinois	40.3%
457	Clinton County, Pennsylvania	40.2%
458	Tipton County, Indiana	40.1%
459	Noble County, Indiana	40.0%
460	Martin County, Indiana	40.0%
461	Somerset County, Pennsylvania	40.0%
462	Rice County, Minnesota	40.0%
463	Piatt County, Illinois	40.0%
464	De Witt County, Illinois	40.0%

Rank	County	Final Composite Score
465	Wilkin County, Minnesota	39.9%
466	Sandusky County, Ohio	39.9%
467	Shelby County, Indiana	39.9%
468	Renville County, Minnesota	39.9%
469	Bedford County, Pennsylvania	39.9%
470	Wayne County, New York	39.8%
471	DeKalb County, Indiana	39.8%
472	Lac qui Parle County, Minnesota	39.8%
473	Adams County, Wisconsin	39.8%
474	Steuben County, Indiana	39.7%
475	Lapeer County, Michigan	39.7%
476	Fulton County, Indiana	39.7%
477	Essex County, New York	39.7%
478	Hancock County, Indiana	39.6%
479	Florence County, Wisconsin	39.6%
480	Elk County, Pennsylvania	39.6%
481	Christian County, Illinois	39.6%
482	Shelby County, Illinois	39.6%
483	Warren County, Ohio	39.5%
484	Washington County, New York	39.5%
485	Tioga County, Pennsylvania	39.5%
486	St. Joseph County, Michigan	39.5%
487	Harrison County, Ohio	39.4%
488	Jackson County, Minnesota	39.4%
489	Putnam County, New York	39.3%
490	Fairfield County, Ohio	39.3%
491	Benton County, Indiana	39.3%
492	Cameron County, Pennsylvania	39.2%
493	Murray County, Minnesota	39.1%

Rank	County	Final Composite Score
494	Logan County, Illinois	39.1%
495	Steele County, Minnesota	39.1%
496	Delaware County, Ohio	39.0%
497	Livingston County, Michigan	39.0%
498	Carroll County, Ohio	38.9%
499	Geauga County, Ohio	38.9%
500	Portage County, Wisconsin	38.9%
501	Houston County, Minnesota	38.9%
502	Door County, Wisconsin	38.8%
503	Redwood County, Minnesota	38.7%
504	Nicollet County, Minnesota	38.6%
505	York County, Pennsylvania	38.6%
506	Huntington County, Indiana	38.5%
507	Norman County, Minnesota	38.4%
508	Marshall County, Minnesota	38.4%
509	Winnebago County, Wisconsin	38.3%
510	Jasper County, Illinois	38.3%
511	Champaign County, Ohio	38.2%
512	Decatur County, Indiana	38.2%
513	Washington County, Illinois	38.2%
514	Oneida County, Wisconsin	38.1%
515	Monroe County, Michigan	38.1%
516	Orleans County, New York	38.1%
517	Douglas County, Wisconsin	38.0%
518	Miami County, Ohio	37.9%
519	Wells County, Indiana	37.8%
520	Wayne County, Ohio	37.7%
521	Wabasha County, Minnesota	37.7%
522	Van Wert County, Ohio	37.7%

Rank	County	Final Composite Score
523	Pickaway County, Ohio	37.6%
524	Madison County, New York	37.6%
525	Kandiyohi County, Minnesota	37.6%
526	Langlade County, Wisconsin	37.6%
527	Livingston County, New York	37.5%
528	Cayuga County, New York	37.5%
529	Snyder County, Pennsylvania	37.5%
530	Mille Lacs County, Minnesota	37.5%
531	Lewis County, New York	37.5%
532	Otter Tail County, Minnesota	37.5%
533	Montgomery County, Indiana	37.3%
534	Tuscarawas County, Ohio	37.2%
535	Warren County, Indiana	37.2%
536	Pope County, Minnesota	37.1%
537	Grant County, Wisconsin	37.0%
538	Faribault County, Minnesota	37.0%
539	Mercer County, Ohio	36.9%
540	Ashland County, Ohio	36.8%
541	Juneau County, Wisconsin	36.8%
542	Preble County, Ohio	36.8%
543	Benton County, Minnesota	36.8%
544	Darke County, Ohio	36.8%
545	Fillmore County, Minnesota	36.8%
546	Huron County, Ohio	36.7%
547	Ionia County, Michigan	36.7%
548	Franklin County, Pennsylvania	36.7%
549	Madison County, Ohio	36.7%
550	Pepin County, Wisconsin	36.7%
551	Wadena County, Minnesota	36.7%

Rank	County	Final Composite Score
552	Whitley County, Indiana	36.7%
553	Burnett County, Wisconsin	36.6%
554	Putnam County, Indiana	36.5%
555	Clinton County, Illinois	36.5%
556	Seneca County, New York	36.5%
557	Fulton County, Pennsylvania	36.4%
558	Scott County, Minnesota	36.4%
559	Anoka County, Minnesota	36.4%
560	Williams County, Ohio	36.4%
561	Jackson County, Wisconsin	36.3%
562	Kanabec County, Minnesota	36.3%
563	Adams County, Pennsylvania	36.2%
564	Forest County, Pennsylvania	36.2%
565	Barry County, Michigan	36.1%
566	Morrison County, Minnesota	36.1%
567	Sauk County, Wisconsin	36.1%
568	Dunn County, Wisconsin	36.1%
569	Medina County, Ohio	36.1%
570	Freeborn County, Minnesota	36.0%
571	Hubbard County, Minnesota	36.0%
572	Marathon County, Wisconsin	35.9%
573	Washington County, Minnesota	35.9%
574	Allegan County, Michigan	35.8%
575	Union County, Ohio	35.8%
576	Martin County, Minnesota	35.7%
577	Marinette County, Wisconsin	35.7%
578	Iowa County, Wisconsin	35.5%
579	Watonwan County, Minnesota	35.4%
580	Wyandot County, Ohio	35.4%

Rank	County	Final Composite Score
581	Dodge County, Minnesota	35.4%
582	Genesee County, New York	35.2%
583	Roseau County, Minnesota	35.2%
584	Buffalo County, Wisconsin	34.8%
585	Defiance County, Ohio	34.8%
586	Shelby County, Ohio	34.7%
587	Jefferson County, Wisconsin	34.7%
588	Barron County, Wisconsin	34.6%
589	Branch County, Michigan	34.6%
590	Fulton County, Ohio	34.6%
591	Outagamie County, Wisconsin	34.4%
592	Jasper County, Indiana	34.4%
593	Sibley County, Minnesota	34.2%
594	Mifflin County, Pennsylvania	34.2%
595	Lake County, Minnesota	34.1%
596	Seneca County, Ohio	34.0%
597	Washington County, Wisconsin	34.0%
598	Waushara County, Wisconsin	33.8%
599	Putnam County, Ohio	33.8%
600	Fond du Lac County, Wisconsin	33.7%
601	Brown County, Minnesota	33.6%
602	Sheboygan County, Wisconsin	33.5%
603	Trempealeau County, Wisconsin	33.5%
604	Carlton County, Minnesota	33.4%
605	Swift County, Minnesota	33.3%
606	Moultrie County, Illinois	33.3%
607	Paulding County, Ohio	33.2%
608	Chippewa County, Minnesota	33.2%
609	Lafayette County, Wisconsin	33.0%

Rank	County	Final Composite Score
610	Sherburne County, Minnesota	33.0%
611	Le Sueur County, Minnesota	32.9%
612	Juniata County, Pennsylvania	32.9%
613	Richland County, Wisconsin	32.7%
614	Henry County, Ohio	32.6%
615	Waseca County, Minnesota	32.6%
616	Rusk County, Wisconsin	32.6%
617	Shawano County, Wisconsin	32.5%
618	Auglaize County, Ohio	32.3%
619	Wyoming County, New York	32.3%
620	McLeod County, Minnesota	32.1%
621	Green County, Wisconsin	31.9%
622	Polk County, Wisconsin	31.9%
623	Monroe County, Wisconsin	31.8%
624	Pierce County, Wisconsin	31.8%
625	Pennington County, Minnesota	31.7%
626	Green Lake County, Wisconsin	31.6%
627	Clark County, Wisconsin	31.5%
628	Morrow County, Ohio	31.5%
629	Manitowoc County, Wisconsin	31.5%
630	Waupaca County, Wisconsin	31.4%
631	Chippewa County, Wisconsin	31.4%
632	Price County, Wisconsin	31.3%
633	Yellow Medicine County, Minnesota	31.1%
634	St. Croix County, Wisconsin	30.9%
635	Marquette County, Wisconsin	30.9%
636	Taylor County, Wisconsin	30.8%
637	Isanti County, Minnesota	30.7%
638	Columbia County, Wisconsin	30.7%

Rank	County	Final Composite Score
639	Wright County, Minnesota	30.5%
640	Calumet County, Wisconsin	30.4%
641	Meeker County, Minnesota	30.0%
642	Perry County, Pennsylvania	29.7%
643	Chisago County, Minnesota	29.7%
644	LaGrange County, Indiana	29.4%
645	Todd County, Minnesota	29.3%
646	Ohio County, Indiana	28.3%
647	Lake of the Woods County, Minnesota	28.1%
648	Dodge County, Wisconsin	28.1%
649	Kewaunee County, Wisconsin	28.1%
650	Oconto County, Wisconsin	28.0%
651	Lincoln County, Wisconsin	27.3%
652	Red Lake County, Minnesota	27.2%
653	Holmes County, Ohio	26.6%





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