A Spatial Cluster Analysis of Average Infant Mortality Rates, Michigan, 2012-2016

Prepared by the Maternal and Child Health (MCH) Epidemiology Section,
Michigan Department of Health and Human Services (MDHHS)
Data sources: Michigan resident live birth files linked with infant mortality files (08/06/2018),
Division for Vital Records and Health Statistics, MDHHS
October 2018

This presentation describes the results of a spatial cluster analysis of average infant mortality rates, 2012-2016, for the State of Michigan.

This presentation was prepared by the Michigan Department of Health and Human Services (MDHHS), Maternal and Child Health (MCH) Epidemiology Section

Data source: Michigan resident live birth files linked with infant mortality files (08/06/2018), Division for Vital Records and Health Statistics, MDHHS

Revised: October 2018

Overview

- Currently, trends in infant mortality are not widely examined in Michigan and there may be spatial patterns that are not being detected.
- The objective of this analysis is to examine spatial trends in infant mortality average rate in Michigan over a five year period from 2012-2016 in order to better inform public health resource allocation.
- Hot spot cluster analysis is a useful method for determining where geographic clusters of disease exist (Getis & Ord, 1992). These analyses have been conducted to find clusters of disease and mortality occurrence in a variety of settings (Burra, Jerrett, Burnett, & Anderson, 2002; Gundogdu, 2010).
- Stopka et. al. have developed a five-step process to detect valid clusters of disease (Stopka, Krawczyk, Gradziel, & Geraghty, 2014). This method was used to determine geographic patterns of infant mortality in this analysis.

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Introduction --- Hot Spot Analysis

- Hot spot analysis is a statistically based method to assess geographic clustering.
- Specifically, hot spot analysis is used to pinpoint locations of statistically significant high- and low-value clusters of an outcome of interest by evaluating each feature (e.g., census tract) within the context of neighboring features and against all features in the dataset (Ord & Getis, 1992).
- A feature with a high value may be a statistically significant hot spot if it is also surrounded by other features with high values, as opposed to simply being a data outlier.
- The local mean for a feature and its neighbors is compared proportionally with the global mean of all features (e.g., all census tracts in a state). When the observed local mean is much different than the global mean and that difference is too large to be the result of random chance, a statistically significant *z* score results and a hot spot cluster is detected (Mitchell, 2005).

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Data

- Infant mortality is defined as a death of a baby before his or her first birthday and is expressed as a rate per 1,000 live births.
- 2012-2016 Michigan live birth files linked with infant mortality files
  - Geocoded maternal residential addresses
- 2010 Michigan census tract shapefile for ArcGIS
- Infant mortality rates per 1,000 live births over the five-year period were calculated and aggregated to the census tract level.
- The average infant mortality rate over the five-year period (2012-2016) is **6.9** per 1,000 live births (3,895 infant deaths and 567,485 live births).

Data source: Michigan resident live birth files and infant mortality files, Division for Vital Records and Health Statistics, MDHHS

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This study used 2012-2016 Michigan live birth files linked with infant mortality files, with geocoded maternal residential addresses (i.e. residence of mothers at child's birth).

The 2010 Michigan census tract ArcGIS shapefile was used for mapping.

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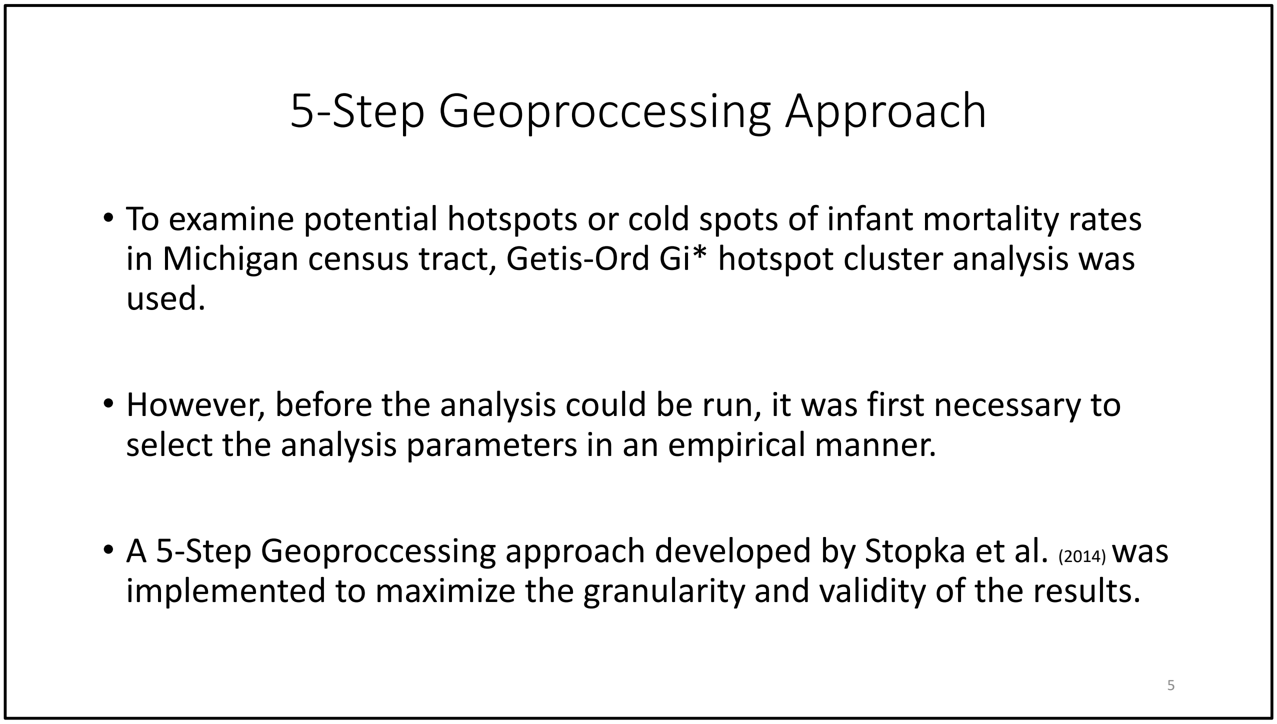

This slide gives an introduction to the 5-step geoprocessing approach.

For this study, to examine potential hotspots or cold spots of infant mortality in Michigan census tracts, Getis-Ord Gi* hotspot cluster analysis was used.

However, before the analysis could be run, it was first necessary to select the analysis parameters in an empirical manner.

A 5-Step Geoproccessing approach developed by Stopka et al. (2014) was implemented to maximize the granularity and validity of the results.

5-Step Geoproccessing Approach

Step 1—Analysis of Variation in Michigan Census Tract Areas

- In order to determine a proper spatial scale for running the hotspot analysis, all census tracts over 1.5 standard deviations of the Michigan census tract mean area were removed as they may distort the ideal sphere of influence in determining a cluster.

- Any tracts that did not share a border with at least two other tracts and tracts in which there were no live births were also removed.

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This slide details step 1 of the 5-step geoprocessing approach: analysis of variation in Michigan census tract areas.

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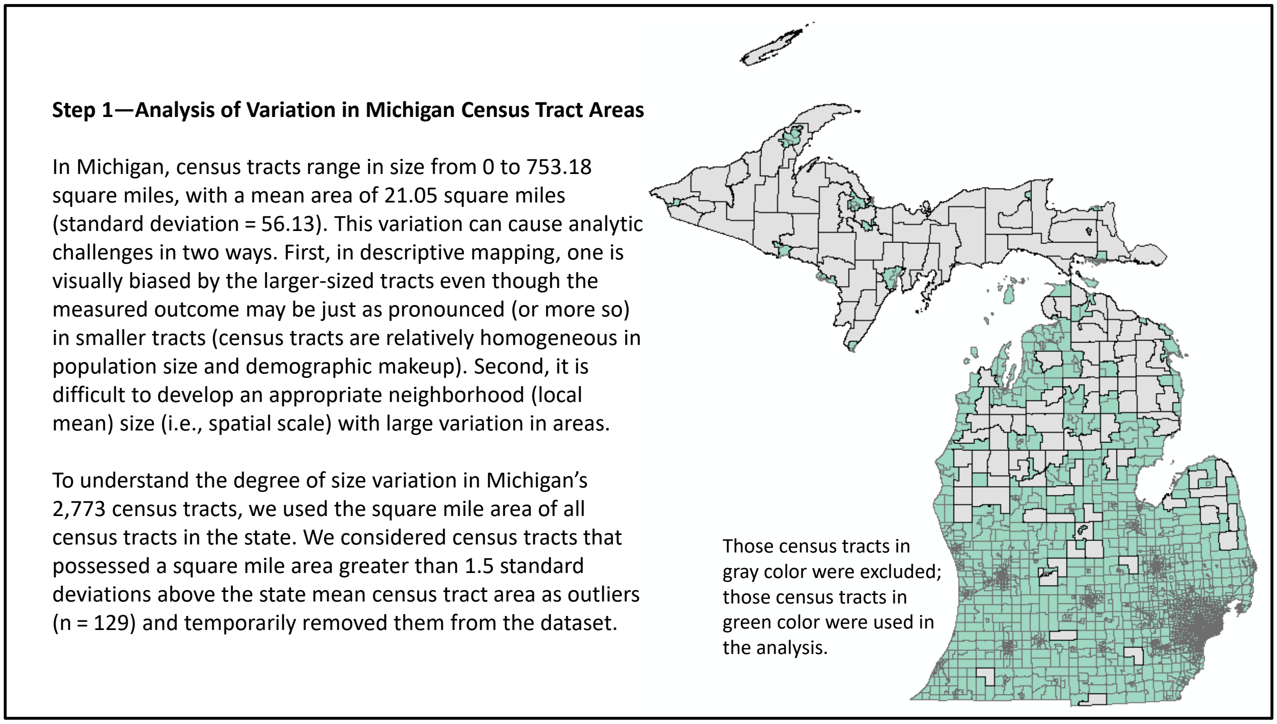


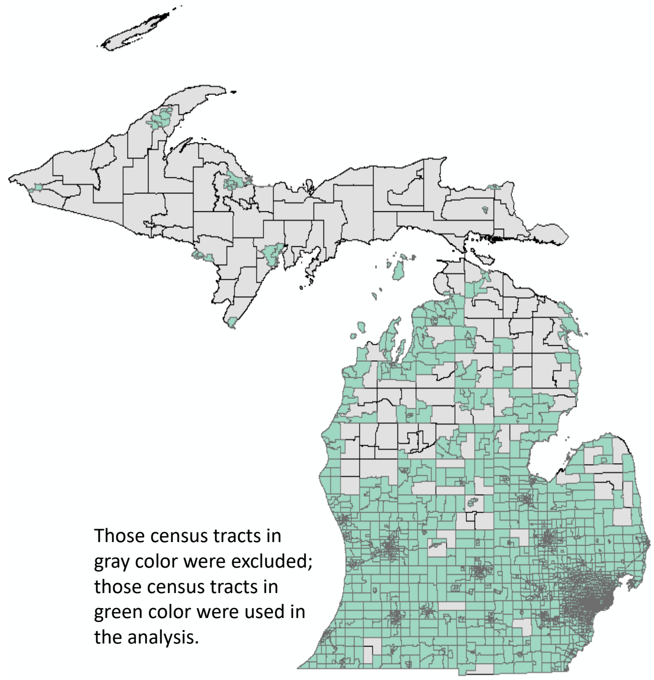
This slide continues to detail step 1 of the 5-step geoprocessing approach: analysis of variation in Michigan census tract areas.

In Michigan, census tracts range in size from 0 to 753.18 square miles, with a mean area of 21.05 square miles (standard deviation = 56.13). This variation can cause analytic challenges in two ways. First, in descriptive mapping, one is visually biased by the larger-sized tracts even though the measured outcome may be just as pronounced (or more so) in smaller tracts (census tracts are relatively homogeneous in population size and demographic makeup). Second, it is difficult to develop an appropriate neighborhood (local mean) size (i.e., spatial scale) with large variation in areas.

To understand the degree of size variation in Michigan's 2,773 census tracts, we used the square mile area of all census tracts in the state. We considered census tracts that possessed a square mile area greater than 1.5 standard deviations above the state mean census tract area as outliers (n = 129) and temporarily removed them from the dataset.

Step 1—Analysis of Variation in Michigan Census Tract Areas

We also removed small census tracts that were adjacent to the previously removed ones (and appeared as “islands”; n = 18).



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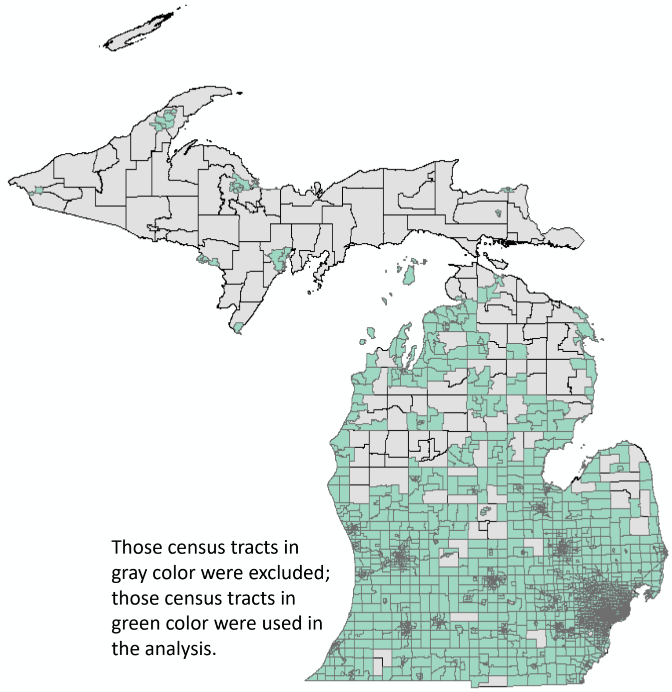
Step 1—Analysis of Variation in Michigan Census Tract Areas

In addition, we removed those census tracts in which there were no live births during the study period (n = 20). In the end, 2,606 census tracts were used in the next step of this analysis.



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5-Step Geoproccessing Approach

Step 2: Determination of Spatial Scale, Part A

- In order to determine what distance should be used as a benchmark for cluster identification among the 2,606 Michigan census tracts, the average and maximum distances between each tract and its two closest neighbors were calculated.
- The average distance was 3,794 meters (2.4 miles) and the maximum distance was 50,019 meters (31.1 miles) between each tract.

This slide details step 2 of the 5-step geoprocessing approach: determination of spatial scale, part A.

In order to determine what distance should be used as a benchmark for cluster identification among the 2,606 Michigan census tracts, the average and maximum distances between each tract and its two closest neighbors were calculated.

The average distance was 3,794 meters (2.4 miles) and the maximum distance between each tract was 50,019 meters (31.1 miles).

5-Step Geoproccessing Approach

Step 3: Determination of Spatial Scale, Part B

- For the greatest public health utility, it is necessary to calculate the smallest distance at which clustering of infant mortality is intense.
- The Moran I spatial autocorrelation test is a statistical measure of the degree of clustering for a given condition.
- To find the most adequate distance at which clustering is significant, two-thirds of the maximum distance calculated in step 2 (33,346 meters, 20.7 miles) was used as a baseline distance for the Moran I test.
- 30 tests were run at increasing increments of half of the average distance calculated in the last step (1,897 meters, 1.2 miles) to find the smallest distance at which clustering (the z-score) peaks.
- For infant mortality rates, the smallest distance at which clustering peaks was at 8,588 meters (5.3 miles).

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5-Step Geoproccessing Approach

Step 4: Accounting for the Larger Polygons

- All of the census tracts were reintroduced into the map to be used in the creation of a spatial weights matrix, which takes into account a selected distance and a minimum number of neighbors in order to weight the relationship between each feature in the map.

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This slide details step 4 of the 5-step geoprocessing approach: accounting for the larger polygons.

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5-Step Geoproccessing Approach

Step 5: Hot Spot Analysis

- In the final step, a Getis-Ord Gi* Hot Spot Analysis was conducted for infant mortality rates using spatial relationships of the fixed distance band (8,588 meters) and the spatial weights matrix.
- The Getis-Ord Gi* test calculates a Z-score for each feature (i.e., census tract) indicating whether that feature exhibited clustering compared to the global mean.
- If there are enough high or low values in close vicinity to one another, then a hotspot or coldspot will be indicated.

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This slide details the final step in the 5-step geoprocessing approach: hot spot analysis.

In the final step, a Getis-Ord Gi* Hot Spot Analysis was conducted for infant mortality rates using spatial relationships of the fixed distance band (8,588 meters) and the spatial weights matrix.

The Getis-Ord Gi* test calculates a Z-score for each feature (i.e., census tract) indicating whether that feature exhibited clustering compared to the global mean.

If there are enough high or low values in close vicinity to one another, then a hotspot or coldspot will be indicated.

Results---Descriptive Maps

- Descriptive thematic maps portray the number of live births, the number of infant deaths, and infant mortality rates across Michigan by census tract.
- These maps indicated that census tracts in certain counties possessed large counts and rates of infant mortality and provided initial information about the burden of infant mortality reduction needs.

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The following three slides show the descriptive results within maps.

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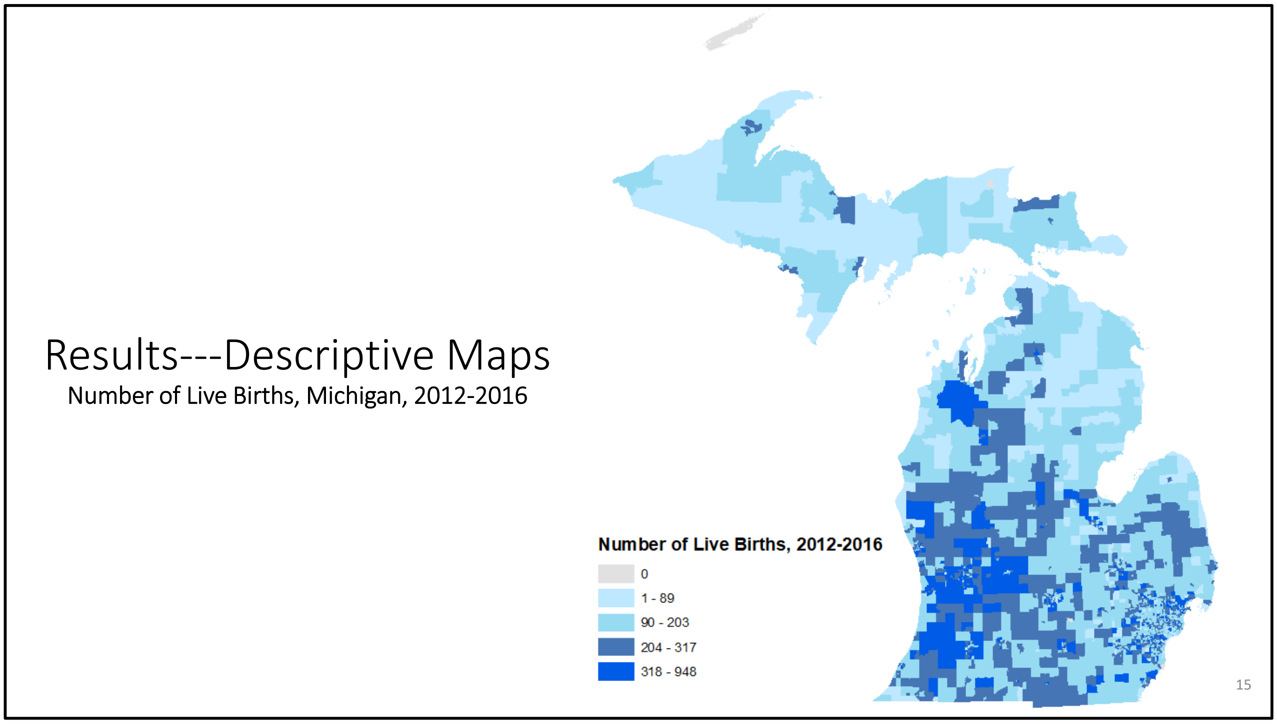
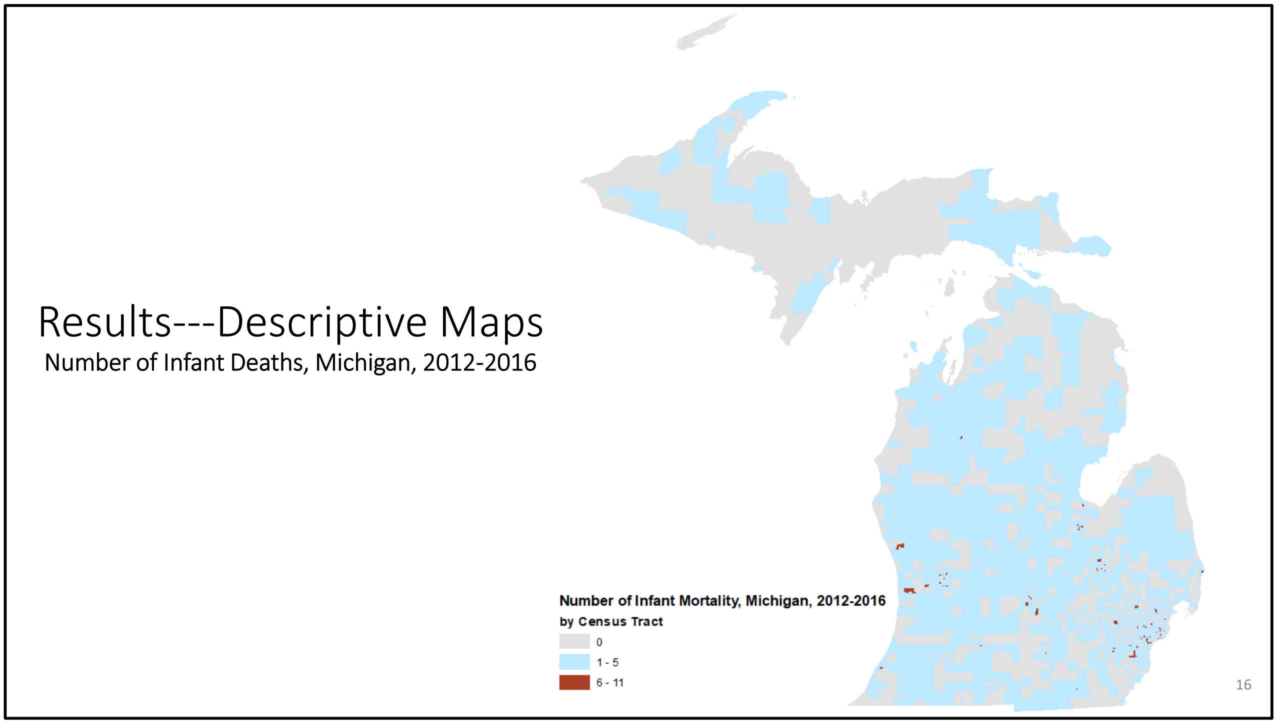


This map shows the number of live births by census tract for the State of Michigan, 2012-2016.

There were **203** births in the mean census tract in Michigan, ranging from **1** to **948** births and standard deviation was **114**.

From 2012 to 2016, **26** census tracts had no live births; **328** census tracts had over one and at most 89 (mean: 203 – standard deviation: 114 = 89) live births; **1,243** census tracts had over 90 and at most 203 (mean) live births; **795** census tracts had over 204 and at most 317 (mean: 203+ standard deviation: 114 = 317) live births; and **381** census tracts had over 318 and at most 948 live births.

From 2012 to 2016, among those **2,747** census tracts with live births in Michigan, **42.8** percent of census tracts (1176 out of 2,747) had more live births than the mean for the state of Michigan; **13.9** percent of census tracts (381 out of 2,747) had more live births than one standard deviation above the state average.

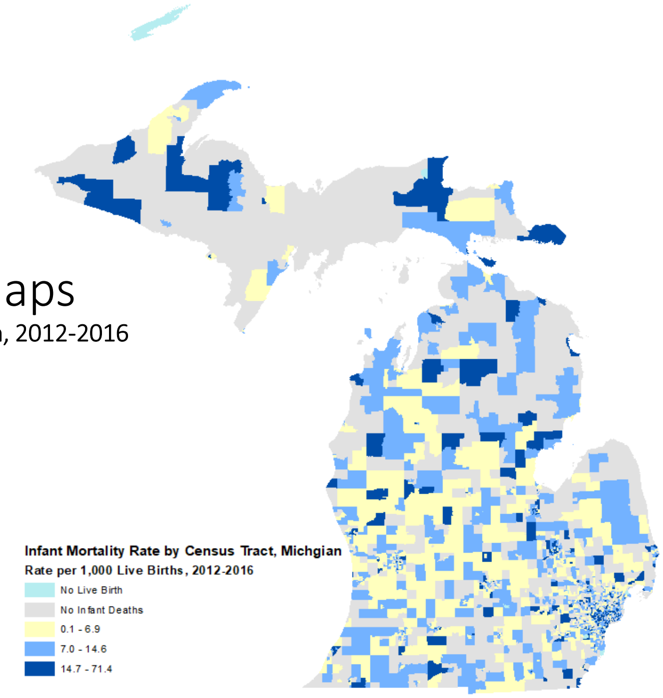


This map shows the number of infant deaths by census tract for the State of Michigan, 2012-2016.

From 2012 to 2016, **26** census tracts had no live births; **964** census tracts had no infant deaths; **1,711** census tracts had 1 to 5 infant deaths; and **72** census tracts had six or more infant deaths.

Results---Descriptive Maps

Infant Mortality Rate per 1,000 Live Births, Michigan, 2012-2016



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This map shows the average infant mortality average rates by census tract for the State of Michigan, 2012-2016.

From 2012 to 2016, **26** census tracts had no live births and **964** census tracts had no infant deaths.

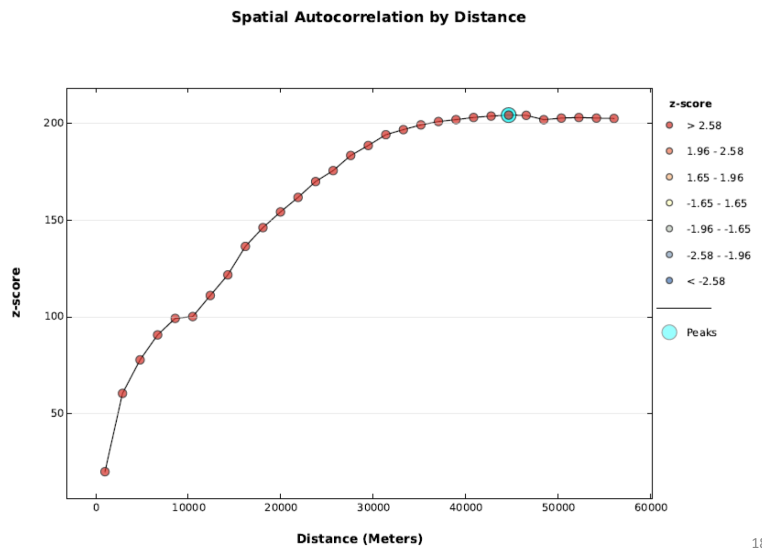
The infant mortality rate in the mean census tract was 6.9 deaths per 1,000 live births, with a standard deviation of 7.7 deaths.

From 2012 to 2016, the average infant mortality rate was between 0.1 and 6.9 (mean) per 1,000 live births in **676** census tracts; between 7.0 and 14.6 (mean: 6.9 + standard deviation: 7.7 = 14.6) per 1,000 live births in **752** census tracts; and over 14.7 per 1,000 live births in **355** census tracts.

From 2012 to 2016, among those **1,783** census tracts with live births and infant deaths in Michigan, **62.1** percent of census tracts (1,107 out of 1,783) had infant mortality rate greater than the mean for the state of Michigan; **19.9** percent of census tracts (355 out of 1,783) had infant mortality rates greater than one standard deviation above the state average.

Results --- Incremental Spatial Autocorrelation

When considering the 2,606 Michigan census tracts included in this study, the smallest distance at which clustering z-score of infant mortality rates was great was at 8,588 meters (5.3 miles; *P* < .001).



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This slide shows the results of the incremental spatial autocorrelation.

Incremental Spatial Autocorrelation measures spatial autocorrelation for a series of distances and optionally creates a line graph of those distances and their corresponding z-scores. Z-scores reflect the intensity of spatial clustering, and statistically significant peak z-scores indicate distances where spatial processes promoting clustering are most pronounced.

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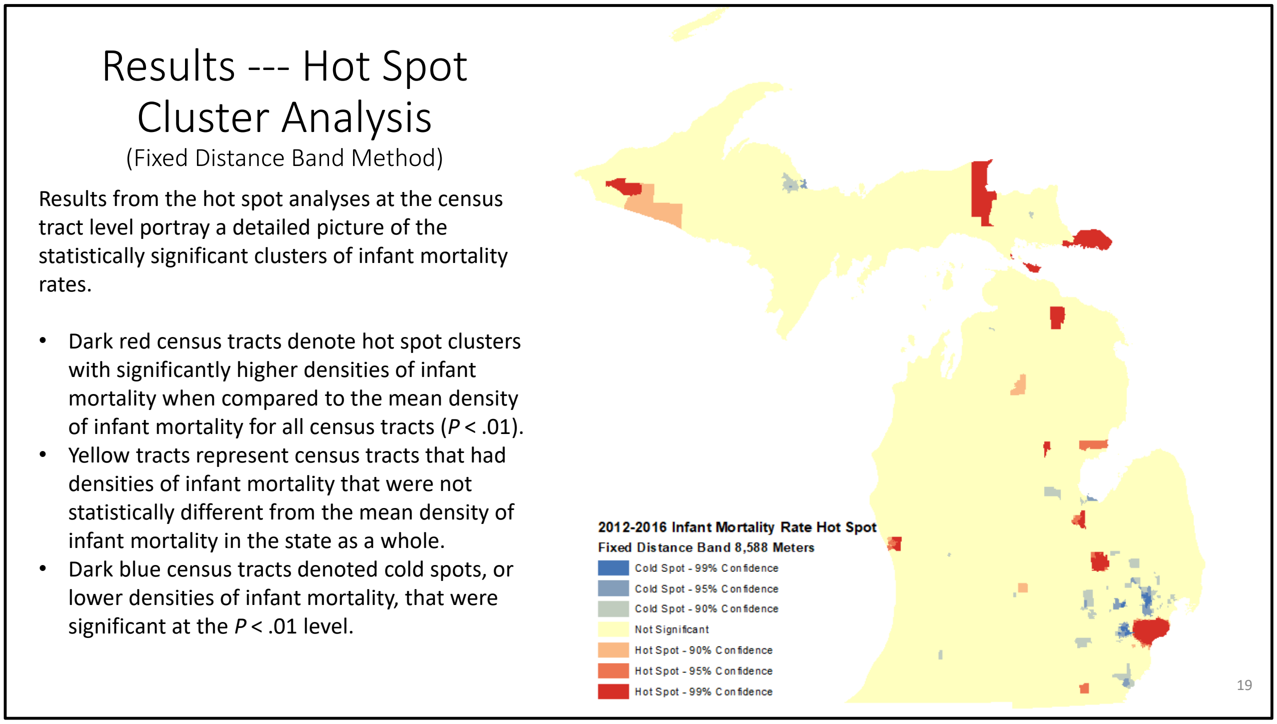
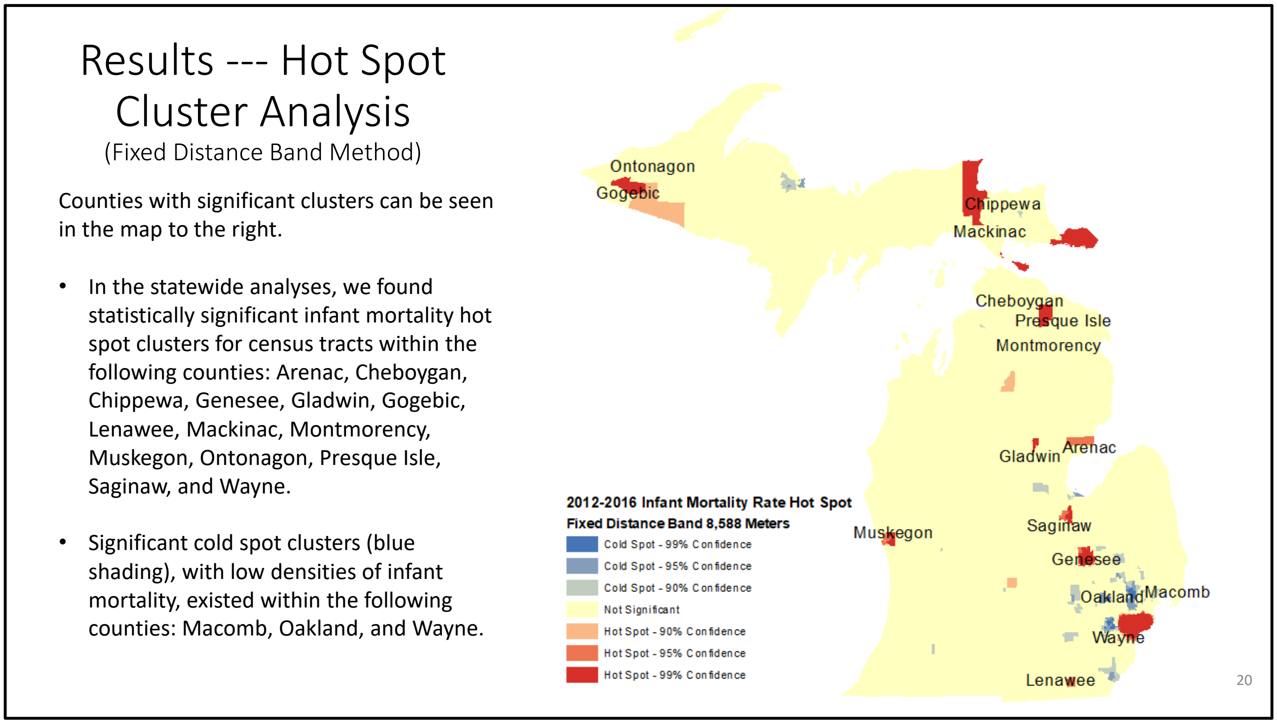


This map shows the results of the hot spot cluster analysis using fixed distance band (8,588 meters) method.

Using fixed distance band method, each feature is analyzed within the context of neighboring features. Neighboring features inside the specified critical distance (Distance Band or Threshold Distance) receive a weight of one and exert influence on computations for the target feature. Neighboring features outside the critical distance receive a weight of zero and have no influence on a target feature's computations.

Results from the hot spot analyses at the census tract level portray a detailed picture of the statistically significant clusters of infant mortality rates.

- Dark red census tracts denote hot spot clusters with significantly higher densities of infant mortality when compared to the mean density of infant mortality for all census tracts ($P < .01$).
- Yellow tracts represent census tracts that had densities of infant mortality that were not statistically different from the mean density of infant mortality in the state as a whole.
- Dark blue census tracts denoted cold spots, or lower densities of infant mortality, that were significant at the $P < .01$ level.



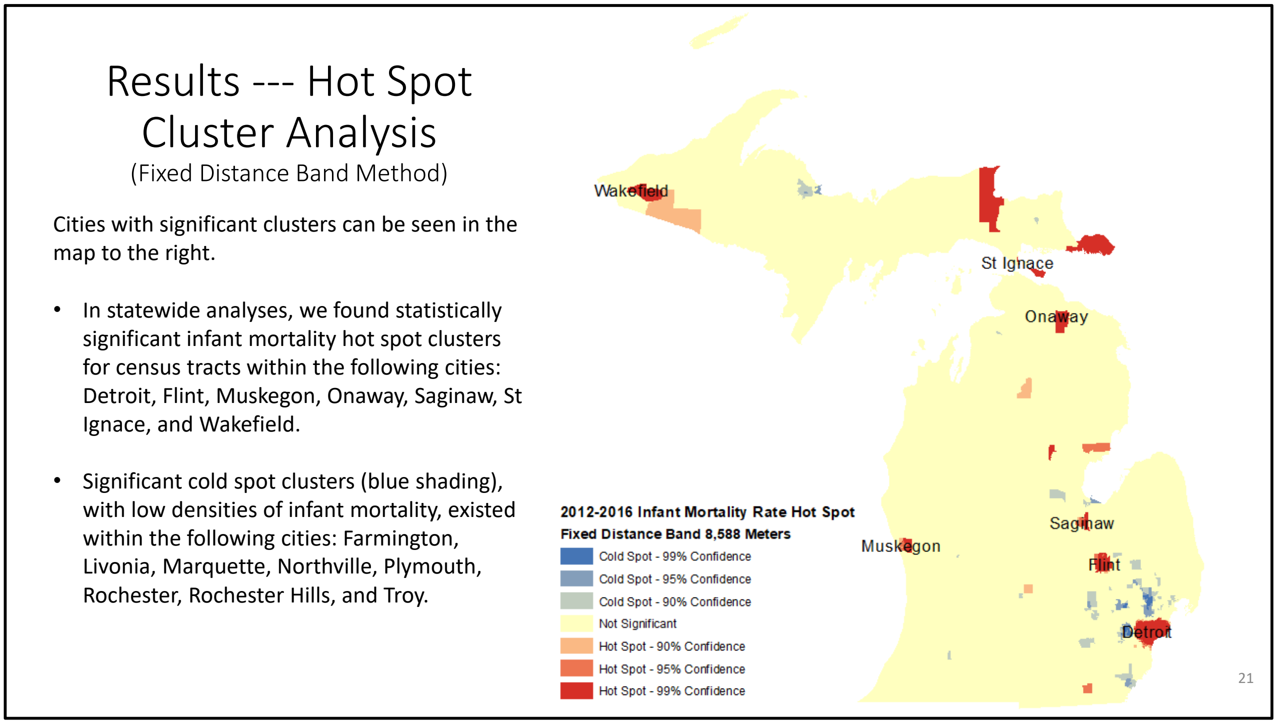
This map shows the results of the hot spot cluster analysis using fixed distance band (8,588 meters) method and includes the county names that have hot spots.

Using fixed distance band method, each feature is analyzed within the context of neighboring features. Neighboring features inside the specified critical distance (Distance Band or Threshold Distance) receive a weight of one and exert influence on computations for the target feature. Neighboring features outside the critical distance receive a weight of zero and have no influence on a target feature's computations.

Counties with significant clusters can be seen on the map.

- In the statewide analyses, we found statistically significant infant mortality hot spot clusters for census tracts within the following counties: Arenac, Cheboygan, Chippewa, Genesee, Gladwin, Gogebic, Lenawee, Mackinac, Montmorency, Muskegon, Ontonagon, Presque Isle, Saginaw, and Wayne Counties.

- Significant cold spot clusters (blue shading), with low densities of infant mortality, existed within the following counties: Macomb, Oakland, and Wayne Counties.



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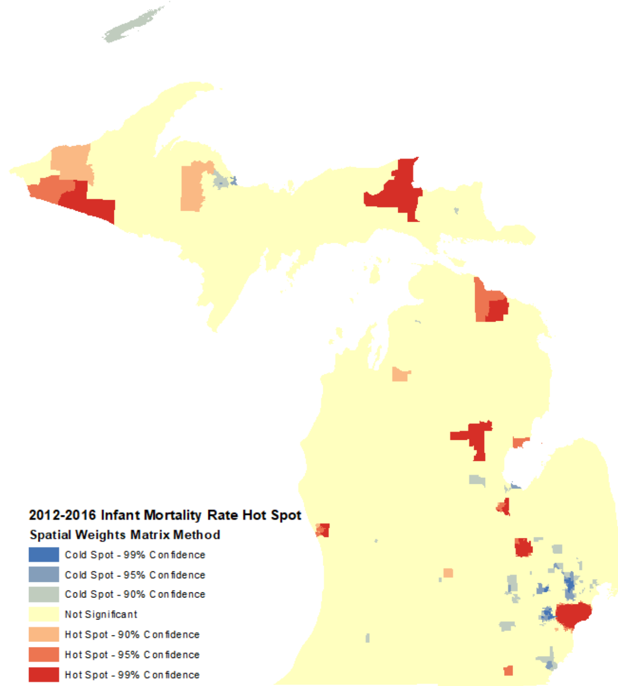
Cities with significant clusters can be seen on the map.

- In statewide analyses, we found statistically significant infant mortality hot spot clusters for census tracts within the following cities: Detroit, Flint, Muskegon, Onaway, Saginaw, St Ignace, and Wakefield.

- Significant cold spot clusters (blue shading), with low densities of infant mortality, existed within the following cities: Farmington, Livonia, Marquette, Northville, Plymouth, Rochester, Rochester Hills, and Troy.

Results --- Hot Spot Cluster Analysis

(Spatial Weights Matrix Method)



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This map shows the results of the hot spot cluster analysis using spatial weights matrix method.

Using spatial weights matrix method, spatial relationships are defined by a specified spatial weights file and the path to the spatial weights file is specified by the Weights Matrix File parameter. Spatial weights are numbers that reflect the distance between each feature and every other feature in the dataset. Nearer features have a larger weight than features that are farther away.

Results from the hot spot analyses at the census tract level portray a detailed picture of the statistically significant clusters of infant mortality rates.

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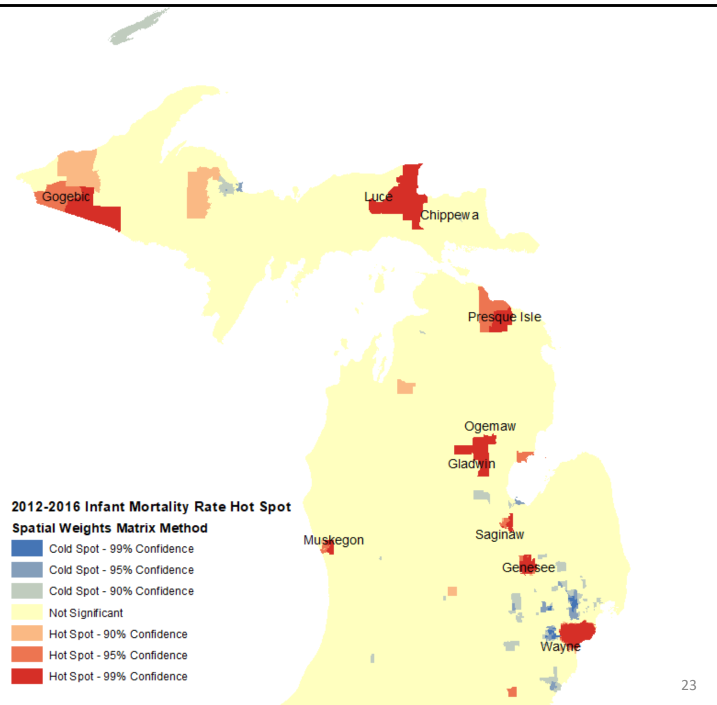
Results --- Hot Spot Cluster Analysis with Names of Counties

(Spatial Weights Matrix Method)



This map shows the results of the hot spot cluster analysis using spatial weights matrix method and includes the county names that have hot spots.

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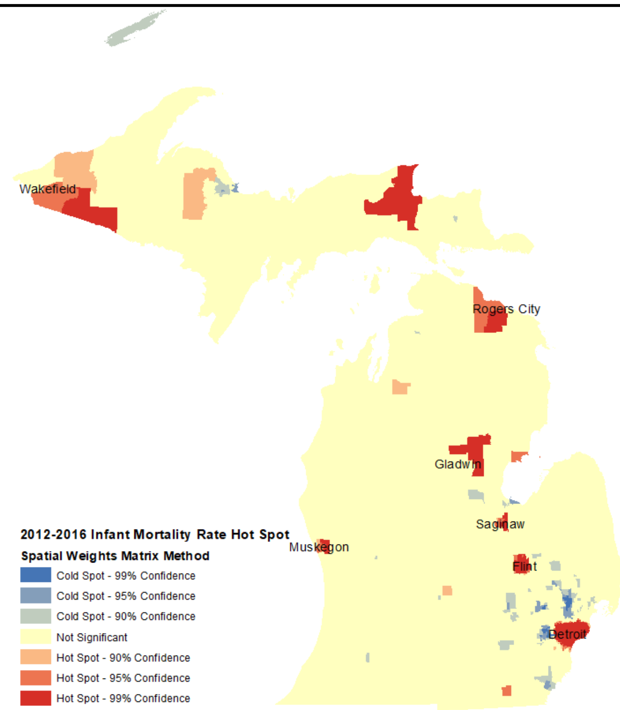
Counties with significant clusters can be seen in the map.

- In the statewide analyses, we found statistically significant infant mortality hot spot clusters for census tracts within the following counties: Chippewa, Genesee, Gladwin, Gogebic, Luce, Muskegon, Ogemaw, Presque Isle, Saginaw, and Wayne Counties.

- Significant cold spot clusters (blue shading), with low densities of infant mortality, existed within the following counties: Macomb, Oakland, and Wayne Counties.

Results --- Hot Spot Cluster Analysis with Names of Cities

(Spatial Weights Matrix Method)



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This map shows the results of the hot spot cluster analysis using spatial weights matrix method and includes the city names that have hot spots.

Using spatial weights matrix method, spatial relationships are defined by a specified spatial weights file and the path to the spatial weights file is specified by the Weights Matrix File parameter. Spatial weights are numbers that reflect the distance between each feature and every other feature in the dataset. Nearer features have a larger weight than features that are farther away.

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- Significant cold spot clusters (blue shading), with low densities of infant mortality, existed within the following cities: Farmington, Livonia, Marquette, Northville, Plymouth, Rochester, Rochester Hills, and Troy.

Conclusions

- After performing hot spot cluster analysis following the 5-step Geoprocessing approach, there were 719 census tracts out of 2,773 that were included in a statistically significant infant mortality cluster (p<.05). 610 of the infant mortality rate clustered census tracts were hotspots while 109 were coldspots.

- This analysis found several significant infant mortality hotspots and coldspots, which presents a valuable resource for public health practitioners in identifying locations of high priority.

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Discussions

- The 5-step geoprocessing analysis that culminated in these hot spot maps provided a rigorous and systematic method to determine the location of statistically significant infant mortality clusters.
- Use of this approach and the traditional data visualization techniques (e.g., thematic maps) provides policymakers and program managers with an evidence base for important public health program and funding decisions.
- Similar analyses can be conducted for other public health programs to help assess the coverage and breadth of services in specified catchment areas that can facilitate targeting of public health services (Stopka, Krawczyk, Gradziel, & Geraghty, 2014).
  - During good budgetary times, hot spot analyses can point to counties, cities, and local neighborhoods in which services can be enhanced.
  - During less favorable economic times, cold spot clusters can help inform policymakers and program directors to provide services in more efficient ways or relocate services to areas of higher need.

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References

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This slide shows the references for this study.

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