Evaluating Stream Health Based Environmental Justice Model Performance at Different Spatial Scales

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Abstract: This study evaluated the effects of spatial resolution on environmental justice analysis concerning stream health. The Saginaw River Basin in Michigan was selected since it is an area of concern in the Great Lakes basin. Three Bayesian Conditional Autoregressive (CAR) models (ordinary regression, weighted regression and spatial) were developed for each stream health measure based on 17 socioeconomic and physiographical variables at three census levels. For all stream health measures, spatial models had better performance compared to the two non-spatial ones at the census tract and block group levels. Meanwhile no spatial dependency was found at the county level. Multilevel Bayesian CAR models were also developed to understand the spatial dependency at the three levels. Results showed that considering level interactions improved models' prediction. Residual plots also showed that models developed at the block group and census tract (in contrary to county level models) are able to capture spatial variations.

Keywords: Multilevel; Conditional Autoregressive; Biological Indicators; Socioeconomic; Physiographical; Bayesian

1. Introduction

Human and natural ecosystems are interconnected and affect one another. Studies show that human activities can substantially alter ecosystems, changing biological diversity, land surface, and other resources that often have long-term environmental effects (Skole and Tucker, 1993; Vitousek et al., 1997, Halpern et al., 2008, Einheuser et al., 2013a). Anthropogenic activities have changed more than one-third of land surfaces (Vitousek et al., 1997; Allan 2004). Halpern et al. (2008) reported that no marine ecosystem has been left untouched by human activities, while more than forty percent of these ecosystems have faced notable changes. Fresh water contamination is one of the more apparent impacts of human interventions, which also negatively affects human health (Smith et al., 1999; Pomati et al., 2006; Vairavamoorthy et al., 2007; Vörösmarty et al., 2010; Harwood et al., 2014; Barnhoorn et al., 2015) through waterborne diseases such as diarrhea, cholera, SARS, and hepatitis (Levine et al., 1990; Wu et al., 1999; Ashbolt, 2004; Mieiro et al., 2009). Therefore, sustaining healthy streams can be beneficial to both human and natural systems.

A healthy stream is a stream that is sustainable and resilient, while maintaining both societal and ecological necessities (Meyer, 1997; Welsh and Hodgson, 2008; Walsh et al., 2016). In order to evaluate stream health conditions, biological indicators are used to quantify the ecological integrity of river systems (Cairns and Pratt, 1993; Jackson and Füreder, 2006; Dijk et al., 2013; Herman et al., 2015; Woznicki et al., 2016). In other words, biological indicators represent aquatic communities' response to human and natural disturbances (Barbour et al., 1999; Flinders et al., 2008). Fish and macroinvertebrates are commonly used for the development of biological indicators (Meyer, 1997; Hering et al., 2006; Wang et al., 2007; Walters et al., 2009; Holguin-Gonzalez et al., 2013; Muñoz-Mas et al., 2014). Macroinvertebrates are used for assessing local

67 habitat conditions due to limited mobility, while fish are often used for large-scale stream health
68 assessment because of seasonal migrations within stream systems (Karr, 1981; Lenat, 1988;
69 Plafkin et al., 1989; Lammert and Allan, 1999; Young et al., 2000; Herman and Nejadhashemi,
70 2015).

71 On the contrary, unhealthy streams negatively affect ecosystem services that ultimately influence
72 human well-being, social health, and access to resources (Corvalan et al., 2005; Schwarzenbach
73 et al., 2010; Azizullah et al., 2011; Katukiza et al., 2014). However, the levels of influences are
74 different between racial or ethnic groups, in particular minorities and low-income communities
75 are generally more affected (Pollock and Vittas, 1995; Helfand and Peyton, 1999; Gwynn and
76 Thurston, 2001; Taylor, 2014; Kim, 2015). In order to address these issues, the concept of
77 ‘Environmental Justice’ was introduced that deals with the fair distribution of resources to all
78 people regardless of race, color, national origin or income (EPA, 2015a). Therefore,
79 environmental justice by nature deals with different elements that vary across space, time and
80 organizational units (Picket et al., 2005; Liu et al., 2007; An, 2012). Compared to
81 ‘Environmental Equity’, which aims to evenly distribute risks among population from
82 environmental degradations, environmental justice aims to eliminate those risks especially within
83 the vulnerable population such as minorities and lower class people (Cutter, 1995; Brulle and
84 Pellow, 2006; Ewall, 2012). Therefore, environmental justice became a key factor in public
85 health studies (Lee, 2002; Brulle and Pellow, 2006; Holifield 2012; Wolch et al., 2014). Many
86 environmental justice studies are done with respect to air pollution (Jerret et al., 2001; Maantay,
87 2007; Gilbert and Chakraborty, 2011; Zou et al., 2014), while a few studies (e.g. Sanchez et al.,
88 2014; Sanchez et al., 2015) have used biological indicators in order to evaluate environmental
89 justice with respect to stream health integrity.

While both environmental and socioeconomic data can be collected at different scales, studies have shown that the scale of study plays an important role in the analysis and using the wrong scale can be misleading (Wilson et al., 1999; Maantay, 2007; Silver, 2008; Maantay and Maroko, 2009). For example, while census tract is the most commonly used in environmental justice studies (Jerret et al., 2001; Corburn et al., 2006; Gilbert and Chakraborty, 2011; Sanchez et al., 2014; Sanchez et al., 2015), socioeconomic data are also collected at county, block group, and census block scales (U.S. Census Bureau, 2010).

Zimmerman (1993) reported that using jurisdictional boundaries, such as counties, results in different environmental equity results compared to non-jurisdictional boundaries, such as census tract (Zimmerman, 1993). Fisher et al. (2006) studied air toxic pollution (point source) in the context of environmental justice and across various spatial levels (census tract, block group, and census block). They concluded that using census tract data is not a proper scale for a point source pollutants study, since it assumes uniform distribution of pollutant and population among census tracts, regardless of their size or shape (Fisher et al., 2006). Zou et al. (2014) used socioeconomic data at three spatial levels (zip code, census tract and block group) in an environmental justice study in the context of sulfur dioxide exposure. Using whites as a reference for racial inequality analysis, they showed that not only pollutant source (e.g. industrial or vehicle) but also spatial scale (e.g. county or census tract) affect final outcomes. For example, less exposure to pollutants was reported at the block group level compared to the zip code and census tract levels in black populations. In general, more reliable results were obtained at the smallest spatial scale, which was the block group (Maantay, 2007). Apart from that, multilevel analysis has been shown to produce better predictions than single level analysis in public health studies (Geronimus and Bound, 1998; Pickett and Pearl, 2000; Krieger et al., 2002a; Arcaya et al., 2012). For example,

Geronimus and Bound (1998) showed that multilevel analysis measures of health data collected at the zip code and census tract levels outperform health outcome predictions compared to single level analysis. Similarly, using composite socioeconomic data collected at the zip code, census tract, and block group levels, improved the measures in mortality and cancer incidence studies (Krieger et al., 2002a). Arcaya et al. (2012) also showed that considering multilevel dependency between the U.S. life dataset of 1999 at different scales (county, state, and region) improved projection of the life expectancy pattern (Arcaya et al., 2012).

The goal of this study is to evaluate the effects of spatial data resolution on environmental justice analysis with respect to stream health integrity. We hypothesis that the environmental justice analysis using socioeconomic data at the block group level is the most reliable and will capture more spatial dependency between socioeconomic and environmental (stream health) parameters compare to census track and county levels. We also hypothesis that considering multilevel dependency between socioeconomic data may improve the predictably of the environmental justice models. This study is unique since to the best of knowledge no study has considered both the effects of socioeconomic spatial resolutions and multilevel interactions in the context of stream health. The specific objectives are to: a) measure the degree of dependency between stream health indicators and control parameters across the three spatial scales (county, census tract, and block group); b) understand the spatial dependency at the three levels and among stream health indicators and control parameters using regression analysis; and c) evaluate the importance of multilevel analysis in improving the environmental justice model predictability.

2. Methodology

2.1 Study area

The study area is the Saginaw River Basin, the largest six-digit hydrologic unit located in Michigan. Each hydrologic unit is identified by a unique hydrologic unit code (HUC). The HUC for the Saginaw River Basin is 040802. The study area contains six hydrologic units: Tittabawassee (04080201), Pine (04080202), Shiawassee (04080203), Flint (04080204), Cass (04080205) and Saginaw (04080206), which drains to the Lake Huron (Figure 1a). The size of the study area is 16,120 square kilometers. Approximately, half of the study area is agricultural land, mostly covered by corn and soybean, 25% is forestlands, while developed areas, wetlands, rangeland, and surface water cover the rest.

Increase in soil erosion, contaminated sediment, and nutrients, has degraded aquatic life and recreational values in the study area to the extent that the US Environmental Protection Agency (EPA) has identified the Saginaw River as an area of concern in the Great Lakes basin (EPA 2015b).

2.2 Stream health indicators

In order to evaluate stream health, four biological indicators, which represent macroinvertebrates and fish abundance, were used in this study (Karr, 1981; Lenat, 1988; Hilsenhoff, 1987; Lyons 1992; Kerans and Karr, 1994; Sponseller et al., 2001; Infante et al., 2008; Einheuser et al., 2012; Einheuser et al., 2013b). The first indicator is the Index of Biotic Integrity (IBI); it describes a series of fish measures such as species richness and composition, trophic composition, abundance and condition that are evaluated by a numeric score that ranges from 0 to 100 (Karr, 1981; Kerans and Karr, 1994, Herman and Nejadhashemi, 2015). The lower scores represent high level of stream disturbance and vice versa. The Hilsenhoff Biotic Index (HBI) is a common macroinvertebrate indicator, which represents tolerance values of organic pollution within different species. It is varied from 0 to 10, where 10 suggests very poor water quality and 0

represents an excellent water quality in terms of organic pollution (Hilsenhoff, 1987). The next macroinvertebrate indicator is the Family-level Index of Biological Integrity (FIBI), which relates the composition of species in a family taxonomic resolution to pollution tolerance, ranging from 0 to 45 (Woznicki et al., 2015). For this index, higher values represent better stream health conditions. *Ephemeroptera* (mayflies), *Plecoptera* (stoneflies), and *Trichoptera* (caddisflies), also known as EPT taxa, are orders that are sensitive to degradation and commonly used in bioassessment. EPT scores below three will be considered as very poor stream health conditions and scores above 10 will be classified as excellent (Woznicki et al., 2015).

Fish monitoring was performed in 193 monitoring sites from 1982 to 2007, while macroinvertebrate were monitored between 1996 to 2003 for 262 sites within the study area (MDEQ 1997; Seelbach and Wiley, 1997). Electrofishing techniques such as backpack, tow-barge and boom units were used for fish sampling in the field (Seelbach and Wiley, 1997). While sampling methods such as hand picking and dip nets were used to obtain about 300 ± 60 organism within the minimum 20 min for each site for macroinvertebrates (Einheuser et al., 2012). The ranges of the four indices recorded within the study area are summarized in Table 1.

Using the Soil and Water Assessment Tool (SWAT) and Adaptive Neural Fuzzy Interface System (ANFIS) a predictive model was developed to calculate stream health indicators throughout the study area (Einheuser et al., 2012; Einheuser et al., 2013a). The current average (2002-06) stream health conditions based on the four biological indicators for the 13,831 stream segments are presented in Figure 2.

2.3 Socioeconomic and physiographical indicators

From numerous reported socioeconomic measures, 16 indicators were selected in this study (Table 2). These indicators were selected since they have been widely used in many environmental justice researches and represent concentrated disadvantage (Bowen et al., 1995; Bowen, 2002, Taquino et al., 2002, Brulle and Pellow, 2006, Bullard et al., 2008, Sampson et. al. 2008; Lin and Morefield, 2011, Malley et al., 2012). Selected indicators represent population (S2 and S3), household composition (S4, S5, S8, S9), racial composition of household (S6), female-headed households (S7), housing (S10, S11), educational disadvantage (S12), economic disadvantage (poverty) (S13, S14, S15), welfare receipt (S16) and unemployment (S17). These indicators were obtained from the U.S. Census Bureau for three census levels of county, census tract, and block groups (U.S. Census Bureau, 2010). The Saginaw River Basin was covered by 21 counties (Figure 1b), 393 census tracts (Figure 1c), and 1,076 block groups (Figure 1d). According to U.S. Census Bureau (2010), more than 2.8 million people are living in the study area. 71.6% of the population are living in urban and 28.6% in rural area. The race distribution is: 83.1% white, 10.6% black or African American, 2.8% Asian and 3.5% others.

In addition to socioeconomic indicators, a watershed physiographical indicator called drainage density was used to account for the accessibility of people to water bodies. In this study, the drainage density was defined as the ratio of the total length of all rivers divided by the socioeconomic area of interest (counties boundary, census tract, and block group). Scale adjustment was also performed to match socioeconomic and stream health measures, because stream health was calculated in much finer resolution (13,831 stream segments) than the socioeconomic data. This was accomplished by calculating the weighted average of stream health scores by length for the different census levels.

2.3 Data Analysis and Modeling

Scatterplot matrices including histograms of each individual variable distribution (the four stream health indicators, drainage density, and sixteen socioeconomic indicators) and pairwise correlation coefficients at three census levels were calculated based on the Spearman's rank correlation coefficient, a non-parametric measure of statistical dependence between two variables (Lehmann and D'Abrera 1998). However, to better understand the spatial dependency among control parameters and stream health indicators, regression analysis was performed using spatial Conditional Autoregressive (CAR) models (Banerjee et al., 2004).

First, assume counties are represented by $i = 1, 2, \dots, I$, census tracts are represented by $j = 1, 2, \dots, J$, and block groups are represented by $k = 1, 2, \dots, K$. Since the three levels are nested, $K = \sum_{j=1}^J K_j$ where K_j is the number of block groups in the j th census tract, and $J = \sum_{i=1}^I J_i$ where J_i is the number of census tracts in the i th county. Therefore, the total observation for each block group at the finest resolution is $K = \sum_{j=1}^J K_j = \sum_{i=1}^I \sum_{j=1}^{J_i} K_j$.

For each resolution level of data presentation, the spatial CAR model is presented as follows:

a) County level data: Assume Y_i represents the steam health indicator, X_i includes the corresponding p socioeconomic indicators plus an intercept to account for the mean level of the response, i.e. $X_i = (1, S_{i1}, \dots, S_{ip})$ for the i th sample. We consider:

1) Spatial CAR model (Model [1]):

$$Y_i = X_i \beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 (M_I - \gamma_I W_I)^{-1}) \quad (1)$$

where, W_I denotes the spatial neighborhood matrix for the I counties and M_I represents the diagonal matrix with the number of total neighbors as the diagonal entries. In this model, τ_I^2 measures the variation and γ_I measures the spatial

dependence. The vector $\beta = (\beta_0, \beta_1, \dots, \beta_p)$ includes the regression coefficients,

hence $X_i\beta = \beta_0 + \sum_{t=1}^p S_{it}\beta_t$ in (1).

To evaluate the importance of modeling spatial dependence, two partial

implementations were considered:

i) the weighted regression model (Model [2]):

$$Y_i = X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 M_I^{-1}), \quad i = 1, 2, \dots, I \quad (2)$$

where, $\gamma_I = 0$ is fixed, i.e., no spatial dependence but the residual variance is

weighted by the number of neighbors; and

ii) the ordinary regression model (Model [3]):

$$Y_i = X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 I_I), \quad i = 1, 2, \dots, I \quad (3)$$

where, $M_I = I_I$ the identity matrix. In this model, no spatial information is

included; therefore, it becomes the ordinary regression model.

In the following context whenever a CAR structure is incorporated, the full and the two partial implementations (weighted least squares and ordinary least squares) were considered.

b) Census tract level data:

2) Spatial CAR model with no random effect (single level):

$$Y_j = X_j\beta + \varepsilon_j, \quad \varepsilon \sim N(0, \tau_J^2 D_J(\gamma_J)), \quad j = 1, 2, \dots, J \quad (4)$$

with a total of three submodels and double index for [county, census tract], $D_J(\gamma_J) =$

$(M_J - \gamma_J W_J)^{-1}$ as full implementation (Model [0.1]) that accounts for the spatial

dependence, and two partial implementations $D_J(\gamma_J) = M_J^{-1}$ (Model [0.2]) that

considers spatial heterogeneity using the number of surrounding regions as weights,

and $D_J(\gamma_J) = I_J$ (Model [0.3]) that is just simple multiple regression without considering any spatial information.

3) Spatial CAR model with random effect on county (multilevel):

$$Y_{ij} = X_{ij}\beta + u_i + \varepsilon_{ij}, \quad \boldsymbol{\varepsilon} \sim N(0, \tau_J^2 D(\gamma_J)), \quad \mathbf{u} \sim N(0, \tau_I^2 D(\gamma_I)) \quad (5)$$

$$j = 1, 2, \dots, J_i, \quad i = 1, 2, \dots, I$$

with a total of $3 \times 3 = 9$ submodels while considering the full implementation and two partial implementations on both levels, indexed from Model [1.1] to Model [3.3].

c) Block group level data:

4) Spatial CAR model with no random effect (single level)

$$Y_k = X_k\beta + \varepsilon_k, \quad \boldsymbol{\varepsilon} \sim N(0, \tau_K^2 D_K(\gamma_K)), \quad k = 1, 2, \dots, K \quad (6)$$

with a total of three submodels and triple index for [county, census tract, block group], $D_K(\gamma_K) = (M_K - \gamma_K W_K)^{-1}$ as full implementation (Model [0.0.1]), and two partial implementations $D_K(\gamma_K) = M_K^{-1}$ (Model [0.0.2]) and $D_K(\gamma_K) = I_K$ (Model [0.0.3]).

5) Spatial CAR model with nested random effects on county and census tract (multilevel):

$$Y_{ijk} = X_{ijk}\beta + u_i + v_{ij} + \varepsilon_{ijk}, \quad (7)$$

$$\boldsymbol{\varepsilon} \sim N(0, \tau_K^2 D(\gamma_K)), \quad \mathbf{u} \sim N(0, \tau_I^2 D(\gamma_I)), \quad \mathbf{v} \sim N(0, \tau_J^2 D(\gamma_J))$$

$$k = 1, 2, \dots, K_j, \quad j = 1, 2, \dots, J_i, \quad i = 1, 2, \dots, I$$

with the total of $3 \times 4 \times 4 - 3 = 45$ submodels by considering the full implementation and two partial implementations on all three levels, and with either $\mathbf{u}$

or $\mathbf{v}$ fixed at 0 (but not both), indexed from Model [0.1.1] to Model [3.3.3] with the triple index for [county, census tract, block group].

In total, 63 models (3 + 12 + 48) were fitted to the data at different resolution level and by considering the interactions between levels and spatial dependence structure. The model fit is carried out by running six Markov chain Monte Carlo (MCMC) per model with distinct starting values and a total of 6,000 iterations. After convergence, the last 1,000 samples for each chain is stacked as posterior samples for inference.

2.4 Markov chain Monte Carlo Implementation Details

Equation 7 is considered as the full spatial CAR model with nested random effects on county and census tract for the block group data. Other models are either nested or reduced at simpler levels but having similar format. Equation (7) can be rewritten in format of the mixed-effect model as follows:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}_u\mathbf{u} + \mathbf{Z}_v\mathbf{v} + \boldsymbol{\varepsilon} \quad (8)$$

$$\boldsymbol{\varepsilon} \sim N(0, \tau_K^2 D(\gamma_K)), \quad \mathbf{u} \sim N(0, \tau_I^2 D(\gamma_I)), \quad \mathbf{v} \sim N(0, \tau_J^2 D(\gamma_J))$$

The associated model parameters were estimated through the full Bayesian framework by eliciting prior assumptions. A flat prior on the regression coefficient $\boldsymbol{\beta}$ but a conjugate prior for the variation parameters τ_I^2 , τ_J^2 , and τ_K^2 were assumed. This is an inverse-gamma distribution with shape a and scale b . One option is to assume $a = 2$ and $b = 0.01$ that yields a rather dispersed prior distribution when there is a lack of strong prior knowledge. In addition, uniform prior distributions were considered on γ_I , γ_J and γ_K over their required ranges to guarantee the corresponding matrices $D(\gamma_I)$, $D(\gamma_J)$ and $D(\gamma_K)$ would be valid covariance matrices for CAR

284 model. In the next step, posterior samples of the parameters were drawn by combining the selected
 285 diffused prior distributions and data likelihood via the MCMC technique. More specifically, the
 286 Gibbs sampler was used, which involves updating a set of parameters given the data and the
 287 remaining parameters, from their full conditional densities at each iteration of the MCMC runs.
 288 Due to the conjugate prior choice, the full conditional distribution of β is $N(\mu_\beta, \Sigma_\beta)$ was adopted
 289 where;

$$290 \quad \begin{cases} \Sigma_\beta = \tau_K^2 (\mathbf{X}'(M_K - \gamma_K W_K) \mathbf{X})^{-1} \\ \mu_\beta = \Sigma_\beta \mathbf{X}'(M_K - \gamma_K W_K) (\mathbf{Y} - Z_u \mathbf{u} - Z_v \mathbf{v}) \end{cases} \quad (9)$$

291 and at each Gibbs circle a sample of β from the full conditional distribution above was first
 292 simulated. Similarly, the full conditional distribution of county random effect $\mathbf{u}$ is $N(\mu_u, \Sigma_u)$
 293 where;

$$294 \quad \begin{cases} \Sigma_u = \tau_K^2 \left(Z_u' (M_K - \gamma_K W_K) Z_u + (M_I - \gamma_I W_I) \frac{\tau_K^2}{\tau_I^2} \right)^{-1} \\ \mu_u = \Sigma_u Z_u' (M_K - \gamma_K W_K) (\mathbf{Y} - \mathbf{X}\beta - Z_v \mathbf{v}) / \tau_K^2 \end{cases} \quad (10)$$

295 The full conditional distribution of census tract random effect $\mathbf{v}$ is $N(\mu_v, \Sigma_v)$ where;

$$296 \quad \begin{cases} \Sigma_v = \tau_K^2 \left(Z_v' (M_K - \gamma_K W_K) Z_v + (M_J - \gamma_J W_J) \frac{\tau_K^2}{\tau_J^2} \right)^{-1} \\ \mu_v = \Sigma_v Z_v' (M_K - \gamma_K W_K) (\mathbf{Y} - \mathbf{X}\beta - Z_u \mathbf{u}) / \tau_K^2 \end{cases} \quad (11)$$

297 The full conditional distribution of τ_I^2 is inverse-gamma with shape a_I and scale b_I , where;

$$298 \quad \begin{cases} a_I = a + I/2 \\ b_I = b + \mathbf{u}'(M_I - \gamma_I W_I) \mathbf{u} / 2 \end{cases} \quad (12)$$

299 The full conditional distribution of τ_J^2 is inverse-gamma with shape a_J and scale b_J , where;

$$\begin{cases} a_J = a + J/2 \\ b_J = b + \mathbf{v}'(M_J - \gamma_J W_J)\mathbf{v}/2 \end{cases} \quad (13)$$

The full conditional distribution of τ_K^2 is inverse-gamma with shape a_K and scale b_K , where;

$$\begin{cases} a_K = a + K/2 \\ b_K = b + \frac{\mathbf{e}'(M_K - \gamma_K W_K)\mathbf{e}}{2} \\ \text{with } \mathbf{e} = \mathbf{Y} - \mathbf{X}\beta - Z_u\mathbf{u} - Z_v\mathbf{v} \end{cases} \quad (14)$$

γ_I was also sampled from its full conditional distribution with density proportional to

$$|M_I - \gamma_I W_I|^{1/2} \exp \{ \gamma_I \mathbf{u}' W_I \mathbf{u} / (2\tau_I^2) \} \quad (15)$$

Similar sampling was performed for γ_J and γ_K . Updating all parameters completes one Gibbs circle, and this procedure is repeated over a large number of iterations in order to obtain posterior samples for inferential stage after convergence of multiple MCMC runs. Finally, Deviance Information Criterion (DIC₄) was used for mixed-effect model evaluation (Celeux et al 2006).

3. Results and Discussions:

3.1 Variables distribution and pairwise correlations

Figures 3, A1, and A2 show the correlation matrices for the three census levels of county, census tract, and block group, respectively. Histograms of each individual variable distribution are shown on the diagonal of each matrix. The upper and lower parts of the matrices are spearman rank correlation coefficients and scatter plots of each pair of variables, respectively.

3.1.1 Variables distribution:

317 Understanding the variable distribution is important for selecting appropriate analysis techniques
318 or examining the underlying assumption about a set of variables. Among the four stream health
319 indicators at the three levels (country, census tract, and block group), the HBI and IBI had the
320 most bell-shaped histograms, especially at the census tract (Sanchez et al., 2014) and block
321 group levels, while a little skewness to the right can be seen in both indices at the county level. A
322 normal distribution of the IBI at the census tract and block group level means that the majority of
323 census units (census tract or block group) have close to average IBI scores. This is also
324 consistent with previous studies on IBI measure in this region (Einheuser et al., 2013a), showing
325 that streams with good or fair condition are dominant. While at the county level, the IBI
326 distribution has changed, showing that counties with fair or poor IBI score become dominant.
327 The same variation for HBI scores distribution was seen among the three levels. This shows that
328 the level of study has an effect on variable distribution as the aforementioned indices have
329 normal distributions at the census tract and block group levels but skewed at the county level.
330 Besides that, these two indices are less sensitive to aggregation at the county level compared to
331 the FIBI and EPT. The FIBI and EPT were right-skewed at the census tract (Sanchez et al., 2014)
332 and block group level meaning that most of the units (census tracts or block groups) have low
333 scores, which is consistent with low stream health scores reported at the reach level (Figure 2 (c)
334 and (d)). However, their distributions were the opposite at the county level and showed left-
335 skewness, meaning that most of units have high FIBI and EPT scores. The FIBI and EPT indices
336 represent the abundance and integrity of macroinvertebrate communities and are known to be
337 reliable for local stream health evaluation due to their limited mobility (Kerans and Karr, 1994;
338 Butcher et al., 2003; Herman and Nejadhashemi, 2015). Sponseller et al. (2001) also reported
339 that evaluation of macroinvertebrate indices is dependent on the spatial scale of the study. These

results show how using coarse census resolutions can be misleading in stream health data analysis, especially for macroinvertebrate indices, which are more sensitive to the level change than fish index (IBI). Unlike macroinvertebrates, fish can move through the entire riverine system and the IBI index is used for overall riverine system evaluation (Karr, 1981; Herman and Nejadhashemi, 2015). That justifies the observed lower variation in the IBI scores distribution among the three levels compared to macroinvertebrates indices. Considering stream health scores at the reach level (Figure 2) also suggests that census tract and block group levels can better represent stream health data distribution compared to the county level.

Regarding the socioeconomic data, most of them had consistent distributions at the census tract and block group levels, and in general, were less affected at the county level than the stream health measures. This means that these indices are less sensitive to aggregation than the stream health measures. Among the 16 socioeconomic parameters, only S17 (percentage of unemployed population of 16 years old and above) had normal distributions at all three levels. The S3 (percentage of land area), S9 (average house size) and S11 (percentage of housing units occupied) parameters were left-skewed. The left skewness of S3 means that the majority of census units (at each level) have few water bodies and are mostly covered by land. While the distributions for S9 and S11 show that the majority of house units in the study area are larger than average and most of them are occupied. The rest of the parameters were right-skewed. The right skewness of S2 and S10 showed that many of the census units have low population densities (S2) and few housing units (S10), which correlates with the house size (S9) distribution mentioned above. This can be explained by the land use within the study area, which mainly consists of agricultural and forestlands. In general, lower population density is expected within

these land uses compare to urban and residential area such as Flint. That is why many census units (covering these lands) have low population densities, few housing units, and large houses. The same pattern was seen for S6 (percentage of black or African American population), meaning that only a few census units have the majority of the population as black or African American. The S7 (percentage of households with female householder) and S8 (percentage of householders living alone) distributions, also showed that few units of study have a high percentage of households with a female householder or householders living alone. Poverty and welfare receipt indicators also showed that only a few census units are dominated by people with low incomes (S14 and S15), incomes below poverty level (S13), or receive public assistance (S16). These distributions can help decision makers to select areas, which have higher priorities for environmental justice practices.

3.1.2 Stream health indicators correlations at three levels:

Considering the census tract and block group levels, the IBI, FIBI and EPT were positively correlated with each other and all were negatively correlated with HBI, which is consistent with their definitions where high values for the IBI, FIBI and EPT indicate better stream health conditions, while for the HBI lower values indicate better stream health conditions. The same pattern among stream health measures was seen in a previous study at the census tract level (Sanchez et al., 2014). However, this consistency is lost at the county level, where the IBI had a reversed correlation with macroinvertebrates indices. This means that streams, which had better conditions for macroinvertebrates (having high FIB, high EPT and low HBI scores), had worse conditions for fish (low IBI scores). Furthermore, significant correlations between the IBI and FIBI and EPT indices at the census tract and block group levels were also lost at the county

level. Overall, correlations among stream health measures show how sensitive they are to the scale and how their aggregation at the county level can result in inaccurate conclusions compared to the census tract and block group levels. This is also in agreement with previous studies showing the importance of spatial scale on stream health evaluation (Boulton, 1999; Karr, 1999; Marchant et al., 1999; Bush et al., 2012). For example, Boulton (1999) reported that not only the quality of data, but also the scale of analysis highly influences the outcomes from a stream health evaluation. In general, finer resolutions were reported to predict stream health more accurately (Boulton, 1999; Karr, 1999; Chessman et al., 2007; Heino 2014). These changes in data interpretation among different census levels also match with their histograms comparison.

3.1.3 Socioeconomic/physiographic indicators correlations at three levels:

Almost all of the socioeconomic/physiographic indicators had significant correlations with each other at the county level with thirty-one absolute correlation coefficients above 0.7 (shown in red and blue) and three correlation coefficients above 0.9 among S2 (population density) and S10 (housing units), S2 and S15 (aggregate household income), and S10 and S15. However, moving from county to census tract level, these correlation values drastically dropped with only three absolute values above 0.7 among S8 (householders living alone) and S9 (average household size), S12 (population above 25 years old and education less than high school) and S14 (average household income), and S13 (families with income below poverty level) and S14. However, none of them were significant. Like the census tract level, only three absolute correlation values were above 0.7, for S8 and S9, S13 and S14, and S14 and S15 at the block group level. Overall, correlation values were even less at block group level. For example, correlation coefficients between S13 and S14 dropped from -0.83 to -0.71 at the block group compared to the census tract level. In addition, the correlation coefficients of S12 and S14 dropped from -0.75 at the

census tract to -0.58 at the block group, while correlation coefficients for S14 and S15 increased from 0.65 to 0.73 when the block group level is compared to the census tract level. These examples show how correlations found between different indicators can vary among census levels and lead to different interpretations. This is also in agreement with previous studies showing the role of census level data aggregation on public health statistical analysis. For example, comparing data collected at zip code, census tract, and block group levels, Geronimus and Bound (1998) showed that aggregated socioeconomic data in coarse resolution (e.g. zip code), does not capture variations in finer resolutions (e.g. census tract and block group) while affecting the overall correlations among dependent and independent variables (Schmidtlein et al., 2008; Martinich et al., 2013). Krieger et al., (2002b) examined aggregated data at three resolution levels: a) zip code level (with average population of 30,000), b) census tract (with average population of 4,000), and c) block group (with average population of 1,000) in socioeconomic, inequality, and health studies. The results showed that zip code level analysis are in contrary with results obtained from census tract, block group, and literature. However, results obtained from census tract and block group analysis were more similar (Krieger et al., 2002b). In general, socioeconomic/physiographic data showed high correlations among each other at coarse resolutions (e.g. county level) while these correlations were lost at finer census levels (e.g. census tract and block groups), which are more detailed and can better represent spatial distribution.

3.1.4 Interaction of stream health measures and socioeconomic/physiographic indicators at three levels:

Like the interactions of the socioeconomic/physiographic indicators with each other, the highest correlation coefficients with the four stream health measures were also found at the county level,

followed by the census tract and block group levels. In addition, more variables are significantly correlated at the county level. However, the values reported for these correlations were much lower than the numbers found among the socioeconomic/physiographic indicators. For example, the highest correlation of EPT with a socioeconomic/physiographic indicator at the county level was 0.43 with S13 (families with income below poverty level), which is much smaller than the correlations reported in the previous section (e.g. three correlation coefficients were above 0.9). This can be explained due to the fact that both dependent (stream health) and independent (socioeconomic/physiographic) variables were averaged in the scale that they were studied. As it was expected, lower correlations were observed when averaging was performed at the larger scale. This makes the analysis at the larger scale less sensitive to cause and effect relationships. Furthermore, significantly correlated socioeconomic/physiographic indicators for each stream health measure vary across the census levels. For example, at the county level the HBI had significant correlations with three household composition indicators (S5, S8, and S9). However, of these three only S8 continued to be significant at the census tract level. S9 was replaced with another household indicator (S7: Female-headed households). Besides that, a racial composition indicator (S6) and one population indicator (S3: percentage of land area) became significant at this level. While at the block group level, one more population indicator (S2: population density) was also added to this list.

In general, all stream health measures had higher correlation coefficients at the county level, compared to the census tract and block group levels. Furthermore, the significant socioeconomic/physiographic indicators were not the same at all three levels, which again shows the role of census level resolution in data interpretation for each stream health measure.

3.2 Understand the spatial dependency between stream health indicators and control parameters using regression analysis:

3.2.1 Spatial CAR Models with no random effect (single level)

Considering each stream health indicator, three models (spatial, weighted regression, and ordinary regression) were developed. These models were applied for each census level, so 36 models (4 response variables, 3 levels, and 3 models) were developed at this stage (Tables 3-7 and A1 to A8). In these tables, DIC, which is a measure of relative quality of a statistical model, was used to identify the best model at each level. However, this value should not be used to compare the models' performances from multiple levels (e.g. county versus census tract) due to differences in sample sizes. In addition to DIC, γ was reported to present spatial dependence in which 0 means no spatial effect while 1 mean full spatially dependency. Finally, each dependent parameter that its regression coefficient (β_1 - β_{17}) that does not contain zero in the range of their upper and lower bands can be considered as a significant parameter and are bolded for each model.

At the county level (Tables 3 to 6) none of the models (spatial, weighted regression, and ordinary regression) had significant spatial dependency (all four γ ranges had zero). For each stream health measure, the exact same significant parameters were highlighted among the three developed models. Besides that, the comparison of the three DICs showed only slight differences meaning that there is no major difference between spatial, weighted regression, and ordinary regression models at the county level and all of them have the same pattern. This again proves that aggregated data at the county level reduces variations and resulted in removing spatial dependency among stream health measures and socioeconomic/physiographic indices. Similar pattern was also observed in public health studies. Schuurman et al., (2007) evaluated several

population health indices at different spatial levels (e.g. census block, tract, district, county and region) and observed that scale of study impacts the correlation between relative deprivation and self-reported health. Reid et al. (2012) also found differences between the Heat Vulnerability Index calculations based on data collected at both the census tract and zip code levels due to higher aggregation at the zip code level because in general it is larger than the census tract. Overall, a weighted regression model for EPT, and ordinary regression models for FIBI, HBI and IBI were identified to be the best predictive models considering DIC.

However, within in census tract level (Tables A1 to A4), more variations were seen among spatial, weighted regression and ordinary regression models. In contrast to the county level, significant parameters for all three models and for all four stream health measures were not the same. In general, spatial models gave better prediction (lower DICs), meaning that the use of the census tract level can capture more spatial patterns, while these variations were lost at the low detailed county level. Besides that, fewer dependent parameters showed significant correlations with each of the stream health measures at the census tract compared to the county level. For example, the IBI at the county level had significant correlations with nine out of seventeen indicators including one physiographic (S1), one population (S3), one household (S7), one housing (S11), one educational disadvantages (S12), three poverty/welfare receipt (S13, S14, S16), and one unemployment (S17). However, at the census tract level, only one welfare receipt indicator (S16) showed significant correlation with the IBI index. Other stream health measures also had fewer significant correlations with socioeconomic/physiographic indicators at the census tract level, compared to the county level. This indicates that using more detailed census data reveals more distinctions among dependent variables and as a result reduces the number of parameters required to predict stream health measures; while, some of these variables became

correlated at the county level due to the aggregation at this coarse level. Similar reductions in the number of significant parameters were seen in the comparison of pairwise correlations at the two levels (Figures 3 and A1) for all other stream health measures.

At the block group level, spatial models showed even better performance (lower DICs) compared to weighted regressions and ordinary regression models (Tables A5 to A8). However, comparison of γ values between spatial census tract (Tables A1 to A4) and block group models (Tables A5 to A8) showed that higher spatial dependency exists for the three macroinvertebrates models at the block group level than at the census tract (higher γ values and/or narrower range of γ variations). While for the IBI, higher spatial dependency was seen at the census tract level than at the block group level. This can be explained, since macroinvertebrates are better representatives of local habitat conditions, while fish are representative of large-level stream health due to their mobility (Herman and Nejadhashemi, 2015). Therefore, at the block group level, which is the finest level, macroinvertebrates indices have more spatial dependency on socioeconomic/physiographic parameters, while the IBI has higher spatial dependency at the census tract, which is a larger scale than the block group.

Like the census tract level models, significant parameters were not the same for the spatial, weighted regression, and ordinary regression models, which again shows that, unlike the county level, these models differ from each other at the block group level. In addition, the significant parameters were also different for each stream health measure at different census levels. For IBI spatial models for example, only S16 (percentage of households receiving public assistance) was highlighted as significant parameter at the census tract level, while at the block group level, S2

(population density) and S7 (percentage of households with female householder) were also found to be significant.

3.2.2 Spatial CAR Models with random effects (Multilevel)

Using three (spatial, weighted regression and ordinary regression) models for each census level interacting with its coarser resolutions (random effects) resulted in 63 models for each stream health measure. Table 7 presents the DICs for all of these models. The best models at each census level (lowest DIC) are bolded for each stream health measure. It is important to note that the single-level models in subsection 3.2.1 can be viewed as special cases of the multi-level modeling where we fix some of the random effects on other levels to be exactly 0.

The county level is the coarsest resolution with no higher-level interactions (no random effect), so the first three rows in Table 7, represent the spatial, weighted regression, and ordinary regression models that exist at this level. Like the single level (no random effect) results (Tables 3 to 6), all three models have very close DICs meaning that their performances are likely to be the same. Here also the weighted regression and ordinary regression models had slightly lower DICs compared to spatial models.

Regarding the census tract level, interactions with the county level (random effects) were also considered, so twelve models (rows 4 to 15) were developed at this level. Like tables A1 to A4, the spatial models had lower DICs compared to the weighted regression and ordinary regression models. Adding county level data improved model predictions; however, it is important to note that adding country level random effect had a lower impact on the overall DIC than the models used at the census level. This is also in agreement with Tables 3 to 6, which showed that the three models had very close values at the county level. Considering the interactions of the two levels (random effects), the FIBI combined spatial models at both the census tract and county

levels resulting in a lower DIC; while for EPT, HBI and IBI, coupled spatial models at the census tract and weighted regression models at the county level had lower DICs, indicating better predictions.

The next 48 rows in Table 7 belong to models developed for the block group level interacting with the census tract and county levels (nested random effects). In general, models that considered the spatial effect for the block groups had lower DICs compared to non-spatial ones. Compared to single level (no random effect) models, inputting census tract and county levels also had a positive impact on the models' predictions. This is also in agreement with previous studies, showing how multilevel analysis improved public health predictive models compared to single level analysis. Geronimus and Bound (1998) reported that combined census data at both census county and census tract levels improved health outcome predictive equations. Arcaya et al. (2012) also showed that considering nested county data in states, improve life expectancy pattern prediction and resulted in lower DIC.

The lowest DIC for the IBI was achieved through the combination of spatial models at all three (county, census tract and block group) levels. While for the three macroinvertebrate stream health indicators, the combination of spatial models at the block group level, weighted regression models at the census tract level, and spatial (for HBI) and ordinary regression (for FIBI and EPT) models at county levels produced the lowest DICs. Since the IBI is based on fish, the selection of all spatial models resulting in the lowest DIC makes sense due to the large mobility of fish throughout a river network (Allan et al. 1997; Flinders et al. 2008; Paller et al., 2014). Spatial models selected for macroinvertebrates at the block group level is also in agreement with tables A5 to A8. However, considering the interactions of data at the census tract and block group levels (nested random effects) suggests that weighted regression models work better with census

tract data. That can be due to the macroinvertebrate behavior of limited movement within the river systems (Herman and Nejadhashemi, 2015). Meanwhile, for county level data used in the block group level study (nested random effect) ordinary regression models worked better for the FIBI and EPT, while weighted regression models worked better for HBI. These variations among models is also in agreement with previous results that all three (spatial, weighted regression and ordinary regression) models performances were very close at county level and each of them can be selected as the best.

Table 8 presents the dependent parameters that were significant in the best models at each level. Except for ETP taxa at the block group level, all stream health indicators at each level (both for single level or no random effect models and models across different levels having random effects) have the same significant parameters. In other words, while DIC values can differ and the model performances can be improved with the addition of interactions among the different levels (random effects), the significant parameters are not affected. However, these significant parameters may be lost by changing the resolution level and some new parameters may show significant effects, revealing potentially misleading results that arise from selecting an inaccurate level or scale.

3.2.3 Residual plots

Figures 4 and A3 through A6 show the residual plots for the selected models at both multilevel (with random effects) and single level (no random effect) cases (Tables 3 to 7 and A1 to A8). As mentioned before, county level data is not likely to be a good predictor and may cause misinterpretations. This is further reinforced by Figure 4, which shows that the models developed at this level have little to no variation across the study area. This lack in variation shows that these models are unable to uncover the complexities of relations among the variables

due to attenuation caused by aggregated data (Pucher et al., 2010; Phillips and Land, 2012). As an important contrast, for the more detailed levels (census tract and block group), shown in Figures A3 through A6, more variations are captured.

EPT and HBI show very low residuals in the study area and values ranging from -5 to +5 are reported for the majority of the study area in both census tract and block group models developed for these indices (Figures A3 and A4). It means that developed models for these two stream health measures have acceptable performances in this region. In contrast, the FIBI and IBI have some significant residuals in the study area (Figures A5 and A6). Most of the high residual areas are located in highly populated areas and close to the watershed outlet, which means model predictions for the FIBI and IBI at the given areas have less accuracy, compared to the rest of the study area.

4. Conclusion

The goal of this study was to evaluate the effects of spatial data resolution on environmental justice analysis with respect to stream health integrity. Seventeen socioeconomic/physiographic indicators representing population, household composition, racial composition of household, female headed households, housing, educational disadvantage, economic disadvantage, welfare receipt, and unemployment in addition to four stream health measures (including one fish and three macroinvertebrates indices) were used.

Data distributions and pairwise correlations at all three levels showed that stream health data is highly sensitive to census level resolution. In addition, some variables had opposite skewness and/or even correlation sign at the county level compared to two finer resolutions (census tract and block group levels). Meanwhile, socioeconomic/physiographic data distributions were less

sensitive to census level change and most of them had similar distributions among all three levels. Many significant correlation coefficients were found at the county level, while moving to the census tract and block group levels, the number of significant correlations and correlation coefficients drastically dropped. This showed that the use of the country level data can be misleading due to aggregation.

For each stream health measure, three regression models including spatial, weighted regression and ordinary regression were developed at each level. County level models for each stream health measure had similar significant parameters. Besides that, each set of three models had similar predictions with no spatial dependency. However, at the census tract and block group levels, spatial models had better predictions with fewer number of significant parameters, meaning that the census tract and block group levels were able to capture spatial variations, which were aggregated in county level. Furthermore, using multilevel models (with random effects) also improved model prediction compared to single level models (with no random effects); however, did not affect significant parameters. The difference between spatial models and weighted regression and ordinary regression models was even more pronounced at the block group level, compared to the census tract level. The IBI had higher spatial dependency at the census tract level, while the three macroinvertebrates indices had higher spatial dependency on dependent variables at the block group level. This matched the movement patterns of fish and macroinvertebrates within river systems.

Residual plots also proved that the county level models are not able to capture spatial patterns while the census tract and block group levels do. This confirmed that the block group level models performed better than both the country and census level models. Residual plots also showed that for the best developed IBI and FIBI models prediction in densely populated areas

and close to the watershed outlet was less accurate compared to other places, while the best models for EPT and HBI worked well for the whole region.

To better understand the interactions between socioeconomic variable and stream health, it is recommended that additional studies will be performed in larger regions and different timeframes. This provides additional information to examine the importance of spatial and temporal variations in the context of environmental justices.

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6. References

Allan, J., 2004. Landscapes and Riverscapes: The Influence of Land Use on Stream Ecosystems. *Ann. Rev. Ecol., Evol. S.* 35, 257–284.

Allan, J., Erickson, D., Fay, J., 1997. The influence of catchment land use on stream integrity across multiple scales. *Freshwater Biol.*, 37, 149–161.

An, L., 2012. Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecol. Model.* 229, 25–36.

Arcaya, M., Brewster, M., Zigler, C.M., Subramanian, S.V., 2012. Area variations in health: A spatial multilevel modeling approach. *Health Place, Infectious Insecurities* 18, 824–831.

Ashbolt, N.J., 2004. Microbial contamination of drinking water and disease outcomes in developing regions. *Toxicol.*, 198, 229–238.

658 Azizullah, A., Khattak, M.N.K., Richter, P., Häder, D.-P., 2011. Water pollution in Pakistan and its
 659 impact on public health — A review. *Environ. Int.* 37, 479–497.

660 Banerjee, S., Carlin, B.P., Gelfand, A.E., 2004. *Hierarchical Modeling and Analysis for Spatial Data*.
 661 Chapman and Hall/CRC Press, Boca Raton, Florida.

662 Barbour, M., Gerritsen, J., Snyder, B., Stribling, J., 1999. *Rapid bio Assessment Protocols for Use in*
 663 *Streams and Wadeable Rivers: Periphyton, Benthic Macroinvertebrates and Fish*, second ed.
 664 Environmental Protection Agency, Office of Water, Washington, DC. EPA 841-B-99-002.

665 Boulton, A.J., 1999. An overview of river health assessment: philosophies, practice, problems and
 666 prognosis. *Freshwater Biol.* 41, 469–479. Bowen, W. 2002. An Analytical Review of Environmental
 667 Justice Research: What Do We Really Know? . *Environ. Manage.*, 29, 3-15.

668 Barnhoorn, I.E.J., van Dyk, J.C., Genthe, B., Harding, W.R., Wagenaar, G.M., Bornman, M.S., 2015.
 669 Organochlorine pesticide levels in *Clarias gariepinus* from polluted freshwater impoundments in South
 670 Africa and associated human health risks. *Chemosphere* 120, 391–397.

671 Bowen, M.W., Salling, M.J., Haynes, K.E., Cyran, E.J., 1995. Toward environmental justice: spatial
 672 equity in Ohio and Cleveland. *Ann. Assoc. Am. Geogr.* 85, 641–663.

673 Brulle, R., Pellow, D. 2006. Environmental Justice: Human Health and Environmental Inequalities. *Ann.*
 674 *Rev. Pub. Health* , 27, 103–124.

675 Bullard, R., Mohai, P., Saha, R., Wright, B. 2008. Toxic Wastes and Race at Twenty: Why Race Still
 676 Matters after All of These Years. *Envtl. L.* 38, 371-411.

677 Bush, A., Nipperess, D., Turak, E., Hughes, L., 2012. Determining vulnerability of stream communities to
 678 climate change at the landscape scale. *Freshwater Biol.* 57, 1689–1701.

679 Butcher, J.T., Stewart, P.M., Simon, T.P., 2003. A Benthic Community Index for streams in the Northern
680 Lakes and Forests Ecoregion. *Ecol. Indic.* 3, 181-193.

681 Cairns Jr, J., Pratt, J.R., 1993. A history of biological monitoring using benthic macroinvertebrates.
682 *Freshwater biomonitoring and benthic macroinvertebrates* 10, 27.

683 Celeux G., Forbes F., Robert C.P., Titterton D.M., 2006. Deviance Information Criteria for missing
684 data models, *Bayesian Anal.*, 1, 651-673.

685 Chessman, B., Williams, S., Besley, C., 2007. Bioassessment of streams with macroinvertebrates: effect
686 of sampled habitat and taxonomic resolution. *J.N. Am. Benthol. Soc.* 26, 546–565.

687 Corburn, J., Osleeb, J., Porter, M., 2006. Urban asthma and the neighbourhood environment in New York
688 City. *Health Place*, 12, 167–179.

689 Corvalan, C., Hales, S., McMichael, A., 2005. Health synthesis report of the millennium ecosystem
690 assessment: Ecosystems and human well-being. Geneva: World Health Organization.

691 Cutter, S.L., 2012. *Hazards Vulnerability and Environmental Justice*. Routledge. Einheuser, M.,
692 Nejadhashemi, A.P., Sowa, S., Wang, L., Hamaamin, Y., Woznicki, S. 2012. Modeling the effects of
693 conservation practices on stream health. *Sci. Total Environ.*, 435–436, 380 - 391.

694 Dijk, T.C.V., Staalduinen, M.A.V., Sluijs, J.P.V. der, 2013. Macro-Invertebrate Decline in Surface Water
695 Polluted with Imidacloprid. *PLOS ONE* 8, e62374.

696 Einheuser, M., Nejadhashemi, A.P., Wang, L., Sowa, S., Woznicki, S., 2013a, Linking Biological
697 Integrity and Watershed Models to Assess the Impacts of Historical Land Use and Climate Changes on
698 Stream Health. *Environ. Manage.* 51, 1147–1163.

699 Einheuser, M., Nejadhashemi, A.P., Woznicki, S., 2013b. Simulating stream health sensitivity to
700 landscape changes due to bioenergy crops expansion. *Biomass Bioenerg.* 58, 198–209.

701 EPA, 2015a, Environmental Justice, URL: <http://www3.epa.gov/environmentaljustice/> (Last Accessed
702 1.13.16).

703 EPA, 2015b, Saginaw River and Bay Area of Concern, URL: <http://www.epa.gov/saginaw-river-bay-aoc>
704 (Last Accessed 1.13.16).

705 Ewall, M., 2012. Legal Tools for Environmental Equity vs. Environmental Justice. *Sustainable Dev. L. &*
706 *Pol’y* 13, 4.

707 Fisher, J.B., Kelly, M., Romm, J., 2006. Scales of environmental justice: Combining GIS and spatial
708 analysis for air toxics in West Oakland, California. *Health Place*, 12, 701–714.

709 Flinders, C.A., Horwitz, R.J., Belton, T., 2008. Relationship of fish and macroinvertebrate communities
710 in the mid-Atlantic uplands: Implications for integrated assessments. *Ecol. Indic.* 8, 588–598.

711 Geronimus, A.T., Bound, J., 1998. Use of Census-based Aggregate Variables to Proxy for Socioeconomic
712 Group: Evidence from National Samples. *Am. J. Epidemiol.* 148, 475–486.

713 Gilbert, A., Chakraborty, J., 2011. Using geographically weighted regression for environmental justice
714 analysis: Cumulative cancer risks from air toxics in Florida. *Soc. Sci. Res.* 40, 273–286.

715 Gwynn, R.C., Thurston, G.D., 2001. The burden of air pollution: impacts among racial minorities.
716 *Environ Health Perspect* 109, 501–506.

717 Halpern, B.S., Walbridge, S., Selkoe, K.A., Kappel, C.V., Micheli, F., D’Agrosa, C., Bruno, J.F., Casey,
718 K.S., Ebert, C., Fox, H.E., Fujita, R., Heinemann, D., Lenihan, H.S., Madin, E.M.P., Perry, M.T., Selig,
719 E.R., Spalding, M., Steneck, R., Watson, R., 2008. A Global Map of Human Impact on Marine
720 Ecosystems. *Science* 319, 948–952.

721 Harwood, V.J., Staley, C., Badgley, B.D., Borges, K., Korajkic, A., 2014. Microbial source tracking
 722 markers for detection of fecal contamination in environmental waters: relationships between pathogens
 723 and human health outcomes. *FEMS Microbiol. Rev.* 38, 1–40.

724 Heino, J., 2011. A macroecological perspective of diversity patterns in the freshwater realm. *Freshwater*
 725 *Biol.* 56, 1703–1722.

726 Helfand, G.E., Peyton, L.J., 1999. A Conceptual Model of Environmental Justice. *Soc. Sci. Quart.* 80, 68–
 727 83.

728 Hering, D., Johnson, R.K., Kramm, S., Schmutz, S., Szoszkiewicz, K., Verdonshot, P.F.M., 2006.
 729 Assessment of European streams with diatoms, macrophytes, macroinvertebrates and fish: a comparative
 730 metric-based analysis of organism response to stress. *Freshwater Biol.* 51, 1757–1785.

731 Herman, M.R., Nejadhashemi, A.P., 2015. A review of macroinvertebrate- and fish-based stream health
 732 indices. *Ecohydrology Hydrobiology* 15, 53–67.

733 Herman, M.R., Nejadhashemi, A.P., Daneshvar, F., Ross, D.M., Woznicki, S.A., Zhang, Z., Esfahanian,
 734 A.-H., 2015. Optimization of conservation practice implementation strategies in the context of stream
 735 health. *Ecol. Eng.* 84, 1–12.

736 Hilsenhoff, W.L., 1987. An improved biotic index of organic stream pollution. *Great Lakes Entomol.* 20,
 737 31–40.

738 Holguin-Gonzalez, J.E., Everaert, G., Boets, P., Galvis, A., Goethals, P.L.M., 2013. Development and
 739 application of an integrated ecological modelling framework to analyze the impact of wastewater
 740 discharges on the ecological water quality of rivers. *Environ. Model. Softw.* 48, 27–36.

741 Holifield, R., 2012. Environmental Justice as Recognition and Participation in Risk Assessment:
 742 Negotiating and Translating Health Risk at a Superfund Site in Indian Country. *Ann. Assoc. Am. Geogr.*

743 102, 591–613. Infante, D.M., Allan, J.D., Linke, S., Norris, R.H., 2008. Relationship of fish and
 744 macroinvertebrate assemblages to environmental factors: implications for community concordance.
 745 *Hydrobiologia* 623, 87–103.

746 Jackson, J.K., Füreder, L., 2006. Long-term studies of freshwater macroinvertebrates: a review of the
 747 frequency, duration and ecological significance. *Freshwater Biol.* 51, 591–603.

748 Jerrett, M., Burnett, R.T., Kanaroglou, P., Eyles, J., Finkelstein, N., Giovis, C., Brook, J.R., 2001. A GIS-
 749 environmental justice analysis of particulate air pollution in Hamilton, Canada. *Environ. Plann. A* 33,
 750 955–974.

751 Karr, J.R., 1999. Defining and measuring river health. *Freshwater Biol.* 41, 221–234.

752 Karr, J.R., 1981. Assessment of Biotic Integrity Using Fish Communities. *Fisheries* 6, 21–27.

753 Katukiza, A. y., Ronteltap, M., van der Steen, P., Foppen, J. w. a., Lens, P. n. l., 2014. Quantification of
 754 microbial risks to human health caused by waterborne viruses and bacteria in an urban slum. *J Appl*
 755 *Microbiol* 116, 447–463.

756 Kerans, B.L., Karr, J.R., 1994. A Benthic Index of Biotic Integrity (B-IBI) for Rivers of the Tennessee
 757 Valley. *Ecol. Appl.* 4, 768–785.

758 Kim, L.Y., 2015. Disproportionate Impacts of Hazardous Waste Facilities in Los Angeles County: A
 759 Deeper Look into Immigrant Populations and the Environment. Doctoral Dissertation, University of
 760 Michigan.

761 Krieger, N., Chen, J.T., Waterman, P.D., Soobader, M.-J., Subramanian, S.V., Carson, R., 2002a.
 762 Geocoding and Monitoring of US Socioeconomic Inequalities in Mortality and Cancer Incidence: Does
 763 the Choice of Area-based Measure and Geographic Level Matter? The Public Health Disparities
 764 Geocoding Project. *Am. J. Epidemiol.* 156, 471–482.

765 Krieger, N., Waterman, P., Chen, J.T., Soobader, M.-J., Subramanian, S.V., Carson, R., 2002b. Zip Code
 766 Caveat: Bias Due to Spatiotemporal Mismatches Between Zip Codes and US Census-Defined Geographic
 767 Areas-The Public Health Disparities Geocoding Project. *Am J Public Health* 92, 1100–1102. Lammert,
 768 M., Allan, J.D., 1999. Assessing Biotic Integrity of Streams: Effects of Scale in Measuring the Influence
 769 of Land Use/Cover and Habitat Structure on Fish and Macroinvertebrates. *Environ. Manage.* 23, 257–
 770 270.

771 Lee, C., 2002. Environmental justice: building a unified vision of health and the environment. *Environ*
 772 *Health Persp.* 110, 141–144.

773 Lehman E.L., D'Abrera H.J.M., 1998. Nonparametrics: Statistical methods based on ranks. Rec. ed.
 774 Englewood Cliffs, NJ:Prentice-Hall

775 Lenat, D.R., 1988. Water Quality Assessment of Streams Using a Qualitative Collection Method for
 776 Benthic Macroinvertebrates. *J. N. Am. Benthol. Soc.* 7, 222–233.

777 Levine W.C., Stephenson W.t., Craun G.F., 1990. Waterborne disease outbreaks, 1986-1988. *MMWR*
 778 *CDC Surveill Summ* 39, 1–13.

779 Lin, B.B., Morefield, P.E., 2011. The Vulnerability Cube: A Multi-Dimensional Framework for
 780 Assessing Relative Vulnerability. *Environ. Manage.* 48, 631–643.

781 Liu, J., Dietz, T., Carpenter, S.R., Folke, C., Alberti, M., Redman, C.L., Schneider, S.H., Ostrom, E., Pell,
 782 A.N., Lubchenco, J., Taylor, W.W., Ouyang, Z., Deadman, P., Kratz, T., Provencher, W., 2007. Coupled
 783 Human and Natural Systems. *AMBIO: A J. Hum. Environ.* 36, 639–649.

784 Lyons, J., 1992. Using the index of biotic integrity (IBI) to measure environmental quality in warmwater
 785 streams of Wisconsin. URL: http://www.nrs.fs.fed.us/pubs/gtr/gtr_nc149.pdf (Last Acceded: 1.13.16)

786 Maantay, J., 2007. Asthma and air pollution in the Bronx: Methodological and data considerations in
787 using GIS for environmental justice and health research. *Health Place*, 13, 32–56.

788 Maantay, J., Maroko, A., 2009. Mapping urban risk: Flood hazards, race, & environmental justice in New
789 York. *Appl. Geogr.* 29, 111–124.

790 Malley, S., Scroggins, J., Bohon, S.A., 2012. US EPA enforcement of environmental regulations in
791 Tennessee: 2005–2008. *Soc. Natur. Resour.* 25, 87–96.

792 Marchant, R., Hirst, A., Norris, R., Metzeling, L., 1999. Classification of macroinvertebrate communities
793 across drainage basins in Victoria, Australia: consequences of sampling on a broad spatial scale for
794 predictive modelling. *Freshwater Biol.* 41, 253–268.

795 Martinich, J., Neumann, J., Ludwig, L., Jantarasami, L., 2012. Risks of sea level rise to disadvantaged
796 communities in the United States. *Mitig Adapt Strateg Glob Change* 18, 169–185.

797 MDEQ, 1997. GLEAS Procedure #51 Survey Protocols for Wadable Rivers. Report No.: Fisheries
798 Special Report 25. Michigan Department of Environmental Quality, Surface Water Quality Division, Ann
799 Arbor, MI.

800 Meyer, J.L., 1997. Stream Health: Incorporating the Human Dimension to Advance Stream Ecology. *J. N.*
801 *Am. Benthol. Soc.* 16, 439–447.

802 Mieiro, C.L., Pacheco, M., Pereira, M.E., Duarte, A.C., 2009. Mercury distribution in key tissues of fish
803 (*Liza aurata*) inhabiting a contaminated estuary-implications for human and ecosystem health risk
804 assessment. *J Environ. Monit.* 11, 1004–1012.

805 Muñoz-Mas, R., Martínez-Capel, F., Garófano-Gómez, V., Mouton, A.M., 2014. Application of
806 Probabilistic Neural Networks to microhabitat suitability modelling for adult brown trout (*Salmo trutta*
807 L.) in Iberian rivers. *Environ. Model. Softw.* 59, 30–43.

808 Paller, M.H., Sterrett, S.C., Tuberville, T.D., Fletcher, D.E., Grosse, A.M., 2014. Effects of disturbance at
809 two spatial scales on macroinvertebrate and fish metrics of stream health. *J. Freshwater Ecol.* 29, 83–100.

810 Pickett, K.E., Pearl, M., 2001. Multilevel analyses of neighbourhood socioeconomic context and health
811 outcomes: a critical review. *J Epidemiol. Commun. H.* 55, 111–122. Pickett, S.T.A., Cadenasso, M.L.,
812 Grove, J.M., 2005. Biocomplexity in Coupled Natural–Human Systems: A Multidimensional Framework.
813 *Ecosystems* 8, 225–232.

814 Phillips, J., Land, K.C., 2012. The link between unemployment and crime rate fluctuations: An analysis at
815 the county, state, and national levels. *Soc. Sci. Res.* 41, 681–694.

816 Plafkin, J.L., Barbour, M.T., Porter, K.D., Gross, S.K., Hughes, R.M., others, 1989. Rapid bioassessment
817 protocols for use in streams and rivers: benthic macroinvertebrates and fish, EPA.

818 Pollock, P.H., Vittas, M.E., 1995. Who bears the burdens of environmental pollution? Race, ethnicity, and
819 environmental equity in Florida. *Soc. Sci. Quart.* 76, 294–310.

820 Pomati, F., Castiglioni, S., Zuccato, E., Fanelli, R., Vigetti, D., Rossetti, C., Calamari, D., 2006. Effects
821 of a Complex Mixture of Therapeutic Drugs at Environmental Levels on Human Embryonic Cells.
822 *Environ. Sci. Technol.* 40, 2442–2447.

823 Pucher, J., Buehler, R., Bassett, D.R., Dannenberg, A.L., 2010. Walking and Cycling to Health: A
824 Comparative Analysis of City, State, and International Data. *Am J Public Health* 100, 1986–1992.

825 Reid, C.E., Mann, J.K., Alfasso, R., English, P.B., King, G.C., Lincoln, R.A., Margolis, H.G., Rubado,
826 D.J., Sabato, J.E., West, N.L., Woods, B., Navarro, K.M., Balmes, J.R., 2012. Evaluation of a Heat
827 Vulnerability Index on Abnormally Hot Days: An Environmental Public Health Tracking Study. *Environ.*
828 *Health Persp.* 120, 715–20.

829 Sampson, R.J., Sharkey, P., Raudenbush, S.W., 2008. Durable effects of concentrated disadvantage on
830 verbal ability among African-American children. *PNAS* 105, 845–852.

831 Sanchez, G., Nejadhashemi, A.P., Zhang, Z., Woznicki, S., Habron, G., Marquart-Pyatt, S., Shortridge,
832 A., 2014. Development of a socio-ecological environmental justice model for watershed-based
833 management. *J. Hydrol.*, 518, 162–177.

834 Sanchez, G., Nejadhashemi, A.P., Zhang, Z., Marquart-Pyatt, S., Habron, G., Shortridge, A., 2015.
835 Linking watershed-scale stream health and socioeconomic indicators with spatial clustering and structural
836 equation modeling. *Environ. Model. Softw.*, 70, 113-127.

837 Schmidtlein, M.C., Deutsch, R.C., Piegorsch, W.W., Cutter, S.L., 2008. A Sensitivity Analysis of the
838 Social Vulnerability Index. *Risk Anal.* 28, 1099–1114.

839 Schuurman, N., Bell, N., Dunn, J.R., Oliver, L., 2007. Deprivation Indices, Population Health and
840 Geography: An Evaluation of the Spatial Effectiveness of Indices at Multiple Scales. *J Urban Health* 84,
841 591–603.

842 Schwarzenbach, R.P., Egli, T., Hofstetter, T.B., Gunten, U. von, Wehrli, B., 2010. Global Water Pollution
843 and Human Health. *Annu. Rev. Env. Resour.* 35, 109–136.

844 Seelbach, P.W., Wiley, M.J., 1997. Overview of the Michigan Rivers Inventory (MRI) project. Report
845 No.: Fisheries Technical Report 97-3. Michigan Department of Natural Resources, Fisheries Division,
846 Lansing, MI.

847 Silver, J.J., 2008. Weighing in on Scale: Synthesizing Disciplinary Approaches to Scale in the Context of
848 Building Interdisciplinary Resource Management. *Soc. Nat. Resour.*, 21, 921–929.

849 Skole, D., Tucker, C., 1993. Tropical Deforestation and Habitat Fragmentation in the Amazon: Satellite
850 Data from 1978 to 1988. *Science* 260, 1905–1910.

851 Smith, K.R., Corvalán, C.F., Kjellström, T., 1999. How much global ill health is attributable to
852 environmental factors? *Epidemiology* 10, 573–584.

853 Sponseller, R.A., Benfield, E.F., Valett, H.M., 2001. Relationships between land use, spatial scale and
854 stream macroinvertebrate communities. *Freshwater Biol.* 46, 1409–1424.

855 Taquino, M., Parisi, D., Gill, D.A., 2002. Units of Analysis and the Environmental Justice Hypothesis:
856 The Case of Industrial Hog Farms. *Soc. Sci. Quart.* 83, 298–316.

857 Taylor, D., 2014. *Toxic Communities: Environmental Racism, Industrial Pollution, and Residential*
858 *Mobility*. NYU Press.

859 U.S. Census Bureau 2010, Social Explorer. URL: <http://www.socialexplorer.com/6f4cdab7a0/explore>
860 (Last Accessed 1.13.16).

861 Vairavamorthy, K., Yan, J., Galgale, H.M., Gorantiwar, S.D., 2007. IRA-WDS: A GIS-based risk
862 analysis tool for water distribution systems. *Environ. Model. Softw.* 22, 951–965.

863 Vitousek, P.M., Mooney, H.A., Lubchenco, J., Melillo, J.M., 1997. Human Domination of Earth's
864 Ecosystems. *Science* 277, 494–499.

865 Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S.,
866 Bunn, S.E., Sullivan, C.A., Liermann, C.R., Davies, P.M., 2010. Global threats to human water security
867 and river biodiversity. *Nature* 467, 555–561.

868 Walsh, C.J., Booth, D.B., Burns, M.J., Fletcher, T.D., Hale, R.L., Hoang, L.N., Livingston, G., Rippy,
869 M.A., Roy, A.H., Scoggins, M., Wallace, A., 2016. Principles for urban stormwater management to
870 protect stream ecosystems. *Freshwater Science* 35, 398–411.

871 Walters, D.M., Roy, A.H., Leigh, D.S., 2009. Environmental indicators of macroinvertebrate and fish
872 assemblage integrity in urbanizing watersheds. *Ecol. Indic.* 9, 1222–1233.

873 Wang, L., Robertson, D.M., Garrison, P.J., 2007. Linkages Between Nutrients and Assemblages of
874 Macroinvertebrates and Fish in Wadeable Streams: Implication to Nutrient Criteria Development.
875 Environ. Manage. 39, 194–212.

876 Welsh Jr, H.H., Hodgson, G.R., 2008. Amphibians as metrics of critical biological thresholds in forested
877 headwater streams of the Pacific Northwest, U.S.A. Freshwater Biol. 53, 1470–1488.

878 Wilson, J., Low, B., Costanza, R., Ostrom, E., 1999. Scale misperceptions and the spatial dynamics of a
879 social–ecological system. Ecol. Econ. 31, 243–257.

880 Wolch, J.R., Byrne, J., Newell, J.P., 2014. Urban green space, public health, and environmental justice:
881 The challenge of making cities “just green enough.” Landscape Urban Plan. 125, 234–244.

882 Woznicki, S.A., Nejadhashemi, A.P., Abouali, M., Herman, M.R., Esfahanian, E., Hamaamin, Y.A.,
883 Zhang, Z., 2016. Ecohydrological modeling for large-scale environmental impact assessment. Sci. Total
884 Environ. 543, Part A, 274–286.

885 Woznicki, S.A., Nejadhashemi, A.P., Ross, D.M., Zhang, Z., Wang, L., Esfahanian, A.-H., 2015.
886 Ecohydrological model parameter selection for stream health evaluation. Sci. Total Environ. 511, 341–
887 353. Wu, C., Maurer, C., Wang, Y., Xue, S., Davis, D.L., 1999. Water pollution and human health in
888 China. Environ Health Perspect 107, 251–256.

889 Young, W.J., Lam, D.C.L., Ressel, V., Wong, I.W., 2000. Development of an environmental flows
890 decision support system. Environ. Model. Softw. 15, 257–265.

891 Zimmerman, R., 1993. Issues of classification in environmental equity: how we manage is how we
892 measure. Fordham Urb. LJ 21, 633. Zou, B., Peng, F., Wan, N., Wilson, J.G., Xiong, Y., 2014. Sulfur
893 dioxide exposure and environmental justice: a multi-scale and source-specific perspective. Atmos. Pol.
894 Res. 5, 491–499.

Figure captions

Figure 1. The map of the study area (a) and associated census boundaries obtained from the U.S. Census Bureau at three levels of county (b), census tract (c), and block groups (d).

Figure 2. Stream health condition across Saginaw River Basin: (a) IBI, (b) HBI, (c) FIBI, and (d) EPT (Adapted from Einheuser et al., 2012 and 2013a).

Figure 3. Spearman rank correlation matrix between dependent and independent variables at the county level. Histograms of each individual variable distribution are shown on the diagonal of each matrix. The upper and lower parts of the matrices are spearman rank correlation coefficients and scatter plots of each pair of variables. **Boldfaced** value indicates significance at the 0.05 level and correlation less than 0.7, **Boldfaced** value in red indicates significance at the 0.05 level and strongly positive correlation equal or above 0.7, and value in blue indicates significance at the 0.05 level and strongly negative correlation equal or below -0.7.

Figure 4. Model prediction residuals at county level for a) EPT, b) FIBI, c) HBI, d) IBI.

Figure 1

Figure 2

Figure 3

Figure 4

Table 1. Summary of Stream health measures in Saginaw River Basin

Variable	Min	Max
IBI	0	100
HBI	3.61	7.89
FIBI	0	36
EPT	0	17

Table 2. List of the socioeconomic/physiographic indicators (Census bureau, 2010)

ID	Socioeconomic/physiographic indicators
S1	Drainage density
S2	Population density (per sq. mile)
S3	Percentage of land area
S4	Percentage of population under 18 years
S5	Percentage of population age 65 and over
S6	Percentage of black or African American population:
S7	Percentage of family households: Female householder, no husband present
S8	Percentage of households: Nonfamily households: Householder living alone
S9	Average household size
S10	Housing units
S11	Percentage of occupied housing units
S12	Percentage of population 25 years and over: Less than high school education level
S13	Percentage of families: Income in 2010 below poverty level
S14	Average household income (In 2010 inflation adjusted dollars)
S15	Aggregate household income (In 2010 inflation adjusted dollars)
S16	Percentage of households: With public assistance income
S17	Percentage of unemployed civilian population 16 years and over

Table 3. Regression models for FIBI at county level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	14.68	14.15	15.22	14.69	14.29	15.09	14.64	14.18	15.09
β_1	0.09	-0.63	0.78	0.08	-0.63	0.84	0.05	-0.82	0.90
β_2	-18.32	-26.10	-10.70	-18.39	-26.17	-10.72	-18.26	-27.05	-9.66
β_3	2.18	0.87	3.54	2.21	0.78	3.54	2.26	0.77	3.72
β_4	-0.79	-2.38	0.77	-0.82	-2.35	0.75	-0.78	-2.63	1.018
β_5	1.81	-0.36	4.03	1.83	-0.45	4.06	1.79	-1.11	4.65
β_6	-3.25	-5.45	-1.03	-3.22	-5.39	-1.00	-3.10	-5.54	-0.72
β_7	0.98	-1.10	3.11	0.96	-1.23	3.09	0.82	-1.53	3.26
β_8	-0.38	-4.88	4.17	-0.36	-5.04	4.27	-0.57	-5.73	4.68
β_9	-0.51	-6.18	5.13	-0.47	-6.40	5.23	-0.77	-7.21	5.84
β_{10}	47.36	29.04	66.21	47.39	28.51	66.04	47.69	27.80	67.81
β_{11}	-0.38	-2.07	1.36	-0.37	-2.16	1.42	-0.20	-2.25	1.81
β_{12}	-0.98	-3.47	1.62	-0.94	-3.67	1.58	-0.88	-3.77	1.98
β_{13}	-1.33	-3.20	0.57	-1.35	-3.25	0.58	-1.26	-3.12	0.66
β_{14}	-1.41	-4.44	1.61	-1.40	-4.51	1.50	-1.52	-4.86	1.72
β_{15}	-28.88	-41.66	-16.28	-28.89	-41.93	-15.89	-29.28	-43.40	-15.06
β_{16}	0.06	-1.36	1.39	0.07	-1.33	1.52	-0.02	-1.74	1.69
β_{17}	-3.91	-6.15	-1.54	-3.94	-6.33	-1.58	-4.03	-6.70	-1.28
τ^2	3.2	1.0	8.5	3.5	1.1	10.34	1.1	0.3	3.4
γ	-0.12	-0.97	0.93	0	0	0	0	0	0
DIC		71.55			71.47			75.60	

Table 4. Regression models for EPT at county level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.16	4.86	5.46	5.16	4.94	5.37	5.15	4.95	5.35
β_1	-0.42	-0.81	-0.02	-0.42	-0.81	-0.03	-0.44	-0.83	-0.07
β_2	-3.03	-7.20	1.05	-3.03	-7.01	0.96	-3.03	-7.26	0.86
β_3	1.56	0.81	2.28	1.56	0.83	2.29	1.50	0.85	2.13
β_4	-0.79	-1.62	0.01	-0.79	-1.61	0.02	-0.76	-1.57	0.04
β_5	1.63	0.42	2.81	1.61	0.41	2.79	1.56	0.28	2.82
β_6	-0.56	-1.69	0.61	-0.54	-1.69	0.64	-0.51	-1.58	0.58
β_7	-0.56	-1.69	0.61	-0.59	-1.69	0.49	-0.63	-1.76	0.51
β_8	3.19	0.74	5.63	3.23	0.77	5.84	3.28	0.72	5.55
β_9	3.37	0.28	6.37	3.40	0.39	6.54	3.47	0.42	6.26
β_{10}	8.96	-1.01	18.87	8.94	-0.75	18.89	8.73	-0.30	18.09
β_{11}	0.86	-0.08	1.79	0.87	-0.04	1.81	0.85	-0.07	1.75
β_{12}	0.28	-1.13	1.63	0.29	-1.02	1.68	0.19	-1.07	1.38
β_{13}	-0.30	-1.31	0.71	-0.30	-1.36	0.70	-0.25	-1.13	0.61
β_{14}	0.69	-0.96	2.25	0.70	-0.92	2.35	0.75	-0.78	2.29
β_{15}	-6.94	-13.89	-0.06	-6.94	-13.95	-0.21	-6.75	-13.35	-0.38
β_{16}	0.30	-0.44	1.06	0.31	-0.46	1.04	0.33	-0.41	1.11
β_{17}	-0.82	-2.06	0.41	-0.80	-2.05	0.46	-0.71	-1.89	0.51
τ^2	1.0	0.3	2.8	1.0	0.3	3.1	0.2	0.1	0.6
γ	-0.04	-0.96	0.93	0	0	0	0	0	0
DIC		44.79			43.89			42.80	

Table 5. Regression models for HBI at county level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	4.85	4.70	5.01	4.85	4.75	4.95	4.85	4.76	4.95
β_1	0.14	-0.04	0.32	0.14	-0.05	0.32	0.13	-0.06	0.31
β_2	3.44	1.60	5.32	3.47	1.62	5.28	3.27	1.39	5.16
β_3	-0.67	-1.01	-0.35	-0.67	-1.01	-0.33	-0.66	-0.98	-0.32
β_4	0.35	-0.01	0.72	0.35	-0.03	0.73	0.32	-0.07	0.72
β_5	-1.00	-1.54	-0.46	-1.00	-1.53	-0.46	-1.01	-1.62	-0.39
β_6	0.43	-0.09	0.96	0.43	-0.11	0.96	0.38	-0.14	0.89
β_7	-0.46	-0.97	0.06	-0.45	-0.95	0.06	-0.38	-0.92	0.15
β_8	-0.62	-1.75	0.52	-0.61	-1.78	0.53	-0.66	-1.83	0.53
β_9	-0.66	-2.01	0.72	-0.65	-2.10	0.76	-0.70	-2.19	0.76
β_{10}	-6.15	-10.67	-1.60	-6.21	-10.72	-1.67	-5.88	-10.45	-1.43
β_{11}	0.13	-0.30	0.54	0.13	-0.31	0.55	0.13	-0.33	0.58
β_{12}	0.31	-0.31	0.93	0.32	-0.30	0.93	0.35	-0.26	0.96
β_{13}	0.56	0.10	1.0	0.57	0.11	1.04	0.56	0.11	0.99
β_{14}	0.36	-0.37	1.11	0.37	-0.40	1.13	0.41	-0.32	1.14
β_{15}	3.12	-0.06	6.24	3.14	-0.03	6.28	3.01	-0.18	6.28
β_{16}	-0.30	-0.64	0.04	-0.31	-0.65	0.03	-0.29	-0.66	0.07
β_{17}	1.38	0.82	1.93	1.38	0.83	1.94	1.32	0.73	1.92
τ^2	0.19	0.06	0.54	0.21	0.07	0.62	0.05	0.02	0.15
γ	0.06	-0.94	0.96	0	0	0	0	0	0
DIC		12.82			11.68			12.50	

Table 6. Regression models for IBI at county level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	50.02	49.56	50.47	50.02	49.70	50.34	50.04	49.73	50.35
β_1	0.61	0.01	1.17	0.61	0.01	1.22	0.69	0.07	1.30
β_2	4.16	-1.78	10.19	4.11	-1.78	10.12	4.50	-1.56	10.67
β_3	-2.34	-3.41	-1.23	-2.36	-3.52	-1.28	-2.34	-3.39	-1.29
β_4	-0.21	-1.43	1.02	-0.21	-1.37	1.01	-0.20	-1.49	1.11
β_5	-0.44	-2.17	1.30	-0.45	-2.25	1.33	-0.29	-2.30	1.67
β_6	-1.61	-3.34	0.13	-1.63	-3.31	0.12	-1.65	-3.36	0.05
β_7	2.20	0.57	3.85	2.21	0.48	3.95	2.24	0.59	3.95
β_8	-1.97	-5.72	1.71	-2.01	-5.52	1.63	-1.89	-5.68	1.87
β_9	-2.88	-7.36	1.45	-2.93	-7.44	1.47	-2.74	-7.55	2.12
β_{10}	-9.62	-24.83	5.43	-9.45	-24.09	4.84	-10.20	-24.81	4.04
β_{11}	3.27	1.91	4.63	3.29	1.89	4.70	3.19	1.72	4.59
β_{12}	2.42	0.37	4.42	2.40	0.33	4.51	2.38	0.34	4.42
β_{13}	2.88	1.35	4.34	2.87	1.40	4.41	2.79	1.40	4.12
β_{14}	3.98	1.56	6.31	3.99	1.66	6.42	3.87	1.41	6.32
β_{15}	4.95	-5.75	15.45	4.85	-5.05	15.04	5.28	-4.96	15.74
β_{16}	-1.43	-2.52	-0.28	-1.42	-2.50	-0.28	-1.45	-2.68	-0.26
β_{17}	2.23	0.34	4.06	2.25	0.43	4.22	2.25	0.37	4.15
τ^2	2.03	0.62	6.09	2.24	0.68	6.95	0.53	0.17	1.55
γ	-0.03	-0.96	0.95	0	0	0	0	0	0
DIC		61.34			61.13			62.56	

Table 7. DICs for multilevel models with random effects (**boldfaced** values represent best models at each census level)*.

Model Level	FIBI	EPT	HBI	IBI	County	Census Tract	Block Group	
County	72.06	43.93	12.74	61.42	S	-	-	
	70.02	43.44	12.28	61.67	WR	-	-	
	76.23	41.38	12.16	61.14	OR	-	-	
Census Track	1943.57	1606.15	1062.99	2146.48	-	S	-	
	2011.43	1743.71	1124.47	2216.50	-	WR	-	
	2030.39	1774.0	1150.45	2246.78	-	OR	-	
	1866.06	1531.67	989.11	2071.61	S	S	-	
	1938.10	1717.27	1096.36	2141.15	S	WR	-	
	1956.05	1800.30	1123.93	2174.01	S	OR	-	
	1867.88	1531.13	985.37	2070.07	WR	S	-	
	1939.19	1736.73	1096.97	2139.39	WR	WR	-	
	1957.50	1765.388	1124.67	2173.79	WR	OR	-	
	1897.97	1558.115	1016.58	2100.25	OR	S	-	
	1974.39	1758.908	1093.39	2179.20	OR	WR	-	
	1986.60	1795.37	1121.14	2208.49	OR	OR	-	
	Block Group	4369.31	3505.23	2305.20	5120.27	-	-	S
		3175.85	2292.42	968.30	3885	-	S	S
		3166.25	2173.78	1228.27	3793.52	-	WR	S
		3614.55	2845.55	1615.11	4367.52	-	OR	S
	4297.06	3428.30	2228.81	5046.62	S	-	S	
	3044.48	2224.19	928.11	3730.10	S	S	S	
	3072.51	2127.33	822.83	3740.65	S	WR	S	
	3506.49	2777.09	1413.94	4298.93	S	OR	S	
	4296.65	3431.07	2228.07	5044.30	WR	-	S	
	3154.50	2145.78	1011.15	3757.87	WR	S	S	
	2988.34	2145.87	876.93	3860.37	WR	WR	S	
	3602.88	2780.58	1442.18	4531.91	WR	OR	S	
	4322.78	3458.86	2258.74	5072.66	OR	-	S	
	3155.93	2374.83	959.11	3915.40	OR	S	S	
	2981.18	2117.40	980.45	3778.31	OR	WR	S	
	3531.47	2716.33	1508.92	4326.08	OR	OR	S	
	4622.22	3843.96	2528.03	5215.88	-	-	WR	
	5782.70	4656.31	2804.94	4928.61	-	S	WR	
	5172.72	4140.10	3002.87	4124.09	-	WR	WR	
	5970.25	4894.86	2981.39	5341.34	-	OR	WR	
	4640.88	3770.08	2484.65	5143.59	S	-	WR	
	4902.58	4579.76	2724.49	5771.39	S	S	WR	
	5043.04	4078.78	2914.90	3865.1	S	WR	WR	
	5894.27	4857.45	2551.23	6696.03	S	OR	WR	
	4640.55	3769.05	2483.71	5140.31	WR	-	WR	
	5701.90	4582.33	2726.72	4867.69	WR	S	WR	
	3350.02	4844.90	2915.35	3899.55	WR	WR	WR	
	5923.63	4821.54	2869.64	5153.44	WR	OR	WR	
	4636.55	3846.81	2479.80	5208.41	OR	-	WR	
	5736.15	4609.32	2752.76	4850.89	OR	S	WR	
	4229.44	2653.88	2910.95	3888.06	OR	WR	WR	
	5969.41	4896.13	2843.53	4471.86	OR	OR	WR	
	4744.05	3956.18	2651.11	5275.56	-	-	OR	
	5114.78	4770.84	2966.77	4863.84	-	S	OR	

4364.45	4264.09	3157.07	5061.88	-	WR	OR
6137.42	5076.35	3178.44	6144.27	-	OR	OR
4756.91	3967.19	2608.60	5276.87	S	-	OR
5046.17	4696.45	2889.99	3924.74	S	S	OR
5194.36	4199.25	3097.25	4035.92	S	WR	OR
6075.38	5069.57	3119.79	6843.7	S	OR	OR
4756.48	3966.91	2608.91	5197.52	WR	-	OR
5083.31	4692.98	2888.83	3978.51	WR	S	OR
5254.76	4966.44	3098.74	3879.62	WR	WR	OR
6124.29	5070.39	3119.43	6065.81	WR	OR	OR
4751.88	3963.71	2605.37	5298.28	OR	-	OR
5075.60	4719.87	2917.87	4002.86	OR	S	OR
5221.79	5039.66	3094.77	5040.38	OR	WR	OR
6135.05	5063.93	3113.07	6086.95	OR	OR	OR

* S: spatial, WR: weighted regression, OR: ordinary regression, -: no random effect

Table 8. Significant parameters among all selected best models

Levels	FIBI	EPT	HBI	IBI
Block group multilevel model (with nested random effects)	S2, S5, S6, S7	S17	S1, S16	S2, S7, S16
Block group single level model (no nested random effects)	S2, S5, S6, S7	-	S1, S16	S2, S7, S16
Census tract multilevel model (with random effects)	S2, S10	S4, S5, S7, S9	S3	S16
Census tract single level model(no random effects)	S2, S10	S4, S5, S7, S9	S3	S16
County level	S2, S3, S6, S10, S15, S17	S1, S3, S5, S8, S9, S15	S2, S3, S5, S10, S13, S17	S1, S3, S7, S11, S12, S13, S14, S16, S17