Characterizing Spatial Pattern in Ecosystem Service Values when Distance Decay Doesn't Apply: Choice Experiments and Local Indicators of Spatial Association

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Abstract

Stated preference analyses commonly impose strong and unrealistic assumptions in response to spatial welfare heterogeneity. These include spatial homogeneity or continuous distance decay. Despite their ubiquity in the valuation literature, global assumptions such as these have been increasingly abandoned by non-economics disciplines in favor of approaches that allow for spatial patchiness. This paper develops parallel methods to evaluate local patchiness and hot spots in stated preference welfare estimates, characterizing relevant patterns overlooked by traditional approaches. The analysis draws from a choice experiment addressing river restoration. Results demonstrate shortcomings in standard treatments of spatial heterogeneity and insights available through alternative methods.

Keywords

Willingness to Pay, Hot Spot, Stated Preference, Ecosystem Service, Valuation

Introduction

Willingness to pay (WTP) for nonmarket ecosystem goods and services often displays spatial heterogeneity or sensitivity to spatial factors; an expanding literature addresses related considerations for stated preference (SP) welfare estimation (e.g., Bateman et al. 2006; Brouwer et al. 2010; Campbell et al. 2008, 2009; Johnston et al. 2002; Johnston and Duke 2009; Pate and Loomis 1997). Despite the growing awareness of these issues and their relevance for policy, most SP applications still apply relatively simple approaches to account for spatial heterogeneity. For example, when spatial pattern is modeled at all, analyses typically assume that WTP decays as a monotonic function of distance, or displays discrete thresholds over geopolitical boundaries (e.g., Bateman et al. 2000, 2006; Brouwer et al. 2010; Pate and Loomis 1997; Bateman and Langford 1997; Hanley et al. 2003; Georgiou et al. 2000; Sutherland and Walsh 1985). These assumptions can be unrealistic, particularly when WTP includes nonuse components, for which economic theory provides little insight regarding ways in which values should vary over space (Bateman et al. 2006; Loomis 2000; Pate and Loomis 1997).

In contrast to the treatment of spatial heterogeneity in the valuation literature, parallel assumptions regarding global, continuous spatial patterns (e.g., global distance decay) have been increasingly questioned by disciplines such as conservation biology and geography in favor of approaches that allow for spatial patchiness and local rather than global patterns (Tiwari et al 2006; Cincotta et al 2000; Myers et al 1999; Mittermeier et al 1998; Sanchirico and Wilen 1999, 2005; Getis and Ord 1992). Research in the broader environmental and resource economics literature has also recognized the advantages of more nuanced spatial perspectives (e.g., Bauer et al. 2010; Bateman et al. 2002; Bockstael 1996; Irwin and Bockstael 2002; Sanchirico and Wilen 1999, 2005), including methods that better convey spatial attributes of SP scenarios (e.g., Brouwer et al. 2010; Horne et al. 2005; Johnston et al. 2002; Roe et al. 2004). Yet despite this growing recognition, methods used to characterize spatial patterns in SP welfare measures almost universally rely on global measures and associated simplifying assumptions. With few exceptions (e.g., Campbell et al. 2009), the robustness of resulting SP welfare estimates to alternative, more nuanced treatments of spatial pattern remains unknown.

This paper proposes novel methods to evaluate local patchiness and hot spots in stated preference welfare estimates, characterizing relevant patterns overlooked by traditional approaches. These methods to evaluate welfare heterogeneity based on local rather than global measures of spatial association via local indicators of spatial association (i.e., LISAs). The resulting models allow identification of spatial patchiness and hot spots in WTP, even in the absence of identifiable global patterns such as continuous distance decay. Such approaches are well established in geography and other sciences, but to the knowledge of the authors have been entirely overlooked as a means to characterize spatial heterogeneity within SP valuation. The empirical analysis draws from a spatially explicit choice experiment addressing migratory fish passage restoration in Rhode Island watersheds (Johnston et al. 2011). Results suggest that alternative methods for spatial welfare analysis can reveal patterns in nonmarket WTP that are both directly relevant to benefit cost analysis and obscured by standard approaches.

Spatial Pattern in Nonmarket Willingness to Pay

Analyses of global distance decay (e.g., Bateman et al. 2000, 2006; Pate and Loomis 1997; Bateman and Langford 1997; Hanley et al. 2003; Georgiou et al. 2000; Sutherland and Walsh 1985) and geopolitical threshold effects (e.g., Brouwer et al. 2010; Johnston and Duke 2009; Morrison and Bennett 2004; van Beuren and Bennett 2004) are uncommon but increasing in the SP literature. The former typically evaluates the decline in per household WTP as distance to an affected site increases. The latter contrasts the WTP of households for changes that occur in versus out of an identified home region (e.g., town, state, watershed). For example, Brouwer et al. (2010) evaluate whether respondents value water quality changes that occur in their own river basin differently than changes in other basins. With few exceptions (e.g., Campbell et al. 2008, 2009), these represent the sole mechanisms used to address spatial heterogeneity in SP welfare estimates, with the majority of the literature ignoring such patterns.

Theoretical and other justifications for distance decay are discussed by Bateman et al. (2006). Summarizing these arguments briefly, there are many intuitive reasons for an expectation of distance decay, depending on whether use or nonuse values are considered (Bateman et al. 2006; Pate and Loomis 1997; Loomis 2000).[1] Similar though not identical intuition applies to discrete geopolitical thresholds (Johnston and Duke 2009; Brouwer et al. 2010). Empirical assessments often confirm at least some distance decay in use values (Bateman et al. 2006). Findings for nonuse or nonuser values are mixed, with spatial heterogeneity often smaller or less statistically significant when these values predominate (e.g., Sutherland and Walsh 1985; Imber et al. 1991; Loomis 2000; Bateman et al., 2000). This may, however, be attributable to differences in the type of welfare measure considered (i.e., equivalent loss versus compensating surplus; Bateman et al. 2006).

Despite these expectations, there is no necessary theoretical reason for WTP to follow the global distance decay or threshold patterns commonly assumed in the valuation literature. Hence it is possible—or perhaps even likely—for the constraints imposed by a continuous distance decay or universal threshold function to at least occasionally obscure other relevant spatial

[1] These include a higher proportion of users versus nonusers as one moves closer to a valued resource and a cultural identity or ownership dimension to nonuse values for those who live closer to a site, among others.

variations in WTP. For example, failure to reject a null hypothesis of zero distance decay may lead analysts to assume that WTP is spatially homogeneous, when in fact statistically significant local patchiness or non-continuous spatial variation may occur.

More generally, a defining characteristic of these spatial models that they are *global* in nature; they seek universal, often continuous patterns across large areas. In contrast, other disciplines such as conservation biology and geography have increasingly focused on spatial patchiness and local rather than global spatial associations (Tiwari et al 2006; Cincotta et al 2000; Myers et al 1999; Mittermeier et al 1998; Nelson and Boots 2008). A common theme is that examination of spatial pattern from a localized perspective can reveal policy relevant insights obscured by global analyses (Getis and Ord 1992). As noted by Sanchirico and Wilen (1999, p. 130) in the context of patchiness within dynamic fisheries models, "in systems in which the resource is distributed heterogeneously in space, we are most likely missing a considerable amount of interesting behavior by aggregating out the [local] spatial aspects."

Within the context of SP estimation, spatial patchiness would manifest as statistically significant spatial variation of WTP that did not conform to global, continuous patterns. Such patterns could have substantial implications for benefit analysis and aggregation. For example, assume that a valuation researcher has identified a point in space, n units distant from a natural resource, at which average household WTP for a marginal resource change is zero. A typical global distance decay model would therefore presume that all households living beyond n units of radius from the natural resource would have a WTP of zero.[2] A model of local heterogeneity, in contrast, could allow for the possibility that WTP might be zero at distance n but greater than zero within specific local areas at distances greater than n. More generally, such models allow for WTP at distance $n+i$ to exceed WTP at distance n for localized patches, where i is a positive,

[2] This presumes that negative WTP is not a possibility.

non-zero unit of distance. Overlooking such patterns in benefit aggregation could result in biased estimates and misguided policy.

Such patterns are almost universally overlooked within the SP literature. One of few exceptions, Campbell et al. (2009) apply spatial kriging methods to interpolate information from individual specific WTP estimates for landscape improvements across the Republic of Ireland. While the results allow for WTP patterns that are not globally continuous, kriging methods rely on the global assumption that "nearby values contribute more to the interpolated values than do distant observations" (Campbell et al. 2009, p. 106). Similar patterns are implied by global spatial autocorrelation analyses (Campbell et al. 2008).

While global assumptions such as these sometimes apply, they may also mask relevant local patterns. In response, many sciences have given increased attention to the potential for localized hot spots in studied phenomena. In the abstract, hot spots may be characterized as "as regions of high density that are separated by regions of lower density of some phenomenon (Nelson and Boots 2008, p. 556; Azzalini and Torelli 2007). Past applications have been made to characterize patterns in biodiversity (e.g., Myers et al. 2000), crime (e.g., Ratcliffe and McCullagh 1999), disease (e.g., Besag and Newell 1991), pest infestation (e.g., Nelson and Boots 2008), and species richness (e.g., Stohlgren et al. 2006), among many other phenomena. The goal of hot spot analysis is to characterize atypical spatial patterns, or patterns that do not observe global patterns or correlations; these patterns can be directly policy relevant yet invisible to global analyses (Nelson and Boots 2008). Despite increasing use of these methods elsewhere, the authors are aware of no published applications of these methods to characterize policy relevant spatial pattern in WTP—and particularly WTP estimated using SP methods.

Hot Spot Analysis and Local Indicators of Spatial Association (LISAs)

Methods commonly used to detect hot spots in empirical analysis include kernel estimators and LISAs (Getis and Ord 1992; Nelson and Boots 2008). Kernal estimators transform individual data points into continuous surfaces which may be used to characterize the density or intensity of studied events (Nelson and Boots 2008; Silverman 1986). The latter quantifies variations in local spatial autocorrelation compared to surrounding areas – or areas in which clusters of density or intensity are distinct from patterns in the surrounding landscape. A primary advantage of LISAs is the capacity to statistically identify hot spots at a given level of statistical significance; they can be used "to assess the statistical hypothesis that observed patterns could have risen by chance, [with] rejection of the null hypothesis […] used as the threshold for defining hot spots" (Nelson and Boots 2008). Within the context of SP estimation, such methods can potentially be used to identify areas with local clusters of WTP estimates that are either higher or lower than one would expect through random chance, at a chosen level of statistical significance. Such hot spots can occur regardless of the presence of global patterns.

To explore the presence of WTP hot spots in an SP application, the present analysis applies the Getis-Ord G_i^* statistic (Getis and Ord 1992), one of the most commonly used LISAs (Nelson and Boots 2008). The statistic may be calculated as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} c_j - \bar{C} \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{[n\sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2]}{n-1}}} \tag{1}$$

Where c_j is the attribute value for observation j, $w_{i,j}$ is the spatial weight between observation i and j, and n is the total number of observations. Within (1), $\bar{C} = \frac{\sum_{j=1}^{n} c_j}{n}$ and $S = \sqrt{\frac{\sum_{j=1}^{n} c_j^2}{n} - (\bar{C})^2}$.

Equation (1) compares, proportionally, the local sum of an attribute value (e.g., WTP) for a spatially located observation (e.g., a household or group of households) and its neighbors to the sum of all attribute values in the data. The resulting G_i^* score is distributed standard normal (z distribution), with a high positive or negative value indicating that the local attribute sum is very different from the expected local sum, based on the full range of attribute values in the data. Given a chosen level of statistical significance (e.g., p<0.05), the hypothesis test identifies high (low) value observations surrounded by other high (low) value observations, where the difference between values observed for these identified clusters and those for the surrounding observations is too great to be the result of random chance. These are defined as statistically significant hot spots (Getis and Ord 1992; Nelson and Boots 2008).

The present analysis adapts the concept of LISAs—specifically Getis-Ord (1992) G_i^* statistics—to characterize localized patchiness in estimated WTP. This novel approach provides an empirical means to identify WTP hot spots obscured by alternative approaches. Results are compared to those of traditional global models of spatial association used in the SP literature, specifically a distance decay model. Data are drawn from the choice experiment questionnaire *Rhode Island Rivers: Migratory Fishes and Dams* (Johnston et al. 2011), with resulting implicit prices used to evaluate insights from these alternative models. The analysis emphasizes the insight provided through these alternative perspectives to spatial welfare heterogeneity, with particular attention to policy relevant patterns obscured by global spatial analyses.

Empirical Application

The choice experiment questionnaire addressed public preferences for the restoration of migratory fish passage in the Pawtuxet watershed of Rhode Island (Johnston et al. 2011). The watershed currently provides no spawning habitat for migratory fish; access to all 4,347 acres of potential habitat is blocked by 22 dams (Erkan 2002). The spatially explicit choice experiment estimated WTP of Rhode Island residents for options that would provide fish passage to between 225 and 900 acres of historical, but currently inaccessible, habitat. Within this context, restoration of fish passage would not only affect fish populations but also other ecosystem services that rely on the presence or abundance of migratory fish.

The theoretical model for the empirical application is adapted from a standard random utility specification in which household *h* chooses among three policy plans, (*j*=*A*,*B*,*N*), including two multi-attribute restoration options (*A*, *B*) and a status quo (*N*) that includes no restoration and zero household cost. Choice experiment scenarios and restoration options were informed by data and restoration priorities in the *Strategic Plan for the Restoration of Anadromous Fishes to Rhode Island Coastal Streams* (Erkan 2002). Consistent with the strategic plan, the choice experiment addressed restoration methods that neither require dam removal nor would cause appreciable changes in river flows. Fish ladders and fish lifts are the most widespread examples (Schilt 2007). Diadromous fish species that directly benefit from fish passage restoration in this area are alewife (*Alosa pseudoharengus*), blueback herring (*A. aestivalis*), shad (*A. sapidissima*), and American eel (*Anguilla rostrata*). The ecological roles of these species are well understood (Loesch 1987) and formed the basis for conceptual models linking restoration to valued commodities and ecosystem services identified in focus groups.

The questionnaire was developed and tested over 2½ years in a collaborative process involving both economists and ecologists (Johnston et al. 2011). This included meetings with resource managers, natural scientists, and stakeholder groups, and 12 focus groups. In addition to survey development and testing in focus groups, individual interviews were conducted with both ecological experts and non-experts. These included cognitive interviews (Kaplowitz et al. 2004), verbal protocols (Schkade and Payne 1994) and other pretests conducted to gain insight into respondents' interpretation of the questionnaire. Development and testing helped ensure that the survey language and format was easily understood by respondents, that respondents and scientists shared interpretations of terminology and scenarios, and that the scenarios captured restoration outcomes viewed as relevant and realistic by both respondents and scientists.

The development and testing of choice attributes, including justification for the particular attributes considered, is detailed by Johnston et al. (2011). Summarizing this information, choice options are characterized by seven attributes: five ecological indicators, one attribute characterizing public access, and one attribute characterizing unavoidable household cost (Table 1). Ecological indicators included in each choice option characterize: (1) the quantity of river habitat accessible to migratory fishes (*acres*), based upon restorable Pawtuxet habitat acreage in Erkan (2002); (2) the probability that the restored fish run will exist in 50 years, reflecting results calculable through applications of population viability analysis (*PVA*)[3]; (3) the abundance of fish suitable for recreational harvest (*catch*), reflecting abundance measures from statewide sampling; (4) the abundance of fish-dependent wildlife (*wildlife*), reflecting the appearance of identifiable species within restored areas; and (5) overall ecological condition (*IBI*), reflecting the output of a multimetric aquatic ecological condition score (i.e., an index of biotic integrity).

Table 2 illustrates attribute levels included in the choice experiment design. These levels are grounded in feasible restoration outcomes identified by ecological models, field studies and expert consultations (Johnston et al. 2011). Choice scenarios represent each ecological attribute in relative terms with regard to upper and lower reference conditions (i.e., best and worst

[3] For an illustration of population viability analysis applied to diadromous fish, see Lee and Rieman (1997).

possible in the Pawtuxet) as defined in survey materials. Scenarios also present the cardinal basis for relative scores where applicable. Relative scores represent percent progress toward the upper reference condition (100%), starting from the lower reference condition (0%). Information was conveyed via a combination of text, graphics including Geographic Information System (GIS) maps and ecosystem representations, and photographs, all of which were subject to in-depth pretesting. A sample choice question is illustrated by Johnston et al. (2011).

A fractional factorial experimental design was generated using a D-efficiency criterion (Kuhfeld and Tobias 2005; Lusk and Norwood 2005) for main effects and selected two-way interactions, resulting in 180 profiles blocked into 60 booklets. Each respondent was provided with three choice experiment questions and instructed to consider each as an independent, non-additive choice. Prior to administration of choice questions, the survey provided information (1) describing the current status of Rhode Island river ecology and migratory fish compared to historical baselines, (2) characterizing ecological systems and linkages, (3) describing details of fish passage restoration, and (4) providing the definitions, derivations and interpretations of ecological indicators used in survey scenarios.

Surveys were implemented using a dual wave phone-mail approach during June - August 2008. An initial random digit dial (RDD) sample of Rhode Island households was contacted via telephone and asked to participate in a survey addressing “environmental issues and government programs.” Those agreeing to participate were sent the questionnaire via mail, with follow-up mailings to increase response rates (Dillman 2000). A total of 600 questionnaires were sent to Rhode Island residents. The analysis is based on 277 usable returns. These provide 803 completed responses to choice questions.

Mixed Logit Estimation and Results

The random utility model is estimated using simulated likelihood mixed logit (Train 2009) with one hundred Halton draws. The model was specified to account for correlations among the three survey responses from each individual respondent. The final specification was chosen after the estimation of preliminary models with varying specifications of fixed and random coefficients. Within the final model, coefficients on *acres*, *PVA*, *access*, and *IBI* are specified as random with a normal distribution. The coefficient on *cost* is specified as random with a bounded triangular distribution, ensuring positive marginal utility of income, with sign-reversal applied prior to estimation (Campbell et al. 2009; Hensher and Greene 2003). Coefficients on *neither* (the alternative specific constant, or ASC), *catch* and *wildlife* are specified as fixed. Results are reported in Table 3. Coefficients are jointly significant at $p<0.0001$ for both models, with pseudo-$R^2 > 0.30$. All coefficients except for that on *catch* are statistically significant, as are all estimated standard deviations of random parameter distributions. Signs of coefficients match prior expectations in all instances. Because all model variables except *access* and *cost* are specified as percent progress towards the upper reference condition (100%) for each attribute, associated model coefficients may be interpreted as the relative marginal utility given to a one percentage point change.

As the model includes random coefficients with both normal and bounded triangular distributions (cf. Campbell et al. 2009), we estimate implicit prices following Johnston and Duke (2007; 2009), who adapt the general approach of Hensher and Greene (2003).[4] We simulate

[4] The procedure begins with a parameter simulation following the parametric bootstrap of Krinsky and Robb (1986), with R=1000 draws taken from the mean parameter vector and associated covariance matrix. For each draw, the resulting parameters are used to characterize asymptotically normal empirical densities for fixed and random coefficients. For each of these R draws, a coefficient simulation is then conducted for each random coefficient, with S=1000 draws taken from simulated empirical densities. Welfare measures are calculated for each draw, resulting in a combined empirical distribution of $R \times S$ observations from which summary statistics are derived.

implicit price estimates as the mean over the parameter simulation of mean WTP calculated over the coefficient simulation. Resulting distributions are summarized in Table 4, along with p-values for the null hypothesis of zero WTP. For all attributes except *access*, implicit price results are interpreted as WTP for a marginal, one percentage point increase, holding all else constant. For *access*, results indicate WTP for the provision of public access in the restored area, relative to the default of no access. Statistical significance levels (p-values) are determined through percentiles on the empirical distributions (Poe et al. 2005). Implicit prices are statistically significant ($p<0.01$) for all attributes except *catch*.

Results suggest that nonuse values are likely among the important motivations for WTP, given limited direct use motivations associated with such attributes as *PVA* (the probability of migratory fish run survival), *IBI* (aquatic ecological condition) and *acres* (river acres accessible to migratory fish). Moreover, while the provision of public access to restoration sites (*access*) is valued highly, WTP for *catch* is not statistically significant. Given these patterns, one might expect the type of spatial distributions reminiscent of welfare dominated by nonuse motivations, rather than those dominated by use motivations (cf. Bateman et al. 2006).

Modeling Spatial Distributions

The aggregate values in table 4, while illustrating mean implicit prices over all sampled households, do not provide insight into spatial distribution. The mixed logit model, however, provides a mechanism whereby information on individual-specific parameter estimates for any sampled individual q may be estimated from the individual's conditional distribution of these estimates, based on observed, within sample, choices (y_q) given choice attributes x_q. Methods to derive individual-specific parameter estimates are detailed by Hensher and Greene (2003) and

Train (2009), among others. Campbell et al. (2009) illustrates an application to choice experiment implicit prices with geo-located households. Adapting these methods, we estimate individual-specific implicit prices for each sampled respondent household, with data on household zip codes used to identify the location of each household across the sampled area.[5]

Individual-specific, geo-coded implicit prices may be derived following Campbell et al. (2008, 2009). Following standard approaches, WTP for a specific aquatic restoration attribute is defined as the negative ratio of the parameter estimate for the attribute (φ) and the parameter estimate on program cost (-γ), WTP =- φ/γ. Drawing from the mixed logit conditional distribution of parameter estimates (Train 2009) and applying Bayes Rule, the expected value of WTP for individual q may be simulated as

$$\hat{E}\left(WTP_q\right) = \frac{1}{R}\sum_{r=1}^{R} -\frac{\hat{\varphi}}{\hat{\gamma}} L(\boldsymbol{\beta_{qr}}|y_q, x_q) \Big/ \frac{1}{R}\sum_{r=1}^{R} L\left(\boldsymbol{\beta_{qr}}\middle|y_q, x_q\right), \tag{2}$$

where R is the number of Halton draws in the simulation, L is the logit probability function (Campbell et al. 2008, 2009), and all other notation and aspects of the mixed logit specification are as detailed above.[6]

Individual-specific WTP estimates for each attribute, derived using (2), are averaged for all respondent households within each zip code, providing unique, mean implicit price estimates for all 56 zip codes within Rhode Island.[7] To illustrate the types of patterns which emerge, Figure 1 illustrates the resulting spatial distribution of WTP for restored acres (*acres*), per percentage point increase. Similar maps may be derived for each choice attribute; these are

[5] Zip codes are used rather than addresses to protect respondents' confidentiality, per Institutional Review Board requirements for participating institutions. The use of household addresses, while providing greater spatial resolution, might allow for identification of individual respondents and is hence disallowed.
[6] For a detailed discussion of the simulation and interpretation of individual-specific estimates see Train (2009).
[7] The number of responding households per zip code is uneven, ranging from 0 (no data, shown as a blank on subsequent maps) to 43. The average number of responses per zip code is 5.

suppressed for the sake of conciseness but are available from the authors upon request. In all cases, as illustrated for *acres* by Figure 1, WTP seems to show considerable spatial heterogeneity. Moreover, the distribution does not suggest an obvious pattern of distance decay; while some zip codes with high average implicit prices occur close to the affected area, others are located at greater distance. Such maps alone cannot, however, evaluate whether this apparent heterogeneity is statistically significant (i.e., greater than one would expect as a result of random chance), or alternatively whether it obscures an underlying global signal (i.e., distance decay). The purpose of subsequent analyses is to identify the statistically significant signals through the noise of raw WTP distributions (e.g., Figure 1).

Evaluating Global Distance Decay

To evaluate global distance decay patterns, we follow the general approach of Campbell et al. (2008) and use distance measures calculated from sampled spatial units (here, zip codes) to calculate proximity between each unit and the policy location or affected area. Centroids for each zip code (calculated using Rhode Island Geographic Information System (RIGIS) data) are assigned as the location for each of the associated implicit prices. To calculate distances from these centroids to policy locations, a specific geographic point must be identified for the policy in question. The Hope Dam in Scituate (RI) is chosen as the policy location (i.e., potentially affected dam) that best characterized the center of potential restoration effects in the Pawtuxet Watershed. The distance from each zip code centroid to the Hope Dam was calculated in miles, with the inverse of this value used within subsequent distance decay models.

Given the resulting distance measures and mean implicit prices for each zip code, specification and estimation of distance decay models follows standard, simple approaches. For each zip code j and statistically significant implicit price for attribute g, where g = *{acres, PVA, wild, access, IBI}*, we estimate the linear model

$$WTP_{gj} = \alpha_{g0} + \alpha_{g1} inv\_dist_j + \sum_{v=2}^{V} \alpha_{gv} D_{vj} + \varepsilon_{gj} \quad (3)$$

using OLS regression with robust standard errors, where WTP_{gj} is the mean implicit price for zip code j and attribute g, inv_dist_j is the inverse distance calculated as above, D_{vj} is a vector of demographic variables, ε_{gj} is equation error, and α_{g0}, α_{g1}, and α_{gv}, are parameters to be estimated. Elements of D_{vj} include *low_income* (the proportion of households in the zip code with income less than $40,000) and *college* (the proportion of households in the zip code with at least two years of college). As there are two demographic variables in the model, V=3 such that v = (2,3), with the associated subscripts referencing the two demographic variables and associated parameters. This approach is comparable in general complexity and format to prior models used to quantify distance decay in the SP literature (cf. Bateman et al. 2006).

Despite the ubiquity of such approaches in the SP literature, results of the distance decay models are disappointing. Estimated models universally fail to find statistically significant heterogeneity. As shown by model results (table 5), neither the estimated distance decay regressions nor inverse distance variables (inv_dist_j) are statistically significant at p<0.10 in any of the estimated models. Moreover, with the exception of the equation for *access*, parameter estimates for inv_dist_j are counter-intuitive in sign. To evaluate the robustness of these results, numerous alternative specifications of the distance decay regressions were estimated, including those with more comprehensive demographic regressors, interactions between these regressors and inv_dist_j, alternative specifications of the distance variable, and different functional forms. Regardless of specification, none of the estimated models showed evidence of statistically significant, global distance decay.

As suggested above, one might not expect welfare estimates such as these—likely dominated by nonuse values—to display the same degree of distance sensitivity as those dominated by use values. Moreover, the size of the sampled area (the state of Rhode Island) is somewhat smaller than many areas over which past analyses have quantified distance decay (Bateman et al. 2006). Nonetheless, the universal lack of a distance signal might be considered surprising given the emphasis in the prior valuation literature on distance decay and other global measures as the primary means through which spatial heterogeneity manifests in SP measures. Relying solely on these models and the associated intuition, traditional assessments would conclude that the null hypothesis of spatial WTP homogeneity could not be rejected, implying equivalent mean WTP across all sampled areas. Such conclusions, however, overlook the possibility of localized patchiness that can contribute to statistically significant and policy relevant welfare heterogeneity, even in the absence of global patterns.

Local Spatial Associations and Willingness to Pay Hot Spots

To evaluate the potential for local WTP patchiness and hot spots, we apply the G_i^* statistic in (1) above to each of the statistically significant implicit prices, with n=56 zip codes as the units or features of observation (j) and mean WTP as the value associated with each unit (c_j). The G_i^* statistic returned for each feature is a z-score. Larger scores are associated with more intense clustering of high values, or hot spots. The weighting matrix ($w_{i,j}$) is defined based on queen contiguity, with a value of 1 for contiguous parcels and zero otherwise. Results are expressed graphically on a map of Rhode Island. For ease of interpretation, the map illustrates the p-value for each zip code. The default is a p-value between 0.10 and 0.99—a statistically insignificant result. Highlighted areas are those for which $p<0.10$ (orange) or $p<0.05$ *(red), indicating a WTP hot spot at the associated level of statistical significance. As noted above, these are areas characterized by unusually high (or low) implicit prices (WTP for changes in an attribute) surrounded by areas with similarly high (or low) implicit prices.

Results are shown in Figures 2-6. For simplicity, the maps do not distinguish between hot spots of high or low WTP, although this can be easily accommodated with more complex graphics. In contrast to analyses of distance decay which find no statistically significant patterns (table 5), G_i^* statistics identify between 4 and 5 statistically significant hot spots for each implicit price. While some of these hot spots are located within or adjacent to the Pawtuxet watershed, others are located in areas quite distant from the affected area. Moreover, while some zip codes are hot spots for more than one implicit price (e.g., Little Compton, the zip code to the far right of the map, which is a high value hot spot at $p<0.05$ for both *wild* and *IBI*), patterns generally differ across implicit prices. That is, there is no single hot spot pattern that applies universally, suggesting that localized WTP patterns differ across attributes.

Unlike global patterns such as distance decay, WTP hot spots such as those found in Figures 2-6 can neither be attributed to simple, uni-metric patterns such as the distance that users must travel to reach an affected site, nor than they be modeled using a simple, continuous functional form. Rather, these results suggest the relevance of localized, non-continuous phenomena for preferences that may overwhelm standard motivations for distance decay. Local areas may be characterized by a variety of characteristics that may contribute to significant variations in WTP for environmental outcomes, beyond those related to simple distance from an affected site. These may include the availability of locally available or known substitutes and/or complements, endogenous sorting of households (cf. Irwin et al. 2009), local differences in culture or history, or other factors. These factors are often unobserved by researchers, revealing themselves only through resulting impacts on local welfare patterns.

The resulting welfare patterns may be unexpected. For example, Figure 2 shows three hot spots for *acres* that are either in or adjacent to the Pawtuxet watershed. Common intuition might suggest that these hot spots would reflect areas of high values, suggesting that people living in areas within the Pawtuxet watershed have a higher WTP for restored river acres within the watershed. The opposite, however, is true; these WTP hot spots reflect areas of particularly low values. That is, for an idiosyncratic reason, three areas within or adjacent to the Pawtuxet watershed are associated with statistically significant reductions in WTP for acres compared to other areas within Rhode Island—individuals living within these areas of the Pawtuxet watershed are willing to pay less for restoration outcomes than those living elsewhere. Conversely, the *wild* and *IBI* hot spots for Little Compton—among the communities most distant from the policy area—reflect atypically high values. An assumption of standard distance decay—implicit or explicit—would directly contradict these and other observed patterns.

Implications and Discussion

If policymakers are solely interested in average or aggregate household WTP over a known jurisdiction, and if the total extent and population of that jurisdiction is appropriately sampled, then spatial welfare heterogeneity might be of little interest. However, as noted by Smith (1993), Bateman et al. (2006), Loomis (2000) and others, such situations are rare. In many instances, issues related to spatial WTP heterogeneity can dominate the outcomes of benefit cost analysis, so that the provision of accurate information regarding spatial distribution is crucial. As shown by Bateman et al. (2006, p. 458), "the use of simple approaches such as aggregation via sample means can severely bias [stated preference WTP] estimates, and is likely to occur given that the survey analyst is very unlikely to have prior knowledge of the correct area over which to aggregate." The implications of these issues are particularly relevant for benefit transfer, in which information on spatial benefit distribution at a study site must be inferred from patterns identified elsewhere (Bateman et al. 2006). Spatial equity and related considerations can also be of substantial direct concern to policymakers, above and beyond issues related to aggregated benefit estimates (van den Bergh and Verbruggen 1999).

Within this context, findings of the present analysis demonstrate the potential for significant, local, and potentially policy relevant welfare patterns that are not detectable through global approaches currently used in the valuation literature. Standard distance decay models universally fail to reject the null hypothesis of spatial homogeneity in choice experiment implicit prices for migratory fish restoration outcomes. In contrast, LISA analysis relying on Getis-Ord G_i^* statistics identifies statistically significant WTP hot spots for all implicit prices, universally rejecting the null hypothesis of WTP homogeneity. Numerous hot spots are identified, many located at a considerable distance from the policy site. We also find that spatial distributions vary across different implicit prices, and that these distributions fail to comply with commonly-imposed global notions of distance decay. These results demonstrate the potential limitations of distance decay models viewed in isolation, as well as the additional information that may be provided by approaches that emphasize local rather than global spatial associations.

Findings such as these show that the global methods commonly used to evaluate spatial heterogeneity in the SP literature provide only a partial, and in some cases misleading, perspective on the distribution of WTP. As a result, these methods used in isolation may contribute to improper inferences and misguided policy. For example, when WTP is locally patchy, distance decay models used to identify the extent of the market may provide incorrect results. Similarly, failure to reject the null hypothesis of spatial homogeneity within a global distance decay model may occur despite the presence of statistically significant but local WTP heterogeneity. Analyses of localized welfare patterns—here WTP hot spots—provides a mechanism for insight into these patterns, and hence more reliable benefits analysis. Unlike distance decay and other global models, these analyses do not assume or impose assumptions regarding the effect of distance on WTP, and are hence better able to capture non-continuous and sometimes unexpected patterns.

The mechanisms for analyses of localized patterns and hot spots—while unknown in the valuation literature—have an established history in other disciplines. These models may be easily implemented using a combination of spatial information already collected by most SP questionnaires (e.g., zip codes of responding households), increasingly accessible geographic information system (GIS) data, and individual-specific parameter estimates that are now a straightforward extension of mixed logit models. These are the same types of inputs required for traditional distance decay analysis of choice experiment data. LISA statistics are increasingly available as components of GIS and other statistical analysis packages, and results are directly applicable to the types of hypothesis tests common in welfare analysis. Hence, with relatively modest effort and expertise beyond that required to estimate standard distance decay or similar global models, it is possible to supplement these approaches with a more nuanced array of spatial analyses able to characterize both local and global patterns in WTP heterogeneity. General policy implications of such localized patterns are well established (Boots and Nelson 2008).

With an awareness of, and ability to characterize, localized welfare patterns, however, comes additional challenges for benefit cost analysis. For example, WTP patchiness diminishes the ability of distance decay, threshold, or other global models to unambiguously identify the extent of the market from data samples typical in SP welfare analysis (see examples in Bateman et al. 2006). That is, WTP hot spots could occur outside of areas predicted by global models to have zero values—leading to the potential for significant biases if the market extent is misidentified. Similarly, the capacity of kriging (Campbell et al. 2009) or analysis of global spatial autocorrelation (Campbell et al. 2008) to accurately characterize spatial welfare heterogeneity can be substantially reduced if WTP variation is driven by local rather than global associations. That is, the presence of statistically significant spatial patchiness casts into doubt the simplifying assumptions often applied within spatial analysis of SP welfare estimates, or at a minimum suggests that additional patterns may be relevant.

Conclusion

This paper illustrates methods that may be used to provide more comprehensive analysis of spatial pattern in WTP for ecosystem services and other nonmarket outcomes, emphasizing local patterns that do not conform with standard assumptions such as distance decay. These methods adapt local indicators of spatial association (LISAs) developed in geography and other non-economic literatures to identify welfare patchiness and hot spots. These alternatives are capable of revealing statistically significant patterns in nonmarket WTP that are both directly relevant to benefit cost analysis and obscured by standard approaches used to model spatial welfare heterogeneity. Although standard approaches (e.g., distance decay models) remain relevant, results here suggest that researchers should consider supplementing these methods with spatial analysis that evaluate otherwise invisible, yet similarly relevant local patterns.

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Table 1. Choice Experiment Variables and Descriptive Statistics

Variable	Definition	Mean (Std. Dev.)[a]
acres	The number of acres of river habitat accessible to migratory fish, presented as a percentage of the established reference value for the Pawtuxet watershed (Erkan 2002). Range 0-100%.	8.1794 (8.1550)
PVA	Population viability analysis (PVA) score: Estimated probability, in percentage terms, that migratory species will continue to appear in the river in 50 years. Reference condition is estimated based from surveys of experts in fish restoration, and interpreted following standard mechanisms for PVA models. Range 0-100%.	33.4413 (28.1265)
catch	The number of catchable-size fish in restored areas, estimated from the number of fish per hour caught by scientific sampling crews. Presented as a percentage of the reference value for the watershed, defined as the highest average level sampled in any Rhode Island river (from Rhode Island Department of Environmental Management sampling data). Range 0-100%.	79.9087 (7.5807)
wildlife	Number of fish-eating species that are common in restored areas, such as egrets, osprey, otters, eagles, turtles and mink. Presented as a percentage of the reference value for the watershed, quantified from surveys of regional experts in wildlife biology. Range 0-100%.	65.0125 (10.3920)
IBI	Index of biotic integrity (IBI) score: A linear multimetric index of aquatic ecological condition following Karr (1981), reflecting the similarity of the restored area to the most undisturbed watershed area in Rhode Island. Index components include overall fish abundance, number of mussel species, number of native fish species, number of sensitive fish species, number of feeding types in fishes, percentage of individual fish that are native, percentage of individual fish that are migratory, and percentage of individual fish that are tumor	71.6978 (6.0762)

	free. Presented as a percentage of the reference condition. Range 0-100%.	
access	Binary (dummy) variable indicating whether the restored area is accessible to the public for walking and fishing; a value of 1 indicates that the public can access the area. Range 0-1.	0.3296 (0.4702)
cost	Household annual cost, described as the mandatory increase in annual taxes and fees required to implement the restoration plan. Household cost for the status quo is zero. Range 0-25.	11.9762 (14.1019)
neither	Alternative specific constant (ASC) associated with the status quo, or a choice of neither plan.	0.3333 (0.4715)

[a] Means and standard deviations include status quo option of no restoration.

Table 2. Attribute Levels in Choice Experiment Design

Variable	Levels
acres	1. 0% (0 acres accessible to fish)[a] 2. 5% (225 acres accessible to fish) 3. 10% (450 acres accessible to fish) 4. 20% (900 acres accessible to fish)
PVA	1. 0% (probability of 50 year fish run survival)[a] 2. 30% (probability of 50 year fish run survival) 3. 50% (probability of 50 year fish run survival) 4. 70% (probability of 50 year fish run survival)
catch	1. 70% (102 fish/hour sampling abundance) 2. 80% (116 fish/hour sampling abundance)[a] 3. 90% (130 fish/hour sampling abundance)
wildlife	1. 55% (20 species common)[a] 2. 60% (22 species common) 3. 70% (25 species common) 4. 80% (28 species common)
IBI	1. 65% (aquatic ecological condition score)[a] 2. 70% (aquatic ecological condition score) 3. 75% (aquatic ecological condition score) 4. 80% (aquatic ecological condition score)
access	1. Public Cannot Walk and Fish in Area[a] 2. Public Can Walk and Fish in Area
cost	1. \$0 (cost to household per year)[a] 2. \$5 (cost to household per year) 3. \$10 (cost to household per year) 4. \$15 (cost to household per year) 5. \$20 (cost to household per year) 6. \$25 (cost to household per year)

[a] Status quo value.

Table 3. Mixed Logit Results: Pawtuxet Restoration Choice Experiment

Choice Attribute	Coefficient (Std. Error)
Random Parameters	
acres	0.0487
	(0.0138)***
PVA	0.0183
	(0.0056)***
IBI	0.0539
	(0.0209)***
access	1.2208
	(0.2247)***
cost (bounded triangular, sign-reversed)	0.0623
	(0.0085)***
Non-Random Parameters	
catch	0.0035
	(0.0092)
wildlife	0.0280
	(0.0095)***
neither	-1.6367
	(0.4522)***
Distributions of Random Parameters[a]	
std. dev. acres	0.0896
	(0.0254)***
std. dev. PVA	0.0448
	(0.0079)***
std. dev. access	1.5585
	(0.3702)***
std. dev. IBI	0.1492
	(0.0329)***
spread cost (bounded triangular)	0.0623
	(0.0085)***
-2 Log Likelihood χ^2	533.62***
Pseudo-R^2	0.30
Observations (*N*)	803

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

[a] Normal distributions are characterized by standard deviations. Triangular distributions are characterized by the spread.

Table 4. Marginal Implicit Prices: Empirical Distributions [a]

Variable	WTP	Standard Deviation	Percentiles (1%, 99%)	Pr > |t| [b]
acres	1.0910	0 .3523	(0.39, 2.03)	<0.01
PVA	0 .4136	0.1462	(0.11, 0.86)	<0.01
catch	0.0688	0.2073	(-0.38, 0.56)	0.72
wildlife	0.6369	0.2088	(0.15, 1.17)	<0.01
IBI	1.1879	0.5017	(0.00, 2.42)	<0.01
access	27.3285	6.0602	(15.87, 43.70)	<0.01

[a] Results reflect the mean over the parameter simulation of mean WTP over the coefficient simulation (see text). Estimates are per household, per year. For all variables except *access*, estimates represent WTP for a one percentage point increase.
[b] P-values are two-tailed, for the null hypothesis of zero WTP.

Table 5. Implicit Price Distance Decay Regression Results (OLS; robust standard errors)

	Mean (std. dev.)	Parameter Estimates (t-statistics in parentheses)				
		acres	*pva*	*wild*	*access*	*ibi*
inv_dist ($^1/_{miles}$)	0.137	-1.369	-0.634	-0.0790	25.80	-3.004
	(0.99)	(-1.14)	(-0.86)	(-0.50)	(1.60)	(-1.59)
low_income (proportion of responding households in zip code below $40,000 annual income)	0.268	-0.204	-0.117	-0.0158	1.572	0.366
	(0.45)	(-0.71)	(-0.67)	(-0.42)	(0.41)	(0.81)
college (proportion of responding households in zip code with at least two years of college)	0.643	-0.247	0.0720	0.00779	0.401	0.456
	(0.48)	(-0.93)	(0.44)	(0.22)	(0.11)	(1.09)
intercept		1.597***	0.581**	0.690***	24.46***	1.229*
		(5.23)	(3.12)	(17.33)	(5.97)	(2.56)
N		56	56	56	56	56
F statistic		0.70	0.64	0.22	0.92	1.43
Prob. > F		0.56	0.59	0.88	0.44	0.24
R^2		0.03	0.04	0.01	0.05	0.08

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

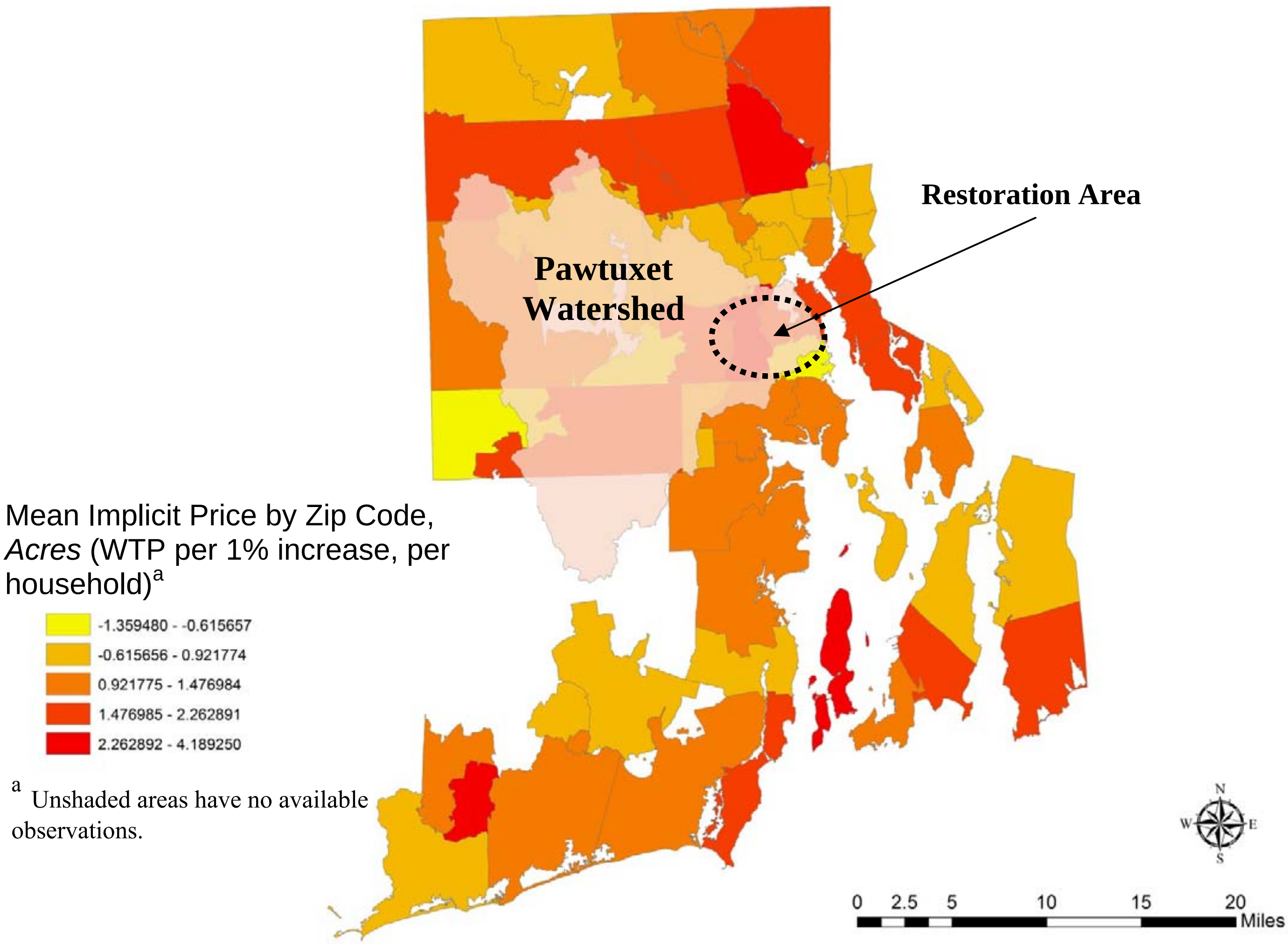

Figure1. Restoration Area and Raw Implicit Price Distribution (*Acres*, by Zip Code)

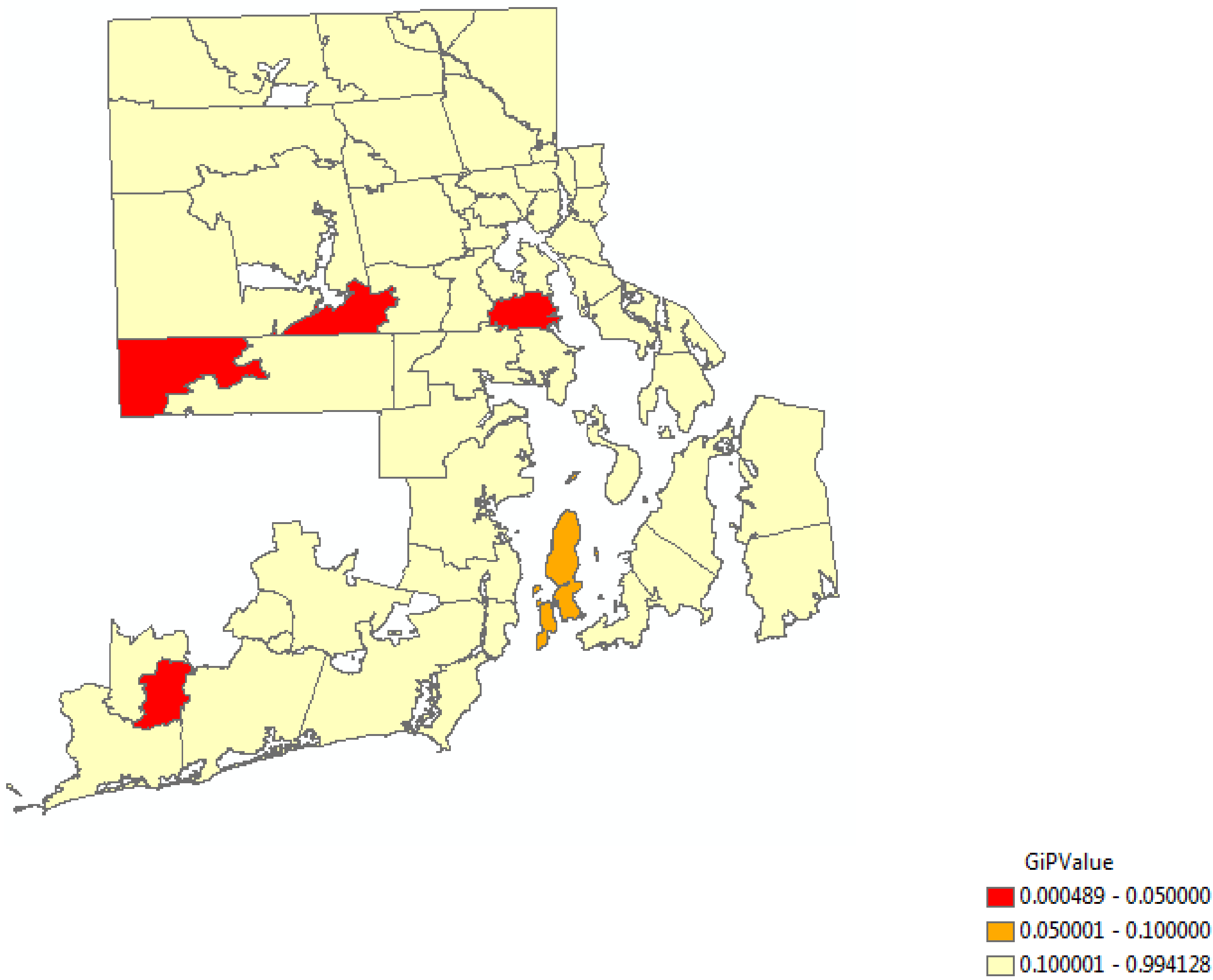

Figure 2. Empirical Implicit Price Hot Spots, *acres* (G_i^* p-values)[a]

[a] Blank zip codes have no response data. Hot spots show areas of atypically high or low values.

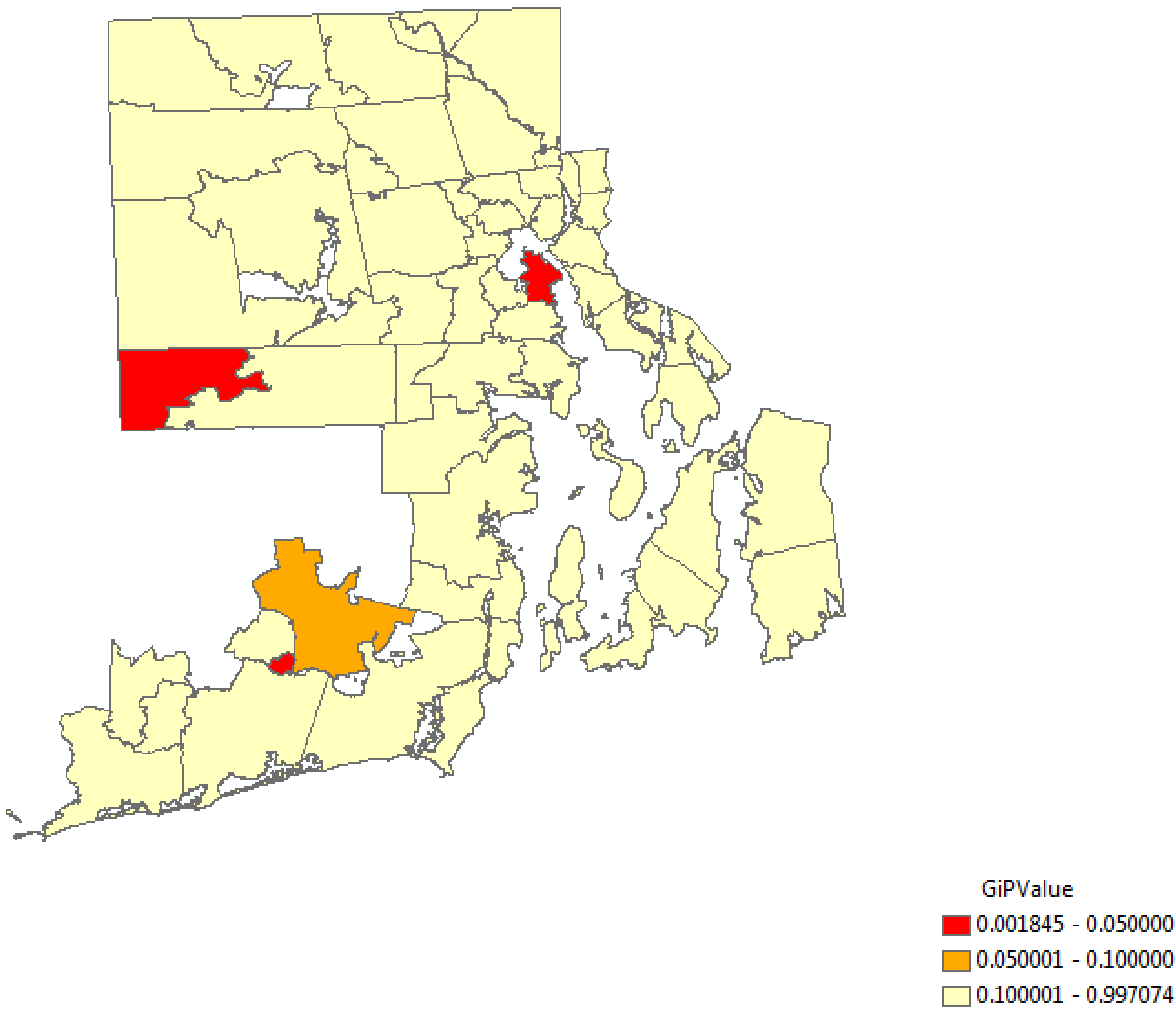

Figure 3. Empirical Implicit Price Hot Spots, *PVA* (G_i^* p-values)[a]

[a] Blank zip codes have no response data. Hot spots show areas of atypically high or low values.

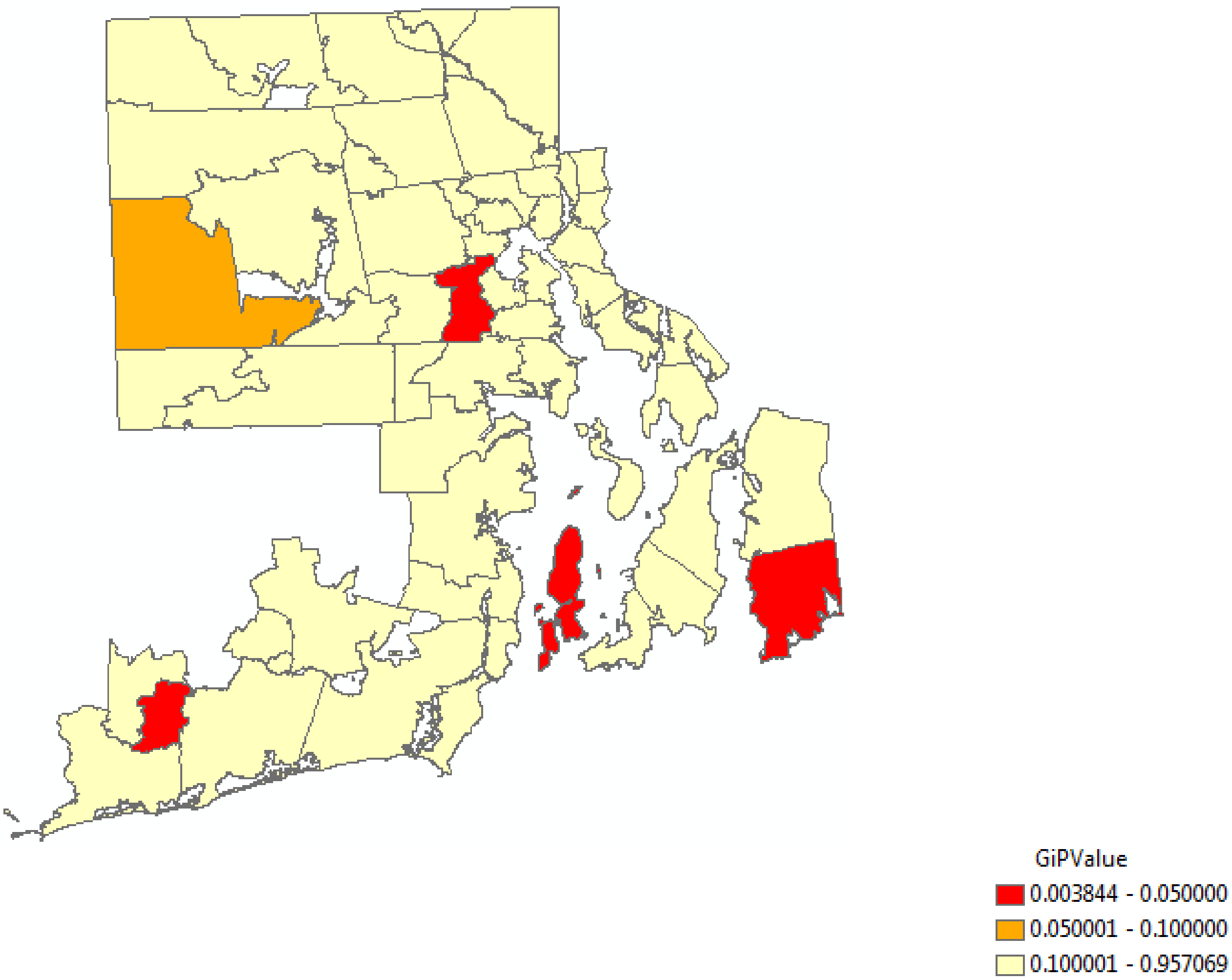

Figure 4. Empirical Implicit Price Hot Spots, *wild* (G_i^* p-values)[a]

[a] Blank zip codes have no response data. Hot spots show areas of atypically high or low values.

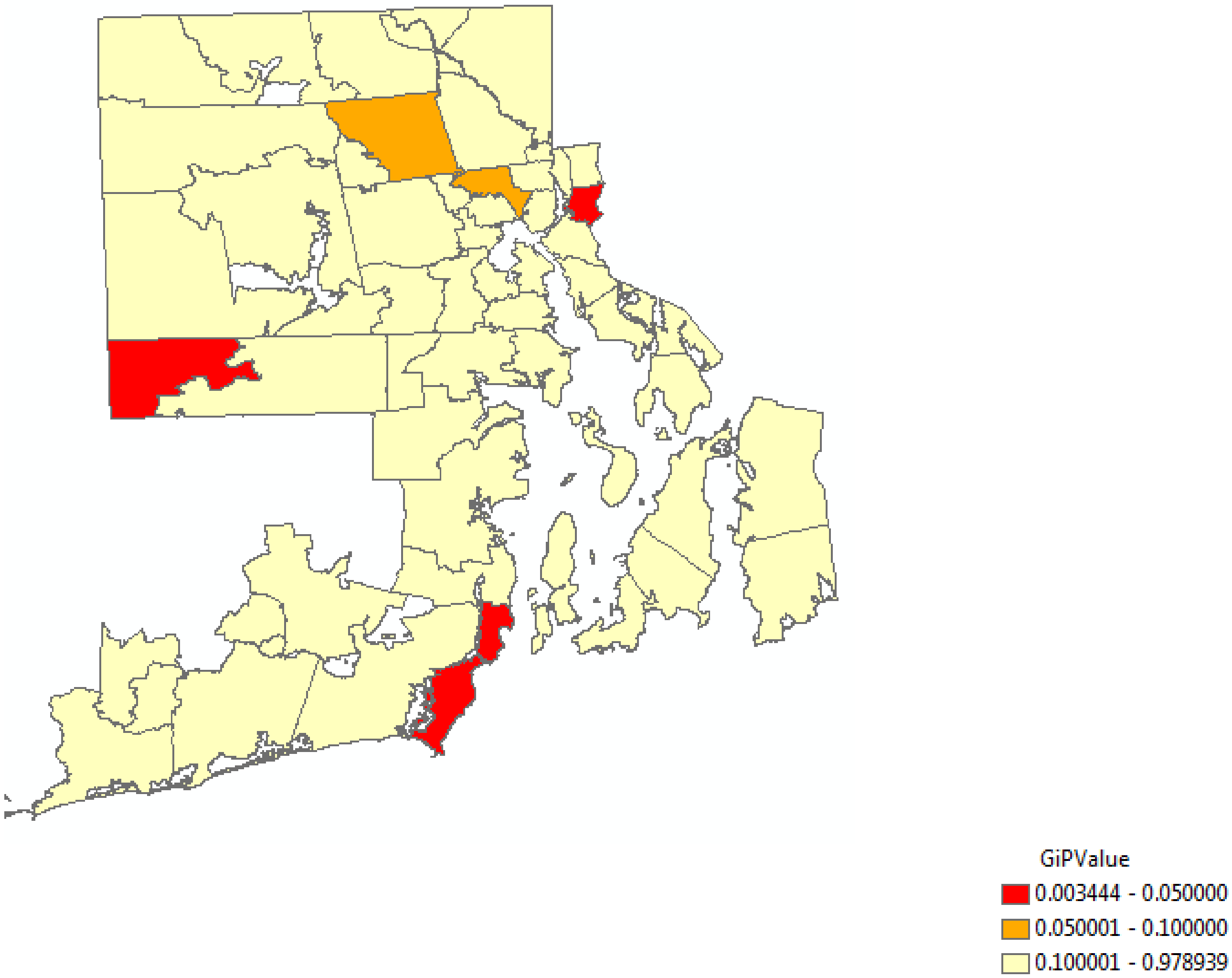

Figure 5. Empirical Implicit Price Hot Spots, *access* (G_i^* p-values)[a]

[a] Blank zip codes have no response data. Hot spots show areas of atypically high or low values.

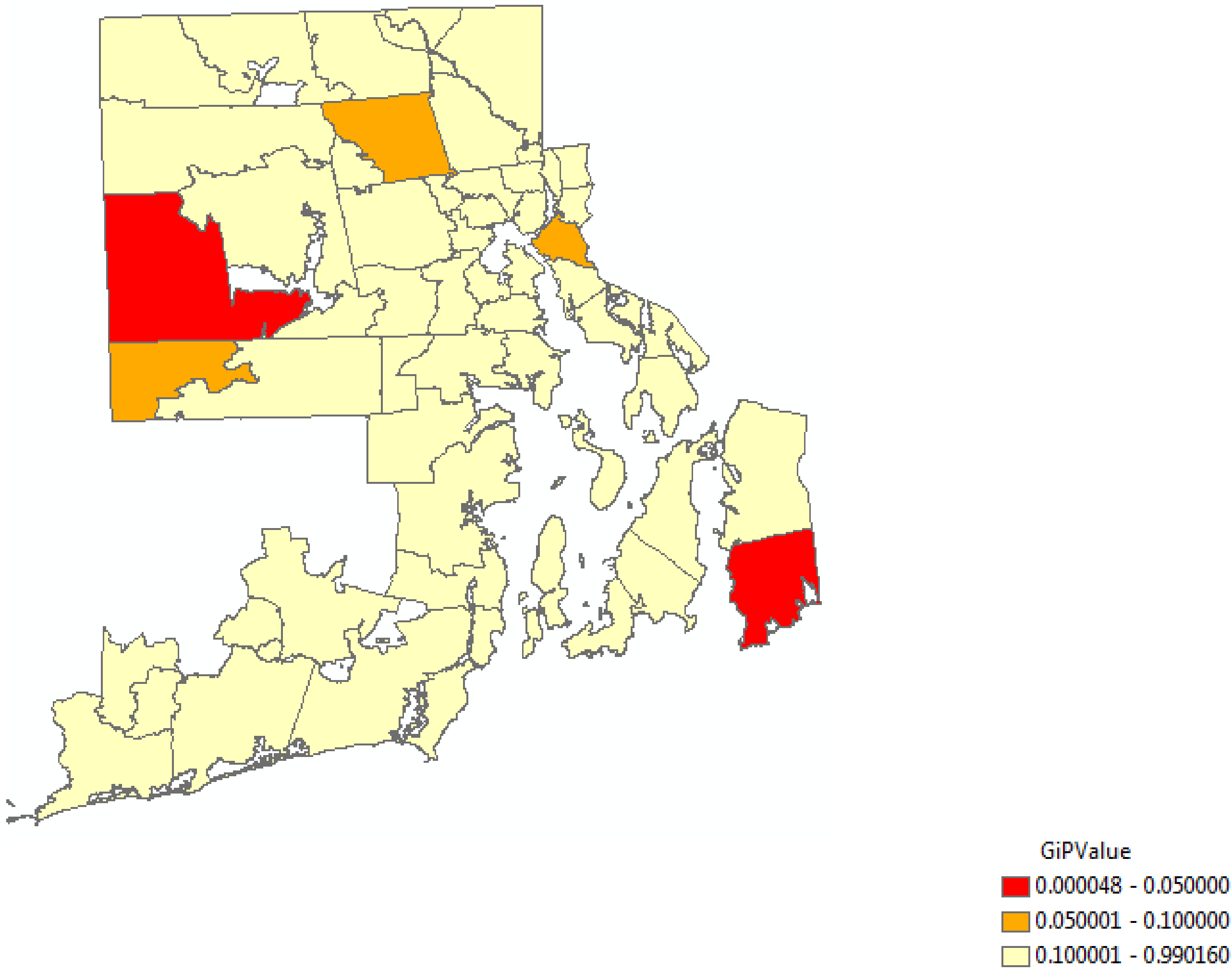

Figure 6. Empirical Implicit Price Hot Spots, *IBI* (G_i^* p-values)[a]

[a] Blank zip codes have no response data. Hot spots show areas of atypically high or low values.