<u>Amenities and Inequality in Rural America: A Preliminary Spatial Analysis</u>

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Favorable local attributes referred to as amenities are viewed as drivers of both tourism and population growth in rural areas. Endowments of natural amenities such as lakes, mountains, and forests, set the stage for built amenities, such as ski trails, public beaches, and tourist attractions. As catalysts of tourism and second home development, these amenities can be viewed as potential generators of economic sustenance from the perspective of planners and community development specialists. The extent to which growing amenity communities may actually invite income inequality is a current topic of discussion in community development and regional science literature. Little nationwide statistical research has been conducted that attempts to link rural income inequality to amenity endowments. Using path analysis as a theoretical aid, we intend for this study to provide a cursory spatial examination of how amenities might act through other variables to influence income inequality in non-metropolitan counties.

Inequality and Rural America

With the rapid restructuring of global trade and commerce, sources of income in the United States and abroad have undergone drastic shifts. Income inequality, the degree of financial disparity between the society's wealthiest and poorest individuals, has been growing both nationally and globally for several decades. In the United States, researchers estimate that the wealthiest one percent of the nation controls more economic resources than the poorest 40 percent.[1] This gap comprises the largest wealth disparity since the great depression, and all signals indicate that it will continue to widen.[2]

Inequality has been widely discussed in academic literature, and as incomes grow increasingly disparate within and across societies, inequality has also entered the realm of public conscience and debate. While researchers recognize inequality in the divergent housing, health, and education outcomes experienced within our society, we have trouble pinpointing why inequality, independent of poverty, is bad for society. The following explanation by Katherine McFate succinctly summarizes the often unarticulated consequences of inequality.

> *We care about economic inequality because when the social distance between the top and the bottom is too great, the trickle-down benefits of economic growth become more questionable, and so growth becomes a less effective mechanism for improving the circumstances of those at the bottom. We care about economic inequality because we worry that too much of it may undermine the legitimacy of our economic system and of the functioning of our political institutions. We fear that too much inequality may fragment society, encouraging the rich to exit public space and institutions and setting in motion centrifugal dynamics that undermine social cohesion.*[3]

One arena in which income inequality has a very clear and tangible impact in the U.S. is education, as it limits the effectiveness of federal mandates protecting equal access to and quality of education. Without equal education, common sense tells us that income inequality will perpetually increase. To date, eighteen states have been forced to implement highly contested education funding methods to redistribute wealth across school districts in a more equitable way.

In Vermont, for example, school funding litigation was born from demographic events of the past several decades, which have impacted rural communities throughout the United States.

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[1] The Congressional Budget Office, *Historical Effective Tax Rates, 1979-1997*, Preliminary Edition, May 2001. http://www.cbo.gov/ftpdoc.cfm?index=2838&type=1>
[2] US Census Bureau. *The Changing Shape of the Nation's Income Distribution.* June 2000. http://www.census.gov/prod/2000pubs/p60-204.pdf
[3] McFate, 1999

Despite the nation's general trend toward urbanization, certain rural areas have steadily attracted new residents from urban areas.[4] Much of this counterurbanization occurs in regions containing specific geographic and cultural amenities, such as forests, mountains, scenic landscape, or cultural institutions like museums or performance venues. Amenity communities, as they are called in the sociological literature, appeal to both seasonal and permanent migrants who wish to live in close proximity to the local recreation opportunities or perceived lifestyle benefits that amenities provide.

Amenity migration has not been limited to Western boomtowns with Rocky Mountain vistas, gargantuan ski resorts and celebrity enclaves. For over a century, proximity to urban areas has driven tourist and seasonal home development along the mountainous and coastal periphery of the East Coast and the Midwest's forests and lakefronts. The highest proportions of seasonal housing in the U.S. are found in the rural New England states of Maine and Vermont, which are within a relatively short drive of the nation's most densely populated metropolitan corridor. Some counties in the Northwoods of the Great Lakes states, which are within a day's drive of Chicago, Minneapolis-St. Paul, Milwaukee, and Detroit, are comprised of over 50% seasonal homes.[5]

Some literature has argued that rural residents make deliberate financial concessions in order to live in places with substantial natural amenities, low crime and a generally high quality of life as opposed to wealthier communities with fewer of these attributes.[6] However, as a result of significant growth in tourism and migration the social and economic landscapes of certain rural areas is being redrawn. The "traditional" lifestyle for which rural residents sacrifice economic opportunity is increasingly juxtaposed with seasonal homes, up-scale shops, resorts, and private clubs for use by more affluent visitors or part-year residents.

The link between amenity migration and disparate income distributions seems to be straightforward. Quite simply, residents of the rural U.S. are categorically less affluent than urban dwellers, and amenity migrants therefore tend to wield more financial resources than their average rural neighbor. To provide a particularly extreme example, a 2004 Colorado study

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[4] McGranahan, 1999
[5] US Census 2000
[6] e.g. Green, Gary P. *Amenities and Community Economic Development: Strategies for Sustainability*. Journal of Regional Analysis and Poverty. Vol. 31, No. 1. 2001

found that in one amenity county, the gap between resident and non-resident (i.e. Seasonal homeowner') annual income was approximately $219,000.[7]

What the ultimate effects of such inequality will be for existing residents of tourism-driven rural areas remains unclear. The growth of amenity communities stems to some degree from a belief in rural development literature and practice that tourism and seasonal home development can be beneficial to rural areas. In recent decades the consolidating agricultural sector, a waning forestry industry, and an increasingly mobile manufacturing climate have stripped rural communities of both jobs and population. Tourism has been and continues to be regarded as desirable for rural communities impacted by such restructuring. However, as the case has been throughout the country, the service sector occupations that have proliferated in recent decades have been slow to breathe life back into sluggish rural economies.

The extent to which amenity-driven employment opportunities generate disparities in rural income has become a pertinent question for researchers. In his initial study, McGranahan finds that amenity counties experienced employment growth that far surpassed non-amenity counties.[8] More recent evidence suggests that such employment growth might create or exacerbate income disparities in amenity communities. Marcouiller et al. (2000) report that concentrations of tourism sector employment in the Great Lake states create a "hollowing" effect on regional income distribution. Goe and Green (2006) contend that improvements in a locality's well-being attributed to amenity-led development are due more to aggregate increases in economic indicators than an equitable distribution of that growth. Research from Florida, alternatively, has found that relative inequality grew at a slower rate in tourism counties than in other counties, suggesting that differential forces of inequality may be at work in amenity communities depending on whether seasonal homeowners or tourists are the more influential actors. [9]

The relationship between amenities, migration and tourism, and inequality over space remains unclear. Local inequality occurs in tandem with the regional inequality that stems from the spatially uneven nature of economic development. Can a spatially sensitive exploration of national trends contribute to a more meaningful understanding of inequality in rural America? We hope that this initial spatial investigation of the forces that drive tourism, migration, and

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[7] NWCOG 2004
[8] McGranahan, 1998
[9] Kim, Jongsup. *Growth Of Regional Economy And Income Inequality: County-Level Evidence From Florida, USA.* Applied Economics, Vol. 36, 2004, 173–183

inequality in the non-metropolitan United States will be a fruitful extension of the amenities literature.

Project Design and Methods

Given the degree to which amenity features, tourism, and migration vary across space, a spatial analysis will be useful for discerning how and why space matters in the context of inequality.[10] Using data from the National Outdoor Recreation Supply Information System (NORSIS),[11] which contains cases for each county in the contiguous United States, we hope to explore the following questions: Through what other variables do natural amenities operate to influence income inequality? How does that influence vary over space? How do amenity differences across communities yield different inequality outcomes?

In attempting to answer these questions, the complexities embedded in relationships between natural amenities, built amenities, tourism, and service work must be acknowledged. To more fully account for these complexities, we will approach this project using path analysis as an exploratory method for determining the direction and magnitude of relationships between the many independent variables that we suspect influence inequality in non-metropolitan counties. We utilize both Ordinary Least Squares estimates of linear regressions and spatial regression analysis using the Maximum Likelihood approach, first on an inequality model conceived without path analysis, and then on a series of interdependent models as outlined using path analysis. We anticipate that path analysis will aid our development of a more spatially nuanced understanding of the amenity variables affecting inequality.

Project Scope

Non-metropolitan counties of the contiguous United States were studied so as to limit the influence of large urban centers in the data. While excluding urban areas may influence the results by ignoring their impact as neighbors and through edge effects, we believe that for this research such influence would be less drastic than what might arise from including them, particularly because urban and rural areas exhibit structurally different relationships between

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[10] Green, 2001
[11] NORSIS: The National Outdoor Recreation Supply Information System (NORSIS) 1997 is a county-level database of outdoor recreation resources in the United States compiled for the 1998 Renewable Resources Planning Act (RPA) Assessment of Outdoor Recreation and Wilderness. It consists of 3,116 observations and 492 variables.

amenities, migration, and inequality. For example, intuitively, the most drastic income inequality occurs in spaces where urban and rural boundaries intersect, suggesting that some sort of pattern in the radial continuum of urban, suburban, and rural areas may exist. However, since they are typically included in the Census' Bureaus Metropolitan Core-Based Statistical Areas, this examination of non-metro counties does not include counties bordering urban counties.

Our initial investigation reveals an extreme outlier among non-metro counties; Monroe County, Florida – which encompasses all the Florida Keys – has a built amenity count nearly 500 percent larger than the next highest amenity county. It was thus removed from analysis, as were counties with no data available for net migration or inequality, including Yellowstone County, Montana, and Menominee County, Wisconsin.

Variables

To measure the forces and relationships in question, we manipulated several of the variables available in NORSIS so that they more closely represent concepts in our research. To gauge the extent of the county's tourism industry, we used IMPLAN variables of both hotel jobs and tourism jobs (normalized by population size) to provide the percentage of local population employed in both sectors.[12] These variables constitute a general measure of the extent to which a county is reliant on service industry employment. From the NORSIS data we recoded variables to provide additive indices of natural amenities, built amenities, and public recreation places. To calculate natural amenities we totaled each county's acreage of forest, mountains, and water and normalized that total by the county's area. Our built amenities variable is a tabulation of all recreation businesses and related infrastructure within each county.[13] It is a consolidation of several categories, which when taken separately proved to have excessively skewed distributions. Aggregated as one variable, however, the non-normality is significantly reduced. The public recreation variable is a tabulation of public park and recreation facilities in each county.[14]

Net migration rates from the decade spanning from 1990-2000, calculated from census data for each county, were added to the dataset to measure the redistribution of population widely observed in many areas[15]. Also added were Gini Coefficients, also derived from census

[12] IMPLAN Resource Dependence Typology
[13] American Business Information, Inc.
[14] Sum total of the number of agencies, recreation centers, or parks per county.
[15]Provided by the Applied Population Laboratory at the University of Wisconsin, Scott McNiven

data, for each non-metro county to measure the degree of inequality in income distribution within each county [16]. The Gini coefficient reflects the degree of income inequality amongst US households on a scale of zero to one, with zero representing perfect equality and one representing complete inequality. For reference, the Gini coefficient for the entire United States is .408, for Canada it is .331, and for Denmark it is .247. [17]

Spatial Considerations

We first theorized that spatial autocorrelation within amenity variables exists at both the global and local levels, and probably includes evidence of both spatial heterogeneity and spatial dependence. We expected that the spatial relationships between built/commercial recreation amenity types reflect substantial heterogeneity in that amenities tend to exist in correlation with cultural, geologic and climactic variables, including mountains, lakes, coastline, wilderness areas, and historical settings. Within a particular cultural or environmental region, recreation amenities might rely on a specific extraordinary natural amenity, such as a particular cove, rock formation, or water fall. However, beyond the initial reliance on culture and environment we expect that contagion-like effects exist in which recreation amenities multiply in a manner dependent largely on their proximity to other recreation amenities, eventually forming amenity clusters.

Because we limited our results to non-metropolitan counties, the spatial plane of our data is punctuated with gaps caused by the exclusion by urban areas. This effectively rules out using contiguity-based spatial weights. After experimenting with distance weights and neighbor-count weights, we opted for a distance weight of 50 miles because it reflects a reasonable maximum commuting distance that would separate county centroids for most of the United States, and it will not err from effects of contiguity.[18]

Path Analysis

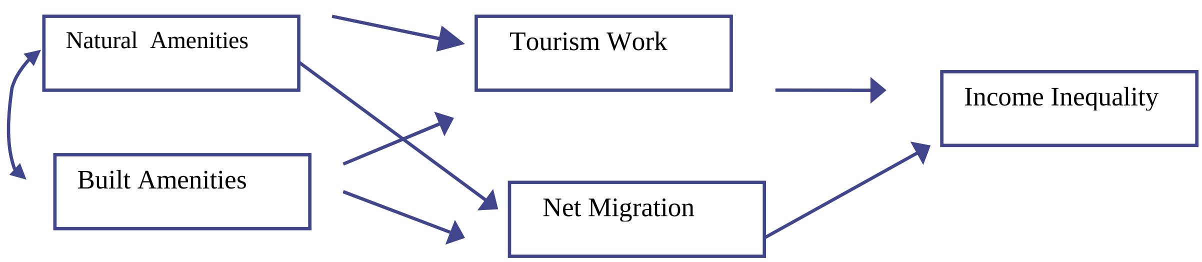
Path analysis is a method of data exploration used by researchers to decompose correlation into different factors of influence and interpret a network of relationships. Path analysis incorporates a schematic visual regiment and a formula for calculations that produce a diagram that displays the order by which dependent variables are influenced by independent

[16] provided via internet by Thomas W. Volscho at the University of Connecticut.
[17] United Nations. *Human Development Report. 2004*
[18] Wheeler, 2001

variables via a path coefficient that indicates the extent to which influence is distributed in the network. Path Analysis is causal only in the sense that the researcher infers organization of the model; results from the analysis are not by themselves evidence of causality. The following are lofty assumptions that the researcher must make before using path analysis: all relations are linear and additive, residuals are uncorrelated with variables being modeled, paths are unidirectional, and variables are standardized and measured in an error-free manner.

In developing a path diagram for our research question we first tried to capture how we perceive that amenities set the stage for tourism and inequality. Inequality is likely to be dependent on the different types of commercial arrangements that arise from either the presence of visitors passing through or the in-migration of more permanent residents. Further, the nature of those commercial arrangements will be dependent on the proportion of temporary visitors, permanent immigrants, and seasonal homeowners coming to the community. After all, they are separate groups with divergent economic needs, spending habits, and general intentions for their encounter with a place. Tourists, who typically sleep in hotels and campgrounds and dine in restaurants, rely more heavily on service workers than do permanent residents. Thus, rural communities that rely disproportionately on tourism jobs might exhibit lower wages than those with extant manufacturing or other primary sectors or more populated areas.

For this project, we initially anticipated a simple relationship using only five variables: natural and built amenities drive tourism and migration, which in turn, result in inequality due to the high proportion of tourism jobs. The path diagram for this relationship is as follows:



Results

Exploratory Data Analysis

Mapping Gini coefficients on a nation scale suggests that they are likely to be indicators of multiple economic scenarios, not of a standard set of social conditions that might be thought to accompany such scenarios. Essentially, they mirror the general patterns of most socioeconomic traits across the United States. That is, the highest clusters of inequality exist in areas associated with high poverty, particularly those in the "Black Belt," Mississippi Delta, and the Texas-Mexico border regions. (See Map1 in Appendix) In these places, a large Gini Coefficient is likely to capture the disparate relationship between a disproportionately large number of poor and a modest middle class. However, in places where poverty and unemployment are less prevalent, a high Gini Coefficient is more likely to reflect a gap between the working poor and a contingent of very wealthy residents. Spatial patterns characterized by structurally different manifestations of inequality are likely to exist across the United States. For the purposes of studying inequality in high amenity counties, which are typically non-poverty counties, it will be useful to include a dummy variable to account for the effect of exceptionally high poverty rates in influencing inequality. This will also help to reduce heterogeneity in the dependent variable, strengthening the reliability of spatial lag tests in the next phase of analysis.

Examing Gini Coefficients through the GeoDa[19] spatial data analysis software confirms significant spatial autocorrelation. The Moran's I for non-metro county Gini coefficients is .4909, indicating a high level of spatial autocorrelation (See Appendix Fig. 1) Using GeoDa's brushing feature allows us to exclude portions of the map to determine the Moran's I of the remaining portions. Employing this technique demonstrates that autocorrelation is indeed reduced when removing the high poverty counties of the South and Midwest.

Next, using Geographically Weighted Regression (GWR)[20] we can explore spatial differentiation in the performance of an OLS regression model, as well view a synopsis of how each variable in the regression contributes to the model's predicted outcomes. GWR achieves this via a process in which a regression is run using a spatial weight at each data point, in this case at each county centroid. While this technique should be regarded as strictly an exploratory

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[19] GeoDa 0.9.5 Luc Anselin. Developer. University of Illinois. http://sal.agecon.uiuc.edu/geoda_main.php.
[20] GWR 3.0. Stewarth Fotheringham, Developer. University of New Castle on Tyne. UK. http://www.nuim.ie/ncg/GWR/index.htm.

tool in the investigation of spatial relationships, it can alert us to unexpected behavior in our data or illustrate trends that were not readily apparent.

In this case, GWR was used with a model to which we will refer as the "whole model," since it includes each of the variables expected to influence inequality in rural counties, including: hotel work, tourism work, natural amenities, built amenities, net migration, public recreation, and dummy variables for urban proximity and poverty. Our GWR results raised some interesting questions. (See Map 5, 6&7 in Appendix A) First, the general fit of the model, as indicated by local R^2, is highly dependent on geography. The highest values are found in a relatively contiguous area that stretches from Northern New England, through the rust belt, to the south to Florida, and also in the Southern Rockies and west coast. The model performed most poorly in regions in the lower Great Plains, Minnesota, Montana and Idaho. Maps of the tourism and hotel variables' influence on the model show an interesting divergence in the two variables over space. Not only do they exhibit different spatial clusters, tourism's effect on inequality -- as reflected by the proportion of a county's population employed in tourism jobs -- is negative in most rural counties, while the effect of hotel jobs on Gini coefficient is almost uniformly positive. This indicates a fundamental difference in the two types of employment, and conceivably, in the economic fabric of the counties in which they are located.

Non-Spatial Results

When estimating the whole model in a global OLS regression, we are able to account for much of the spatial autocorrelation in the distribution of inequality. Running a second regression on the residuals of the first, the Moran's I is reduced to .2372. This indicates that spatial autocorrelation remains, and additional spatial analysis is necessary for understanding the heterogeneity in income inequality that we're not capturing. Finally, mapping the model and its residuals using GeoDa's LISA capabilities demonstrates a pronounced decrease in the number of county clusters where high inequality is surrounded by similar neighbors. However, low inequality clusters persist, particularly in the upper Midwest. (See Maps, 3, 3a, and 4 in Appendix A)

Ordinary Least Squares regression again reveals that hotel jobs and tourism jobs influence inequality differently. As demonstrated by the regression coefficients, the higher percentage of hotel jobs in a county, the higher we can expect the Gini coefficient to be. Tourism jobs, on the other hand, demonstrate a negative effect on Gini coefficients, suggesting that they may reduce income inequality. The discovery of the opposite effects of tourism and hotel work complicates our study, as we expected them to represent similar if not identical relationships.

This finding called into question the model we had originally anticipated, but path analysis' rubric for understanding relationships helped guide the conceptual remapping of our variables, resulting in a more intricate path diagram. (Appendix B) Public recreation appears to rely on available natural amenities, and in turn greatly influence the quantity of built amenities. The model then became more difficult to follow. While inequality is significantly related to hotel work in all models, the extent to which the quantity of hotel work is influenced by amenities is not reflected in particularly high coefficients in the models. In the path analysis, however, the path coefficient quantifies the influence of built amenities on hotels, which have been influenced by public recreation and natural amenities, such that its strength suggests that the revised model as we conceived it is indeed configured appropriately. Also, recent studies have suggested that migration precedes employment growth in amenity communities, which helps to confirm our revised path order but further confounds the distinction we had hoped to establish between tourism communities and migration communities.

Path analysis calculated using a statistical software package indicates an especially strong positive relationship between 'public recreation' and 'built amenities', and between 'built amenities' and 'hotels jobs'. From there, 'hotel jobs' positively influences both net migration and tourism jobs. For the final effect on Gini coefficient, however, 'tourism jobs' produce a small negative effect and migration produces a small positive effect. 'Hotel jobs' produce a much stronger direct positive effect on Gini coefficient. (Please refer to larger path diagram in Appendix B for coefficients.)

Spatial Results

The Robust Lagrange Multiplier from the OLS output overwhelmingly indicates that a spatial error model most appropriately addresses the spatial effects in the data. Running both spatial lag and spatial error models using Maximum Likelihood estimation confirms this, as is evident in the AIC reduction and the its magnitude, the spatial autoregressive coefficient and pseudo R^2. (See whole model Table, Appendix C) Thus, the spatial autocorrelation present in the way inequality is distributed across space appears to be explained by spatial heterogeneity. In other words, inequality's spatial distribution is probably linked to unexplained phenomena that could be encapsulated in a variable added to the model.   It seems probable that remaining autocorrelation might partially be explained by a variable which could account for the pockets of relative equality in the Midwest, just as the poverty variable accounts for relative inequality in Southern counties.

While other coefficients change relatively little across the OLS and MLE models, the coefficient for tourism jobs has been reduced substantially by the error model, and the coefficient for migration has reversed direction. Although these variables are weak in terms of their significance, we will discus potential implications of their performance in the model later.

While a regimented technique that allows spatial considerations within path analysis has yet to be developed, using path analysis as an exploratory framework for multivariate spatial regression might be beneficial. In this study, substantively interesting results appear when regressing each component equation from the path analysis using spatial error and spatial lag models. It becomes apparent that the spatial error model does not offer an overwhelming improvement in comparison to the lag model for any of the component equations. In fact, for three out of the six equations, the lag model outperforms the error model. As dependent variables, net migration, hotel and tourism work (Moran's I's= .4742, .2615, .1648, respectively) all exhibit spatial autocorrelation characteristic of spatial dependence, which implies that their spatial distribution might not be purely attributable to missing variables, but to inherently spatial phenomenon.

In a later attempt to "spatialize" the path framework in its entirety, we have also estimated coefficients by sequentially regressing each independent variable in the path using as dependent variables the values predicted from the preceding equation. Once again, we did this employing OLS regression, as well as the spatial lag and error models. This iterative process demonstrated similar results to our previous analysis. Specifically, we met with slightly greater success in reducing the spatial autocorrelation in Gini Coefficients using the spatial error model, while the component models demonstrated evidence of both spatial lag and spatial error, supporting the findings of our earlier, separate regressions. We discuss potential causes and implications of these patterns below.

Challenges and Limitations

Missing Variables: The process by which tourism is generated in the rural United States is complicated by several geopolitical factors. For example, within mountainous regions, ski resort location might depend on proximity to lodging and transportation infrastructure as well as local zoning and land ownership patterns. Furthermore, the temporal order by which commercial amenities develop and proliferate is probably highly variable and contingent upon additional factors, such as tourism history and population growth in proximate urban areas. It is this host of factors that explains why recreation amenities do not exist in every rural county. We therefore observe a scattered diffusion of recreation amenity-rich counties that roughly follow the patterns of natural amenities but are more precisely determined by a multitude of other factors.

Measurement Problems: Three characteristics of communities with substantial amenity endowments make income inequality difficult to measure. One problem is related to residency status of second home owners. Seasonal home owners with primary residences elsewhere might not be included in local income data. This omission no doubt substantially undercounts inequality, which exists even beyond the months that part-year residents reside in the amenity community. In addition, when vacation home owners congregate on the most desirable real estate, low-wage service workers are less able to afford local housing. Many are therefore forced to commute from more affordable communities, and inequality will be less apparent if service workers commute from other counties. Within counties, inequality belies spatial patterns in housing that are also important aspects of tourism arrangements. Finally, temporary labor in the rural tourism industry is increasingly comprised of guest and exchange workers “in-sourced” from elsewhere. Although their income is recorded locally, their participation in the local economy is veiled. Many may chose to save their earnings or use them to travel throughout the country upon completing their job.

Unit of Analysis Problems: In general, our ability to investigate local spatial effects is limited by the use of counties as units of analysis. Due to their large size, it becomes difficult to identify, much less analyze, localized amenity agglomerations confined within one county’s boundaries. In other words, while a natural amenity region might encompass several counties, a region exhibiting particularly high recreation amenity concentration will be less diffuse.

Multicollinearity: Despite our best efforts to select variables that capture the social and environmental features in which we are interested, it is apparent that overlap exists in the phenomena measured by some of the variables, particularly in the case of built amenities and tourism jobs. While not all “built amenities” are those that necessarily employ workers, many could be. Given that several jobs are seasonal, under the table, and increasingly held by temporary, exchange, and guest workers, we do not expect this to be problematic, which the data seem to support.

Discussion

Though preliminary in nature, this research has yielded interesting findings that demonstrate the need for further space-sensitive research into tourism and inequality. First, statistical evidence suggests that tourism does not automatically equate to inequality across rural America. At an early stage of data exploration it became apparent that hotels and tourism represent different phenomenon in their effect on inequality. While we were not expecting this, it seems logical: tourism enterprises can be small, entrepreneurial businesses that employ fewer people, but provide better income to owners and managers than large hotels or resorts with large payrolls of low-skill and low-wage workers. Still, tourism work needs to be evaluated further. In both the whole model and the path analysis model, the spatial error regression for Gini coefficients reduced tourism's negative influence on inequality, which could indicate that tourism's impact on inequality is influenced by missing variables accounted for in the spatial autoregressive term. Because tourism and hotels are ostensibly overlapping features, those missing variables might explain why they show different effects on inequality in this study. For example, different types of tourism or different classes of tourists might yield different degrees of inequality, in part because they rely on different types of accommodation. A study that further differentiates social forces captured in the hotel work variable from those captured in the tourism variable seems warranted.

Second, tourism does appear to exhibit patterns of agglomeration. Our original conjecture was that the spatial autocorrelation present in inequality would be best accounted for by a spatial error model. Spatial lag, we predicted, would account for tourism agglomeration that happens at a smaller scale, below the county level, such as in locality like the Wisconsin Dells. However, as is evident by the superior performance of the spatial lag model with regard to net migration, tourism, and hotel work, decomposing the many pieces of inequality before examining them spatially might lend credence to our original hypothesis: that we see spillover effects, essentially a tourism contagion, when it comes to hotels and tourism.

Third, the differing effects on inequality exhibited by migration and service jobs might confirm that the two distinct types of amenity development bring different economic opportunities for rural communities. However, the results of our study do not provide statistically significant evidence for this hypothesis. This is an issue that should be more thoroughly investigated, as it might provide development practitioners with a more specific knowledge base with which to assist rural communities seeking to develop their economies.

Finally, tourism cannot be explained by a universal model throughout the United States because the conditions from which it arises appear to vary spatially. This becomes visually evident when mapping the path analysis' tourism component model (Appendix B, Equation 5) in GWR. For example, Map 8 (Appendix A) demonstrates that the tourism model used in this study might be regionally biased because it inadequately accounts for the impetus for tourism in certain places (essentially the Southeast and most of the West). Looking within the tourism component model, we can then observe which individual parameters vary over space in their predictive performance, contributing to an overall inability to predict tourism in certain places. This can also be mapped. Map 9 (Appendix A), for example, suggests that the influence of net migration on tourism might be much differ in the West than the East. This seems to support the notion that there are several different types of relationships between tourism and migration, which geographers have recently attempted to disaggregate.[21] For example, tourism labor migration and retirement migration are distinct types of migration and each is more prevalent in certain areas than others. These distinctions will have a substantial impact on the socioeconomic implications of amenity migration and tourism economies.

The spatial exploration of these data continues. Of particular interest to us is the development of a more conclusive distinction between population growth and seasonal home ownership. This will hopefully result from a more nuanced use of path analysis and future experimentation with methods for combining structural equation models with spatial data exploration.

In conclusion, a spatial analysis of the links between amenity endowments and inequality shows promise for informing two dimensions of research. The first sheds light on the nature of how amenity communities expand and contract in space. Although it requires a finer unit of analysis than what our project offers, this research could potentially benefit landuse planning efforts where amenity-led development is anticipated. The second elaborates on regional variations and patterns affecting demographic change and economic stratification within amenity communities. Although local governments cannot easily overhaul their natural amenities, they exercise much more control over development of built and recreational amenities, which appear to be integral to the development of tourism industries. Utilizing more spatially-attuned and regionalized research, rural communities might be better equipped to foster tourism economies

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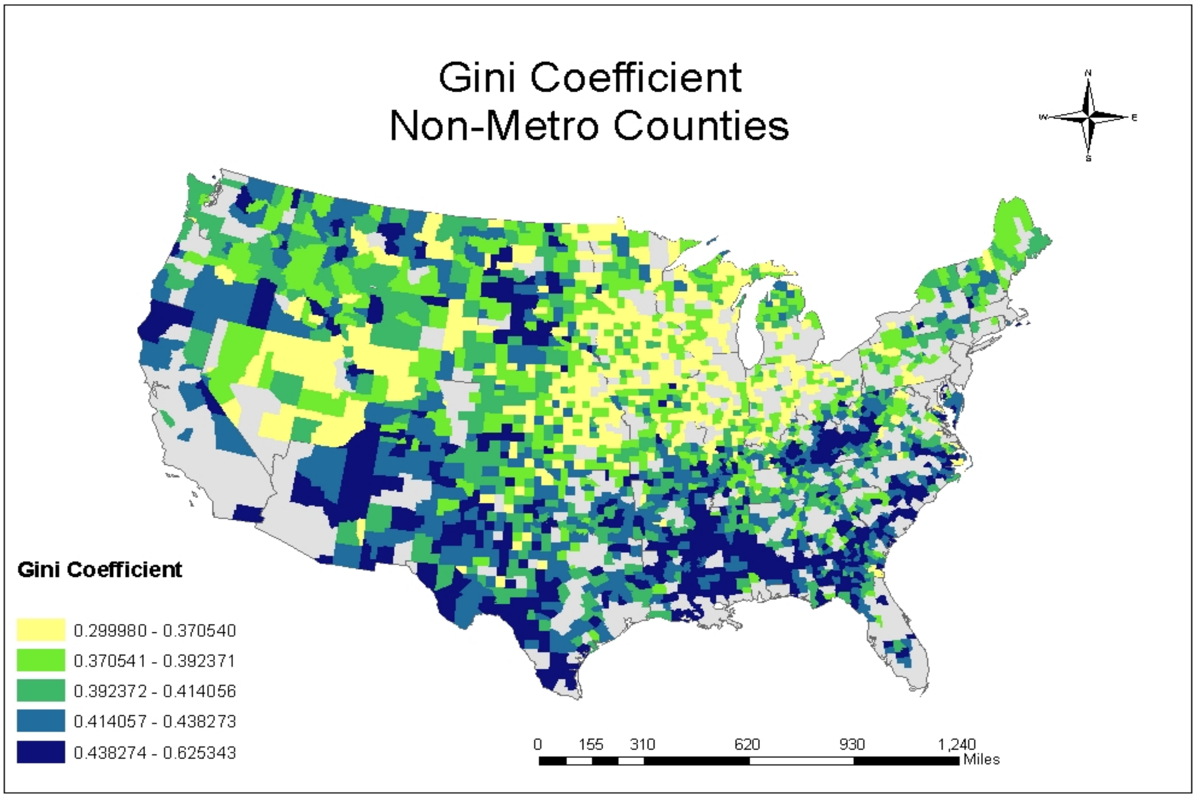
[21] Williams, Allan M. & Hall, C. Michael. *Tourism and Migration: New Relationships between Production and Consumption*. Tourism Geographies. Vol. 2, No. 1. 2000.

that both sustain the amenities that attract visitors and the community members who serve these visitors.

Appendix A

Map 1.



Map 2.

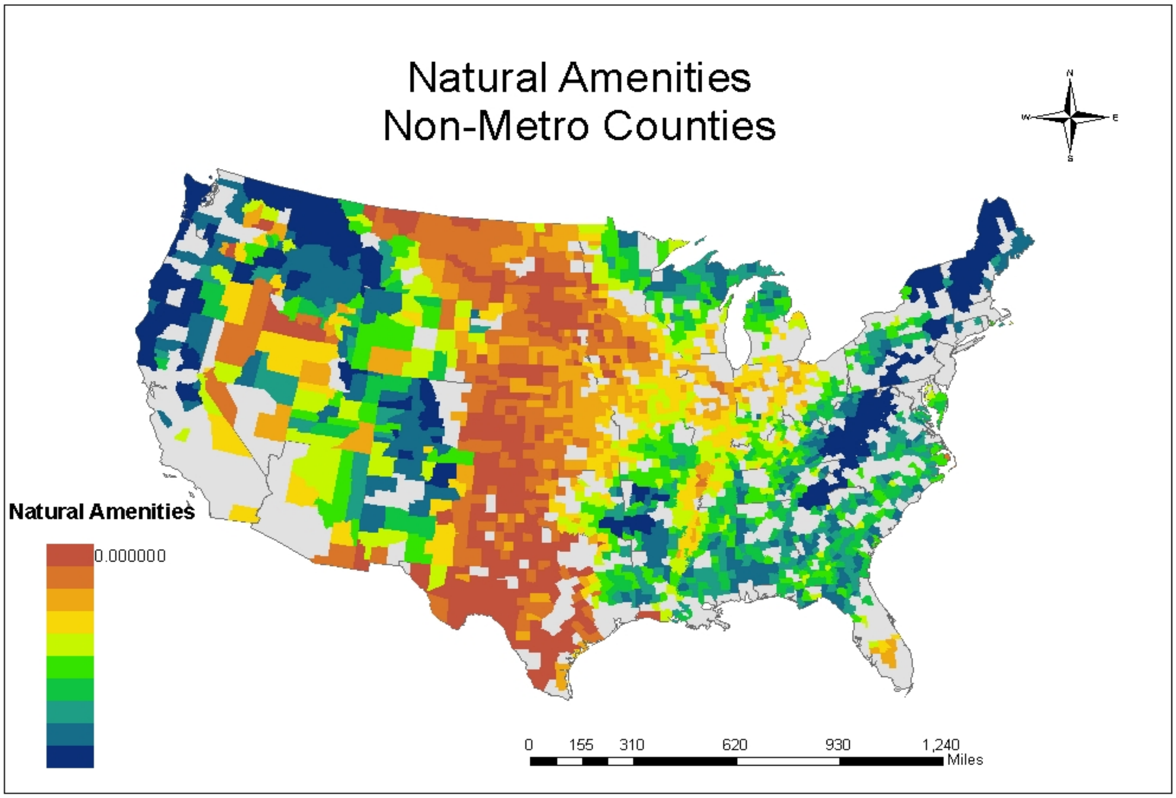
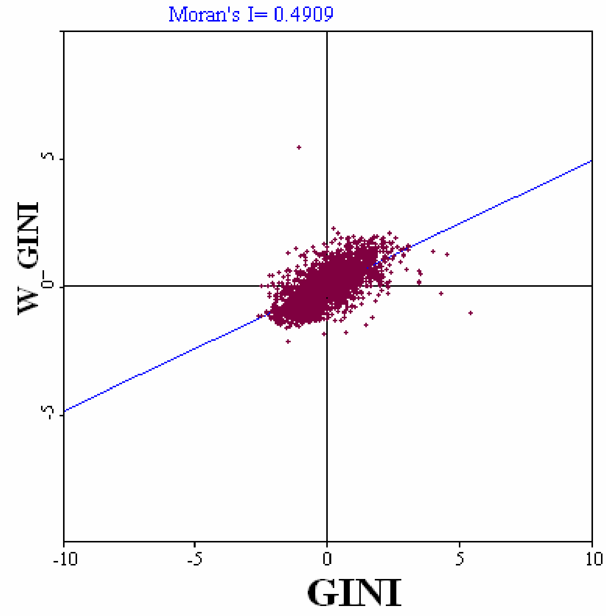

Natural Amenities
Non-Metro Counties
N
W
E
S
Natural Amenities
0.000000
0
155
310
620
930
1,240
Miles

Figure 1.



Map 3.

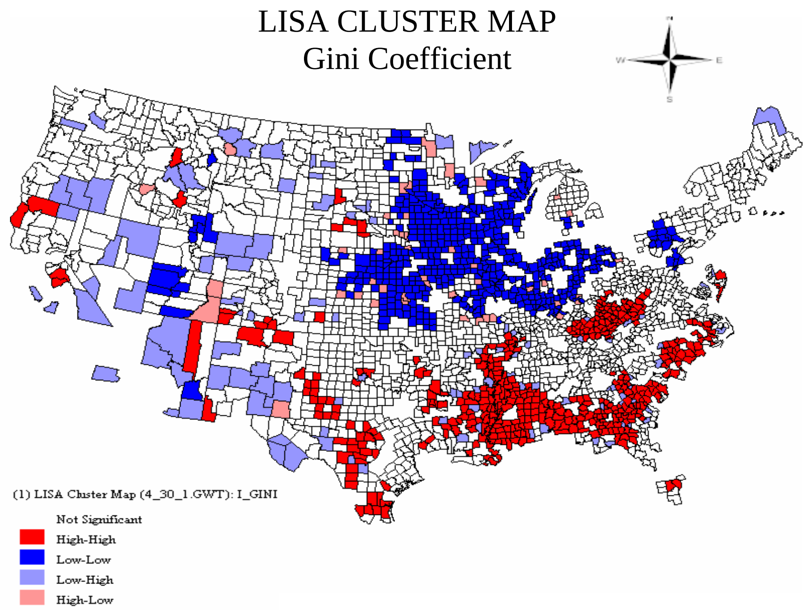
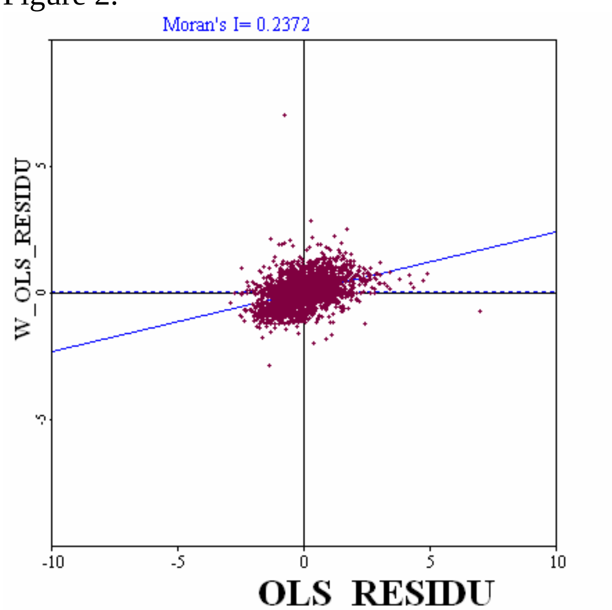


Figure 2.



Map 3a.

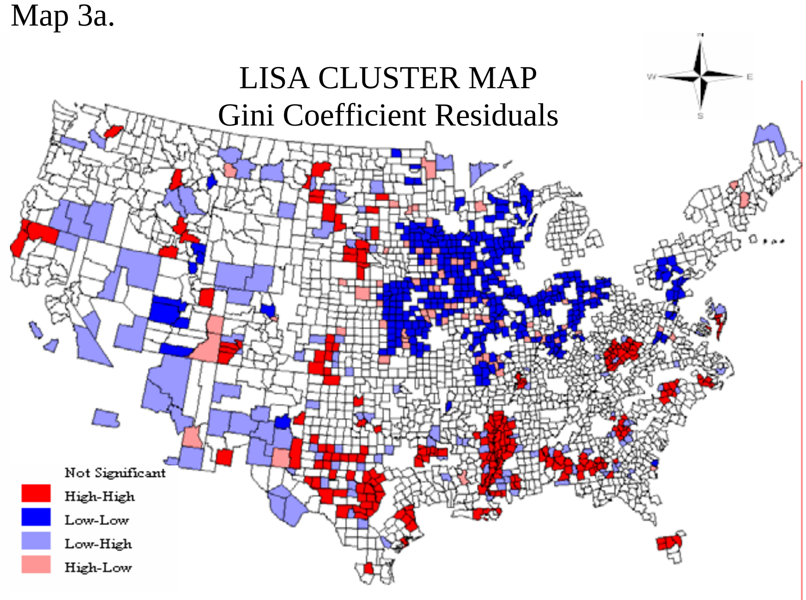
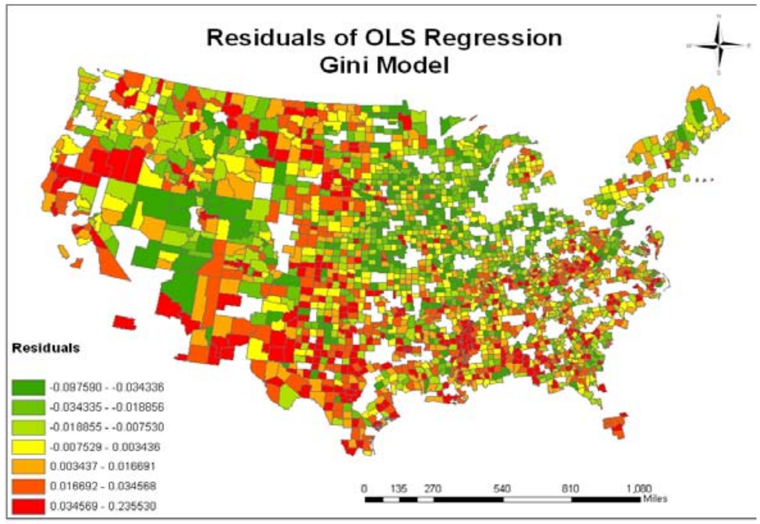


Table 1.

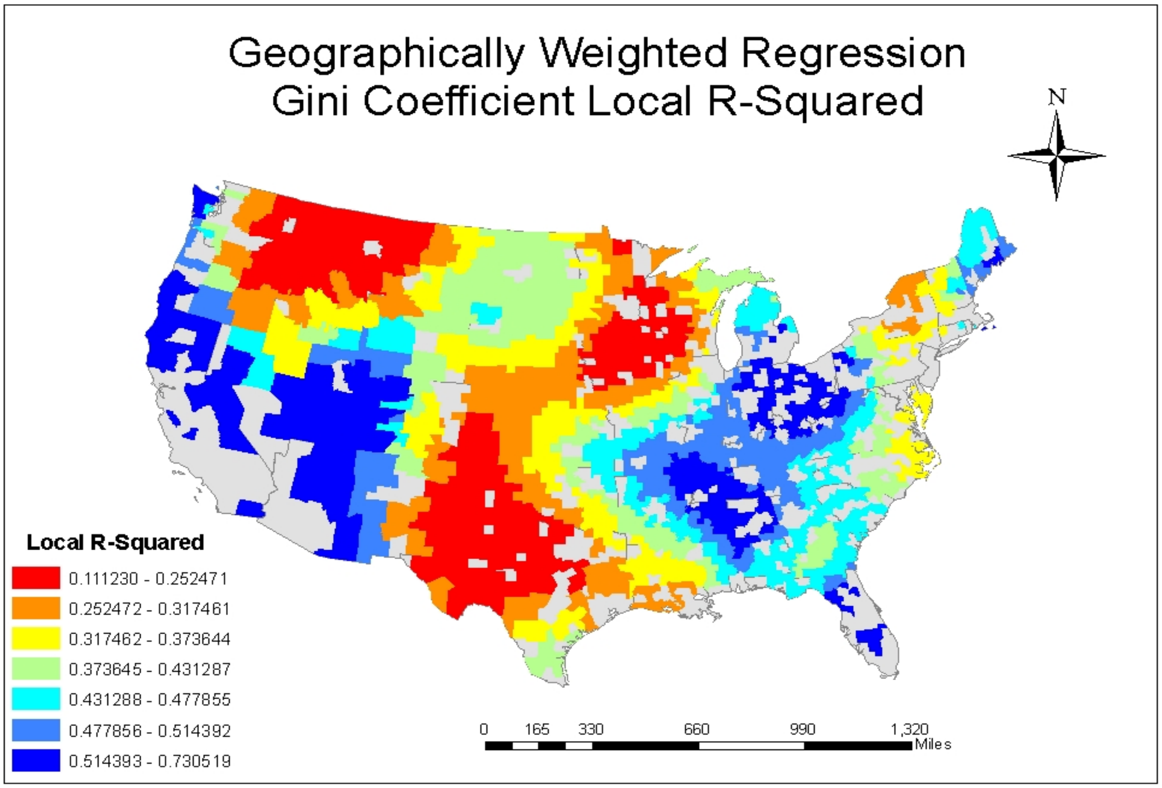
Gini	OLS
Constant	0.39610
Private Clubs**	0.00261
Rural Dummy*	-0.00106
Natural Amenities**	0.00002
Public Recreation**	-0.00169
Built Amenities**	0.00044
Tourism Jobs*	-0.04771
Hotel Jobs**	0.11318
Poverty**	0.04892
R-Squared	0.31514
Lagrange Multiplier	
Breusch-Pagan Test	70.17697

** p<.001, *p<.01

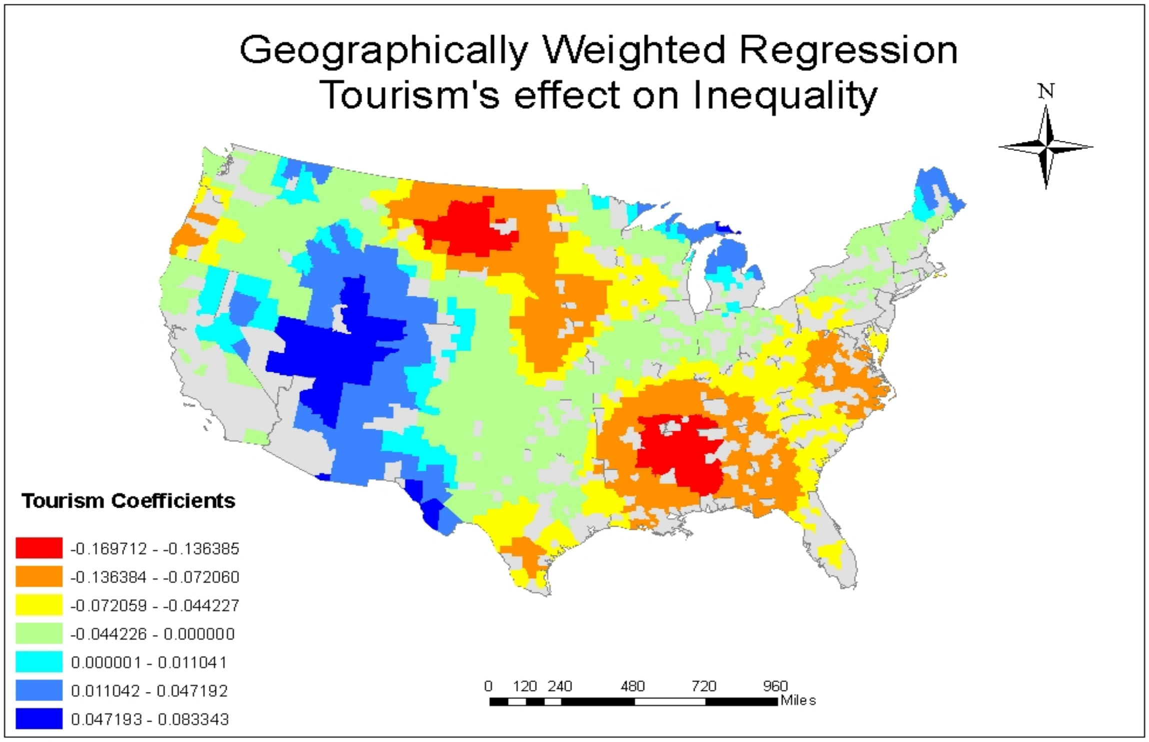
Map 4.



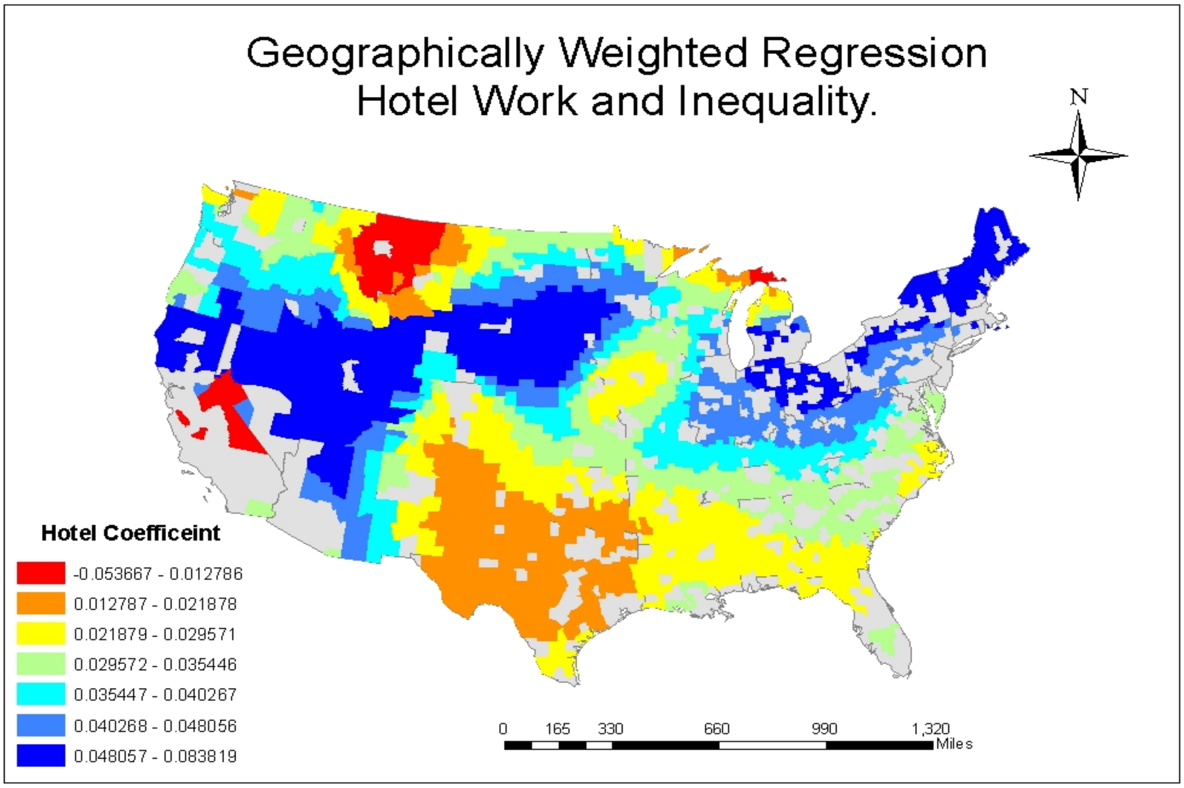
Map 5


Geographically Weighted Regression
Gini Coefficient Local R-Squared
N
Local R-Squared
0.111230 - 0.252471
0.252472 - 0.317461
0.317462 - 0.373644
0.373645 - 0.431287
0.431288 - 0.477855
0.477856 - 0.514392
0.514393 - 0.730519
0 165 330 660 990 1,320
Miles

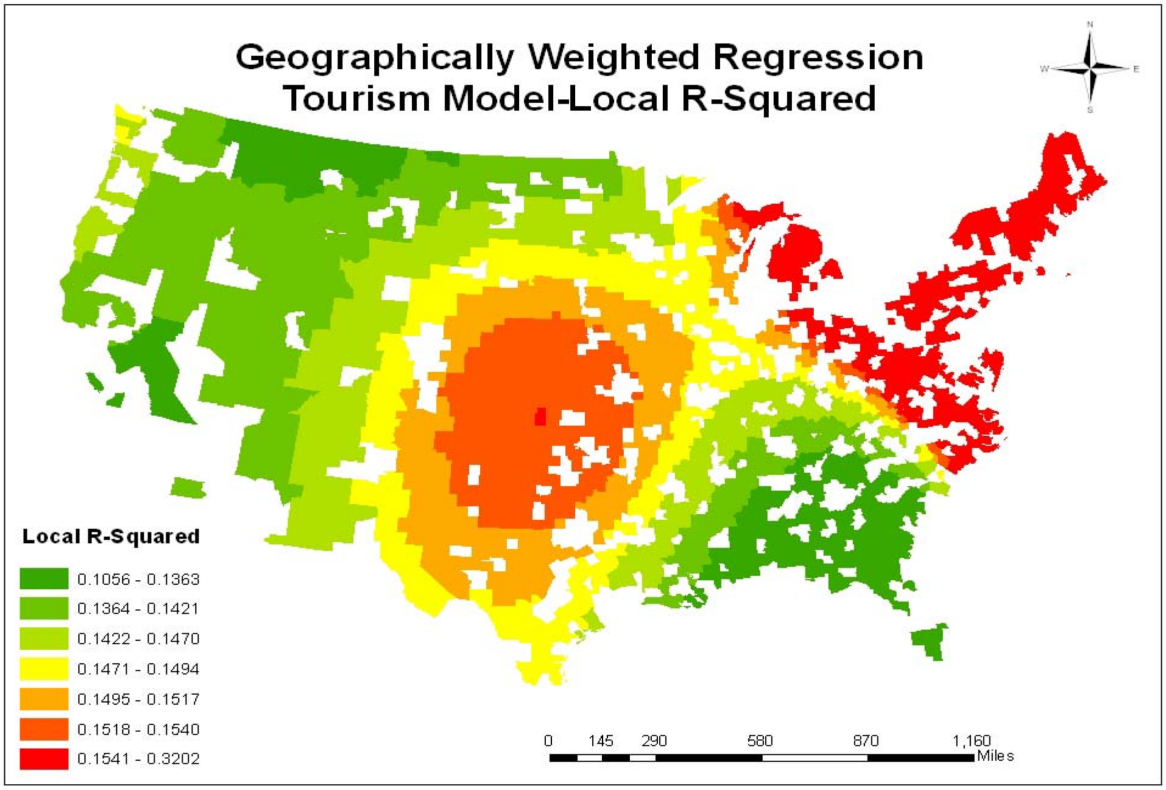
Map 6


Geographically Weighted Regression
Tourism's effect on Inequality
N
Tourism Coefficients
-0.169712 - -0.136385
-0.136384 - -0.072060
-0.072059 - -0.044227
-0.044226 - 0.000000
0.000001 - 0.011041
0.011042 - 0.047192
0.047193 - 0.083343
0 120 240 480 720 960
Miles

Map 7.

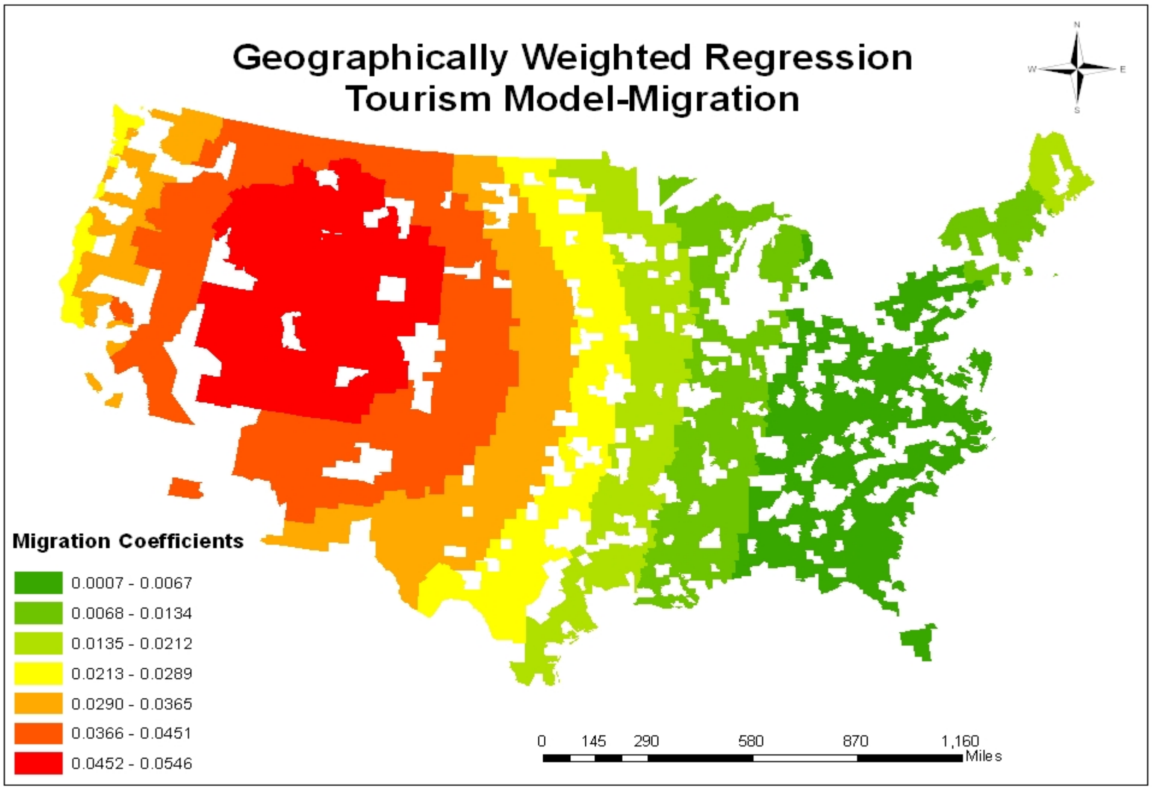

Geographically Weighted Regression
Hotel Work and Inequality.
N
Hotel Coefficeint
-0.053667 - 0.012786
0.012787 - 0.021878
0.021879 - 0.029571
0.029572 - 0.035446
0.035447 - 0.040267
0.040268 - 0.048056
0.048057 - 0.083819
0 165 330 660 990 1,320
Miles

Map 8.



Geographically Weighted Regression
Tourism Model-Local R-Squared
Local R-Squared
0.1056 - 0.1363
0.1364 - 0.1421
0.1422 - 0.1470
0.1471 - 0.1494
0.1495 - 0.1517
0.1518 - 0.1540
0.1541 - 0.3202
0 145 290 580 870 1,160
Miles

Map 9.


Geographically Weighted Regression
Tourism Model-Migration
N
W
E
S
Migration Coefficients
0.0007 - 0.0067
0.0068 - 0.0134
0.0135 - 0.0212
0.0213 - 0.0289
0.0290 - 0.0365
0.0366 - 0.0451
0.0452 - 0.0546
0 145 290 580 870 1,160
Miles

Appendix B

Path Analysis

Component Equations:

1.Public Amenities = a +B1 Natural Amenities + E

2.Build Amenities = a + B1 Natural Amenities + B2 Public Amenities +E

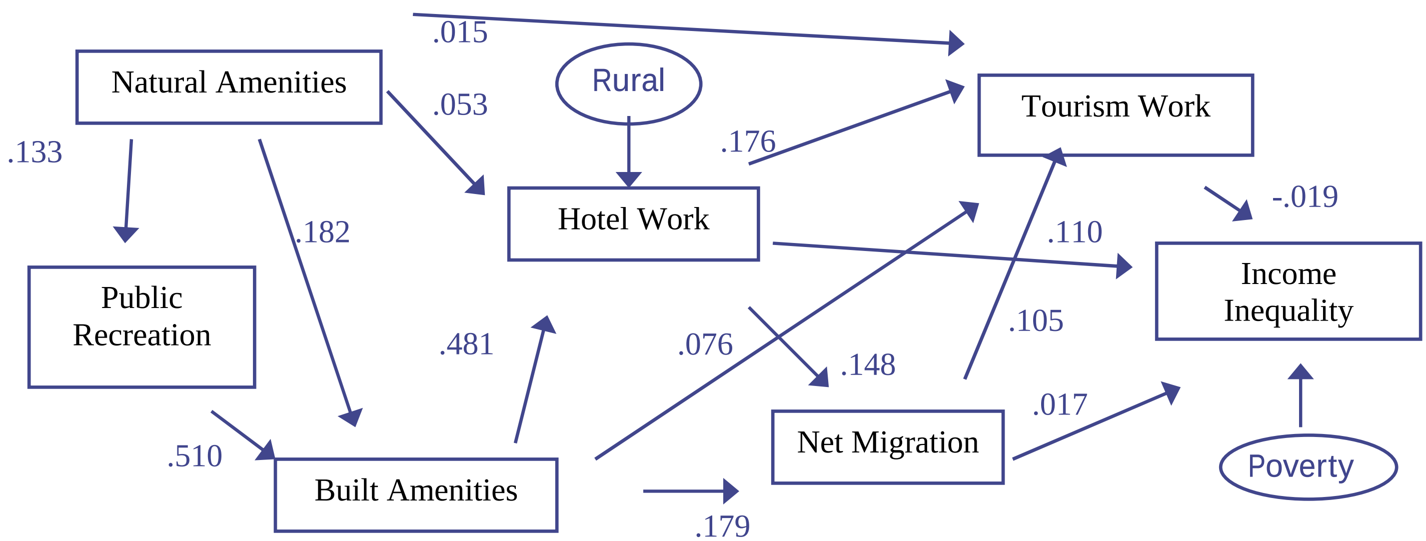
3.Hotel = a + B1 Natural Amenities + B2 Built Amenities + E

4.Net Migration = a + B1 Natural Amenities + B2 Built Amenities + B3 Hotel + E

5.Tourism = a + B1 Natural Amenities + B2 Built Amenities + B3 Hotel + B4 Net Migration

6.Inequality =a + B3 Hotel + B4 Net Migration + B5 Tourism

Path Diagram:



Appendix C.

Path Component Tables

Public Recreation	OLS	Spatial Lag	Spatial Error
Constant	2.24	1.28	2.58
Natural Amenities	0.00	0.45	0.00
R-Squared	0.02	0.18	0.19
Lagrange Multiplier		495.84	517.65
AIC	11388.30	11069.70	11053.40
Breusch-Pagan Test	103.11	87.99	91.29

Built Amenities	OLS	Spatial Lag	Spatial Error
Constant	-1.35	-1.75	-1.00
Public Recreation	2.06	1.91	2.07
Natural Amenities	0.01	0.01	0.01
R-Squared	0.35	0.39	0.41
Lagrange Multiplier		0.20	81.76
AIC	16511.10	16390.10	16351.60
Breusch-Pagan Test	2560.11	2.00	2496.32

Hotel Jobs	OLS	Spatial Lag	Spatial Error
Constant	-0.01791	-0.01609	-0.01485
Natural Amenities*L	0.00000	0.00000	0.00000
Built Amenities	0.00084	0.00076	0.00078
Rural Dummy	0.00272	0.00236	0.00235
R-Squared	0.23701	0.28509	0.28110
Lagrange Multiplier		23.341	4.711
AIC	-11768.7	-11885.6	-11871.7
Breusch-Pagan Test	6333.300	6681.600	7044.700

Net Migration	OLS	Spatial Lag	Spatial Error
Constant	0.003	0.567	0.010
Hotel Jobs	0.928	0.658	0.643
Natural Amenities	0.000	0.000	0.000
Built Amenities	0.002	0.001	0.001
R-Squared	0.155	0.406	0.408
Lagrange Multiplier		993.300	999.600
AIC	-3247.41	-3887.86	-3882.62
Breusch-Pagan Test	101.900	58.180	41.690

Tourism Jobs	OLS	Spatial Lag	Spatial Error
Constant	0.00235	0.00146	0.00275
Hotel Jobs	0.26068	0.00000	0.18731
Built Amenities*E	0.00020	0.00013	0.00000
Natural Amenities*OLE	0.00000	0.20843	0.00008
Net Migration	0.02482	0.02147	0.02500
Lambda/Rho		0.27901	0.26124
R-Squared	0.07693	0.11900	0.10700
Lagrange Multiplier		118.900	76.600
AIC	-9563.05	-9636.08	-9608.96
Breusch-Pagan Test	14628.410	9251.470	41.690

Gini Coefficient	OLS	Spatial Lag	Spatial Error
Constant	0.392	0.350	0.396
Poverty	0.051	0.046	0.031
Tourism Jobs	-0.026	-0.026	-0.008
Hotel Jobs	0.220	0.246	0.193
Net Migration	0.005	0.003	-0.003
R-Squared	0.278	0.306	0.427
Lagrange Multiplier		4.823	385.683
AIC	-8781.17	-8864.26	-9169.5
Breusch-Pagan Test	9.190	12.300	20.800

***p<.01**

Whole Model Table

Gini	OLS	Spatial Lag	Spatial Error
Constant	0.39866	0.36230	0.39776
Net Migration	0.01260	0.00237	-0.01066
Rural Dummy*	-0.00131	-0.00138	-0.00090
Natural Amenities**	0.00002	0.00002	0.00000
Public Recreation**	-0.00160	-0.00136	0.00028
Built Amenities**	0.00055	0.00050	0.00038
Tourism Jobs*	-0.04407	-0.04769	-0.01220
Hotel Jobs**	0.11269	0.13135	0.11741
Poverty**	0.04892	0.04528	0.03278
R-Squared	0.31501	0.33515	0.43782
Lambda/Rho		.0944**	0.5218336**
Lagrange Multiplier		5.34320	286.38800
AIC	-8899.97	-8955.47	-9225.08
Breusch-Pagan Test**	67.42830	47.13130	95.75506

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