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Global and local analysis of fragmentation in a mountain region of Colorado

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Abstract

Although relationships between fragmentation of urban development and other forms of administrative and land cover fragmentation are important, they are poorly understood. This research aimed to better understand these relationships in order to inform land use planning in the Roaring Fork/Colorado River Corridor of Colorado. Change in fragmentation of urban development between 1985 and 1999 was modeled as a function of other forms of administrative and land cover fragmentation using two different regression specifications. While a standard "global" regression provided a good averaged model of change for the entire study area, a geographically weighted regression (GWR) demonstrated how the process changed locally over space. Results of the global regression showed that the intercept was close to zero and therefore the fragmentation of urban development was expected to be close to zero in the absence of other forms of fragmentation. Results of the GWR showed that the relationships between change in fragmentation of urban development and other fragmentation variables (initial edge density of urban development, edge density of public/private interface, farmland density and road density) varied significantly within the study area. By modeling this variation, GWR helped to identify ways to reduce fragmentation of urban development in two different regions of the study area. The analysis suggested that fragmentation of urban development in one area, Aspen–Basalt, was more strongly driven by amenity-related variables, while in the New Castle area fragmentation was more strongly driven by infrastructure-related variables. Ultimately, local analysis may help fine-tune "one-size-fits-all" land use polices for specific regions.

Keywords: Land use change; Fragmentation; Geographically weighted regression; Land use planning

1. Introduction

The disciplines of landscape ecology and land use planning are both concerned with the connection between the spatial configuration of the landscape (form) and the processes that operate on the landscape (function). Despite this similarity, the disciplinary goals are often quite different. Landscape ecologists have typically attempted to quantify and understand landscape form and function, while land use planners have aimed to control form and function (Antrop, 2001). Furthermore, landscape ecologists traditionally have worked in "privileged" landscapes that were chosen for certain attributes such as the absence of built structures. In contrast, land use planners have often studied rapidly changing landscapes with an extensive and complex human footprint (Antrop, 2001). Increasingly, these two different perspectives are converging as landscape ecologists seek out work in human-dominated ecosystems and land use planners look for a better understanding of how the built environment interacts with ecosystems. In a broad sense, research at the nexus of these disciplines seeks to understand the link between form and function,

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Table 1
Environmental/social issues associated with fragmentation

Urban development	Regulatory	Ownership
Habitat fragmentation	Boundaries not appropriate for addressing environmental and social concerns	Conflict with public uses (wildlife, logging, recreation)
Sprawl	Conflicting regulations	Increased development pressure next to public lands
Decreased agricultural output	Annexation/tax base conflicts	Conflict between private land uses (e.g. residential with industrial or agricultural)
Invasive species	Development pressure in areas of weaker regulation	Land use plans harder to implement

both socioeconomic and biophysical, often at broader scales than traditional site-specific studies (Musacchio and Coulson, 2001; Klepeis and Turner, 2001; Grimm et al., 2000).

An important area of convergence between land use planning and landscape ecology is an emphasis on fragmentation, a measure of form that is associated with a number of environmental and social functions (Table 1). Fragmentary urban development, for example, may reduce the productivity of agricultural lands (Brabec and Smith, 2002); degrade, isolate, or shrink habitat patches (Olff and Ritchie, 2002); degrade the scenic beauty of open spaces; or encourage long, polluting commutes (Johnson, 2001). Because of these cross-cutting issues, both land use planners and landscape ecologists promote less fragmentary development patterns and encourage “infill”, the utilization of vacant land within partially developed areas (Calthorpe, 1993; Dramstad et al., 1997).

This study aimed to answer two questions related to fragmentation. First, how were different forms of landscape fragmentation—administrative and land cover—related to change in the fragmentation of urban development in the Roaring Fork/Colorado River corridor of Colorado from 1985 to 1999? Secondly, how can this information be used to identify ways to reduce fragmentation of urban development in two regions within the study area? To answer these questions, a traditional regression and a geographically weighted regression (GWR) were constructed to explain fragmentation of urban development. Traditional regression techniques, henceforth called global regression, produce an average result for the entire study area. In contrast, local analysis such as GWR produces localized output for every observation. The information provided by the global and local analyses ultimately can help tailor land use plans to specific regions to reduce fragmentation of urban development.

The dependent variable in these regression models was the change in edge density of urban development (*z_edge*), which measured fragmentation of urban development. This measure of landscape form provided important information about the function of urbanization; a positive change in *z_edge* indicated increasing fragmentation characteristic of sprawl while a negative change in *z_edge* indicated infill. *z_edge* was calculated as the total length of the boundary of urbanized land per unit area. Administrative and land cover fragmentation were suspected to influence *z_edge* by encouraging or limiting urban development. Fragmentation of administrative boundaries may affect *z_edge* through differential land use policy on either side of the boundary. For example, amenity-minded homeowners have increasingly moved to private lands neighboring undeveloped public lands in Colorado, thus increasing fragmentation (Knight and Clark, 1998). Similarly, the fragmentation of the municipal boundaries may influence *z_edge* through differential land use regulation or taxation on either side of the boundary (Bradshaw and Muller, 1998). Fragmentation of land cover in the form of infrastructure (road density), attractiveness (farm density), and physical constraints (initial edge density of urban development) may also shape *z_edge*. These land cover fragmentation variables are similar to other variables commonly used in land use models, such as distance to roads (Theobald and Hobbs, 1998) and initial land use (Landis and Zhang, 1998). In short, *z_edge* helps connect landscape form to urban function and is thought to be related to other types of administrative and land cover fragmentation.

This study makes three basic contributions. First, it furthers understanding of the relationship between landscape fragmentation and change in the edge density of urban development (*z_edge*) in this Colorado landscape. Secondly, it compares global and local regression approaches. Finally, the study provides a substantive policy interpretation of the spatially varying regression coefficients estimates generated by GWR. This interpretation is important because the literature on GWR has thus far focused on the development of the technique and has provided only a limited interpretation of model output (Brunsdon et al., 1996; Fotheringham and Brunsdon, 1999; Fotheringham et al., 1998). Ultimately, this study will show how global and local analysis can potentially help planners adjust land use plans for specific regions.

2. Background

Many studies use global models to better predict or understand the change in land use/land cover. These models take many forms, including spatially explicit non-economic models (e.g. cellular automata), non-spatially explicit economic models (e.g. bit-rent models) and spatially explicit economic models that address spatial dependence or spatial heterogeneity (e.g. spatial regression models) (Irwin and Geoghegan, 2001). In many cases, such models provide an incomplete understanding of landscape change. While global regression generates general "rules" between independent and dependent variables it does not indicate how these relationships may change locally.

Global models of land use change often employ commonly used logistic or ordinary least squares (OLSs) regression techniques (Schneider and Pontius, 2001; Serneels and Lambin, 2001; Theobald and Hobbs, 1998; Landis and Zhang, 1998; Bradshaw and Muller, 1998). However, two specification problems commonly appear in logistic and OLS regression models. First, errors are often spatially autocorrelated, which violates the assumption of independent observations. These violations are well documented (Anselin, 1988; Anselin and Bera, 1998) and will not be explicitly addressed in this study. Secondly, many spatial models display spatial heterogeneity, in which the fit of the model varies over space. This issue, also called spatial non-stationarity, may be caused by random sampling variations, true spatially varying relationships, or misspecification often from missing "unmeasurable" factors (Fotheringham et al., 2000). Spatial non-stationarity is common in typical global regression models such as the following:

$$Y_i = \alpha + \beta x_i + \varepsilon_i \tag{1}$$

where the intercept α and coefficient β are averages across the data set and ε_i is the error term for observation i. If spatial non-stationarity is present α and β may be locally biased, though the model could still produce the best linear unbiased estimate (BLUE) for the study area as a whole.

Several regression techniques address spatial non-stationarity, including global regression with dummy variables, multilevel modeling, the expansion method, and GWR. Though each method has its appropriate uses, only GWR can model continuous non-stationary processes and identify local "hot spots" of non-stationarity. The first method, global regression with dummy variables, addresses spatial non-stationarity by modeling variation within discrete boundaries (e.g. Serneels and Lambin, 2001). For example, if the process of land use change is known to operate differently within a county, a dummy variable may be used for observations within county. Second, a more sophisticated variation on this procedure is the multilevel model (Duncan and Jones, 2000; Gould et al., 1997). Multilevel models combine a "fixed" model of the aggregate process (the first two terms on the right side of the equation) and a "random" model describing contextual differences (the last two terms on the right side of the equation):

$$Y_{ij} = \alpha + \beta x_{ij} + u_{0j} + \varepsilon_{ij} \tag{2}$$

where i is an observation at place j and u_{0j} is a coefficient that describes contextual differences at place j. Dummy variables and the multilevel model framework are most appropriate for addressing spatial non-stationarity that occurs across discrete boundaries such as counties, municipalities and parcels.

Third, unlike simple dummy variables and multilevel models, the expansion method models parameter drift (change in regression coefficients over space) as functions of other variables, such as geographic location (Cassetti, 1972, 1997):

$$Y_i = \alpha_i + \beta_i x_i + \varepsilon_i \tag{3}$$

where coefficients α_i and β_i are a function of geographic location such that $\beta_i = \beta_0 + \beta_1 u_i + \beta_2 v_i$ and $\alpha_i = \alpha_0 + \alpha_1 u_i + \alpha_2 v_i$, for every location i with coordinates (u_i, v_i). Though useful as a tool to help improve model specification, the expansion method has limitations. For one, it fits trend surfaces—essentially creating a more sophisticated global model—and so reveals little about local relationships (Fotheringham et al., 1998). Furthermore, the functional form of the expansion equations must be assumed *a priori* by the researcher and must be deterministic to avoid estimation problems (Fotheringham et al., 2000). These issues are resolved with GWR.

The fourth method, GWR was used to explore the local relationships between landscape fragmentation and *z_edge*. GWR, like the expansion method, allows regression coefficients to vary continuously (Brunsdon et al., 1996; Fotheringham et al., 1998; Fotheringham and Brunsdon, 1999). Unlike the expansion method, however, GWR calculates coefficients for each variable at every observation. Thus GWR helps to identify "hot spots" of spatial non-stationarity that might otherwise be obscured by trend-fitting. For example, while the expansion method may show that a coefficient increases east to west, GWR will identify this trend as well as exceptions within the trend. The details of GWR will be described in Section 3.

3. Methodology

3.1. Study area

In the 1990s, an economic boom driven by tertiary industries drove rapid land use change in the Colorado Rockies, fragmenting land ownership and land cover at the wildland/urban interface (Riebsame et al., 1996). A prime example of such rapid change is the Roaring Fork/Colorado River corridor, which extends from Aspen to Parachute and includes Pitkin, Garfield, and a part of Eagle County. Along the corridor lie wetlands, significant open space (grassland, shrubland, cropland) and most of the counties' major settlements (Aspen, Carbondale, Glenwood Springs, Rifle). The area is forested at higher elevations.

To explain the change in edge density of urban development (*z_edge*) that Roaring Fork/Colorado River corridor experienced during 1985–1999, both a global regression and a GWR were conducted. The study area included 1130 km^2 of private lands within 3 km of Highways 287 and 70, from Aspen to the border of Garfield County (Fig. 1). This area encapsulated the most populous and dynamic part of the region, including the corridor and adjacent privately owned forestland. Since public lands typically have little urban development and are usually not under the jurisdiction of local planners, they were omitted from the analysis.

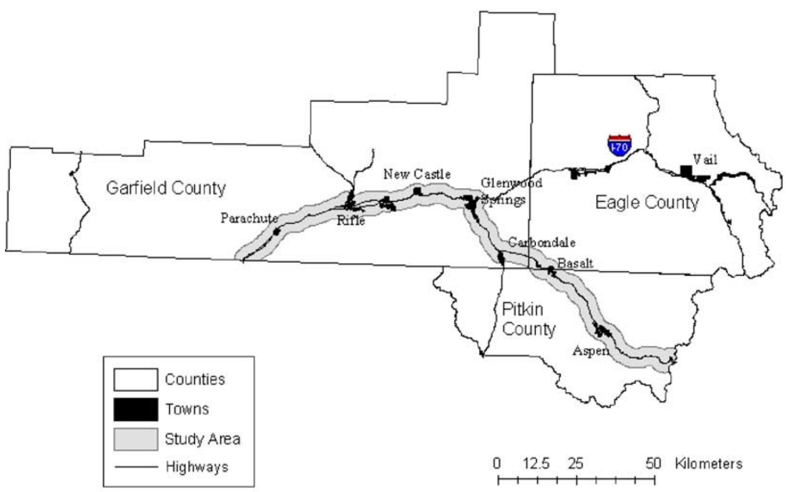

Fig. 1. Roaring Fork/Colorado River Corridor.

Table 2
Variables used in regression models

Variable	Description	Source	Suspected relationship with *z_edge*
z_edge	Change in edge density of urban development between 1985 and 1999	Classified imagery	
dev_dens	Edge density of urban development in 1985	Classified imagery	Negative
own_dens	Edge density of public/private interface	US Geological Survey	Positive
city_dens	Edge density of municipal boundaries	Colorado Department of Local Affairs	Positive
citydev	*dev_dens* × *city_dens*	Interaction variable	Negative
farm_dens	Percentage land cover defined as agricultural in 1992	National land cover data set	Positive
road_dens	Density of highways and major roads	Colorado Department of Transportation	Negative

The effects of public lands, however, were included in the model as an independent variable "edge density of public/private interface" (*own_dens*), as described below.

3.2. Model variables

The analysis was conducted on a random sample comprising 1432 observations across the study area. The two models estimated the dependent variable *z_edge* as a function of the independent variables described in Table 2. These independent variables fell into three categories: fragmentation of administration (*own_dens*, *city_dens*), fragmentation of land cover (*dev_dens*, *farm_dens*, *road_dens*) and an interaction variable (*citydev*). The fragmentation variables were calculated as edge length per unit area of a circle with 0.3 km radius. Edge lengths were derived from several data sources, including publicly available state/county GIS data and classified Landsat imagery.

The classified Landsat imagery was created for Environmental Defense by the Center for the Study of Earth from Space (CSES) at the University of Colorado. A maximum likelihood classifier with a threshold of 55% was used to classify images from 1985 to 1999 (both Landsat path-row 35/32) into developed and non-developed areas (The Sprawl Site, 2002). A majority fitting algorithm and hand-editing were used to clean up misclassified areas. The classification was estimated to be 70% accurate, based on an assessment of a nearby Landsat image classified with the same procedures (The Sprawl Site, 2002).

Several expected relationships guided the selection of variables (Table 2). It was suspected that *dev_dens*, *road_dens* and *citydev* were negatively related to the dependent variable *z_edge*. In other words, everything else equal, it was thought that an environment that started out highly fragmented—in terms of development footprint, road network or the interaction of development footprint and municipal fragmentation—was likely to experience decreased fragmentation of urban development as structures filled out the developable land. This type of environment would tend to have appropriate infrastructure and be suitable for additional high density infill. Conversely, an environment that started out less fragmented in terms of these variables would likely become more fragmented or show little change if it experienced low-density development. Several other variables, including *own_dens*, *city_dens* and *farm_dens* were thought to be positively related to *z_edge*. In other words, areas with a highly fragmented public/private land interface, highly fragmented municipal boundaries or a high density of farmland would likely experience increased fragmentation of urban development. Places with these characteristics were thought to be desirable for their rural character, suitability, and availability. Conversely, an environment that started out less fragmented in terms of these variables would likely become less fragmented, or show little change.

3.3. Procedures

Two models were constructed for this study: a global regression and a GWR. Before constructing the models, the selected variables were tested for evidence of multicollinearity. A matrix of correlation coefficients (Table 3) suggested that *city_dens* and *citydev* displayed moderate multicollinearity, defined as a coefficient between 0.75 and 0.9. However, the inclusion of these related variables improved the fit and did not influence hypothesis testing or change the

Table 3
Correlation coefficients of independent variables

	dev_dens	*own_dens*	*city_dens*	*citydev*	*farm_dens*	*road_dens*
dev_dens	1	−0.106	0.549	0.73	−0.01	0.688
own_dens	−0.106	1	−0.07	−0.071	−0.338	−0.147
city_dens	0.549	−0.07	1	0.804	0.057	0.511
citydev	0.73	−0.071	0.804	1	0.025	0.575
farm_dens	−0.01	−0.338	0.057	0.025	1	0.094
road_dens	0.688	−0.147	0.511	0.575	0.094	1

signs of the coefficients. Ultimately, multicollinearity was not deemed a major problem in this model.

After checking the relationships between independent variables, a global OLSs regression was run and the residuals were tested for normality and heteroskedasticity. A histogram showed that the residuals displayed kurtosis and were skewed to the right but were close to normally distributed. A Cook–Weisberg test revealed significant heteroskedasticity in the residuals ($\chi^2 = 7565.2$, Prob. $> \chi^2 = 0.0000$). To reduce heteroskedasticity, weighted least squares (WLS) was employed with a robust MM estimator (Huber, 1981). The weights were the squared residuals predicted by an OLS regression based on the independent variables. Relative to the OLS regression, robust WLS had a better fit and was not sensitive to heteroskedasticity.

A GWR was then performed with the same variables as the global regression. GWR generates separate regression coefficients for every observation:

$$Y_i = \alpha(u_i, v_i) + \beta(u_i, v_i)x_i + \varepsilon_i \tag{4}$$

where (u_i, v_i) are the coordinates of point i. Though GWR is fairly straightforward, it requires the choice of a weighting function and bandwidth. Both will influence the results of the estimation procedure used by GWR, which is defined as follows:

$$\alpha(u_i, v_i) = (x^t w(u_i, v_i)x)^{-1}x^t w(u_i, v_i)y \tag{5}$$

where x is a matrix of independent observations, y is a matrix of dependent observations and $w(u_i, v_i)$ is an $n \times n$ weights matrix (n is the number of observations) with zeros on the off-diagonal and weights on the diagonal. Note that there is a separate weights matrix for every observation i. In this study, the weights were generated from the distance decay function:

$$w_j = \exp\left(-\frac{d_j}{h^2}\right) \tag{6}$$

where d is the distance between observations i and j, and h the bandwidth beyond which the weights are zero. The bandwidth was determined to be significant out to 28 km by a cross-validation technique (Cleveland, 1979). The cross-validation technique minimizes the score:

$$\sum_{i=1,n} [y_i - y_i(h)]^2 \tag{7}$$

where $y_i(h)$ is the predicted value of y_i using bandwidth h, excluding the observation for point i. This essentially finds the distance out to which, on average, observations continue to provide information about observation i.

The GWR procedure was conducted in two parts. First, a GWR was run to calculate spatially varying regression coefficients for each variable. Secondly, a Monte Carlo simulation using GWR determined which of these variables displayed significant spatial non-stationarity. The simulation tested whether the sampling distribution of the standard deviation of a given coefficient could occur by chance if the data points were randomly shuffled around the study area 1000 times (Fotheringham et al., 1998). The standard deviation of a coefficient is an estimate of the *variation* of that coefficient—in this context it helped determine whether coefficients demonstrate significant spatial variation.

4. Results

4.1. Global regression

The global regression was significant with an R^2 of 0.64; approximately 64% of the change in edge density of urban development (*z_edge*) could be explained by the independent variables. The coefficients confirmed

Table 4
Global[a] regression model of change in edge density of development ($n = 1432$)

	Beta coefficient	Standard error	t	P-value
Constant	0.0009	0.0002	5.78	0.000
dev_dens	−0.1076	0.0181	−5.94	0.000
own_dens	0.6545	0.1160	5.64	0.000
city_dens	1.3033	0.0984	13.24	0.000
citydev	−138.8260	10.2774	−13.51	0.000
farm_dens	0.0016	0.0004	4.34	0.000
road_dens	−0.5978	0.0302	−19.81	0.000

[a] Average regression output for the entire study area.

the expected signs of the relationship between dependent and independent variables (Table 4).

4.2. Geographically weighted regression

The Monte Carlo simulation tested each variable for spatial non-stationarity (Table 5). It showed that *dev_dens*, *own_dens*, *farm_dens* and *road_dens* were significantly spatially non-stationary at $P < 0.01$, while the interept and *citydev* were significantly spatially non-stationary at $P < 0.05$. The Monte Carlo simulation also showed that *city_dens* did not display significant spatial non-stationarity.

Table 5
Results of Monte Carlo test for spatial non-stationarity[a] ($n = 1432$)

	Si	P-value
Constant	0	0.011*
dev_dens	0.0791	0.000**
own_dens	0.0544	0.000**
city_dens	0.0567	0.210
citydev	14.4139	0.035*
farm_dens	0.0003	0.000**
road_dens	0.1931	0.000**

[a] Tests if regression coefficients change over space in a way that is unlikely to occur at random.
* Significant at $P < 0.05$.
** Significant at $P < 0.01$.

The regression coefficients of the four variables that were significantly non-stationary at $P < 0.01$ were then mapped. The first map shows that the negative relationship between *dev_dens* and *z_edge* was strongest between New Castle and Glenwood Springs. East to Aspen, the relationship weakened and approached the mean (Fig. 2). West to Parachute, the relationship progressively weakened and reached its lowest point.

The second map shows that the positive relationship between *own_dens* and *z_edge* was strongest around Aspen and progressively weaker to the west until New

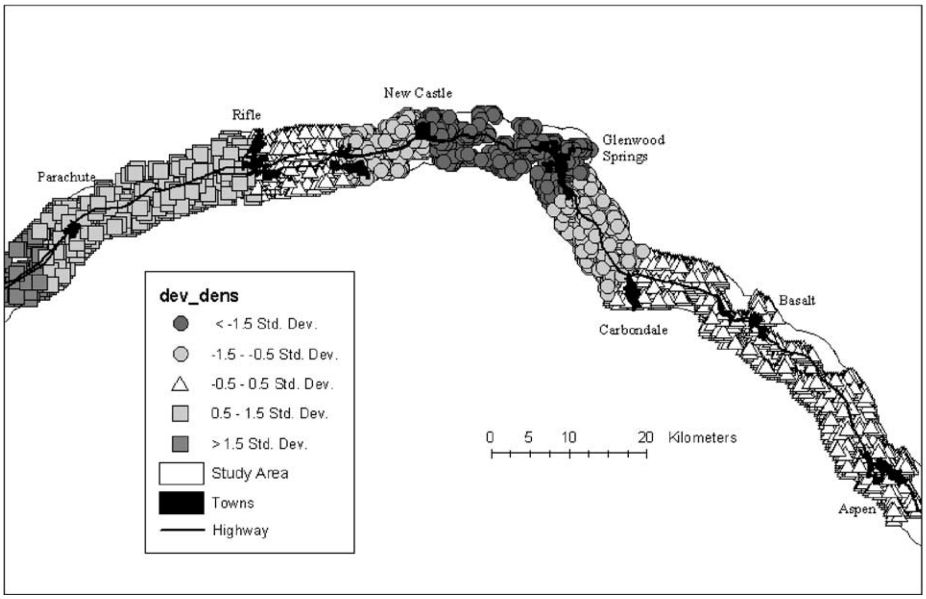

Fig. 2. Spatially varying regression coefficients for *dev_dens* generated by GWR, shown in standard deviations from the mean regression coefficient.

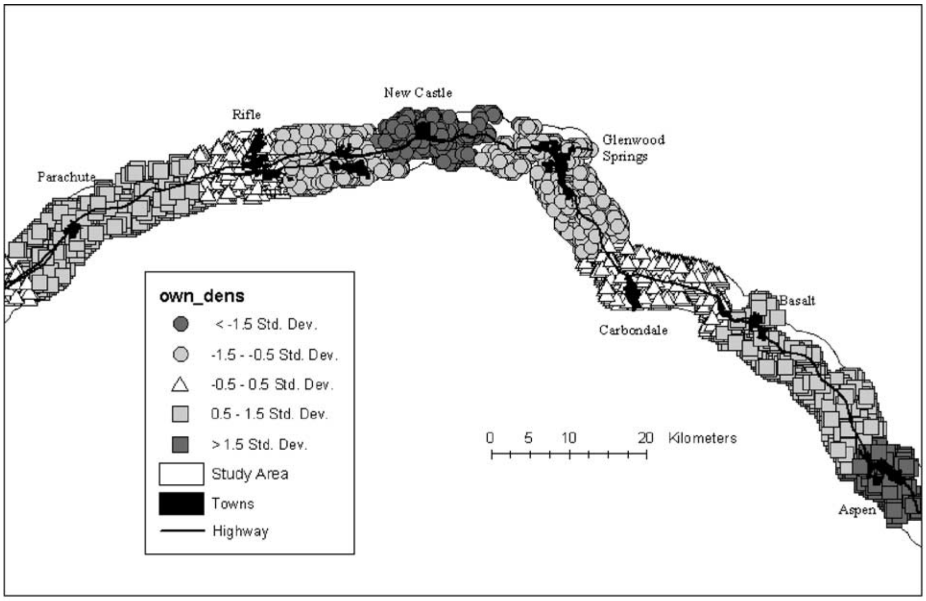

Fig. 3. Spatially varying regression coefficients for *own_dens* generated by GWR, shown in standard deviations from the mean regression coefficient.

Castle (Fig. 3). West from New Castle, the relationship strengthened again until the Parachute area.

The third map shows that the positive relationship between *farm_dens* and *z_edge* was strongest between Rifle and New Castle and weakened along the Aspen–Glenwood Springs corridor (Fig. 4). West from New Castle, the relationship weakened and then approached the mean near Parachute.

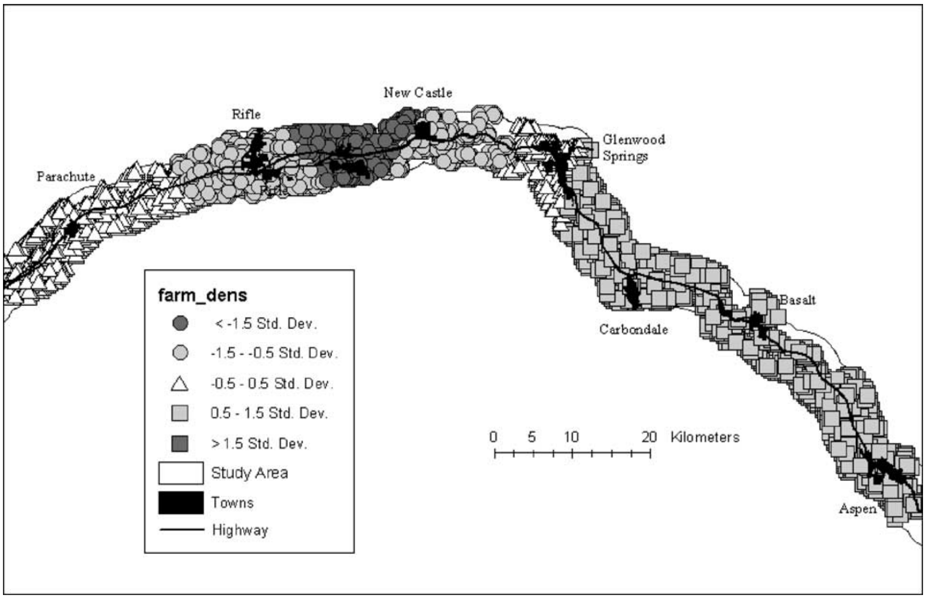

Fig. 4. Spatially varying regression coefficients for *farm_dens* generated by GWR, shown in standard deviations from the mean regression coefficient.

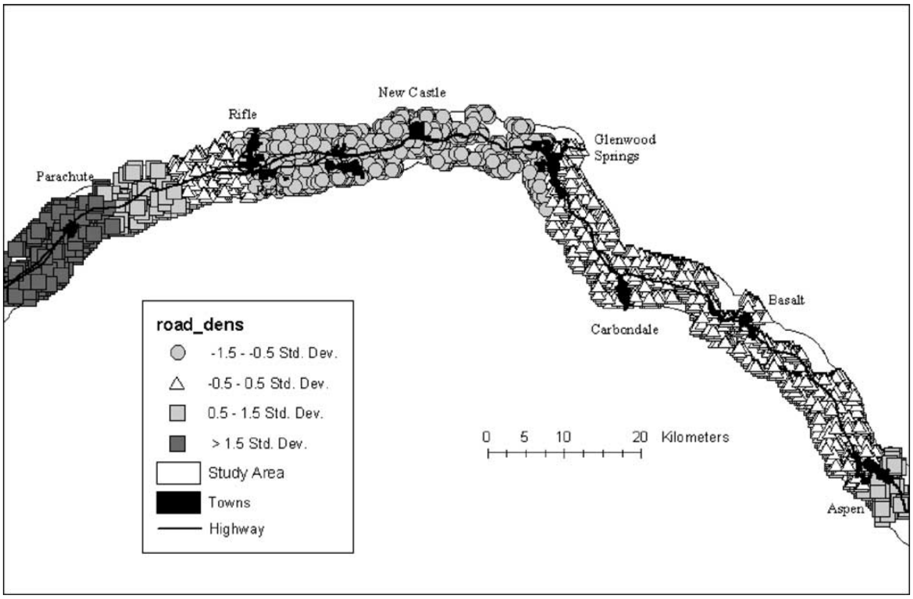

Fig. 5. Spatially varying regression coefficients for *road_dens* generated by GWR, shown in standard deviations from the mean regression coefficient.

Finally, the fourth map shows that the negative relationship between *road_dens* and *z_edge* was strongest between Rifle and Glenwood Springs (Fig. 5). East from Glenwood Springs, the relationship remained close to the mean until weakening east of Aspen. West from Rifle, the relationship weakened and reached its lowest point near Parachute.

The mapped parameter drift shown above provides information that can potentially be used to guide land use policy for reducing fragmentation of urban development in two regions within the study site.

5. Discussion

5.1. Global analysis

The global regression revealed that, on average, the suspected relationships were true. In areas that had dense road networks or high initial edge density of urban development, *z_edge* decreased as infill occurred. In areas with highly fragmented administrative boundaries or high density of farmland, *z_edge* tended to increase. Three specific results of the global regression would be of interest to planners. First, the intercept was close to zero, indicating that if all other forms of fragmentation are zero, *z_edge* would be expected to be close to zero. A planner may use this important finding as general evidence that a change in fragmentation of urban development does not come out of nowhere—it is typically associated with other forms of fragmentation.

Secondly, the global regression confirmed that *city_dens* was positively related to *z_edge*, suggesting that areas on or near fragmented municipal boundaries also increased in development edge density 1985–1999. One explanation for this relationship may be that land near municipal boundaries is simply more plentiful. An additional factor may be differential taxation or other land use regulation which encourages development near municipal boundaries. If this second explanation is true, it suggests that when municipalities grow they should annex adjacent land rather than create “flagpole annexations”, which increase the edge density of municipal boundaries (*city_dens*) over a wider area. In 2001, House Bill 1001 in Colorado restricted flagpole annexations, so it is possible that this relationship may change in coming years (American Planning Association, 2002).

Finally, the global regression confirmed that *city-dev*, which describes the interaction of *city_dens* and *dev_dens*, was negatively related to *z_edge*. Areas that were highly fragmented both in terms of municipal boundaries and in terms of existing development were associated with a decrease in fragmentation of urban development. Though difficult to interpret, this result suggests that the sprawling areas at the edge of municipalities experienced infill during this time period. Overall, planners may use these global results to inform land use policy, supplemented by the following local analysis.

5.2. Local analysis: a comparison of two regions

While the global analysis reveals general trends across the entire study area, it obscures the local variations these relationships. The local analysis provides information that may help develop more effective plans for reducing fragmentation of urban development in two areas: the Aspen–Basalt Corridor and the area surrounding New Castle. A land use policy tailored to these two regions could be more effective than a "one-size-fits-all" policy.

In the Aspen–Basalt region, several local relationships showed that change in *z_edge* was driven to a greater extent by amenity-related fragmentation variables. For example, the relationship between *own_dens* and *z_edge* was strongest in Aspen–Basalt (Fig. 3), indicating that fragmentation of public–private boundaries was associated with an increase in the edge density of urban development. The strength of this relationship in Aspen–Basalt may be explained by preferences: in wealthy Aspen, people often seek large, private houses adjacent to public lands. Unfortunately, this trend threatens wildlife habitat and potentially reduces access to public lands. To minimize the conflict between public and private lands, land use planners should consider several policies. First, private land could be swapped for public land to reduce accessible inholdings and simplify the public/private interface. Secondly, counties could restrict subdivisions in unincorporated areas in order to lessen conflicts with public land.

The local analysis also showed that the relationship between *farm_dens* and *z_edge* was stronger in Aspen–Basalt and up to Glenwood Springs (Fig. 4). Though Pitkin County has actively purchased open space and engaged in restrictive zoning practices, low-density fragmented urban development has proliferated in former agricultural areas. To address this problem, the counties in the region could set very high standards for subdivisions in unincorporated areas and set financial and regulatory incentives for high density and cluster development. Though the state has little control on developments on parcels over 14.16 ha, there is precedent for attaching conditions to subdivisions with parcels smaller than 14.16 ha in unincorporated areas. For example, Spring Valley, a 2428 ha ranch near Carbondale slated for development, changed its plan to include affordable units and a 1619 ha conservation easement (Lutz, 2000). Similar provisions could require less fragmentary development and preserve open space in the remaining agricultural lands of the area.

In the region near New Castle, local analysis revealed that *z_edge* was driven to a greater extent by accessibility and infrastructure-related variables. *Own_dens* and *farm_dens* had weaker relationships with *z_edge* in this area compared with Aspen–Basalt (Fig. 3). At the same time, *road_dens* and *dev_dens* had stronger relationships with *z_edge* (Figs. 2 and 5). The strong negative relationships between *dev_dens* and *z_edge* indicates that areas with high initial fragmentation of urban development experienced infill. Similarly, the strong negative relationship between *road_dens* and *z_edge* suggested that areas with high road density experienced infill. These relationships indicate that fragmentation of urban development around New Castle was less associated with open space, such as farmland and public lands, than in Aspen–Basalt. Instead, *z_edge* was more strongly associated with the existing road network and initial development pattern. This difference may have resulted from local economics, preferences and zoning practices. Compared to Aspen–Basalt, a greater percentage of residents in New Castle work in the service industry or in traditional industries. The New Castle area also has fewer second homes than Aspen–Basalt. Thus "amenity-related" land covers would be comparatively less of a draw than accessible small-lot housing. The results of the local analysis suggested that around New Castle planners could use road placement and potentially other infrastructure, where it is publicly funded, to guide development and promote infill.

5.3. Limitations

The methods used in this analysis provide a potentially important land use planning tool, but have two drawbacks: the failure for the models to account for spatial autocorrelation and the difficulty of interpreting spatially varying regression coefficients. First, neither standard global regression nor standard GWR account for spatial autocorrelation in model residuals. A test of Moran's I indicated that the residuals of the global regression displayed significant positive spatial autocorrelation out to 1.5 km. The residuals produced by the GWR most likely displayed a similar degree of spatial autocorrelation. In both models, this may have resulted in false hypothesis testing (more Type II errors) or in overstated fit. Several global regression models have been developed that address spatial autocorrelation (Anselin, 1988) but were not used here to maintain comparability with GWR. Emerging methods promise to fully address spatial autocorrelation within a GWR framework (Páez et al., 2002; Brunsdon et al., 1998).

Secondly, interpreting spatially varying regression coefficients is region-specific and often not straightforward. For example, a GWR may indicate that a coefficient changes significantly over space, but this change may or not be important for the ecology or planning of a specific area. Because of these difficulties, local analysis is best used to supplement other planning data rather than as a basis for policy.

6. Conclusion

In global change research there is often a trade-off between oversimplified coarse-scale studies and narrow case studies. Global and local analyses in tandem may provide the benefits of both: global analysis reveals broad trends while local analysis shows the deviation from these trends. A perfect candidate for such analyses is land use/land cover change, which is often driven by coarse-scale processes but amplified or mitigated by local factors (Lambin et al., 2001). This study is an example of such an application; the global analysis provided a "coarse filter" that can help guide general land use policy, while local analysis revealed contextual relationships that help fine-tune land use policy.

This research used global and local analysis, based on land use planning and landscape ecology theory, to inform policymaking. A unifying concept was fragmentation, a measure of form that can be connected to the function of urban development. In this Colorado landscape, global regression showed that fragmentation begets fragmentation; when fragmentation in administration and land cover variables was zero, the change in fragmentation of urban development was expected to be zero as well. A local analysis revealed that several of the relationships between administrative and land cover fragmentation and the change in edge density of urban development (*z_edge*) were significantly spatially non-stationary. By mapping how these relationships varied locally, the analysis helped identify ways in which two regions can attempt to reduce fragmentation of urban development. In the case of Aspen–Basalt, land use planners could aim to reduce conflicts between public and private lands, and between residential lands and farmland. In New Castle, planners could emphasize the use of infrastructure such as roads to help guide development. A final caveat is that this analysis should not be a basis for decision making on its own, but should supplement other planning data.

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