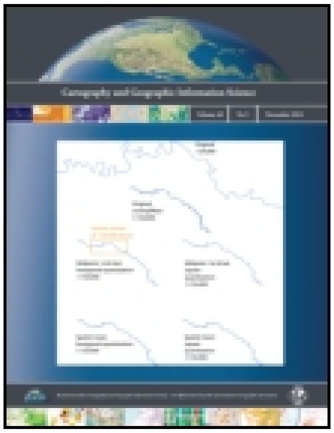

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Spatial eigenvector filtering for spatiotemporal crime mapping and spatial crime analysis

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Spatial and spatiotemporal analyses are exceedingly relevant to determine criminogenic factors. The estimation of Poisson and negative binomial models (NBM) is complicated by spatial autocorrelation. Therefore, first, eigenvector spatial filtering (ESF) is introduced as a method for spatiotemporal mapping to uncover time-invariant crime patterns. Second, it is demonstrated how ESF is effectively used in criminology to invalidate model misspecification, i.e., residual spatial autocorrelation, using a nonviolent crime dataset for the metropolitan area of Houston, Texas, over the period 2005–2010. The results suggest that local and regional geography significantly contributes to the explanation of crime patterns. Furthermore, common space-time eigenvectors selected on an annual basis indicate striking spatiotemporal patterns persisting over time. The findings about the driving forces behind Houston's crime show that linear and nonlinear, spatially filtered, NBMs successfully absorb latent autocorrelation and, therefore, prevent parameter estimation bias. The consideration of a spatial filter also increases the explanatory power of the regressions. It is concluded that ESF can be highly recommended for the integration in spatial and spatiotemporal modeling toolboxes of law enforcement agencies.

Keywords: spatial filtering; spatial autocorrelation; spatiotemporal crime mapping; Poisson regression; negative binomial regression; generalized additive model

Introduction

In times of scarce monetary resources for policing and safety, as well as fiscal constraints, crime surveillance and prevention has gained significant importance and emerges as an intrinsic research topic (Kollias, Mylonidis, and Paleologouc 2013). A solid theoretical background about the spatial and temporal dimension of crime exists (e.g., Chainey and Ratcliffe 2005; Rey, Mack, and Koschinsky 2012; Leitner 2013), including such well-known theories as routine activities (Cohen and Felson 1979), rational choice (Clarke and Cornish 1985), and geometry of crime (Brantingham and Brantingham 1981) and support the understanding of crime mechanisms, which is a crucial initial step toward crime reduction (Andresen 2006; Short et al. 2010). However, just like data mining (e.g., Helbich, Hagenauer, et al. 2013) and geographic profiling techniques (e.g., Mburu and Helbich Forthcoming), statistical modeling of crime remains challenging. Thereby, regression models are of utmost importance to law enforcement agencies and academic researchers alike (e.g., Osgood 2000). These models support the understanding of underlying spatial and social processes affecting the presence or absence of crime. Offenses are an inherently spatially and spatiotemporally occurring phenomenon (Ratcliffe 2011) and do not spread evenly across space; they tend to cluster in certain neighborhoods and residential areas (e.g., Messner et al. 1999; Sampson, Morenoff, and Gannon-Rowley 2002; Townsley 2009; Hagenauer, Helbich, and Leitner 2011; Helbich and Leitner 2012; Ye and Wu 2011; Rey, Mack, and Koschinsky 2012).

Such coincidence of locational and attributional similarity is referred to as spatial autocorrelation (Cliff and Ord 1973; Anselin and Bera 1998; Townsley 2009). Two kinds of spatial autocorrelation may appear, negative and positive. The latter and most prevalent in empirical studies depicts patterns where similar values are closely located in space, while former describes patterns where dissimilar values are in close geographical proximity. If (positive) spatial autocorrelation is not explicitly modeled, serious consequences may arise because model assumptions (e.g., spatial independence), which are mandatory for inference statistics, are violated. Along with the inflation of degrees of freedom, standard errors and estimated coefficients may be biased as well as inconsistent, risking erroneous conclusions on the basis of a misspecified regression model (Anselin and Bera 1998). Empirical evidence that "place matters" is now abundant (Tita and Greenbaum 2008). A classic example is Morenoff, Sampson, and Raudenbush (2001), who analyze homicide rates while considering neighborhood effects through a spatially lagged variable. Their results confirm that spatial effects are most important, surpassing other local characteristics. Subsequent empirical analyses clearly support their findings (see Leitner 2013).

Thus, to receive unbiased estimates and correct inference, spatial autocorrelation must be explicitly modeled in

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statistical analysis (Tita and Radil 2011). This is not trivial in count regressions where the response variable used is the number of crimes within a spatial unit for a certain time period (Griffith and Haining 2006). Counts are a common data type in criminal analysis, for instance, offenses per spatial unit (e.g., Osgood 2000; Braga 2003; Lattimore et al. 2005; Macdonald and Lattimore 2011). Because count data are highly skewed and include solely positive integers, Gaussian models are inappropriate (Griffith and Haining 2006; Ver Hoef and Boveng 2007; O'Hara and Kotze 2010) as they can only furnish approximations in ideal circumstances. Nevertheless, ordinary least squares regression has been widely used in combination with *ex ante* logarithmic and square root transformations of the response to obtain independent and identically distributed residuals. Because a natural logarithm is not specified for zeros, it is necessary to add a small constant to each count, which induces an extra estimation bias as demonstrated by Osgood (2000). Furthermore, ordinary least squares regression tends to predict negative counts and wrongly assumes homoscedasticity (Cameron and Trivedi 1998; Winkelmann 2008). Based on simulation experiments, O'Hara and Kotze (2010) unequivocally discourage (logged) ordinary least squares regression models with counts and strongly recommend that the special nature of count data be explicitly considered. For instance, Huang and Cornell (2012) compare count data regressions with ordinary least squares regression by investigating school victimization in Virginia. As expected, they underpin that Poisson-based analyses result in a more reliable model. Griffith and Haining (2006) argue that spatial independence of counts does not hold true and anticipate that there will be interdependencies in the model residuals. Minor attempts have been made hitherto to consider spatial autocorrelation in criminological count regressions. For example, Osgood (2000) neglects spatial autocorrelation when investigating juvenile arrest rates for robberies.

Despite the importance of spatially explicit regressions for count data, such models are rare and even more rarely applied. Explicitly accounting for area-specific spatial effects, the auto-Poisson model (Besag 1974) is of limited use because it models negatively autocorrelated patterns scarcely present in social science (Griffith and Haining 2006; Griffith 2012). Although this constraint is obviated in the modification by Kaiser and Cressie (1997), the model has not been implemented in software packages, to the best of our knowledge. Recently, Bayesian spatial models (e.g., Sparks 2011; Law and Quick 2013) were introduced to handle spatial autocorrelation in count data. These highly complex approaches are still in an early development stage and rely on Markov Chain Monte Carlo approaches that are computationally intensive. Combined with ESF, generalized linear models (McCullagh and Nelder 1989) – which have been recommended for transportation (e.g., Wang, Kockelman, and Wang 2013) and health studies (e.g., Helbich, Blüml, et al. 2013) and are transferable to crime analysis – are thus highly suitable. A comparative study by Dormann et al. (2007) confirms that generalized linear models linked to ESF are effective to address spatial autocorrelation. Grimpe and Patuelli (2011) were the first to report promising results in linking both the negative binomial model (NBM) with ESF. Recently, Thayn and Simanis (2013) verified the results of Dormann et al. (2007) by exploring real-world and artificial datasets. They found an improved model fit and fewer misspecifications. Based on these studies, ESF should be explored in conjunction with criminological count regression. Unlike generalized linear models, which assume a linear relationship, an advantage of ESF is a possible integration into nonlinear (mixed) smoothing models (Wood 2006), offering additional flexibility when nonlinearities of criminogenic factors are expected.

To conclude, quantitative spatial criminology may profit from bridging count regression and ESF, although not yet introduced to this domain. In this research, we enhance the current count regression methodology by taking advantage of ESF in a reliable and integrative way. Besides producing a comprehensive literature review about count regression in criminological studies, this research makes the following important contributions to the literature:

- First, ESF is utilized to map temporally persistent crime patterns.
- Second, responding to a recent call by Bernasco and Elffers (2011), it is shown how ESF can be effectively applied to obviate a misspecified count regression model by means of considering a (spatiotemporal persistent) spatial filter.
- Third, the suitability of ESF within a linear and nonlinear model is illustrated by analyzing nonviolent crimes for the period 2005–2010 in Houston, Texas. This provides law enforcements with a deeper understanding of the major criminogenic forces and allows formulating more situational policies and actions.

The remainder of this article is structured as follows: The following section introduces both the theoretical foundations of count regressions and ESF. Next, the study area and the data are described. We then demonstrate the effectiveness of ESF for nonviolent crimes in Houston. Finally, key conclusions and directions for future research are highlighted.

Methods

Count regressions

Poisson model

Count regression emerges as a part of the generalized linear models family, extending the linear model to nonnormal error distributions. For count data, the Poisson distribution is well suited, assuming mean and variance equivalence ($E(Y) = \mu$, $\text{var}(Y) = \mu$). Poisson regression linearly relates the mean number of counts within a spatial unit i during a period t to a set of j explanatory variables. This regression has the following form:

$$\text{E}[\log(\lambda)] = \beta_0 + \sum_{j=1}^{p} \beta_j X_j$$

where λ is the expected value of Y, β_0 is the intercept term, β_j is a set of regression coefficients to be estimated for the j independent variable X, and $\log(\lambda)$ represents the canonical link function that connects the response to the related explanatory variables and guarantees that the estimated counts remain positive.

For crime data, equidispersion is a strong and restrictive assumption (Osgood 2000). Usually, overdispersion, which means that the variance exceeds the mean, is present in empiricism. Reasons for variance variations are nonlinear relationships, spatial autocorrelation, and within or between-area heterogeneity of spatial units (White and Bennetts 1996; Griffith and Haining 2006). Ver Hoef and Boveng (2007) supplement this argumentation by stating that grouping effects or a misspecified model are additional causes. Criminological explanations for overdispersion are extensively discussed in Osgood (2000), while statistical reasons (e.g., contagion, state dependence) are discussed in Winkelmann (2008). In contrast, underdispersion, which describes the situation when the variance is below the mean, is scarcely relevant for criminology (Osgood 2000).

A consequence of a missing mean–variance equality is that the standard errors are too narrow although, as long as the conditional mean function is correctly defined, Poisson models still result in consistent parameter estimates. Thus, statistical significance tests could be too liberal and may result in wrong conclusions (Cameron and Trivedi 1998; Kleiber and Zeileis 2008). Depending on the degree of overdispersion, effective options to handle a lacking mean–variance equality are, besides mixed models, either the quasi-Poisson model or the NBM.

Quasi-Poisson model

The quasi-Poisson model offers an ad hoc fix for small amounts of overdispersion (Berk and MacDonald 2008). Due to an additional dispersion parameter, which adapts the variance, equidispersion is enforced. If the quasi-Poisson model's dispersion parameter is larger than 1, it indicates overdispersion. This requires that the model's standard errors must be corrected by multiplying them by the square root of the dispersion parameter (Kleiber and Zeileis 2008). Increasing the standard errors reduces the significance of the parameters, which makes the estimates more reliable, while the estimated coefficients remain unchanged. Obtaining dispersion parameters beyond 20, Zuur et al. (2009) recommend refitting the model using a zero-inflated model or a NBM.

Negative binomial model

The NBM is based on the negative binomial distribution, resulting from a mixture of the Poisson-gamma distribution (Zuur et al. 2009; Vanables and Ripley 2010), which is a Poisson distribution with a gamma distributed mean. The NBM relaxes equidispersion by encouraging heterogeneity among the units (Coxe, West, and Aiken 2009), which might provoke overdispersion. Compared to the Poisson model, the mean–variance relationship is now given by $E(Y) = \mu$ and $\text{var}(Y) = \mu + \mu^2/\theta$, where the second part of the variance specification (θ) is estimated through the data and controls the amount of overdispersion (Vanables and Ripley 2010). If the variance function μ^2/θ equals zero, it leads to the basic Poisson model. Because the NBM yields more accurate estimations, it is heavily promoted by Osgood (2000) and has since received considerable attention in criminology (e.g., Braga 2003; Lattimore et al. 2005; Berk and MacDonald 2008).

A not yet addressed but fundamental assumption of count regressions is residual independence (Griffith and Haining 2006). The abovementioned models assume that counts occur randomly across space and over time, hardly fulfilled by incorporating spatial data in aspatial models. Therefore, the following section introduces ESF, which allows us to model spatial autocorrelation in generalized linear models.

Eigenvector spatial filtering

The first implemented attempt at spatial filtering, following earlier work by Tobler, is by Griffith (1978). Getis (1990, 2010) argues for transforming a spatial autocorrelation-effected variable by splitting it into its actual variable effect without spatial autocorrelation and its related spatial component. Technically, he proposes a combination of $K(d)$-functions and local G-statistics. It is, however, necessary to repeat this routine for each variable separately, resulting in many variables. Undoubtedly, this contradicts the principle of model parsimony (Burnham and Anderson 2002). However, this approach corrects for positive spatial autocorrelation effects and is limited to positively defined variables having a natural origin (Getis and Griffith 2002). Although this study satisfies both conditions, it favors the topology-based ESF approach (Griffith 1996, 2000; Tiefelsdorf and Griffith 2007) because it is flexible and obviates the above-mentioned limitations (e.g., Griffith 2008). A comparison by Getis and Griffith (2002) reveals that both methods filter spatial autocorrelation efficiently and produce similar results. Recently, a third model family emerged, comprising principal coordinates of neighbor matrices and Moran's eigenvector maps (Dray, Legendre, and Peres-Neto 2006), which utilizes distance-based eigenfunctions among locations. Although Griffith and Peres-Neto (2006) found high similarities between the results of ESF and spatial eigenfunction analysis by principal coordinates of neighbor matrices, most regression-based criminological investigations deal with lattice data (e.g., Andresen 2006), which are ill-represented by centroids. Because of this limitation, ESF is clearly preferred.

Based on Tiefelsdorf and Boots (1995), ESF aims to extract eigenvectors from a transformed spatial neighborhood matrix (Griffith 2000), which describes the spatial arrangement and connectivity between entities of spatial systems (Tita and Radil 2011). Even though the matrix definition is exogenous, it requires that the actual spatial process is mimicked most appropriately. For this reason, the neighborhood definition and the subsequent coding are fundamental for ESF and influence the filtering. Several definitions are proposed for the neighborhood matrix (see Getis 2009; Patuelli et al. 2012). Frequently applied in empirical crime studies (e.g., Leitner and Helbich 2011) is the first-order queen contiguity (meaning adjacent spatial units share an edge and/or node). Assuming N spatial units, adjacency is formally represented through an $N \times N$ matrix, $\boldsymbol{C}$. Each matrix element c_{ij} judges the amount of interaction between unit i and j. In the simplest case, $c_{ij} = 1$ if location i and j are neighbors, otherwise $c_{ij} = 0\,(i \neq j)$. Because of issues with interpretation, $\boldsymbol{C}$ is further processed through standardization. Following Patuelli et al. (2012), three standardization schemes are prevalent: (a) The C-coding, which refers to a global standardization. Its computation stresses units with higher linkages; therefore, patterns in the center of the area under investigation are emphasized. Even Tiefelsdorf, Griffith, and Boots (1999) remark an overemphasis. (b) The W-coding style, which was considered because of its appealing interpretation of spatial spillover effects. However, this coding gives too much weight to entities with a low number of spatial links (Tiefelsdorf, Griffith, and Boots 1999). Patuelli et al. (2011) point out that extreme values along the study area's edges are pronounced. (c) The S-style, which stabilizes the variance by compensating the level of variation within weights (Tiefelsdorf, Griffith, and Boots 1999). Because an incorrect specification may have an impact on diagnostic tests and an overspecification reduces the power of statistical tests (Florax and Rey 1995), Cohen and Tita (1999) call for more systematic research dealing with diverse specifications. This research answers this call.

Eigenvector spatial filtering (ESF) decomposes the Moran's I coefficient, which is a spatial statistical test used to determine the nature and degree of spatial autocorrelation, given a predefined spatial weight matrix. Cliff and Ord (1973) calculate the index as follows:

$$\text{Moran's } I = \frac{N \sum_i \sum_j c_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_i \sum_j c_{ij}\right) \sum_i (x_i - \bar{x})^2}$$

where x_i and x_j are the attribute values of location i and j, $\bar{x}$ is the overall mean value, c_{ij} is an element of the spatial weight matrix $\boldsymbol{C}$, and N is the number of spatial units. The range of Moran's I is, but not limited to, –1 and +1, where positive values indicate positive spatial autocorrelation and a negative value represents a negative spatial autocorrelation. 0 represents a random distribution. In detail, ESF utilizes eigenvector decomposition to extract a set of eigenvectors directly from the spatial weight matrix, incorporated in the numerator of the Moran's I coefficient (de Jong, Sprenger, and van Veen 1984; Griffith 2000):

$$\left(\boldsymbol{I} - \frac{\mathbf{1}\mathbf{1}^T}{N}\right) \boldsymbol{C} \left(\boldsymbol{I} - \frac{\mathbf{1}\mathbf{1}^T}{N}\right)$$

where $\boldsymbol{I}$ represents the $N \times N$ identity matrix with 1s in the main diagonal and 0s elsewhere, $\mathbf{1}$ is $N \times 1$ vectors of 1s, $\boldsymbol{C}$ is the spatial weights matrix, and T denotes the matrix transpose. The resulting eigenvectors are orthogonal and independent of each other. Tiefelsdorf and Boots (1995) show that each extracted eigenvectors mimics latent spatial autocorrelation in accordance with the spatial weight matrix. Furthermore, each eigenvector portrays a certain nature and degree of spatial autocorrelation and thus a characteristic map pattern. Closely referring to Griffith (2000), the first eigenvector contains a set of numerical values resulting in the largest possible Moran's I value for any set of real numbers. The second eigenvector expresses the set of values that has the largest obtainable Moran's I by any possible set of eigenvectors that are not correlated with the first eigenvector. This continues for the remaining eigenvectors until the Nth eigenvector is achieved, which is characterized through the highest possible negative spatial autocorrelation. Based on the degree of spatial autocorrelation, the number of eigenvectors can be grouped in three groups where the class boundaries are not strictly defined. The first group comprises eigenvectors that tend to portray broad-scale patterns, basically along the main cardinal directions; i.e., North-South and East-West trends. They are distinguished by a high positive Moran's I values. The second group classifies regionally sized patterns with moderate spatial autocorrelation. The third group portrays a set of local map patterns, mainly dispersed across space at a finer scale, and associated with low Moran's I values.

The eigenvector extraction results in N eigenvectors whose elements are attached to each spatial unit i. Using the complete set of eigenvectors is not feasible due to missing degrees of freedoms (Patuelli et al. 2011). This requires a preselection to uncover potential eigenvector candidates, with a potentially relevant spatial autocorrelation pattern. Tiefelsdorf and Griffith (2007) propose a threshold value[1] of Moran's I divided by Moran's $I_{\max} > 0.25$, where Moran's $I_{\max}$ is the largest positive Moran's I value. This assures that eigenvectors representing more randomly distributed patterns, i.e., Moran's $I \sim 0$, are not further considered. Moreover, this critical Moran's I value guarantees a manageable number of eigenvectors for the subsequent selection procedure. It must be noted that ESF is not limited to positive spatial autocorrelation. The ultimate eigenvectors are achieved by regressing candidate eigenvectors on the response. Due to the orthogonality and independence of eigenvectors, a stepwise selection approach minimizing a quality criterion (e.g., Akaike information criterion (AIC); Burnham and Anderson 2002) is valid. The final model includes only spatial patterns significantly related to the response.

The ESF results have two benefits: (a) Single eigenvectors can be visualized to explore spatial patterns inherent in the response, while common eigenvectors over time refer to persistent spatiotemporal patterns (see Patuelli et al. 2012). (b) Eigenvectors modeled as additional explanatory variables theoretically remove spatial autocorrelation and approve standard statistical techniques. However, instead of considering each eigenvector as a fixed effect, a single and more parsimonious spatial filter comprising all relevant eigenvectors can be computed through a linear combination. Analogous to the separate eigenvectors, this spatial filter accounts for spatial autocorrelation on different scales and serves as a surrogate for possible missing predictors (Thayn and Simanis 2013). Both advantages are demonstrated in the subsequent case study.

Study area and data

The study area is the metropolitan area of Houston, Texas, with a population of nearly 2.1 million (US Census Bureau 2010). Besides being delineated in official spatial units, the metropolitan area is divided into 15 police beat districts used for patrol and statistical purposes by the Houston Police Department. Because of the small number of units, this coarse subdivision lacks sufficient geographic resolution to be suitable for statistical analysis. Hence, to illustrate ESF, this empirical study uses the census tract level, which keeps the computing time feasible and allows linkage to supplementary census data. After removing all enclaves within the metropolitan area, the study area consists of 467 census tracts.

Crime data for the period 2005–2010 were obtained by a data request through the Houston Police Department. Between 2005 and 2010, the annual mean number of offenses was 126,000. In accordance with the Uniform Crime Reporting classification schema (Part 1), all crimes were divided into violent and nonviolent crimes. Since there are more nonviolent crimes in Houston than violent ones, the focus will be on the former and comprise burglaries, larceny, auto theft, and arson. Besides the crime locations, crime type and offense date were compiled. The address where a crime occurred allows geocoding with a Geographic Information System. After excluding incompletely reported crimes, approximately 621,000 nonviolent offenses were successfully geocoded using the TIGER street network. The hit rate of successfully and accurately geocoded crimes ranged between 91% and 93%, which is higher than Ratcliffe's (2004) critical value of 85%, ensuring high overall accuracy. Finally, the absolute number of nonviolent crimes per tract was determined yearly by means of point-in-polygon aggregations. High positional accuracy is crucial and reduces misallocations to geographic units, while having noticeable impact on subsequent spatial statistical analysis (Griffith et al. 2007). This area-based representation permitted the integration of socioeconomic and demographic census data for 2010 obtained from the US Bureau of Census, which was necessary to understand the driving forces of crime. The variable selection was guided by theoretical considerations grounded in previous empirical research (e.g., Leitner and Helbich 2011). All variables are listed in Table 1.

Results

This section discusses the main empirical results. After the initial exploratory analysis, eigenvector mapping is employed to analyze pure spatial effects in yearly, nonviolent crime counts. Moreover, temporally persistent eigenvector-based crime patterns are identified for the 6-year period. Then this spatial filter is used to model spatial autocorrelation in linear and nonlinear count regressions.

Spatiotemporal steady crime patterns

Descriptive statistics in Table 1 and Figure 1a confirm that the distribution of crime counts is skewed. The number of crimes per census tract ranges from 0 to almost 1620 for the year 2010. Mappings show similarity between the crime patterns on a yearly basis, indicating possible eigenvector agreement. The spatial crime distribution for 2010 is given in Figure 1b.

To analytically explore the annual crime patterns, Moran's I coefficients are calculated by selecting the regularly applied first-order queen contiguity. Because Patuelli et al. (2012) demonstrate a high agreement between the queen and rook specification, this analysis is restricted to the former. The queen contiguity results in 2966 nonzero links, corresponding to 1.4% nonzero

Table 1. Variable descriptions and descriptive statistics.

Description	Min.	1st Qu.	Median	3rd Qu.	Max.
Nonviolent crimes					
Crimes 2005	0.0	128.5	199.0	298.0	1340.0
Crimes 2006	0.0	127.5	200.0	296.0	1418.0
Crimes 2007	0.0	127.0	200.0	290.6	1596.0
Crimes 2008	0.0	116.0	178.0	262.5	1412.0
Crimes 2009	0.0	123.0	190.0	286.5	1897.0
Crimes 2010	0.0	117.0	186.0	268.0	1620.0
Explanatory variables					
Total population 2010	33	3134	4231	5600	10,150
% White population 2010	1.4	33.4	54.3	68.0	94.8
% African-American population 2010	0.3	3.9	13.7	34.0	94.8
% Asian population 2010	0.0	0.7	3.9	9.4	45.7
% Owner-occupied housing units 2010	0.0	31.1	50.0	67.5	98.1
% Homeowner vacancy rate 2010	0.0	1.3	2.0	3.2	29.7
% Rental vacancy rate 2010	0.0	8.1	10.9	15.7	55.0
Euclidean distance to police stations and storefronts (meters) 2010	360	1603	2367	3620	9847

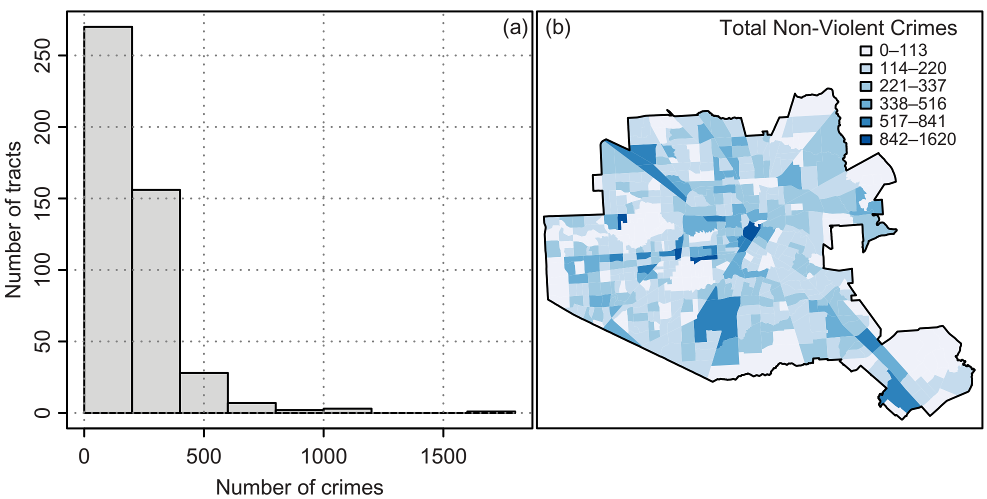

Figure 1. (a) Histogram and (b) spatial distribution of nonviolent crimes for the year 2010.

weights. The average number of links is 6.4. More critical is the specification of the coding scheme, which may induce slightly diverse results (Patuelli et al. 2011). Besides, highly relevant for criminology, the definition is more than ad hoc and defines social interactions too (Leenders 2002). Following the research call of Cohen and Tita (1999), three coding styles (i.e., *W*, *C*, *S*) are compared in this article. The Moran's *I* results for the crimes per year and each coding style are presented in Table 2.

The temporal development of the Moran's *I* values shows similar behaviors of moderate and significant spatial autocorrelation over time. For all coding schemes the maximum Moran's *I* values occurred in 2007, followed by a continuous decrease over 2008 and 2009. The minimum Moran's *I* value occurred in 2009. The Moran's *I* scores increased slightly for 2010. Given these results, the assumption of independent residuals in subsequent regressions might be violated – independently of the coding

Table 2. Moran's *I* statistics for annual crimes on the basis of different spatial weight matrices.

	W-style		*C*-style		*S*-style	
Year	*MC*	*p*-Value	*MC*	*p*-Value	*MC*	*p*-Value
2005	0.208	0.001	0.224	0.001	0.217	0.001
2006	0.230	0.001	0.248	0.001	0.240	0.001
2007	0.234	0.001	0.253	0.001	0.244	0.001
2008	0.200	0.001	0.222	0.001	0.212	0.001
2009	0.175	0.001	0.194	0.001	0.186	0.001
2010	0.186	0.001	0.206	0.001	0.197	0.001

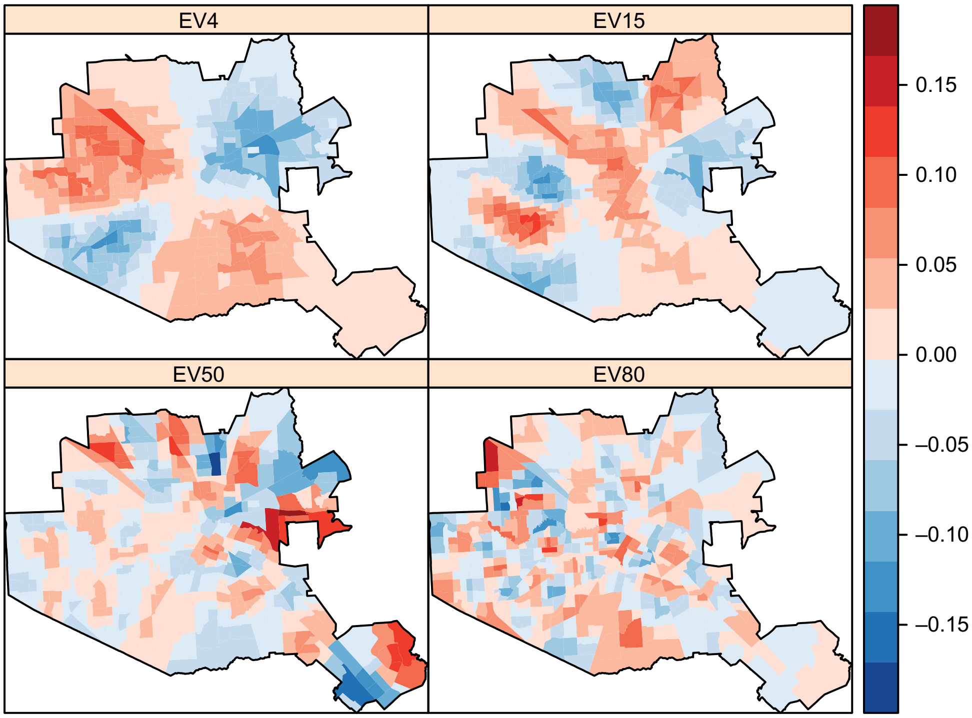

Figure 2. Candidate eigenvectors depicting global (EV4), regional (EV15), and local patterns (EV50, EV80) grounded on the *C*-style weighting.

scheme – providing sound statistical motivations to account for spatial autocorrelation.

To filter out this spatiotemporal autocorrelation, an ESF approach is set up to construct a temporally persistent spatial filter, which is used as a regression proxy variable. The following extraction procedure is repeated for each spatial weight matrix specification: First, 467 eigenvectors are extracted. Due to significant overdispersion, NBMs are applied for selecting significant eigenvectors. Figure 2 depicts four examples of candidate eigenvectors using the *C*-style weighting. Global patterns are characterized by eigenvectors ≤4, regional patterns by eigenvectors 5–25, and local ones by eigenvectors ≥26.

Next, to obtain the final eigenvectors, each yearly crime pattern is repeatedly regressed on the candidate eigenvectors separately through Poisson models and quasi-Poisson models. Once more, as confirmed by the significant overdispersion test ($p < 0.001$), equidispersion must be rejected, which disqualifies the Poisson model and quasi-Poisson model for the final eigenvector selection. Refitting the models as NBM yields substantial improvements. For all regressions, the χ^2-values strongly suggest that NBMs are much more appropriate compared to the Poisson model and quasi-Poisson model. Additionally, NBMs substantially reduce the AIC scores. To decrease the candidate eigenvectors further, backward variable selection is applied by minimizing the AIC. The dispersion parameters of all final NBMs are noticeably reduced to approximately 1.33, only slightly above the ideal value of 1. To correct such a minor deviation from equidispersion, robust standard errors are advised by Kleiber and Zeileis (2008). Figure 3 illustrates the fits of the NBMs, highlighting distinctions between all years and each spatial weighting scheme. All graphs show similar characteristics with a clear peak of the explanatory powers in the year 2007. The pseudo-R^2s range between 0.27 and 0.37. Compared with the other coding styles, the *C*-style performs best, resulting in higher model fits. The *W*-style is the only style with a weak performance; it also results in the lowest pseudo-R^2s. Thus, a considerable part of the variance in the crime distribution is explained by the pure eigenvectors themselves, emphasizing the high relevance of space in the crime patterns.

On average, 46 final eigenvectors were selected (see Tables 3 and 4). Each selected eigenvector portrays a characteristic map pattern. As an example, the best performing *C*-style is outlined. While eigenvectors ≤4 visualize global patterns following a West-East decline, the fourth eigenvector, labeled as EV4, obviously depicts more regional patterns, where two areas show high positive values and two areas show increasingly negative values (Figure 2). High positive values are accumulated in the north-western and south-eastern parts of Houston, declining toward the city center. This map has a Moran's *I* of 0.931. In comparison, EV50 is representative of local map patterns on a finer scale. EV50 has a Moran's I of

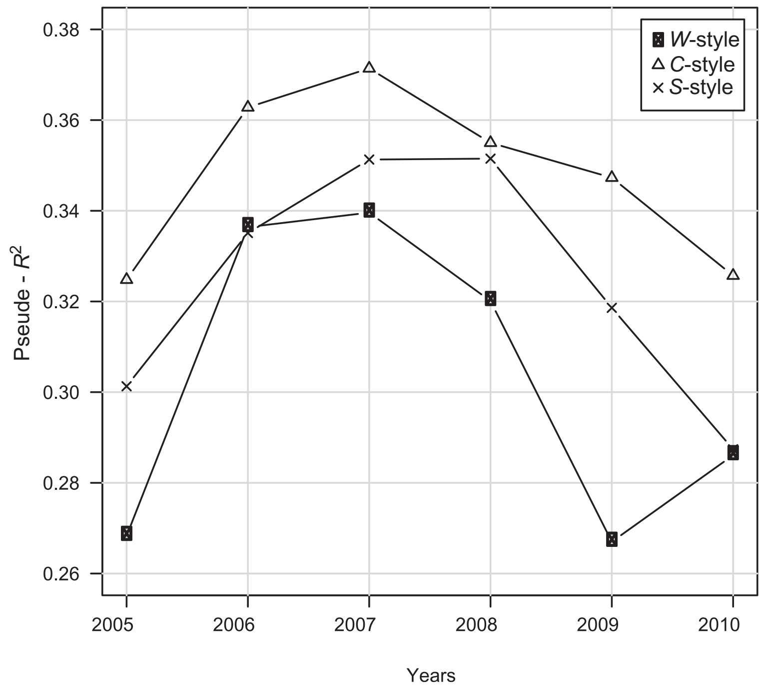

Figure 3. Model fits of the negative binomial models for different coding styles over time.

Table 3. Temporally persistent eigenvectors (EV).

	Global patterns	Regional patterns	Local patterns
W-style	EV4	EV6, EV9, EV10,	EV26, EV28, EV29, EV30, EV32,
		EV14, EV15, EV19,	EV33, EV38, EV41, EV43, EV47,
		EV20, EV24, EV25	EV48, EV49, EV50, EV59, EV62,
			EV66, EV67, EV71, EV72, EV73,
			EV80, EV86, EV91, EV93, EV104
C-style	EV3	EV7, EV8, EV10,	EV26, EV27, EV28, EV29, EV31,
		EV11, EV12, EV15,	EV35, EV40, EV42, EV44, EV45,
		EV16, EV19, EV22,	EV51, EV53, EV55, EV59, EV61,
		EV24	EV62, EV64, EV67, EV70, EV71,
			EV72, EV76, EV78
S-style		EV6, EV7, EV8,	EV27, EV32, EV35, EV36, EV41,
		EV10, EV12, EV13,	EV42, EV45, EV49, EV50, EV63,
		EV15, EV22, EV23,	EV67, EV68, EV71, EV72, EV77,
		EV25	EV83, EV87, EV91, EV92, EV94

Note: Global EVs ≤ 4, regional EV = 5–25, local EVs ≥ 26.

0.533. A straightforward way of achieving a temporally persistent eigenvector pattern is to identify similar eigenvectors for each time stamp (Patuelli et al. 2012). Tables 3 and 4 deal with common and specific eigenvectors, revealing components inherent to temporal spatial crime patterns. The results suggest that the crime patterns during the period 2005–2010 are mainly driven by local and regional eigenvectors; the ESF approach identified several conspicuous similarities on a regional and local scale and over time. This lead to the conclusion that crime primarily acts on local and regional levels over time.

Spatial filtering to account for residual dependency

The previous section dealt with spatiotemporally consistent eigenvector mapping, while this section demonstrates how to use these eigenvectors as a spatial filter to absorb latent spatial autocorrelation in linear and nonlinear NBMs. The focus was on nonviolent offenses occurring in 2010 for which census data were available. This analysis was limited to the queen representation linked to the *C*-style weighting scheme, resulting in the highest fit compared to those of other coding styles (Figure 3). Note, if the intention is to perform regressions for several time stamps during the period 2005–2010, temporally persistent eigenvectors are an ideal choice. Because the following analysis deals exclusively with the year 2010, a spatial filter based on the corresponding eigenvectors for 2010 is more appropriate and contains all relevant

Table 4. Temporally specific eigenvectors (EV).

	Year	Global patterns	Regional patterns	Local patterns
W-style	2005	EV1, EV2, EV3	EV11, EV12	EV37, EV40, EV56, EV74, EV83, EV85, EV97, EV100
	2006	EV1, EV2, EV3	EV7, EV8, EV11	EV37, EV45, EV56, EV61, EV63, EV65, EV83, EV85, EV97, EV100
	2007	EV1, EV2, EV3	EV7, EV8, EV12, EV21	EV37, EV42, EV45, EV56, EV61, EV63, EV74, EV81, EV83, EV85, EV97, EV100
	2008	EV1, EV2, EV3	EV7, EV8, EV12	EV40, EV42, EV45, EV56, EV63, EV65, EV74, EV78, EV81, EV84, EV85, EV97, EV100
	2009	EV3	EV7, EV12	EV40, EV42, EV45, EV56, EV61, EV63, EV74, EV78, EV85, EV97, EV100
	2010	EV1	EV5, EV7, EV8	EV27, EV40, EV42, EV45, EV63, EV74, EV78, EV84, EV92
C-style	2005		EV17, EV20, EV25	EV30, EV36, EV43, EV49, EV52, EV54, EV57, EV75, EV79, EV82, EV87
	2006		EV20	EV30, EV32, EV36, EV43, EV47, EV49, EV63, EV75, EV79, EV82
	2007	EV2	EV17, EV20, EV25	EV36, EV47, EV52, EV56, EV57, EV63, EV87
	2008	EV2	EV20, EV25	EV30, EV36, EV43, EV47, EV58, EV63, EV75, EV79, EV87, EV90
	2009		EV25	EV30, EV47, EV58, EV63, EV75, EV79, EV90, EV91
	2010		EV25	EV30, EV43, EV47, EV49, EV58, EV75, EV82, EV90
S-style	2005		EV20	EV29, EV39, EV43, EV47, EV55, EV57, EV59, EV62
	2006	EV3	EV24	EV29, EV39, EV55, EV57, EV58, EV62, EV65, EV76, EV98
	2007	EV1		EV29, EV39, EV44, EV47, EV48, EV55, EV57, EV59, EV76, EV98
	2008	EV3	EV19	EV29, EV39, EV43, EV44, EV47, EV48, EV55, EV58, EV60, EV62, EV65, EV78, EV88, EV98
	2009	EV3	EV11	EV39, EV44, EV47, EV48, EV55, EV57, EV58, EV52, EV65, EV78, EV88, EV98
	2010		EV11, EV20	EV26, EV43, EV44, EV47, EV48, EV54, EV58, EV60, EV62, EV64, EV65, EV78, EV88, EV98

Note: Global EVs < = 4, regional EV = 5–25, local EVs ≥ 26.

eigenvector patterns. To account for different population sizes within the census tracts, the total population for 2010 was considered as exposure variable and was incorporated as an offset term in subsequent regressions.

Spatially filtered negative binomial model

Starting with a non-spatial Poisson model, crime counts of 2010 were regressed on the covariates listed in Table 4. The initial Poisson model was strongly affected by overdispersion and thus refitted as Quasi-Poisson model. Although this specification reduces overdispersion, it did not remove it, which requires a NBM. Likelihood ratio tests and the AIC score confirm better fit of the NBM. This agrees with Osgood (2000) who favors the NBM. Although the achieved dispersion ratio of approximately 1.187 points to a well-specified model (Griffith and Haining 2006), it did have robust standard errors, as reported in Table 5. To remove insignificant predictors of the full nonspatial NBM, a stepwise selection was applied. Because the AIC tends to be too liberal in penalizing more complex models, the algorithmical selection was coupled with a subsequent manual selection (Venables and Ripley 2010). χ^2-tests were conducted to remove the least significant terms. As long as no significant differences were found, the more parsimonious model was preferred. Table 5 shows the full and the reduced model, along with its robust standard errors and significance values. Residual diagnostics for both models point to a significant Moran's I ($p < 0.05$), which contradicts the NBM assumption of spatial independence.[2] To account for these spatial autocorrelation effects, a spatial filter is required. Instead of using the individual eigenvectors for 2010 listed in Tables 3 and 4, a linear combination of the multiscale map patterns was employed. It is expected that this spatial filter would account for redundancy in the locational information by providing a surrogate for potentially lacking explanatory variables. The results for the spatially filtered NBM are given in Table 5.

The model comparison, the likelihood ratio test, the pseudo-R^2, as well as the reduction of the AIC score all indicated a clear preference for the spatially filtered NBM. The spatial filter was highly significant ($p < 0.001$), eliminating entirely unexplained residual spatial

Table 5. Estimation results of the nonspatial negative binomial models and the spatially filtered negative binomial model.

	Full nonspatial NBM			Reduced nonspatial NBM			Spatially filtered NBM		
	Coefficients	Robust standard errors	*p*-Values	Coefficients	Robust standard errors	*p*-Values	Coefficients	Robust standard errors	*p*-Values
Intercept	−3.852	0.440	***	−4.207	0.684	***	−4.370	0.664	***
% White population	0.024	0.013	†	0.027	0.012	*	0.024	0.012	*
% African-American population	0.022	0.012	†	0.025	0.011	*	0.024	0.010	*
% Asian population	−0.009	0.006							
% Owner-occupied housing units	−0.014	0.006	**	−0.015	0.003	***	−0.009	0.003	**
% Homeowner vacancy rate	0.013	0.035							
% Rental vacancy rate	−0.003	0.016							
Distance to police	0.000	0.000							
Spatial filter	–			–			0.830	0.071	***
θ	1.522			1.503			1.843		
Pseudo-R^2 (%)	32			30			42		
Dispersion ratio	1.187			1.177			1.185		
AIC	5931			5929			5833		

Note: Significance codes: *** < 0.001, ** < 0.01, * < 0.05, † < 0.1.

autocorrelation. This was confirmed by a nonsignificant Moran's I of the residuals ($I = 0.019$; $p = 0.148$). Variance inflation factors did not indicate any multicollinearity. The estimated coefficients of the spatially filtered NBM were slightly lower compared with the aspatial NBMs, although the same three criminogenic predictors were significant at least at the 0.05 level. For example, the estimated regression coefficient for the percentage of the white population was about 0.024. Thus, all other covariates being constant, a one-unit increase in the percentage of Asians multiplies the expected crime rate by 1.024. The same was valid for African-Americans. In contrast, the percentage of owner-occupied housing units has a negative impact on crime rates. A final sensitivity analysis, which involved changing the spatial representation of the spatial filter (i.e., queen to rook), lead to similar conclusions.

Spatially filtered, generalized, additive negative binomial model

The previous NBM assumes that covariates impact the crime pattern linearly. To overcome this restriction, Wood (2006) introduced generalized, additive, negative binomial models (GANBM) that are more flexible and thus more appropriate when effects are not clear. Unlike polynomial terms, which are normally used to model nonlinear effects, smoothing terms can be determined in a data-driven fashion, by means of generalized cross-validation during the fitting process. This requires no *a priori* knowledge about the "true" functional form. Thus, GANBMs offer functional flexibility where required, while linear restrictions are imposed where appropriate. To estimate GANBMs, penalized regression splines were utilized, as described in Wood (2006). The following models are estimated: The first GANBM neglects residual spatial autocorrelation, while the second one accounts for spatial autocorrelation patterns through the previously used spatial filter for 2010. Results for both models are given in Table 6. The variable selection for the nonspatial GANBM resulted in a slightly larger model than the NBMs, containing two significant linear and three significant nonlinear terms. Due to a highly significant residual pattern, an interpretation was omitted and we continued with the spatially explicit GANBM.[3]

The spatially filtered GANBM consisted of four linear covariates and two nonlinear terms. More importantly, the spatially filtered GANBM resulted in a residual Moran's I, which is no longer significant ($p = 0.116$) and thus leads to a well-specified model. The AIC score (5667) clearly prefers this model to all previously reported models, which underpins the virtue of ESF for modeling criminogenic factors. The socioeconomic and environment covariates linearly related to the crime rates included (a) percentage of white population, (b) percentage of African-American population, and (c) distance to police stations. Although being significant, distance to police stations had a minor impact on crime. Compared with those for the NBM, these coefficients did not deviate markedly in their magnitudes (Table 6). The two significant smoothers are shown in Figure 4.

Table 6. Estimation results for the nonspatial and the spatially filtered, generalized, additive, negative binomial models.

	Nonspatial GANBM			Spatially filtered GANBM		
	Coefficients	Standard errors	*p*-Values	Coefficients	Standard errors	*p*-Values
Intercept	−4.178	0.227	***	4.139	0.244	***
% White population	0.016	0.003	***	0.016	0.003	***
% African-American population	0.014	0.003	***	0.016	0.003	***
Distance to police				−0.000	0.000	**
Spatial filter				0.719	0.068	***
	EDF			EDF		
% Owner-occupied housing units	5.027		***	5.042		***
% Rental vacancy rate	7.732		***	6.959		***
% Homeowner vacancy rate	3.542		***			
AIC	5850			5667		

Note: Significance codes: *** < 0.001, ** < 0.01, * < 0.05.

The smoothing effect of the percentage of owner-occupied housing units was highly significant, indicating a positive effect up to approximately 25%; from there on the effect turns out to be negative (Figure 4a). The rental vacancy rate (Figure 4b) shows a significant nonlinear behavior. Up to 8%, this variable has a strong negative effect, while there is no impact on crime rates within 15% and 35%, followed by a positive effect. Note that due to a small number of cases in the second half of this variable range, the confidence intervals were wide.

To sum up, accounting for spatial autocorrelation in the NBM constrains the magnitude of the estimated coefficients; both positive and negative coefficients decrease. In contrast, such an effect is not noticeable in the case of the GANBM. Based on all models, the significant criminogenic factors are (a) percentage of the white population, (b) percentage of the African-American population, (c) percentage of owner-occupied housing units, and (d) the rental vacancy rate.

Discussion and implications

Spatial autocorrelation is a critical feature in regression, especially in area-based analysis, which is a frequently applied methodology in law enforcement. Even though spatial autocorrelation can be well handled in Gaussian

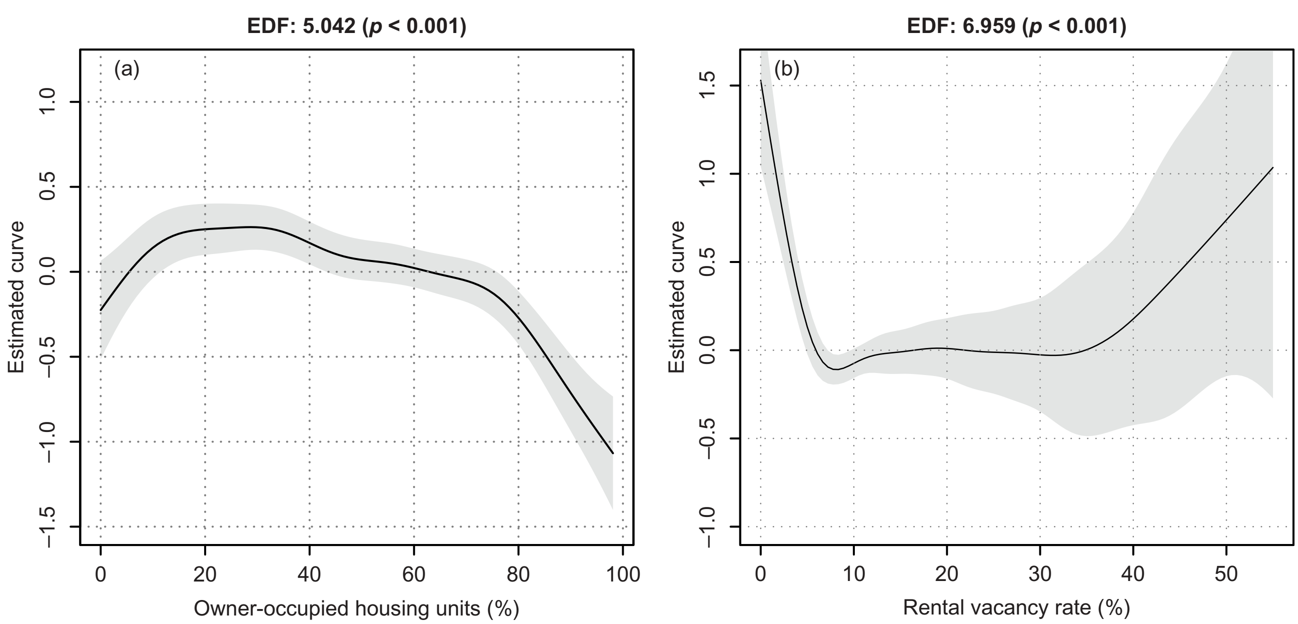

Figure 4. Nonparametric smoothers (black lines) for percentage of (a) owner-occupied housing units and (b) rental vacancy rate. The scale of covariates is given on the horizontal axes and the vertical axes and reports the values for the estimated curves. The shaded regions represent 95% confidence intervals. The associated effective degree of freedom (EDF) is given in the headings. An EDF of freedom around 1 represents a linear relationship while larger values indicate nonlinear functions (Wood 2006).

models, including the family of spatial autoregressive models, an apparent lack is identified for generalized linear models. In particular, this is true for count regression because spatial autocorrelation biases statistical inference and may result in wrong conclusions. In this context, this article contributes to the literature threefold: First, it demonstrates ESF as a spatial statistical technique to map temporally persistent crime patterns on different scales. Second, it shows how this temporally consistent spatial filter efficiently absorbs spatial autocorrelation from the variable's actual effect in linear and nonlinear NBMs, resulting in well-specified regressions that assure model assumptions. Third, the performance of unfiltered and spatially filtered count regressions and the impact on the parameter estimates are compared.

Assessment of temporally persistent patterns in the form of similar eigenvectors indicates that regional and local patterns, rather than global, existed for nonviolent crime in Houston during the period 2005–2010. The results are largely independent of the chosen weighting style. This fact might be interpreted as an absence of a global trend, meaning that the crime patterns over time were principally driven by regional and more local spatial processes. Furthermore, the results demonstrate that redundant information in the form of inherent and temporally constant spatial patterns can bias count regression estimates. Evidence for this conclusion is provided by the case studies involving a linear NBM and a GANBM. In both cases, ESF emerged as a methodological enhancement highly suitable for analytical crime analysis. It turns out that ESF effectively eliminates residual spatial autocorrelation effects by extracting spatially independent and orthogonal patterns. Neglecting spatial filters results in unequivocally misspecified models. Based on this analysis, it is apparent that nonspatial count models should be avoided with spatial crime data because they may lead to false conclusions. This research confirms the findings by Thayn and Simanis (2013) that ESF improves the model fits and reduces prediction errors. This suggests that filtering unexplained residual patterns leads to more precise models. Once more, this can be ascribed to the importance of space (Tita and Greenbaum 2008; Ratcliffe 2011). Another strength of ESF is that generalized linear model parameters can be interpreted in the usual way. The estimated model coefficients of spatially explicit models differ in magnitude compared to those of nonfiltered models. Given the findings of previous nonspatial studies (e.g., Osgood 2000; Braga 2003; Lattimore et al. 2005), this fact suggests that the reported coefficients might be overoptimistic and should be slightly reduced. These findings have important implications for crime prevention policies that build on such models. Future research should be aware of the consequences of spatial autocorrelation in NBMs.

To conclude, quantitative criminology is open for new developments in spatial statistics to model spatially distributed criminal offenses. The ESF approach has been proven to be a flexible and capable methodology to account for spatial autocorrelation in generalized linear models and generalized additive models. Chun and Griffith (2011) reveal that ESF also reduce spatially biasing effects in movement flow data, including journey-to-crime models, which is gaining increased significance in criminology (Levine and Block 2011; Mburu and Helbich Forthcoming). As stated in Leitner and Helbich (2011), criminogenic processes are only partly rendered by global models resulting in average effects valid for the whole study area. Thus, for future research, it is reasonable to interact the eigenvectors with socioeconomic covariates, which permits the exploration of geographically varying model parameters (Griffith 2008, 2012). In addition, it seems advisable to consider a more comprehensive set of explanatory variables (e.g., income and educational levels) in future models. Such research will stimulate the understanding of spatial variation in crime. However, ESF will continue to be a rich research area in criminology.

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Notes

1. For an alternative approach, see Griffith (2012, 19).
2. The investigation of residual spatial autocorrelation for generalized linear models remains "speculative and provisional" (Bivand, Pebesma, and Gómez-Rubio 2008, 298). A first test statistic is proposed by Lin and Zhang (2007).
3. Generalized additive models also make it possible to model spatial autocorrelation by means of bidimensional coordinate smoothers (Wood 2006).

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