Chapter 7
Spatial Econometrics

Pedro Amaral, Luc Anselin and Alain Pirotte

Abstract This chapter traces the evolution of spatial econometrics from the late 1970s, which seem to be a turning point, to a mainstream methodological pillar in the 21th century. The early stages in the development of spatial econometrics, spanning the mid-1970s to the late 1980s. This period laid the conceptual and technical foundations of the field before the widespread availability of microcomputers , starting availability of software tools, growing role of space and place in the mainstream of social sciences, large geo-referenced datasets and desktop geographical information systems (GIS) transformed empirical practice. Then, the 1990s were marked by the field's real take-off mainly by the introduction of new estimation techniques, specification tests, and rigorous theoretical frameworks. Spatial econometrics reaches the mainstream with the 21st century. Spatial effects are now routinely considered in empirical research, and the methodological toolkit has matured to address increasingly complex data structures and research questions. The field has successfully absorbed advances in panels, causal inference under spatial interference, big data, and computational methods. This chapter closes by assessing spatial econometrics practices and future challenges.

7.1 Introduction

Spatial econometrics has a relatively short history compared to the emergence of econometrics as a discipline in 1930. If the term 'spatial econometrics' was introduced

Pedro Amaral ✉
Universidade Federal de Minas Gerais, Belo Horizonte, Brazil, e-mail: pedroamaral@cedeplar.ufmg.br

Luc Anselin
The University of Chicago, Chicago, USA, e-mail: anselin@uchicago.edu

Alain Pirotte
Paris-Panthéon-Assas University, Paris, France, e-mail: alain.pirotte@assas-universite.fr

by Jean Paelinck at the annual meeting of the Dutch Statistical Association, Tilburg, May 1974, see Paelinck and Klaassen (1979, p. vii), it was only really at the end of the 1970s that spatial econometrics began to take hold. The late 1970s seem to be a turning point, as Anselin (2010) points out. Not only with the publication of Paelinck and Klaassen's (1979) book, considered to be the first comprehensive attempt at outlining the field of spatial econometrics and its distinct methodology, but also with those of Bartels and Ketellapper (1979) and Bennett (1979) and some important articles Hordijk and Paelinck (1976), Hordijk (1979), Hordijk and Nijkamp (1977, 1978) among others. Since then, spatial econometrics has become one of the most dynamic and productive branches of quantitative economics. In 2006, creation of the spatial econometrics association[1] (SEA) has officially established the existence of this field in quantitative economics. Recent publication of several textbooks reveal the importance this field now holds (Arbia, 2006, 2014, LeSage & Pace, 2009, Anselin & Rey, 2014, Elhorst, 2014, Kelejian & Piras, 2017, Lee, 2024 since the two traditional textbooks, Paelinck & Klaassen, 1979 and Anselin, 1988c). Over the last 10 years[2], a search on EconLit (peer-reviewed journals) for the term 'spatial econometrics' has brought up more than 2,000 articles compared to 1,500 and 162, respectively for 2000-2014 and the 1990s. Those figures confirm the growing interest in spatial econometrics since the turn of the 21st century. This chapter offers a bird's-eye view of this trajectory, highlighting both the approaches that have aged well and those that have not. Its structure is as follows. Section 7.2 gives the definitions and scopes of spatial econometrics, spatial statistics and standard econometrics. Section 7.3 deals the early stages of spatial econometrics (mid 1970s to late 1980s). Section 7.4 focuses on the emergence of a growing interest in spatial econometrics (the 1990s), while Section 7.5 presents the 21st century as a turning point to reach the mainstream. Finally, Section 7.6 concludes.

7.2 Spatial Econometrics, Spatial Statistics and Standard Econometrics: A Clarification

Arguably the first formal definition of the special characteristics of spatial econometrics that distinguishes it from standard econometrics was given by Paelinck and Klaassen (1979). Specifically, they stressed five important distinguishing principles: "(i) the role of spatial interaction; (ii) the asymmetry of spatial relations; (iii) the importance

---

[1] Article 2 of its statutes stipulated that: *"The purpose of the Association is to promote the development of the theoretical instruments and practical applications of spatial econometrics—including spatial statistics and spatial data analysis. Spatial econometrics should be regarded in abroad sense and inclusive of the developments of statistic models and instruments to analyze externalities, interactions, etc. in different areas such as, without limitation, economics, geography and regional sciences. The mission of the Association is to disseminate and encourage knowledge and good practice among universities and research institutions and in the community in general, becoming a reference point for operators in the field".*

[2] From January 1st, 2015 to December 31, 2025.

of explanatory factors located in other spaces; (iv) differentiation between ex post and ex ante interaction; and the explicit modeling of space (spatial arrangement) in spatial model specifications." Whereas initially mostly confined to models in urban economics and regional science (Anselin, 1988c), the field was defined more generally in Anselin (2006) as "a subset of econometric methods that is concerned with spatial aspects present in cross-sectional and space-time observations. Variables related to location, distance and arrangement (topology) are treated explicitly in model specification, estimation, diagnostic checking and prediction."

Two spatial effects are of interest: *spatial dependence* and *spatial heterogeneity*. Spatial dependence is a special form of cross-sectional dependence in that its properties are driven by spatial aspects of the data, such as location and distance. It is grounded in theories of *spatial interaction*, e.g., as expressed in Tobler's First Law of Geography, 'everything depends on everything else, but closer things more so' (Tobler, 1970). Characteristics of special interest are the range of interaction and the associated distance decay (locations farther apart are less correlated).

Spatial dependence is fundamentally different from dependence considered in time series econometrics in that it is multi-directional, rather than one-directional. This leads to feedback effects (spatial multipliers) and the presence of *simultaneity* that requires appropriate estimation techniques. It also creates a basic identification problem in that interaction is a pair-wise characteristic, which requires observations of $O(N^2)$, whereas typically only N cross-sectional data points are available. Even in spatial panel data settings, the cross-sectional dimension typically dominates the time dimension ($N >> T$), so that there are insufficient observations to extract the pattern of interaction from the data without imposing some prior structure.

The most common form to express this spatial structure is through a so-called spatial weights matrix, W, of dimension $N \times N$, essentially an adjacency matrix that formalizes the network structure of the interaction. This square matrix shows for each observation (row) what other observations (columns) are considered to interact with it. Typically, this reflects a geographical structure, such as contiguity (common borders) or k-nearest neighbors, although it is a perfectly generally concept and applies equally well to social networks, for example. The spatial weights are used to construct a new *spatial* variable, referred to as a spatially lagged variable or spatial lag (Anselin, 1988c). Such variables are essentially a weighted sum of the values for a given variable at neighboring locations, i.e., $\sum_{j=1}^{N} w_{ij} y_j$, where i, j are the pairwise observations. For pairs where there is no neighbor relation, $w_{ij} = 0$. By convention, the diagonal elements of the spatial weights matrix are set to zero (no self-neighbors) and it is typically used in row-standardized form. Also, in most applications, the weights are considered to be exogenous, although more recent approaches have considered endogenous spatial weights as well.

An alternative approach to structure the spatial interaction is through a decay function in the pair-wise distances between observations, either used as is (with parameters pre-set or estimated from the data), incorporated in kernel weights, or embedded in a spatial weights matrix.

A spatial lag operator can be applied to the dependent variable, (some of) the explanatory variables or the error terms, yielding a simple taxonomy of spatial models

(Anselin, Serenini & Amaral, 2025). Common notation uses Wy for a spatially lagged dependent variable, WX for spatially lagged explanatory variables,[3], and We for spatially lagged error terms, with y and e as $N \times 1$ vectors of dependent variables and error terms respectively, and X as a $N \times k$ matrix of explanatory variables. The main model structures for a linear spatial specification then follow as:

- spatial lag or spatial autoregressive model (SAR): $y = \rho W y + X\beta + e$, with ρ as the spatial autoregressive coefficient,
- spatial lag of X model (SLX): $y = X\beta + WX\gamma + e$, with γ as an extra set of regression coefficients,
- spatial Durbin model (SDM): $y = \rho W y + X\beta + WX\gamma + e$,
- spatial error model (SEM): $y + X\beta + e$, and $e = \lambda We + u$, with λ as the spatial autoregressive coefficient[4].

The second major spatial effect, spatial heterogeneity, is a special case of observed or unobserved heterogeneity. In contrast to what holds for spatial dependence, this can often be addressed with standard econometric methods (e.g., random coefficients, mixture models). The distinguishing characteristic is that the structure has a spatial component. This takes the form of so-called spatial regimes, i.e., spatially contiguous subsets of observations that follow a separate structure in the form of a different functional specification or different coefficients. As a result, standard methods need to be extended to account for the contiguity constraints implied by the spatial regimes.

Interest in the spatial aspects of data is not unique to spatial econometrics. In fact, there exists a rich literature in spatial statistics going back to the early twentieth century, initially focused on the design of agricultural experiments. This has evolved into an extensive body of work, summarized early on in a comprehensive manner in Ripley (1981) and Cressie (1991). The distinction between the two fields is subtle. While there is considerable overlap, there are also two important differences. In spatial statistics, the focus is on the data, whereas in spatial econometrics, the *model specification* is central. This is driven by economic theory or behavioral concerns, such as the need to reflect peer influence, network interaction or competition. Secondly, in spatial statistics the predominant paradigm is Bayesian, especially implemented as hierarchical models. In contrast, spatial econometrics largely favors maximum likelihood (ML) and method of moments approaches.

7.3 Early Stages of Spatial Econometrics (Mid 1970s to Late 1980s)

The early stages in the development of spatial econometrics, spanning the mid-1970s to the late 1980s, were characterized by a primary focus on testing for residual

---

[3] Note that for row-standardized row-standardized weights, the spatial lag operator should not be applied to the constant term since it will create perfect multicollinearity.

[4] A spatial moving average (SMA) form is less common, but has $e = \lambda W u + u$.

spatial autocorrelation —primarily through Moran's I statistic applied to ordinary least squares residuals—model specification (especially the spatial lag and spatial error models), basic estimation techniques for linear spatial regression models using ML and the first instrumental-variables approaches, model discrimination and specification testing, and some initial work on space-time models Anselin (2007, 2010). This period laid the conceptual and technical foundations of the field before the widespread availability of microcomputers, large geo-referenced datasets and desktop geographical information systems (GIS) transformed empirical practice.

The intellectual origins of these developments can be traced to the quantitative revolution in geography during the late 1960s, which sought to replace descriptive and largely qualitative approaches with rigorous statistical and mathematical frameworks for analyzing spatial phenomena. Influential contributions from this movement include Berry and Marble (1968), Curry (1970), and Gould (1970), as well as Tobler (1970), whose First Law of Geography provided an intuitive foundation for spatial dependence. At the same time, regional science and regional/urban economics produced operational models that explicitly incorporated spatial effects into econometric frameworks. Notable early examples are Granger (1969, 1974), Fisher (1971), Paelinck and Nijkamp (1975) and Hordijk and Paelinck (1976). These strands converged in the first comprehensive statement of the field's distinct principles by Paelinck and Klaassen (1979).

During the 1970s and 1980s the core spatial regression specifications were formalized and estimation procedures were developed for practical application. The two principal linear models that emerged were the spatial lag (or spatial autoregressive) model and the SEM. Both specifications required specialized estimation techniques because ordinary least squares became inconsistent or inefficient in the presence of spatial dependence. ML estimation, building directly on the pioneering contribution of Ord (1975), became the dominant approach. For the modest sample sizes typical of regional datasets at the time (often less than a hundred observations), the required matrix operations remained computationally feasible, even if they demanded custom programming in FORTRAN, GAUSS, or similar languages.

Alongside estimation, considerable effort was devoted to diagnostic testing and model discrimination. The most widely used tool remained Moran's I statistic, as a simple test for spatial autocorrelation. Early work also explored the properties of this statistic under different forms of the spatial weights matrix and began to consider its power against specific alternatives. Model discrimination between the spatial lag and spatial error specifications was still largely informal or based on residual diagnostics, although the foundations for more formal Lagrange multiplier (LM) tests were being laid by the end of the period. Researchers also started to extend the framework beyond pure cross-sections. Space-time modelling received attention, with Bennett (1979) providing an important early monograph that treated spatial time series in a systematic way. Parallel developments considered spatial versions of seemingly unrelated regressionmodels, allowing for contemporaneous spatial dependence across multiple equations.

By the late 1980s the field experienced a clear acceleration in activity. A growing number of publications appeared, specialist meetings were organized at national and international conferences, and major reference resources began to emerge that would shape the next generation of research. The publication of Anselin's (1988c) monograph *Spatial Econometrics: Methods and Models* represented a major synthesis that codified much of the work of the preceding decade and a half. The book provided a unified treatment of specification, estimation, testing and interpretation, and it quickly became the standard reference for both theoretical and applied researchers. This period also saw the first steps toward making spatial econometric tools more accessible, although user-friendly software packages would not appear until the early 1990s.

Several important lessons emerged from this formative stage. ML remained the dominant estimation paradigm, largely because it offered a coherent framework for models derived from spatial stochastic processes and because the computational burden was manageable for the data sizes then available. At the same time, the period witnessed the first explorations of alternative approaches, including instrumental-variables methods that would later be refined, and the earliest applications of Bayesian techniques to spatial models. A distinct geographical division also characterized the research community. In continental Europe, and particularly in the Netherlands, most contributors came from economics and econometrics backgrounds and were strongly influenced by the regional science tradition of Paelinck and his collaborators. In the United States, by contrast, spatial analysis attracted a smaller group of mathematical geographers and social scientists, while mainstream economists remained largely absent until the very end of the period.

Looking back across more than four decades, certain elements introduced during these early years have proved remarkably durable. The spatial weights matrix W has remained the standard device for encoding spatial structure. Despite later criticism of the assumption that W is exogenous and known a priori, its conceptual transparency and modeling flexibility have ensured its continued centrality. Likewise, Moran's I has retained its position as the benchmark diagnostic for spatial autocorrelation. Its simplicity, relatively good power properties against a range of alternatives, and the later development of its local version by Anselin (1995) have kept it at the center of exploratory spatial data analysis and specification testing.

By contrast, other aspects of the early literature have aged less favorably. ML estimation, while elegant, imposed non-trivial computational costs because it required repeated inversion or decomposition of $N \times N$ matrices. For the larger sample sizes that became common after the mid-1990s this quickly became prohibitive. In addition, the maintained assumption of normality, which underpinned the classical likelihood derivations, was often unrealistic for regional and urban data that frequently exhibit skewness, heavy tails or outliers. These limitations helped create the conditions for the later development of generalized method of moments estimators that avoid distributional assumptions and scale more readily to large datasets, while also stimulating work on quasi-ML and robust inference procedures.

7.4 Emergence of a Growing Interest in Spatial Econometrics (the 1990s)

The previous section has discussed the foundations of spatial econometrics before its real takeoff in the 1990s. To understand the reasons for this growing interest in the field, this section begins by addressing the context and the factors that gave rise to it. Four driving forces are broadly at the root of this takeoff.

The first force concerns the growing role of space and place in the mainstream of social sciences, especially in economics, sociology and political science. The 1990s were marked by important conceptual and theoretical changes. These have created a demand for increasingly sophisticated methodological tools and conceptual frameworks that explicitly incorporate the role of space and social interactions. More precisely, if the centrality of space and place has always been taken for granted in geography, regional science and regional and urban economics, this has not been the case in social sciences in general. Moreover, social interactions (spillover effects and externalities) began to come the foreground in social science theory.

In economics, the new economic geography theory places strong emphasis on explicitly incorporating location and movement into theories of trade and development (Krugman, 1991, 1995, 1996, 1999; Fujita, Krugman & Venables, 1999). The models that emerge—characterized by increasing returns, path dependence, and imperfect competition—induce diverse spatial effects such as externalities, agglomeration economies, and spillovers. Because these phenomena require an explicit treatment of space, their empirical analysis calls for the use of spatial econometric methods. New areas of mathematics and modern computing make it possible to analyse these effects. In sociology, there has been a recent resurgence of interest in the ecological approaches first developed by the Chicago School in the early 1920s. This renewed focus has led to a growing body of research in which computerized mapping and spatial analysis play a central role. These efforts stem from theoretical frameworks that link individual behavior to its broader context, prompting attempts to quantify concepts such as social capital and neighborhood effects (see, Abbot, 1997; Morenoff & Sampson, 1997; Sampson, Morenoff & Earls, 1999, among others). In political science—particularly in the field of international relations—a spatial perspective has become increasingly influential in both theoretical and empirical work, pointing toward the emergence of a new form of geopolitics (see Starr, 1991; Ward, 1992; O'Loughlin et al., 1999).

The second force is related to the fact that many software tools were developed, mostly in the noncommercial academic world (Anselin, 1992, 2012; Anselin & Bao, 1997; Zhang & Griffith, 1997; Symanzik et al., 1998). The incorporation of spatial data analytical techniques into the market-leading statistical and econometric software packages is still largely limited to mapping and some basic geostatistical techniques. The first package to implement a suite of spatial statistics and spatial regression in a free-standing environment was SpaceStat, released in 1991 by the National Center for Geographic Information and Analysis (NCGIA) (Anselin, 1992). Followed up later by the commercial package S+SpatialStats (Kaluzny, Vega, Cardoso & Shelly,

1998) and the Matlab toolboxes by LeSage (1999), Pace and Barry (1998). Overall, it is at the end of this decade that a tremendous amount of progress was made. This spread intensified with the beginning of the 21st century (Anselin, 2010).

The third force is linked to data availability. Anselin (2000) underlined that the widespread growth in the availability of spatial data, notably through increasing volumes of geo-coded socio-economic data sets (place-based search is becoming implemented in digital libraries and web-based initiatives to facilitate spatial data sharing and dissemination), can be considered as one of the main drivers in the acceptance and heightened demand for spatial analysis in conjunction with GIS. The use of GIS techniques has moved from simple data manipulation (mainly data organization and integration) and visualization to spatial analysis. The need has arisen to develop specialized methods of exploratory spatial data analysis (ESDA) that takes the special nature of spatial data explicitly into account (see, among others, Anselin, 1994, 1995; Anselin & Bao, 1997; Bailey & Gatrell, 1995; Cook, Majure, Symanzik & Cressie, 1996; Cressie, 1991; Getis & Ord, 1992; Majure & Cressie, 1997). The use of ESDA with GIS has become fairly common.

The fourth force relates to the 1990s, which witnessed the spread of microcomputing, the growing importance of personal computers (PCs) and decentralized computing power across university researchers, and the number of government analysts and private-sector economists among others. The expansion of the Internet in the mid-to-late 1990s increased the interest in microcomputing. This spread is closely tied to a broader technological and methodological shift in economics and econometrics (large scale data analysis, computing power, etc.).

These four driving forces have prepared the ground for major developments in spatial econometrics in the 1990s. Anselin (2000) emphasized that empirically validating emerging spatial concepts and models requires statistical and econometric approaches that explicitly incorporate location and spatial interactions. In this context, spatial econometric methods are crucial, as they address spatial dependence and spatial heterogeneity, along with their extensions to space–time settings. He further noted that spatial econometrics can be viewed as a subset of spatial statistics: rather than dealing with statistics for any type of spatial data, it focuses specifically on socioeconomic spatial models whose specification is grounded in economic theory (Anselin, 1988c). Despite these nuanced distinctions, it is important to recognize that, in the 1990s, an increasing number of mainstream econometricians have contributed to the development of spatial econometric methods. As a result, spatial econometrics has gained wider acceptance as a valuable component of the econometric toolkit. This progress has fostered the introduction of new estimation techniques (such as the method of moments), specification tests, and rigorous theoretical frameworks—particularly asymptotic results for dependent and heterogeneous spatial processes—with the derivation of their statistical the properties (see, for example, Anselin & Florax, 1995; Anselin & Bera, 1998; Anselin, 1999).

More precisely, the field is attracting many new contributors, including quantitative geographers, regional scientists, students, and the influx of economists from the United States, mostly in applied fields, such as development, regional and urban economics, labor economics, real estate economics, public economics, agricultural and environmental economics or industrial organization among others. At the same time, spatial problems also began to attract the attention of several mainstream theoretical econometricians (e.g., Bera, Durlauf, Kelejian, LeSage, Pinkse, Prucha, Robinson, Slade). It is also during this period that articles started to be published in leading econometrics and field journals such as International Economic Review, International Regional Science Review, Journal of Econometrics, Journal of Real Estate Finance and Economics (Anselin, 2007, 2010).

Research continues to be focused on issues of specification, estimation and testing. Interest starts to center on more rigorous formal proofs of the properties of estimators and test statistics (e.g., specialized laws of large numbers and central limit theorems were developed), new approaches were introduced (e.g., LM statistics, generalized method of moments (GMM) estimation, Bayesian techniques), panel data and discrete choice models were considered, more attention was paid to computational aspects, and accessible software became available, as we have already mentioned. Formal derivations of the asymptotic properties completed by simulation study of small sample properties of estimators and test statistics become standard, contrasting with a more informal approach during the previous stage.

This period marks the emergence of S2SLS[5]/GMM and their capacity to handle large datasets. The two previous decades were dominated by the ML paradigm. Nevertheless, ML procedures are likely to be impractical when the individual sample size is exceptionally large, and sample sizes are increasing with the availability of spatial data. ML calls also for explicit distributional assumptions, which may be difficult to satisfy, although quasi-ML approaches may to some extent allay this problem, and specifying and maximizing likelihood functions appropriate to extensions to more complex models may be problematic. In view of the desirability of estimation approaches that avoid some of the challenges posed by ML, Kelejian and Prucha (1998, 1999) suggested an alternative instrumental-variables estimation procedure for the spatial lag model also including a SAR process for the disturbances. This approach is based on a GMM estimator of a parameter in the SAR process. The procedures suggested in Kelejian and Prucha (1998, 1999) are computationally feasible even for very large sample sizes. As in most of the spatial literature, they consider the case where a single cross section of data is available.

Interest also extends beyond the traditional linear regression model. Spatial effects are being incorporated in models with limited dependent variables, such as spatial probit models (e.g., Case, 1992; McMillen, 1992, 1995; Brock & Durlauf, 1995; Pinkse & Slade, 1998). In parallel, spatial counterparts to the unit root problem in time series have been developed by Fingleton (1999). Research has also shifted from purely cross-section settings toward the analysis of origin destination flows, as in Bolduc, Laferrièrre and Santarossa (1992, 1995). The treatment of spatial heterogeneity initially focused on further elaboration of the expansion method (e.g., Can, 1992; Jones & Casetti, 1992; Casetti, 1997). However, a major breakthrough came with the introduction of geographically weighted regression (GWR), which allows model parameters to vary across space (Fotheringham, 1997; Fotheringham,

[5] Spatial two-stage least squares.

Brundson & Charlton, 1998; Fotheringham & Brundson, 1999). GWR, introduced to the geography literature by Brunsdon, Fotheringham and Charlton (1996), has since become a central paradigm in spatial modelling, but so far with limited adoption among econometricians mainly because of overfitting, sampling issues or residual correlation (see Wheeler & Páez, 2010). Another emerging paradigm is spatial filtering, namely, a method to transform the variables into a model such that spatial effects are eliminated and standard methods can be applied (Getis, 1995). This approach has not aged well in spatial econometrics either because it is seen mainly as a black-box and as providing obscure spatial interpretation.

Meanwhile, a revival interest of Bayesian methods has taken shape with Gelfand and Smith (1990). More precisely, this paves the way for widespread application of the Bayesian approach to estimate the spatial models, greatly facilitated by major advances in practical simulation estimators, such as Markov chain Monte Carlo (MCMC) and the Gibbs sampler (Casella & George, 1992; Gilks, Richardson & Spiegelhalter, 1996). This innovation simplifies the implementation of Bayesian methods compared to earlier approaches that depended on analytical solutions of the posterior distribution. Nevertheless, at this stage, this approach saw only limited adoption, a notable exception being the work by LeSage (1997).

When it comes to testing, if the early spatial econometrics literature was dominated by the Wald (W) and likelihood ratio (LR) tests, Rao's score (RS) test (known as the LM tests in econometrics) became very popular due to its computational simplicity (mainly basing a test on OLS under the null hypothesis) compared to the other two. A number of such tests were developed including a robust form of LM statistics, see Anselin (1988a, 1988b), Bera and Yoon (1993), Anselin, Bera, Florax and Yoon (1996) among others. For an overview of this topic, see Anselin and Bera (1998). Another popular test for spatial autocorrelation in a linear regression model, which has seen new developments, is the Moran I's test, which is similar in structure to the Durbin-Watson test for serial correlation in the time domain. Moran's I statistic and its LM form have been generalized, such as their application to the residuals in 2SLS regressions (Anselin & Kelejian, 1997) and apply to probit and tobit models by Pinkse and Slade (1998). Also, more complex alternative hypotheses were investigated by Mur (1999) and Kelejian and Robinson (1998).

7.5 The 21st Century as a Turning Point to Reach the Mainstream

The early twenty-first century marked a decisive turning point for spatial econometrics. Building on the foundations laid in previous decades, the field experienced a tremendous surge in both theoretical advancements and applied empirical work, leading to its general acceptance as a mainstream component of the econometric toolkit. As noted by Anselin, Florax and Rey (2004), Arbia (2011), Baltagi (2011) and Lee and Yu (2010, 2011, 2015), the number of publications exploded, extending well beyond regional science and geography into leading economics, sociology and political science journals.

A particularly visible sign of this mainstreaming was the publication in 2007 of a special issue of the *Journal of Econometrics* dedicated to the analysis of spatially dependent data (Baltagi, Kelejian & Prucha, 2007), which brought together important theoretical developments and empirical applications from leading researchers in the field. Spatial effects are now routinely considered in empirical research, and the methodological toolkit has matured to address increasingly complex data structures and research questions.

Several interconnected developments characterize this period. Quantitative spatial economics emerged as a prominent paradigm in the early 2000s, evolving from the New Economic Geography of the 1990s into rigorous quantitative frameworks that closely integrate theoretical models with observed spatial data patterns. Spatial panel econometrics advanced rapidly from static models to dynamic specifications. Anselin (2001) and Anselin, Le Gallo and Jayet (2008) provided foundational taxonomies, while testing procedures were refined to distinguish spatial dependence from time-series dynamics and to handle weak versus strong cross-sectional dependence (Holly, Pesaran & Yamagata, 2010, 2011; Chudik, Pesaran & Tosetti, 2011). More recently, attention has turned to multi-dimensional spatial panels that incorporate higher-order contiguity, network structures or multiple spatial dimensions simultaneously (Le Gallo & Pirotte, 2024).

Specialized models proliferated, including spatial stochastic frontier models (Fusco, 2013) and spatial quantile regression (McMillen, 2013; Chen & Tokdar, 2021). Non-linear models were extended to panel settings. Non-parametric approaches such as GWR gained traction, although concerns about overfitting and residual correlation persisted (Wheeler & Páez, 2010). The era of big data brought large-scale geo-referenced datasets, requiring new computational techniques such as sparse matrix algorithms and scalable estimation methods. These advances have been accompanied by a broader methodological evolution, with spatial econometrics techniques themselves becoming more sophisticated and widely adopted; SDMs, for example, moved from rarity to standard practice, although a closer look shows important limitations in the interpretation of their implied spatial multipliers and their consistency with distance-decay principles (Anselin, Serenini & Amaral, 2026). The field now routinely acknowledges that the geographical units of observation cannot be treated as independent entities because they constantly interact, and that this interaction causes economic spillovers from one unit to another (Elhorst, 2024; Fratesi et al., 2026).

These developments were accompanied by significant challenges. The rapid rise of artificial intelligence (AI) and machine learning created both opportunities and tensions: hybrid approaches combining structural spatial models with machine learning methods for estimating weights matrices, pattern detection, or causal inference under interference have proliferated, although the ethical and substantive risks of over-reliance on AI (including illicit replacement of authorial responsibility) have also been noted (Fratesi et al., 2026). Network econometrics emerged as a related but distinct field, raising questions about whether spatial econometrics would retain a clear identity centered on geographic and topological structure. Multi-dimensional asymptotic theory became essential. Causal inference with spatial data posed particularly thorny problems. Spatial dependence and heterogeneity can violate the Stable Unit Treatment Value Assumption through interference and spillover effects, as surveyed in Serenini (2025).

Building on earlier contributions on causal inference under interference, spatial difference-in-differences estimators were developed (Delgado & Florax, 2015; Chagas, Azzoni & Almeida, 2016), with more recent innovations such as spatial extensions of synthetic difference-in-differences that disentangle direct and indirect treatment effects (Serenini, 2025). However, several important challenges remain open. Methods such as matching and inverse probability weighting often address spatial dependence primarily in the selection process but struggle to incorporate spillovers directly into the outcome equation rather than treating them only as a source of contamination. Spatial regression discontinuity designs offer high internal validity near borders but suffer from limited external validity, while difference-in-differences and synthetic control extensions for spatial settings remain incipient, particularly for staggered adoption designs and feedback effects. The choice and specification of the spatial weights matrix W continues to be a critical and debated issue across virtually all these approaches.

An important aspect to highlight is how the software evolution has been transformative over this period. The groundbreaking standalone packages of the 1990s, such as SpaceStat (Anselin, 1991), and the early 2000s, with GeoDa emerging as the flagship for interactive exploratory spatial data analysis (Anselin, Syabri & Kho, 2006), have given way to seamless integration within mainstream data-science environments (see, for example, the integrated workflows across GeoDa, GeoDaSpace, and PySAL in Anselin and Rey (2014). GeoDa itself evolved from a closed-source, Windows-only application tightly linked to Environmental Systems Research Institute (ESRI) MapObjects into a fully open-source, cross-platform ecosystem centered on the libgeoda library, with native interfaces in R (rgeoda) and Python (pygeoda) that deliver competitive performance for core operations such as local spatial autocorrelation statistics (Anselin, Li & Koschinsky, 2022). In parallel, the PySAL ecosystem in Python has matured from an initial monolithic design into a federated collection of specialized packages organized around foundational algorithms (libpysal), exploration (esda, giddy), modeling (spreg), and visualization, greatly enhancing both accessibility and extensibility (Rey et al., 2022). Complementary tools in R (sf, spdep, spatialreg) and Stata have further lowered barriers to entry. Open-source tools now provide accessible, reproducible, and computationally efficient implementations. At the same time, the data revolution—moving from limited official regional statistics to individual-level geo-referenced data (mobile phone, satellite, GPS) and unstructured sources (textual, web-scraped, crowdsourced)—has dramatically expanded what can be analyzed.

By contrast, other developments from this period have aged less favorably, particularly those associated with overparametrization and difficulties of spatial interpretation. GWR has faced persistent criticism for overfitting, weak statistical inference on locally varying coefficients, and limited econometric appeal (Wheeler & Tiefelsdorf, 2005; Wheeler & Páez, 2010). More critically, the general nested spatial model (GNS)—with its three spatial parameters (related to the dependent variable Wy, the explanatory variables WX, and the residuals We)—has seen very limited adoption due to identification problems, multicollinearity, and unstable estimates (see, for example, the 'banana trench' issue raised in Bivand and Piras (2015)). Even the SDM, which is far more widely used in applied work, often suffers from the same underlying issues: many papers adopt the SDM specification without testing the common factor hypothesis that would justify (or reject) the inclusion of the WX term, and even fewer examine whether the implied spatial multipliers respect intuitive distance-decay patterns under Tobler's First Law (Anselin et al., 2026). These limitations have reinforced the value of parsimonious, theory-driven specifications.

In sum, the twenty-first century transformed spatial econometrics from a specialized niche into a mainstream methodological pillar, with widespread recognition that spatial correlation is not the exception. It is rather the norm when dealing with geographical data. The field has successfully absorbed advances in panels, causal inference under spatial interference, big data, and computational methods. Yet it continues to grapple with overparametrisation, clear substantive interpretation of spillovers, and the integration of new tools such as machine learning while maintaining a distinct yet pluralist identity.

7.6 Conclusion

Spatial econometrics has become a continuously evolving field. Since the 1970s, it has emerged as a prominent field in quantitative economics. The widespread availability of microcomputers and software, the growing role of space and place in the mainstream of social sciences, the large geo-referenced datasets and desktop GIS have been the driving forces behind its evolution. The increasing availability of very large geo-referenced dynamic databases has shifted attention from cross-section spatial datasets to multi-dimensional spatial panels that incorporate higher-order contiguity, network structures or multiple spatial dimensions simultaneously. In this context, the multi-dimensional asymptotic theory became essential. This era of big data requires new computational techniques such as sparse matrix algorithms and scalable estimation methods. The rapid rise of AI and machine learning created new opportunities of computational methods but also substantive risks of over-reliance on AI. Network econometrics emerged as a related but distinct field, raising questions about whether spatial econometrics would retain a clear identity centered on geographic and topological structure. Ultimately, the relentless pressure exerted by new and increasingly rich datasets continues to shape the evolution of the field and its ongoing adaptation.

References

Abbot, A. (1997). Of time and space: The contemporary relevance of the Chicago School. *Social Forces*, *75*, 1149-1182.

Anselin, L. (1988a). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical Analysis*, *20*, 1-17.

Anselin, L. (1988b). Model validation in spatial econometrics: A review and evaluation of alternative approaches. *International Regional Science Review*, *11*, 279-316.

Anselin, L. (1988c). *Spatial econometrics: Methods and models*. Dordrecht: Kluwer academic publishers.

Anselin, L. (1991). SpaceStat, a software program for analysis of spatial data [Computer software manual]. National Center for Geographic Information and Analysis (NCGIA), University of California, Santa Barbara, CA.

Anselin, L. (1992). *SpaceStat, a software package for the analysis of spatial data.* Santa Barbara, CA: National Center for Geographic Information and Analysis.

Anselin, L. (1994). Exploratory spatial data analysis and geographic information systems. In M. Painho (Ed.), *New tools for spatial analysis* (p. 45-54). Luxembourg: EuroStat.

Anselin, L. (1995). Local indicators of spatial association — LISA. *Geographical Analysis*, *27*, 93-115.

Anselin, L. (1999). The future of spatial analysis in the social sciences. *Geographic Information Sciences*, *5*, 67-76.

Anselin, L. (2000). GIS, spatial econometrics and social science research. *Journal of Geographical Systems*, *2*, 11-15.

Anselin, L. (2001). Spatial econometrics. In B. H. Baltagi (Ed.), *A companion to theoretical econometrics* (p. 310-330). Blackwell, Oxford.

Anselin, L. (2006). Spatial econometrics. In T. Mills & K. Patterson (Eds.), *Palgrave handbook of econometrics: Volume 1, econometric theory* (p. 901-969). Basingstoke: Palgrave Macmillan.

Anselin, L. (2007). Spatial econometrics in RSUE: Retrospect and prospect. *Regional Science and Urban Economics*, *37*, 450-456.

Anselin, L. (2010). Thirty years of spatial econometrics. *Papers in Regional Science*, *89*, 3-25.

Anselin, L. (2012). From SpaceStat to CyberGIS: Twenty years of spatial data analysis software. *International Regional Science Review*, *35*, 131-157.

Anselin, L. & Bao, S. (1997). Exploratory spatial data analysis linking spacestat and arcview. In M. Fischer & A. Getis (Eds.), *Recent developments in spatial analysis* (p. 35-59). Berlin: Springer-Verlag.

Anselin, L. & Bera, A. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In A. Ullah & D. E. Giles (Eds.), *Handbook of applied economic statistics* (p. 237-290). New York: Marcel Dekker.

Anselin, L., Bera, A., Florax, R. J. G. M. & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, *26*, 77-104.

Anselin, L. & Florax, R. J. G. M. (Eds.). (1995). *New directions in spatial econometrics*. Berlin: Springer-Verlag.

Anselin, L., Florax, R. J. G. M. & Rey, S. J. (2004). Econometrics for spatial models, recent advances. In L. Anselin, R. J. G. M. Florax & S. J. Rey (Eds.), *Advances in spatial econometrics. methodology, tools and applications* (p. 1-25). Springer-Verlag, Berlin.

Anselin, L. & Kelejian, H. H. (1997). Testing for spatial error autocorrelation in the presence of endogenous regressors. *International Regional Science Review*, *20*, 153-182.

Anselin, L., Le Gallo, J. & Jayet, H. (2008). Spatial panel econometrics. In L. Mátyás & P. Sevestre (Eds.), *The econometrics of panel data, fundamentals and recent developments in theory and practice* (p. 625-660). Springer-Verlag, Berlin.

Anselin, L., Li, X. & Koschinsky, J. (2022). Geoda, from the desktop to an ecosystem for exploring spatial data. *Geographical Analysis*, *54*(3), 439–466.

Anselin, L. & Rey, S. (2014). *Modern spatial econometrics in practice: A guide to GeoDa, GeoDaSpace and PySAL.* GeoDa Press, Chicago.

Anselin, L., Serenini, R. & Amaral, P. (2025). Alternative perspectives on spatial econometrics model specification search. *Spatial Economic Analysis*, *21*, 288-335.

Anselin, L., Serenini, R. & Amaral, P. (2026). Spatial durbin meets tobler. *Letters in Spatial and Resource Sciences*, *19*, 1-17.

Anselin, L., Syabri, I. & Kho, Y. (2006). Geoda: An introduction to spatial data analysis. *Geographical Analysis*, *38*(1), 5–22.

Arbia, G. (2006). *Spatial econometrics: Statistical foundations and applications to regional convergence*. Springer-Verlag, Heidelberg.

Arbia, G. (2011). A lustrum of SEA: Recent research trends following the creation of the Spatial Econometrics Association (2007–2011). *Spatial Economic Analysis*, *6*, 377-395.

Arbia, G. (2014). *A primer for spatial econometrics: with applications in R*. Palgrave-MacMillan, Basingstoke.

Bailey, T. & Gatrell, A. (1995). *Interactive spatial data analysis*. New York: Wiley.

Baltagi, B. H. (2011). Spatial panels. In A. Ullah & D. E. A. Giles (Eds.), *Handbook of empirical economics and finance* (p. 397-434). Taylor & Francis Group, New York.

Baltagi, B. H., Kelejian, H. H. & Prucha, I. R. (2007). Analysis of spatially dependent data. *Journal of Econometrics*, *140*, 1–4. (Guest editorial for the special issue)

Bartels, C. P. & Ketellapper, R. (1979). *Exploratory and explanatory analysis of spatial data*. Martinus Nijhoff, Boston, MA.

Bennett, R. (1979). *Spatial time series*. Pion, London.

Bera, A. & Yoon, M. J. (1993). Specification testing with locally misspecified alternatives. *Econometric Theory*, *9*, 649-658.

Berry, B. & Marble, D. (1968). *Spatial analysis: A reader in statistical geography*. Prentice-Hall, Englewood Cliffs.

Bivand, R. S. & Piras, G. (2015). Comparing implementations of estimation methods for spatial econometrics. *Journal of Statistical Software*, *63*, 1–36.

Bolduc, D., Laferrièrre, R. & Santarossa, G. (1992). Spatial autoregressive error components in travel ow models. *Regional Science and Urban Economics*, *22*, 381-385.

Bolduc, D., Laferrièrre, R. & Santarossa, G. (1995). Spatial autoregressive error components in travel ow models, an application to aggregate mode choice. In L. Anselin & R. J. G. M. Florax (Eds.), *New directions in spatial econometrics* (p. 96-108). Heidelberg: Springer-Verlag.

Brock, W. A. & Durlauf, S. N. (1995). *Discrete choice with social interactions i: Theory.* Cambridge, MA: Working Paper W5291, National Bureau of Economic Research.

Brunsdon, C., Fotheringham, A. S. & Charlton, M. (1996). Geographically weighted regression: a method for exploring spatial nonstationarity. *Geographical Analysis*, *28*, 281-298.

Can, A. (1992). Specification and estimation of hedonic housing price models. *Regional Science and Urban Economics*, *22*, 453-474.

Case, A. C. (1992). Neighborhood inuence and technological change. *Regional Science and Urban Economics*, *22*, 491-508.

Casella, G. & George, E. (1992). Explaining the gibbs sampler. *American Statistician*, *46*, 167-174.

Casetti, E. (1997). The expansion method, mathematical modeling, and spatial econometrics. *International Regional Science Review*, *20*, 9-33.

Chagas, A. L., Azzoni, C. R. & Almeida, A. N. (2016). A spatial difference-in-differences analysis of the impact of sugarcane production on respiratory diseases. *Regional Science and Urban Economics*, *59*, 24-36.

Chen, X. & Tokdar, S. C. (2021). Joint quantile regression for spatial data. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *83*(4), 826–852.

Chudik, A., Pesaran, M. H. & Tosetti, E. (2011). Weak and strong cross-section dependence and estimation of large panels. *The Econometrics Journal*, *14*, C45-C90.

Cook, D., Majure, J. J., Symanzik, J. & Cressie, N. (1996). Dynamic graphics in a GIS: a platform for analysing and exploring multivariate spatial data. *Computational Statistics*, *11*, 467-480.

Cressie, N. (1991). *Statistics for spatial data*. New York: Wiley.

Curry, L. (1970). Univariate spatial forecasting. *Economic Geography*, *46*, 241-258.

Delgado, M. S. & Florax, R. J. G. M. (2015). Difference-in-differences techniques for spatial data: Local autocorrelation and spatial interaction. *Economics Letters*, *137*, 123-126.

Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. Springer-Verlag, Heidelberg.

Elhorst, J. P. (2024). Raising the bar in spatial economic analysis: Two laws of spatial economic modeling. *Spatial Economic Analysis*, *19*, 115–132.

Fingleton, B. (1999). Spurious spatial regression: Some monte carlo results with spatial unit root and spatial cointegration. *Journal of Regional Science*, *39*, 1-19.

Fisher, W. D. (1971). Econometric estimation with spatial dependence. *Regional and Urban Economics*, *1*, 19-40.

Fotheringham, A. S. (1997). Trends in quantitative methods i: Stressing the local. *Progress in Human Geography*, *21*, 88-96.

Fotheringham, A. S. & Brundson, C. (1999). Local forms of spatial analysis. *Geographical Analysis*, *31*, 340-358.

Fotheringham, A. S., Brundson, C. & Charlton, M. (1998). Geographically weighted regression: A natural evolution of the expansion method for spatial data analysis. *Environment and Planning A*, *30*, 1905-1927.

Fratesi, U., Abreu, M., Bond-Smith, S., Corrado, L., Ditzen, J., Felsenstein, D., . . . Yu, J. (2026). 20 years of Spatial Economic Analysis: evolution, achievements and perspectives on the field. *Spatial Economic Analysis*, *21*, 1–10.

Fujita, M., Krugman, P. & Venables, A. (1999). *The spatial economy: Cities, regions and international trade*. Cambridge, MA: MIT Press.

Fusco, E. (2013). Spatial stochastic frontier models: Controlling spatial global and local heterogeneity. *International Review of Applied Economics*, *27*, 786–804.

Gelfand, A. E. & Smith, F. M. (1990). Sampling-based approaches to calculating marginal densities. *Journal of the American Statistical Association*, *85*, 398-409.

Getis, A. (1995). Spatial filtering in a regression framework: Examples using data on urban crime, regional inequality, and government expenditures. In L. Anselin & R. J. G. M. Florax (Eds.), *New directions in spatial econometrics* (p. 172-185). Heidelberg: Springer-Verlag.

Getis, A. & Ord, J. K. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis*, *24*, 189-206.

Gilks, W., Richardson, S. & Spiegelhalter, D. (1996). *Markov chain monte carlo in practice*. London: Chapman and Hall.

Gould, P. (1970). Is statistix inferens the geographical name for a wild goose? *Economic Geography*, *46*, 439-448.

Granger, C. (1969). Spatial data and time series analysis. In A. Scott (Ed.), *Studies in regional science, london papers in regional science* (p. 1-24). Pion, London.

Granger, C. (1974). Aspects of the analysis and interpretation of temporal and spatial data. *The Statistician*, *24*, 197-210.

Holly, S., Pesaran, M. H. & Yamagata, T. (2010). A spatio-temporal model of house prices in the USA. *Journal of Econometrics*, *158*, 160-173.

Holly, S., Pesaran, M. H. & Yamagata, T. (2011). The spatial and temporal diffusion of house prices in the UK. *Journal of Urban Economics*, *69*, 2-23.

Hordijk, L. (1979). Problems in estimating econometric relations in space. *Papers in Regional Science*, *42*, 99-115.

Hordijk, L. & Nijkamp, P. (1977). Dynamic models of spatial autocorrelation. *Environment and Planning A*, *9*, 505-519.

Hordijk, L. & Nijkamp, P. (1978). Estimation of spatio-temporal models: New directions via distributed lags and markov schemes. In A. Karlquist, L. Lundquist, F. Snickars & J. Weibull (Eds.), *Spatial interaction theory and planning models* (p. 177-199). North Holland, Amsterdam.

Hordijk, L. & Paelinck, J. H. P. (1976). Some principles and results in spatial econometrics. *Recherches Économiques de Louvain*, *42*, 175-197.

Jones, J. P. & Casetti, E. (1992). *Applications of the expansion method*. London: Routledge.

Kaluzny, S. P., Vega, S. C., Cardoso, T. P. & Shelly, A. A. (1998). *S+SpatialStats*. Springer.

Kelejian, H. H. & Piras, G. (2017). *Spatial econometrics*. Academic Press, Cambridge.

Kelejian, H. H. & Prucha, I. R. (1998). A generalized spatial two stage least squares procedures for estimating a spatial autoregressive model with autoregressive disturbances. *Journal of Real Estate Finance and Economics*, *17*, 99-121.

Kelejian, H. H. & Prucha, I. R. (1999). A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review*, *40*, 509-533.

Kelejian, H. H. & Robinson, D. P. (1998). A suggested test for spatial autocorrelation and/or heteroscedasticity and corresponding monte carlo results. *Regional Science and Urban Economics*, *28*, 389-417.

Krugman, P. (1991). Increasing returns and economy geography. *Journal of Political Economy*, *99*, 483-499.

Krugman, P. (1995). *Development, geography and economy theory*. Cambridge, MA: MIT Press.

Krugman, P. (1996). Urban concentration: The role of increasing returns and transport costs. *International Regional Science Review*, *19*, 5-30.

Krugman, P. (1999). The role of geography in development. *International Regional Science Review*, *22*, 142-161.

Lee, L.-F. (2024). *Spatial econometrics: Spatial autoregressive models*. World Scientific, Singapore.

Lee, L.-F. & Yu, J. (2010). Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, *40*, 255-271.

Lee, L.-F. & Yu, J. (2011). *Estimation of spatial panels*. Boston: Foundations and Trends in Econometrics, NOW Publisher.

Lee, L.-F. & Yu, J. (2015). Spatial panel data models. In B. H. Baltagi (Ed.), *The oxford handbook of panel data* (p. 363-401). Oxford University Press, Oxford.

Le Gallo, J. & Pirotte, A. (2024). *Multi-dimensional models for spatial panels.* Cham: Springer.

LeSage, J. P. (1997). Bayesian estimation of spatial autoregressive models. *International Regional Science Review*, *20*, 113-129.

LeSage, J. P. (1999). *Spatial econometrics.* The Web Book of Regional Science, Regional Research Institute, West Virginia University, Morgantown, WV.

LeSage, J. P. & Pace, K. (2009). *Introduction to spatial econometrics*. CRC Press, Boca Raton.

Majure, J. J. & Cressie, N. (1997). Dynamic graphics for exploring spatial dependence in multivariate spatial data. *Geographical Systems*, *4*, 131-158.

McMillen, D. P. (1992). Probit with spatial autocorrelation. *Journal of Regional Science*, *32*, 335-348.

McMillen, D. P. (1995). Spatial effects in probit models: Amonte carlo investigation. In L. Anselin & R. J. G. M. Florax (Eds.), *New directions in spatial econometrics*

(p. 189-228). Heidelberg: Springer-Verlag.

McMillen, D. P. (2013). *Quantile regression for spatial data*. Berlin: Springer.

Morenoff, J. D. & Sampson, R. J. (1997). Violent crime and the spatial dynamics of neighborhood transition: Chicago 1970-1990. *Social Forces*, *76*, 31-64.

Mur, J. (1999). Testing for spatial autocorrelation: Moving average versus autoregressive processes. *Environment and Planning A*, *31*, 1371-1382.

O'Loughlin, J., Ward, M. D., Lofdahl, C. L., Cohen, J. S., Brown, D. S., Reilly, D., . . . Shin, M. (1999). The diffusion of democracy, 1946-1994. *Annals of the Association of American Geographers*, *88*, 545-574.

Ord, J. K. (1975). Estimation methods for models of spatial interaction. *Journal of the American Statistical Association*, *70*, 120-126.

Pace, R. K. & Barry, R. (1998). *Spatial statistical toolbox 1.0.* Lousiana State University, Baton Rouge, LA.

Paelinck, J. H. P. & Klaassen, L. H. (1979). *Spatial econometrics*. Saxon House, Farnborough.

Paelinck, J. H. P. & Nijkamp, P. (1975). *Operational theory and method in regional economics*. Saxon House, Farnborough.

Pinkse, J. & Slade, M. E. (1998). Contracting in space: An application of spatial statistics to discrete-choice models. *Journal of Econometrics*, *85*, 125-154.

Rey, S. J., Anselin, L., Amaral, P., Arribas-Bel, D., Cortes, R. X., Gaboardi, J. D., . . . Wolf, L. J. (2022). The pysal ecosystem: Philosophy and implementation. *Geographical Analysis*, *54*, 467–487.

Ripley, B. D. (1981). *Spatial statistics*. New York: Wiley.

Sampson, R. J., Morenoff, J. D. & Earls, F. (1999). Beyond social capital: Spatial dynamics of collective efficacy for children. *American Sociological Review*, *64*, 633-660.

Serenini, R. (2025). *Essays in spatial econometrics and causal inference* (Unpublished doctoral dissertation). Sapienza University of Rome. (Chapter 1)

Starr, H. (1991). Democratic dominoes: Diffusion approaches to the spread of democracy. *Journal of Conflict Resolution*, *35*, 6-31.

Symanzik, J., Kotter, T., Schmelzer, S., Klinke, S., Cook, D. & Swayne, D. (1998). Spatial data analysis in the dynamically linked ArcView/Xgobi/XploRe environment. *Computing Science and Statistics*, *21*, 561-569.

Tobler, W. (1970). A computer movie simulating urban growth in the detroit region. *Economic Geography*, *46*, 234-240.

Ward, M. D. (1992). *The new geopolitics*. London: Gordon and Breach.

Wheeler, D. C. & Páez, A. (2010). Geographically weighted regression. In M. M. Fisher & A. Getis (Eds.), *Handbook of applied spatial analysis* (p. 461-486). Berlin: Springer-Verlag.

Wheeler, D. C. & Tiefelsdorf, M. (2005). Multicollinearity and correlation among local regression coefficients in geographically weighted regression. *Journal of Geographical Systems*, *7*(2), 161–187.

Zhang, Z. & Griffith, D. (1997). Developing user-friendly spatial statistical analysis modules for GIS, an example using ArcView. *Computers, Environment and Urban Systems*, *21*, 5-29.

Index