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Thirty Years of Spatial Econometrics

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Abstract

In this paper, I give a personal view on the development of the field of spatial econometrics during the past thirty years. I argue that it has moved from the margins to the mainstream of applied econometrics and social science methodology. I distinguish three broad phases in the development, which I refer to as preconditions, take off and maturity. For each of these phases I describe the main methodological focus and list major contributions. I conclude with some speculations about future directions.

1 Introduction

It has been some thirty years since Jean Paelinck and Leo Klaassen published a small volume entitled *Spatial Econometrics* (Paelinck and Klaassen 1979), which arguably was the first comprehensive attempt at outlining the field of spatial econometrics and its distinct methodology. So, somewhat arbitrarily, I am taking 1979 as the historical starting point for spatial econometrics. This is not solely motivated by the publication of the Paelinck-Klaassen book, but also by a number of other important volumes and articles that appeared in that year. For example, two related books that put the importance of spatial and space-time data analysis front and center were the edited volume by Bartels and Ketellapper (1979) on *Exploratory and Explanatory Analysis of Spatial Data* and the book by Bennett (1979) on *Spatial Time Series*. In addition, there was an important paper by Hordijk (1979) that appeared in Volume 42 of the *Papers of the Regional Science Association* on "Problems in Estimating Econometric Relations in Space."

Even though 1979 is a convenient reference point, it should be noted that the introduction of the term *spatial econometrics* itself predates this by some time. As mentioned in Paelinck and Klaassen (1979, p. vii), Jean Paelinck argued for the creation of this new field at the Annual Meeting of the Dutch Statistical Association in Tilburg in May 1974. He motivated this by pointing to the need to develop a "systematic branch of econometrics" to provide the methodological foundation for regional and urban econometric models.[1]

In this paper, I provide a very personal (and thus admittedly biased) view of the evolution of the field of spatial econometrics over the past thirty-some years. I take a fairly narrow view of spatial econometrics and specifically do not include the considerable amount of work (or authors) that deals with "spatial data analysis" in general, if it does not take an explicit regression approach. The paper builds on several earlier reviews, including material from the introduction to Anselin and Florax (1995a), the literature review in Anselin et al. (2004b), and the recent assessment of contributions to *Regional Science and Urban Economics* in Anselin (2007).

[1]As mentioned in a footnote in Paelinck and Klaassen (1979, p. vii), there were even earlier precursors of this idea in a report Jean Paelinck prepared for the Annual Meeting of the Association de Science Régionale de Langue Française in 1966, which appeared in 1967 as Paelinck (1967), specifically on p. 58. This appears to be the first published reference to the field of spatial econometrics.

I start with an overview of some definitions and next argue that the discipline has moved from the margins to the mainstream of quantitive methods in the social sciences. I categorize the development of the field and its impact in the literature into three broad phases. Paraphrasing (and simplifying) Rostow (1960), I refer to these as the preconditions for growth ("take-off"), the take-off, and maturity. For each phase, I elaborate on the nature of methodological advances, identify the main contributors, and list some milestone publications.

In this review, it is not my intent to be comprehensive, so the reader should not feel slighted if their (or their favorite) publications are not mentioned. Also, given the context in which these ideas were presented, the focus is on the evolution of my own work, without therefore diminishing the value of the contributions of others. The main objective is to provide a sense of the change in emphasis over time and to illustrate how the field has matured and grown.

I close with some concluding remarks about future directions.

2 Definitions and Scope

Before proceeding with the historical overview, it may be interesting to briefly consider how the definition and scope of spatial econometrics evolved in the literature over the last thirty years. To illustrate this, I consider three perspectives, formulated at different points in time. I start with the original discussion in Paelinck and Klaassen (1979) and its elaboration in Ancot et al. (1990) (see also Paelinck 1982), followed by my own definition given in Anselin (1988c), and its most recent incarnation, for example, as outlined in Anselin (2006).

Paelinck and Klaassen (1979, pp. 5–11) do not define spatial econometrics per se, but start out by specifying five important principles to guide the formulation of spatial econometric models. The five "rules" consist of: (i) the role of spatial interdependence; (ii) the asymmetry in spatial relations; (iii) the importance of explanatory factors located in other spaces ("space-distant explanatory factors"); (iv) differentiation between ex post and ex ante interaction; and (v) the explicit modeling of space (topology) in spatial models.

Interestingly, these rules stress the importance of a realistic expression of spatially explicit variables in econometric model specification, such as measures of potential ("allotropy"), distance decay functions, and spatial arrangement ("topology"). They also point to the fundamental difference between spatial series and time series due to the feedback and simultaneity that follows from spatial interaction (see also Ancot et al. 1990, for several further illustrations of these principles).

The focus on specifying models in the realm of regional science is also present in the definition provided in Anselin (1988c), although there is a definite shift in emphasis to estimation and specification testing *methods*. Specifically, the domain of spatial econometrics is delineated as "the collection of techniques that deal with the peculiarities caused by space in the statistical analysis of regional science models" (Anselin 1988c, p. 7). Viewed some twenty years later, it is intriguing how in both the Paelinck-Klaassen and my early definition of the subject, the scope of the field is constrained to urban and regional modeling, which fails to anticipate the enormous growth in importance and application of spatial techniques in economics and the other mainstream social sciences.

Contrasting spatial econometrics to standard econometrics, a narrow definition is offered as dealing with "the specific spatial aspects of data and models in regional science that preclude a straightforward application of standard econometric methods" (Anselin 1988c, p. 8). This is followed by a classification of the spatial aspects into two main *spatial effects*, i.e., spatial dependence and spatial heterogeneity.

In this context, spatial dependence is viewed as a special case of cross-sectional dependence, in the sense that the *structure* of the correlation or covariance between random variables at different locations is derived from a specific ordering, determined by the relative position (distance, spatial arrangement) of the observations in geographic space (or, in general, in network space). While similar to correlation in the time domain, the distinct nature of spatial dependence requires a specialized set of techniques. Importantly, these are *not* a straightforward extension of time series methods to two dimensions. This difference is emphasized in the definition above (see also Anselin 1990b).

Spatial heterogeneity is a special case of observed or unobserved heterogeneity, a familiar problem in standard econometrics. In contrast to spatial dependence, tackling this issue does not always require a separate set of methods. The only spatial aspect of the heterogeneity is the additional information that may be provided by spatial structure. For example, this may inform models for heteroskedasticity, spatially varying coefficients, random coefficients and spatial structural change.

Spatial heterogeneity becomes particularly challenging since it is often difficult to separate from spatial dependence. This is known in the literature as the inverse problem. It is also related to the impossible distinction between true and apparent contagion. The essence of the problem is that cross-sectional data, while allowing the identification of clusters and patterns, do not provide sufficient information to identify the *processes* that led to the patterns. As a result, it is impossible to distinguish between the case where the cluster is due to structural change (apparent contagion) or follows from a true contagious process.

In practice, this is further complicated because each form of misspecification may suggest the other form in diagnostics and specification tests. For example, tests against residual spatial autocorrelation have power against heteroskedasticity, and tests against heteroskedasticity have power against residual spatial autocorrelation (Anselin and Griffith 1988). Spatial heterogeneity provides the basis for the specification of the structure of the heterogeneity in a spatial model.

Finally, in Anselin (2006, p. 902), the limiting context of urban and regional modeling and regional science is removed and the definition of spatial econometrics is placed squarely within the methodological toolbox of (applied) econometrics. In addition, the scope is broadened from the cross-sectional setting to the space-time domain. The subject of spatial econometrics is defined 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."

In sum, four important dimensions can be identified that define the scope of modern spatial econometric methodology: model specification, estimation, specification testing and spatial prediction. I briefly consider each in turn.

2.1 Components of Spatial Econometrics

Model specification deals with the formal mathematical expression for spatial dependence and spatial heterogeneity in regression models. For spatial dependence, this typically takes the form of including spatially lagged variables, i.e., weighted averages of observations for the "neighbors" of a given location. An important aspect of this is the definition of what is meant by neighbors, typically carried out through specification of a spatial weights matrix. Spatially lagged variables can be included for the dependent variable (leading to so-called spatial lag models), explanatory variables (spatial cross-regressive models) and error terms (spatial error models), as well as combinations of these, yielding a rich array of spatially explicit models (see, e.g., Anselin 2003).

The specification of spatial heterogeneity can be classified into discrete heterogeneity and continuous heterogeneity. The former consists of a pre-specified set of spatially distinct units, or spatial regimes (Anselin 1990a), between which model coefficients and other parameters are allowed to vary. Continuous heterogeneity specifies how the regression coefficients change over space, either following a predetermined functional form (in the so-called spatial expansion method of Casetti 1997), or as determined by the data through a local estimation process, as in the geographically weighted regression (GWR) of Fotheringham et al. (2002). A different perspective, more often taken in the statistical literature (as contrasted with econometrics) specifies the spatial heterogeneity as a special case of random coefficient variation (see, e.g., Gelfand et al. 2003, for an overview).

Once spatial effects are formally incorporated into a regression specification, appropriate estimation methods need to be applied that account for the simultaneity that follows from spatial dependence, or to handle a non-spherical error structure and other model features. The two dominant paradigms in spatial econometrics are based on maximum likelihood (Ord 1975) and instrumental variables/general method of moments (Anselin 1980, Kelejian and Prucha 1998, 1999). Methods have also been developed that tackle both spatial dependence and spatial heterogeneity within a unified framework (e.g., Kelejian and Prucha 2007a, 2009). Similarly, a Bayesian approach, prevalent in the statistical literature, deals with dependence and heterogeneity within the same statistical framework. However, this has seen more limited application in spatial econometrics (a notable exception is the work of LeSage 1997, LeSage and Pace 2009).

A slightly different perspective is offered by specification testing, where the focus is on detecting deviations from standard (non-spatial) model specifications that suggest spatial alternatives. Early on, interest centered on applying

Moran's I and similar correlation tests to linear regression residuals (e.g., Cliff and Ord 1972, Kelejian and Robinson 1992). This has been generalized to include residuals in nonlinear models, such as specifications with limited dependent variables (Kelejian and Prucha 2001). A different paradigm, based on the maximum likelihood framework, is offered by Lagrange Multiplier or Rao Score tests, which have been developed to deal with a range of simple and complex spatial model alternatives, including both dependence and heterogeneity (Anselin 2001a). More recently, this has been extended to the panel regression case to encompass tests against spatial correlation as well as heterogeneity in the form of random effects variation (Baltagi et al. 2007b).

The fourth component, spatial prediction, has seen rather limited attention in spatial econometrics. The bulk of the work in this area is carried out in geostatistics (e.g., Schabenberger and Gotway 2005). It should be noted that aspects of the geostatistical approach other than prediction (e.g., model specification and estimation) have seen a considerable number of applications in real estate economics (see the overview in Dubin et al. 1999). A rare example of a spatial econometric perspective on prediction is given by Kelejian and Prucha (2007b).

In sum, the definition and scope of spatial econometrics has evolved substantially over the thirty year period, moving from the "margins" of urban and regional modeling to the "mainstream" of econometric methodology.

I pursue this in more detail in the next section.

3 From Margins to Mainstream

The evolution of the way in which the definition and scope of spatial econometrics is expressed over time reflects a major move of the field from the margins in applied urban and regional economic analysis to the mainstream of economics and other social sciences. Early work in the 1970s and 1980s, including theoretical and methodological advances, appeared primarily in regional science and quantitative geography journals. The spatial perspective was conspicuously absent in the major economic and econometric journals at the time and generally ignored by econometricians.[2] This contrasted with the situation in statistics, where an attention to spatial pattern and spatial stochastic processes dates back to the pioneering results of Whittle (1954), followed by other now classic articles, such as Besag (1974), Besag and Moran (1975), Ord (1975), and the book by Ripley (1981).

The situation has changed dramatically. In recent years, the interest in spatial analysis in general and spatial econometric analysis in particular has seen an almost exponential growth, especially in the social sciences (Goodchild et al. 2000, Bivand 2008). For example, Table 1.1 in Anselin et al. (2004b, p. 3) lists several articles that appeared in the late 1990s and early 21st century in the main theoretical journals in econometrics (including *Econometrica*, the *Journal*

[2]A notable exception is some of the early work of Clive Granger, such as Granger (1969, 1974).

of Econometrics, the *Review of Economics and Statistics*, *Econometric Reviews* and *Econometric Theory*). If anything, the spatial perspective has become even more prevalent since then, perhaps best epitomized by the recent special issue of the *Journal of Econometrics* devoted to the "Analysis of Spatially Dependent Data" (Baltagi et al. 2007a).

A cursory Google search on the term "spatial econometrics" reveals no less than 949,000 entries ("spatial statistics" returns 26,400,000).[3] Placing this into context, this compares to generic "econometrics" with 3,960,000 entries, "microeconometrics" with 76,500, "micro econometrics" with 494,000 and "panel econometrics" with 755,000.

In sum, the attention on spatial effects in econometrics is no longer obscure, but part and parcel of theory and empirical practice. To some extent, this is undoubtedy due to the ready availability of increasing volumes of geo-referenced data and a user friendly technology to manipulate these in geographic information systems. However, equally important is the growing attention to a spatial perspective stimulated by an important shift in theoretical focus. Models of interacting agents and social interaction in economics change the emphasis from the individual behavior of traditional atomistic agents to the *interaction* among these agents (e.g., Glaeser et al. 1996, Akerlof 1997). This provides new theoretical perspectives to analyze phenomena, such as peer effects, neighborhood effects, spatial spillovers, and network effects (for a review, see Manski 2000, Glaeser et al. 2002). To empirically verify models of social and spatial interaction, an explicit accounting for spatial effects is required (Brock and Durlauf 2001, 2007, Brueckner 2003). The legitimization of space and geography is also evidenced by the recent World Bank Development Report, devoted to economic geography (The World Bank 2009), and the 2008 Nobel Prize in Economic Sciences awarded to Paul Krugman, in part in recognition of his work on spatial economics and the "new" economic geography (see also the commentary in Fujita and Thisse 2009).

To further illustrate this important evolution, I provide some evidence on five dimensions of change: journal publications, textbooks, software, research funding and job advertisements.

As mentioned earlier, there has been a virtual explosion in the number of articles dealing with spatial data analysis and spatial econometrics appearing in both the econometrics journals as well as applied field journals in economics (for extensive examples, see Anselin et al. 2004b, Bivand 2008). This is in addition to a continued steady stream of articles in regional science and spatial analysis journals. This was not always the case. For example, in Anselin and Griffith (1988), the content of three major spatial journals is analyzed for the period 1985–1987 (the *Journal of Regional Science*, *Geographical Analysis* and *Environment and Planning A*). Out of the 40 articles that dealt with cross-sectional data, only three considered spatial effects explicitly. In Anselin and Hudak (1992), a similar comparison is carried out for *Regional Science and Urban Economics*, the *Journal of Regional Science* and the *Journal of Urban*

[3]Most recently accessed September 13, 2009.

Economics for the period 1988–1991. Of the 409 articles considered, some 23 dealt with cross-sectional analysis, of which only one took spatial effects into consideration.

In contrast to the journal literature, the most popular econometrics textbooks have not yet fully embraced spatial econometric topics. In Anselin (1988c), it was pointed out that spatial effects were still largely ignored in standard econometric texts, with a few exceptions, such as a cursory mention in Kmenta (1971) and Johnston (1984). Ten years later, at the time of Anselin and Bera (1998), the situation had not substantially changed and spatial topics were still essentially absent in econometrics textbooks. By the early 21st century, the situation is somewhat improved, although most standard texts continue to essentially ignore the topic. Several niche texts, however, mention spatial autocorrelation, such as Kennedy (2003), Wooldridge (2003), and Cameron and Trivedi (2005) (see also the review in Arbia 2006, pp. 4–6). Others begin to move beyond a mere listing of spatial autocorrelation as a specification problem and include a discussion of actual spatial methods. For example, in 2001, the second edition of Badi Baltagi's classic text on the *Econometric Analysis of Panel Data* (Baltagi 2001b) includes for the first time an extensive discussion of spatial panels, which is maintained in later editions as well (most recently in the fourth edition, Baltagi 2008).

Whereas introductory texts still largely eschew the topic, spatial econometrics has become a recognized subfield in several recent "handbooks" of econometrics. Starting with Anselin and Bera (1998) in the *Handbook of Applied Economic Statistics* (Ullah and Giles 1998), Baltagi's *Companion to Theoretical Econometrics* (Baltagi 2001a), Mills and Patterson's *Palgrave Handbook of Econometrics*, Volume 1, devoted to theoretical econometrics (Mills and Patterson 2006), and Matyas and Sevestre's third edition of *The Econometrics of Panel Data* (Matyas and Sevestre 2008) all contain a chapter dealing with spatial econometrics (respectively, Anselin 2001b, 2006, Anselin et al. 2008). In the recently published second volume of the *Palgrave Handbook of Econometrics*, which focuses on applied econometrics, the editors argue that "problems with a spatial dimension ... is an area that has grown in application and importance, particularly over the last decade, and it is natural that we should continue to emphasize its developmental importance" (Mills and Patterson 2009, p. xxvii). This volume includes two chapters with spatial econometric applications, one on spatial hedonics (Anselin and Lozano-Gracia 2009), the other on regional economic convergence (Rey and Le Gallo 2009), topics for which accounting for spatial effects has become part of the standard research protocol. This handbook also constitutes the first time that a completely separate section (Part IX) is reserved for spatial econometrics, on equal footing with other more traditional topics, such as micro-econometrics and financial econometrics. Arguably, the presence of spatial econometrics in these mainstream compendia has facilitated its diffusion to accepted empirical practice.

A third important dimension that illustrates the move of the field from the margins to the mainstream pertains to software. In the late 1980s and early 1990s, the lack of appropriate spatial data analytical software was often cited as a major impediment for the adoption of a spatial perspective in empirical work (e.g., Anselin and Griffith 1988, Haining 1989, Goodchild et al. 1992). For example, Robert Haining concludes the introduction to his 1990 text (Haining 1990, pp. 9–10) with a discussion of a "hidden agenda," which is to provide an impetus for the development of "specialist packages" to carry out spatial data analysis.

Initial efforts focused on embedding spatial econometric capability into existing commercial statistical software, mostly by means of specialized macros or scripts (for early overviews, see, e.g., Griffith 1988b, Anselin and Hudak 1992). It was not until SpaceStat was released (Anselin 1992b) that a truly self-contained spatial econometric analysis was possible. This was soon followed by the commercial product S+Spatialstats (Kaluzny et al. 1996), as well as a flurry of activity to develop specialized packages complementing commercial GIS or statistical software, primarily in the academic world.

By the early 21st century, the situation had completely changed. Academic efforts have continued unabatedly and have yielded a rich set of specialized toolboxes, some in conjunction with commercial software tools such as Matlab, others as open source ventures. By this time, the lack of readily available software can no longer be invoked as an impediment to carry out spatial analysis. Some reviews of the state of the art in software tools can be found in Anselin (2000, 2005), Rey and Anselin (2006) and Bivand (2008), among others.

Some specific examples warrant some further discussion. First is the tremendous success among applied econometricians of the spatial econometrics toolboxes developed for Matlab by James LeSage, Kelly Pace, Paul Elhorst and colleagues, which include facilities to carry out spatial regression, Bayesian spatial econometrics and spatial panel regression (for an overview and applications, see LeSage and Pace 2009). Paralleling this is the growing community of open source developers associated with the R project that have focused on functionality for spatial data analysis. Foremost among these is group around Roger Bivand and co-workers, who have created the spdep package, which includes a rich set of functions to carry out spatial autocorrelation analysis, as well as the estimation of a range of spatial regression specifications. In addition to the spdep project, several other packages that deal with a range of spatial data analytical problems have been developed by the R community (see Bivand et al. 2008, for a recent review). A third development is the growing interest to include spatial data analytical problems in efforts to create a cyberinfrastructure. This includes taking advantage of grid computing and parallelization to tackle the associated computational issues (examples are Yan et al. 2007, Wang and Armstrong 2009). Fourth is the astounding rate of adoption of the GeoDa software package, a freestanding program to carry out geovisualization, exploratory spatial data analysis and spatial regression (Anselin et al. 2006). Since its release in late 2003, GeoDa has been downloaded by more than 45,000 users worldwide[4] and it is quickly becoming a de facto standard to teach introductory spatial analysis. Finally, the commercial sector has not lagged behind. Since version 9.2, ESRI's

[4] As of September 2009.

ArcGIS GIS software includes a spatial statistics toolbox, with functionality for spatial autocorrelation analysis and spatial regression (e.g., Mitchell 2005, Allen 2009). In sum, while there are still some spatial econometric problems for which software is limited (notably for space-time analysis), the situation at this point is such that applied spatial econometric work can no longer be deemed to be constrained by the lack of software tools.

Two remaining dimensions of change warrant a brief consideration. One is the significant influx of research funding focused on geospatial technologies, spatial statistics and spatial econometrics. In the U.S., in addition to the usual sources of funding (such as the National Science Foundation), this has resulted in additional resources provided by specialized agencies such as the National Institutes of Health (NIH) and the National Institute of Justice (NIJ). This has not only yielded research support to further advance theory and methods, but has also provided the needed resources to develop state of the art software tools.

A final dimension pertains to job advertisements. Until very recently, spatial econometrics was virtually unknown as a discipline and taught at only a handful of institutions. Remarkably, recent positions in applied economics advertised by the American Economic Association and the Agricultural and Applied Economics Association have begun to list spatial econometrics as a desired field of specialization. It also is increasingly included as a topics course in graduate econometrics curricula. A final point is that the October 2009 Newletter of the American Association of Geographers contains what I believe is the first job advertisement that requires knowledge of GeoDa for a postdoctoral position.[5]

The transition from the margins to the mainstream did not happen overnight. I now distinguish three broad phases of development. The first, which I label *preconditions for growth*, I situate from the early 1970s to the late 1980s. The second stage, *take off*, happened in the 1990s. The final stage, *maturity* or steady state, was attained in the early 21st century. Next, I consider each in more detail.

4 Stage 1 – Preconditions for Growth

The preconditions for growth developed during the mid 1970s up until the late 1980s. By then, several texts had appeared that defined the field more rigorously and took stock of the state of the art at the time (see also Table 1). This marks the transition to the second stage.

I see the origins of the field as coming from two important sources. One dates back to the quantitative revolution in geography, with the stage set by the important Berry and Marble book on spatial analysis (Berry and Marble 1968). This was followed by several now classic papers by luminaries such as Les Curry (e.g., Curry 1970), Peter Gould (e.g., Gould 1970) and Waldo Tobler (e.g., Tobler 1970). By the mid 1970s, several quantitative geographers were working on problems related to the specification and estimation of spatial models.

[5]AAG Newsletter, Vol. 44, no. 9, p. 23.

Table 1: Early Compilations, Preconditions for Growth

Precursors, up to 1979	
Cliff and Ord (1973)	Spatial Autocorrelation
Getis and Boots (1978)	Models of Spatial Processes
Bartels and Ketellapper (1979)	Exploratory and Explanatory Analysis of Spatial Data
Bennett (1979)	Spatial Time Series
Paelinck and Klaassen (1979)	Spatial Econometrics
Post 1979	
Anselin (1980)	Estimation Methods for Spatial Autoregressive Structures
Cliff and Ord (1981)	Spatial Processes: Models and Applications
Ripley (1981)	Spatial Statistics
Diggle (1983)	Statistical Analysis of Spatial Point Patterns
Bahrenberg et al. (1984)	Recent Developments in Spatial Data Analysis
Upton and Fingleton (1985)	Spatial Data Analysis by Example
Taking Stock	
Anselin (1988c)	Spatial Econometrics, Methods and Models
Griffith (1988a)	Advanced Spatial Statistics
Griffith (1990)	Spatial Statistics, Past, Present and Future
Haining (1990)	Spatial Data Analysis in the Social and Environmental Sciences
Cressie (1991)	Statistics for Spatial Data

The second origin stems from work in regional science and regional and urban economics that reflected a need to incorporate spatial effects into operational models. Interestingly, the main statement on regional science methods of the time, i.e., Walter Isard's *Methods of Regional Analysis* (Isard 1960), only briefly mentions regression and analysis of covariance (Isard 1960, pp. 19–27), but otherwise does not touch upon statistical concerns related to model parameters. Early approaches towards explicit spatial methods were reflected in Granger (1969, 1974) and Fisher (1971). The latter dealt with "Econometric Estimation with Spatial Dependence." It constitutes one of the first papers in the applied economic literature addressing the topic of spatial autocorrelation and its implication for estimation in linear regression for urban modeling. The need for operational spatial methods in regional science was further expressed in Paelinck and Nijkamp (1975), and one of the first references to spatial econometric methods appeared in Hordijk and Paelinck (1976). By 1977, the *International Regional Science Review* featured an extensive assessment of the treatment of spatial autocorrelation (Arora and Brown 1977). However, the emphasis in that article was not so much on developing new methods, but on arguing how standard techniques could handle the "problem" of spatial correlation, something which has turned out to be largely ineffective. By the late

1970s and early 1980s several compilations had appeared that stimulated further interest in spatial econometric methodology. They are listed in the top two sections of Table 1. Most of these are rather eclectic and deal with methods to analyze spatial data in a general sense, and not necessarily from an econometric point of view.

During the first stage of development of spatial econometrics, interest focused on testing for residual spatial autocorrelation (primarily using Moran's I), the specification of spatial models, basic estimation methods, model discrimination and specification testing, as well as some initial work on space-time models. I briefly elaborate.

In 1972, the article by Cliff and Ord appeared in *Geographical Analysis* that demonstrated how the Moran's I test statistic for spatial autocorrelation could be applied to residuals from an ordinary least squares regression (Cliff and Ord 1972). This was followed by several papers that focused on the properties and power of this statistic, and its application to different types of residuals, such as the uncorrelated recursive residuals (BLUS, RELUS) that were popular at the time. Often cited examples include Hordijk (1974) and Bartels and Hordijk (1977). Much later in the period, attention shifted to maximum likelihood based test statistics, such as the Likelihood Ratio and Lagrange Multiplier statistics (Burridge 1980, Anselin 1988a).

Model specification interest initially centered on the mixed regressive, spatial autoregressive (spatial lag) and spatial error models introduced in Ord (1975) and popularized through Cliff and Ord (1981). Various extensions dealt with formal properties of the models and alternative specification strategies (Anselin 1980, Blommestein 1983, 1985), higher order models, such as specifications with two different spatially lagged dependent variables (a so-called biparametric model as in Brandsma and Ketellapper 1979), and the spatial common factor or spatial Durbin model (Burridge 1981). While most attention focused on spatial autoregressive and simultaneous models, a spatial moving average model was discussed early on in Haining (1978), and the difference between a conditional and simultaneous perspective was illustrated in Haining (1984), both theoretically and empirically. Spatial correlation is introduced in linear structural equation models in Folmer and van Der Knaap (1981) and Folmer and Nijkamp (1984). Finally, spatial heterogeneity in model specification was tackled through the introduction of the spatial expansion method by Casetti (1972, 1986), and the adaptive filtering approach suggest by Gorr and co-workers (Foster and Gorr 1986).

Interestingly, this work in quantitative geography and regional science was paralleled in social network analysis, with early discussions of formal analogues to the spatial lag and error models in Doreian (1980), and a consideration of higher order specifications in Dow et al. (1982) and Dow (1984), among others.

The treatment of estimation methods for spatial econometric models was dominated by the use of the maximum likelihood approach, first introduced by Ord (1975). Further elaboration centered on exploring the formal and empirical properties of this estimator (e.g., Hepple 1976, Anselin 1980, 1988c), as well as the consideration of more complex error specifications, such as those based on distance decay functions in Bodson and Peeters (1975) and Cook and Pocock (1983), and the geostatistical approach introduced by Dubin (1988). Again, paralleling this in the social network literature are discussions of maximum likelihood estimation in Doreian (1981, 1982).

While the maximum likelihood paradigm is clearly dominant during this first stage, other approaches are beginning to be considered as well, such as instrumental variables (Anselin 1980) and Bayesian methods (Hepple 1979, Anselin 1980, 1982). An interesting precursor of the later spatial filtering methods is the spatial differencing introduced in Martin (1974), although it was based on an inadmissible value of one for the spatial autoregressive coefficient.

In the 1980s, considerable attention was paid to model discrimination and specification tests of spatial models, going beyond testing for residual spatial autocorrelation. Different specification tests and methods to adjust model fit were proposed (for overviews, see, e.g. Horowitz 1982, 1983, Bivand 1984, Blommestein and Nijkamp 1986, Anselin 1988b), as well as tests on non-nested hypotheses (Anselin 1984, 1986).

Finally, this early period also saw some initial work on space-time modeling (Bennett 1979), focusing primarily on various interesting model specifications, most notably the spatial seemingly unrelated regression model (e.g., Hordijk and Nijkamp 1977, 1978, Hordijk 1979, Anselin 1988d).

Interestingly, the major contributors at the time show an intriguing geographical and disciplinary split. In continental Europe, interest comes primarily from researchers in the Netherlands, who are almost all trained in economics and econometrics. Examples include Paelinck, Klaassen, Hordijk, Brandsma, Bartels, Blommestein, Folmer, Nijkamp and Ketellapper, among others. In contrast to this, in the Anglo-Saxon world, the contributions are dominated by scholars from the quantitative geography tradition, such as Bennett, Bivand, Cliff, Fingleton, Haining, Hepple and Martin in the United Kingdom, and Casetti and Griffith in the U.S. In addition, in the U.S., there is a small group of mathematical social network analysts, such as Doreian and Dow, but with the exception of Dubin, economists are mostly absent.

I situate the transition to the second stage around 1990. By that time, several books and edited volumes had appeared that took stock of the progress to date and further defined and refined the field. These are listed in the bottom part of Table 1. Arguably, only Anselin (1988c) is specifically about spatial econometrics, but both Griffith (1988a, 1990) and Haining (1990) consider many of the same methods and methodological questions, albeit from a slightly different perspective. Importantly, the publication of Cressie's text of *Statistics for Spatial Data* in 1991 (Cressie 1991) affirms the growing interest in spatial questions in the statistics profession. Given their scope and attempt at taking stock of a growing discipline, I see these publications as evidence that the initial development had reached a point where the conditions are set for the field to take off.

Interestingly, the late 1980s also mark the establishment of the National Center for Geographic Information and Analysis in the United States (Abler 1987, NCGIA 1988). This commitment of major resources by the National Science

Foundation created an institutional setting that stimulated the development and promotion of spatial analytical methodology well beyond the initial scope of the research center (e.g., the research agendas developed by other groups, such as URISA, Craig 1989). This also helped in attracting the attention of other social scientists, through participation in many specialist meetings and as a result of the broad dissemination activities of NCGIA.

5 Stage 2 – Take Off

The take off stage is characterized by the influx of many new individuals. The original cast of quantitative geographers and regional scientists remains active and is extended with some new participants. Some of these are regional scientists from the "Dutch School," such as Rietveld (Rietveld and Wintershoven 1998), others are geographers who shift their interest to specific spatial regression questions, such as Getis (Getis 1990), Boots (Tiefelsdorf and Boots 1995), and Fotheringham and co-workers (Fotheringham et al. 1998).

In addition, a new generation joins the field, consisting primarily of students of scholars who were active during the first stage. Examples include Can (Can 1992), Florax (Florax and Folmer 1992), Rey (Anselin and Rey 1991), Smirnov (Anselin and Smirnov 1996) and Tiefelsdorf (Tiefelsdorf and Boots 1995).

However, the most significant change is represented by the influx of U.S. economists, primarily in applied fields, such as development, regional and urban economics, public economics, real estate economics, and labor economics. Examples include Case (Case 1991, published in *Econometrica*) in development, Murdoch and colleagues (Murdoch et al. 1993) in public economics, McMillen (McMillen 1992) in urban economics, and Pace (Gilley and Pace 1996) and Thibodeau (Basu and Thibodeau 1998) in real estate economics. Similarly, spatial regression begins to appear in the literature on sociological methods as well (e.g., Land and Deane 1992). More importantly, several mainstream econometricians begin to consider spatial problems in their research, including Bera (Anselin et al. 1996), LeSage (LeSage 1997), Durlauf (Brock and Durlauf 1995), Pinkse and Slade (Pinkse and Slade 1998), and, most visibly, Kelejian (Kelejian and Robinson 1992) and Prucha (Kelejian and Prucha 1997). In addition, the first doctoral dissertations start to appear that are devoted solely to spatial econometric questions. Remarkably, these are developed at leading centers of theoretical econometrics, such as the University of Chicago, e.g., the dissertations of Conley (Conley 1996) and Topa (Topa 1996).

In this second stage in the evolution of the field, research in spatial econometrics becomes significantly more rigorous. Formal derivations of the asymptotic properties of estimators and test statistics become standard, contrasting with a more informal approach during the first stage. Illustrative examples are the introduction of the generalized moment and general method of moments estimators by Kelejian and Prucha (1998, 1999) and Conley (1999). This is also reflected in the outlets for these articles, which increasingly include mainstream economic and econometric journals, such as the *International Economic Review* and the *Journal of Econometrics*.

A second important characteristic of the research is a growing attention to small sample properties of the various methods, addressed by means of extensive simulation experiments. These are increasingly more carefully designed, use larger and larger numbers of replications (several thousands, compared to hundreds during the first stage) and realistic data settings (e.g., Anselin and Rey 1991, Anselin and Florax 1995b, Kelejian and Robinson 1998).

Research continues to be focused on issues of model specification, estimation and testing. Alternative spatial models are being suggested, such as the spatial error components of Kelejian and Robinson (1995). Test statistics are being refined, with new approaches based on moment considerations, as well as including a combined treatment of spatial correlation and heteroskedasticity (Kelejian and Robinson 1992, 1998). A robust form of the Lagrange Multiplier statistics is developed, which greatly facilitates specification search in practice (Anselin et al. 1996). Extensions of Moran's I to different models are developed, such as its application to the residuals in two stage least squares regression (Anselin and Kelejian 1997).

Interest also moves beyond the context of the standard linear regression model. Spatial effects are beginning to be considered in models with limited dependent variables, such as spatial probit models (e.g., Case 1992, McMillen 1992, 1995, Brock and Durlauf 1995, Pinkse and Slade 1998). Spatial analogues to the unit root problem in time series are developed by Fingleton (1999). Also, interest moves from the pure cross-section to the analysis of origin-destination flows, as in Bolduc et al. (1992, 1995).

The treatment of spatial heterogeneity initially focuses on further elaboration of the expansion method (e.g., Can 1992, Jones and Casetti 1992, Casetti 1997). However, the most important development in this respect is the advent of geographically weighted regression (GWR) as a way to model parameter variability across space (Fotheringham 1997, Fotheringham et al. 1998, Fotheringham and Brunsdon 1999). GWR goes on to develop into a major paradigm for spatial modeling, but so far with limited adoption among econometricians. Another emerging paradigm is that of spatial filtering, i.e., a method to transform the variables in a model such that spatial effects are eliminated and standard methods can be applied (Getis 1995). This approach is not adopted by econometricians either.

In spatial statistics, a Bayesian approach becomes the standard way to treat spatial models, greatly facilitated by major advances in practical simulation estimators, such as Markov Chain Monte Carlo (MCMC) and the Gibbs sampler (Casella and George 1992, Gilks et al. 1996). In spatial econometrics, this only sees limited adoption during this stage, an important exception being the work by LeSage (LeSage 1997).

A further distinguishing characteristic of the take off stage is a much greater attention to computational aspects and software development. With the release by NCGIA of *SpaceStat* in 1992 (Anselin 1992b), estimation and specification testing in spatial regression models became practical. This was followed later in the period by the commercial package S+SpatialStats (Kaluzny et al. 1996) and the Matlab toolboxes developed by LeSage (LeSage 1999), Pace (Pace and Barry 1998) and co-workers, as well as many specialized scripts and macros for existing commercial statistical and econometric software.

Paralleling the software development was an interest in computational aspects, in particular pertaining to the estimation of spatial regression models by means of maximum likelihood. Technical advances, such as the efficient construction of higher order spatial lag operators (Anselin and Smirnov 1996), the application of sparse matrix operations and various approximations to the likelihood function (e.g., Martin 1993, Pace 1997, Pace and Barry 1997) allow empirical practice to move from the analysis of hundreds of data points to thousands and even tens of thousands.

By the end of the decade, there is a much greater acceptance of spatial questions in applied econometrics. Several journal special issues have appeared during this period (e.g., Anselin 1992a, Anselin and Rey 1997, Pace et al. 1998) and the leading econometrics journals publish a growing number of spatial papers (e.g., Blommestein and Koper 1998, Pinkse and Slade 1998, Conley 1999, in the *Journal of Econometrics*). In addition, the focus on social interactions begins to come to the foreground in the social science theory (e.g., Abbot 1997, Akerlof 1997). The Ullah and Giles *Handbook of Economic Statistics* (Ullah and Giles 1998) is the first to include a chapter on spatial econometrics. The time is right for transition to the final stage.

Coinciding with the end of the take off period is the establishment of the Center for Spatially Integrated Social Science, funded by the National Science Foundation. This new center has the specific objective to provide research infrastructure to disseminate the spatial perspective to the broader social sciences (Goodchild et al. 2000). It undoubtedly contributed to the further acceptance of spatial econometric methodology in the mainstream.

6 Stage 3 – Maturity

As I argued in Section 3, there is strong evidence that by the early 21st century spatial econometrics has reached the mainstream, as reflected in journal articles and special issues, handbook chapters, software, job opportunities and research funding. The field has grown to the point that in 2006 a formal Spatial Econometrics Association was established, which has held well attended annual international meetings since then.

I consider the field to have reached a stage of maturity because of the general acceptance of both spatial statistics and spatial econometrics as mainstream methodologies. For example, by the early 21st century, spatial statistics plays an important role as a methodology for applied empirical work in crime analysis, environmetrics, epidemiology, and public health. Several generalist textbooks are available, such as Haining (2003), Waller and Gotway (2004), Banerjee et al. (2004), Fortin and Dale (2005), Schabenberger and Gotway (2005), Pfeiffer et al. (2008), Lawson (2009), as well as a number of specialist texts dealing with point pattern analysis and geostatistics. Similarly, in spatial econometrics, a number of new textbooks have appeared, including Arbia (2006) and LeSage and Pace (2009), as well as multiple edited volumes, such as Anselin et al. (2004a), LeSage and Pace (2004), Getis et al. (2004), and Arbia and Baltagi (2009).

In terms of personnel, the number of applied empirical workers that use spatial econometric techniques in their work sees a near exponential growth. Also, interestingly, several leading theoretical econometricians start to publish papers dealing with spatial topics. This includes well known and widely published scholars, such as Andrews (e.g., Andrews 2005), Baltagi (e.g., Baltagi and Li 2001a), Lee (e.g., Lee 2002), Pesaran (Pesaran 2006), and Robinson (Robinson 2008). Especially Baltagi and Lee make several contributions that provide new theoretical insights as the basis for several test statistics and estimation methods.

No new topics are introduced at this stage other than those considered in the first two stages of development. Nevertheless, important advances are achieved in several areas of investigation that were started during the take off period. Most important among these is perhaps the collection of formal results developed by Kelejian, Prucha and Lee on the asymptotic properties of the two main estimation methods used for spatial regression models, the maximum likelihood (ML) and generalized method of moments (GMM) estimators.[6] Among others, this includes a formal proof of the asymptotic distribution of ML and quasi-ML estimators in Lee (2004), and the derivation of optimal GMM estimators in Lee (2003, 2007) (see also Das et al. 2003, Kelejian et al. 2004). Equally significant are the generalization of the GMM estimators to models that include both spatial dependence and heteroskedasticity in Kelejian and Prucha (2009) and Arraiz et al. (2009), and the heteroskedastic and autocorrelation consistent (HAC) approach based on kernel estimation in Kelejian and Prucha (2007a). Jenish and Prucha (2009) provide a a collection of central limit theorems and laws of large numbers that form the basis for many of these formal results.

Attention focuses on model specifications other than the familiar spatial lag and spatial autoregressive error models as well, such as a general framework to deal with spatial externalities outlined in Anselin (2003). Some specifications are a special case of a standard model, such as the spatial lag model with equal weights (i.e. where all observations are neighbors of each other) considered by Lee (2002) and Kelejian and Prucha (2002). Others consider the moving average error specification (e.g., Fingleton 2008a,b), and new expressions for the error variance-covariance matrix, such as the matrix exponential (LeSage and Pace 2007). Systems of simultaneous equations and endogeneity combined with spatial correlation are considered in Kelejian and Prucha (2004), Rey and Boarnet (2004), Fingleton and Le Gallo (2008) and Anselin and Lozano-Gracia (2008). Limited interest continues to focus on models with parameters near the edge of the parameter space, similar to the unit root and spurious regression problem in time series, e.g., in Mur and Trivez (2003), Lauridsen and Kosfeld (2006, 2007), and Lee and Yu (2009b).

[6]Bayesian estimation is primarily reflected in the work of LeSage and Pace (2009). It should be noted that Fernández-Vázquez et al. (2009) also suggest the application of generalized maximum entropy estimation to spatial models, but this has not seen widespread adoption.

Three types of models receive considerably more attention than in previous periods, i.e., spatial panel models, models for spatial latent variables and models for flows. Panel spatial econometrics in particular sees a significant increase of both theoretical and applied papers. General model specifications and estimation strategies (both ML and GMM) are proposed, e.g., in Elhorst (2001, 2003), Kapoor et al. (2007), Fingleton (2008b) and Lee and Yu (2009a). A large number of specification tests are developed for a range of alternative consisting of spatial effects, random effects as well as general cross-sectional dependence, among others, in Baltagi et al. (2003, 2007b), Kapetanios and Pesaran (2007), and Pesaran et al. (2008). Prediction is considered by Baltagi and Li (2004, 2006) and Fingleton (2009). Models for spatial latent variables, in particular the spatial probit and spatial tobit models are further explored by Kelejian and Prucha (2001) (generalizing Moran's I), LeSage (2002), Beron et al. (2003), and Fleming (2004), among others. In addition, these models are increasingly used in empirical work, e.g., Holloway et al. (2002), Murdoch et al. (2003). The spatial econometric aspects of estimating and specification testing in origin-destination flow models that incorporate spatial correlation are explored by LeSage and Pace (2008), Fischer and Griffith (2008), LeSage and Polasek (2008), Chun (2008), and Griffith (2009), among others.

Specification testing enters a stage of maturity as well, with extensions of LM tests to detect multiple sources of misspecification, including functional form (Baltagi and Li 2001b), different types of spatial error correlation (Anselin 2001a, Anselin and Moreno 2003), various model selection strategies (Mur and Angulo 2006, 2009), and tests on non-nested hypotheses (Kelejian 2008). Spatial filtering gains some attention as an approach to remove spatial correlation from variables in a range of models, including models for counts, e.g., in Getis and Griffith (2002), Griffith (2003), Griffith and Peres-Neto (2006), and Tiefelsdorf and Griffith (2007).

A final distinguishing characteristic of this period of maturity is the attention paid to computational aspects and software. Further advances in computational techniques focus on various algorithms to extend the limits of maximum likelihood estimation and its associated inference, e.g., in Smirnov and Anselin (2001, 2009), Smirnov (2005), and Pace and LeSage (2004, 2009). As mentioned earlier, this is accompanied by a virtual explosion of software availability, in particular as part of the open source movement, e.g., Rey and Anselin (2006, 2007), Bivand (2006), Bivand et al. (2008), and Rey (2009).

7 Conclusions

In this paper, I have attempted to describe the evolution of the field of spatial econometrics during the past thirty years, arguing that it moved from the margins of applied regional science to the mainstream of econometric methodology. I have structured the progression into three broad phases and highlighted the major methodological advances in each.

Now that the field has reached maturity, what is next? In all likelihood, research will advance on methodological aspects related to estimation, specification testing and prediction, continuing the process of incorporating spatial effects into the model specifications dictated by theory and practice. Paralleling this, the use of spatial techniques in applied work is not likely to slow down. But what are exciting new directions and challenges that have been only partially addressed? I see at least three.

First, there is a need to better understand the fundamental processes behind the spatial and space-time correlation that is incorporated into our models. The complex dynamics that result in the existence of spatial interaction are still poorly reflected in model specifications. While factor models and kernel estimators are elegant ways to incorporate very general forms of interaction, they do not help us in understanding how or why these interactions occurred. Similarly, in models of spatial heterogeneity, the spatial regimes or spatially varying coefficients show evidence of the heterogeneity, but do not explain it. Ideally, one would want to make the structure of dependence and/or the structure of heterogeneity endogenous. For example, an endogenous spatial weights matrix would jointly determine who interacts (and why) and how that interaction affects the rest of the model. Much progress remains to be made in linking the formation of social networks to their spatial imprint, and further connect social and spatial interaction.

A second challenge is to deal with the conceptual questions raised by using ever-larger data sets, many of which result from automatic data recording. Systems of sensors, both in the natural and in the social sciences, provide ever larger streams of extremely fine grained data (on a time scale, geographical scale and individual scale). The standard sample-population paradigm or even the spatial stochastic process paradigm are insufficient to meaningfully address the questions raised in the analysis of such massive data sets. The notions of equilibrium (like spatial stationarity) on which we rely to develop and assess our models likely become unrealistic in this context. Also, traditional concepts such as "significance" have little use in the analysis of massive data sets, since everything is likely to be significant. Other ways of interpreting and assessing models for such settings need to be developed. Important in this respect is the need for a better understanding of how errors (of measurement, of location, of model specification) propagate through our inferential systems and bring into question our traditional methods for quantifying uncertainty.

A final challenge parallels the previous one and pertains to the computational techniques needed to handle the complex space-time interactions in increasingly large data sets. New algorithms will need to be developed and effective use made of the rapidly changing computing technology, such as distributed computing, cloud computing and the use of handheld devices.

No doubt, others may suggest different priorities or would have emphasized alternative aspects in the evolution of the spatial econometric methodology. With this paper, I hope to have provided a stimulus so that these questions may continue to be pursued in the future. With sustained progress, maybe thirty years from now, someone will be able to meaningfully assess "60 years of spatial econometrics."

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