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Between the Quantitative and GIS Revolutions: Towards an SDA-centered GIScience

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계량혁명과 GIS혁명 사이에서: 공간데이터분석-중심의 지리정보과학을 지향하며

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Abstract: This review paper is based on an observation that there exists a 'generation gap' between the quantitative and GIS revolutions, even though paradigmatic homology of spatial science is often presumed and cross-fertilization is straightforwardly promised. It is argued that each revolution needs to be edified to establish an integrative, sustainable research framework: SDA needs to become more accessible, applicable, and GIS-friendly; GIS needs to migrate from GISystems to GIScience to place conceptual and analytical aspects of handling geographic information on its center. An SDA rendered more GIS-friendly and practiced in a GIS environment can be seen as an 'SDA-centered GIScience'. A 'SAM-based ESDA-GIS framework' is proposed to demonstrate the viability of the SDA-centered GIScience. Within the framework, local SAMs and associated ESDA techniques are expected to allow researchers to effectively investigate spatial dependence and heterogeneity.

Key Words: quantitative revolution, GIS revolution, geographic information science, spatial association measures, ESDA

요약: 이 리뷰 논문은 계량혁명과 GIS혁명의 관계에 대한 사람들의 일반적인 생각, 즉 두 혁명은 공간과학이라는 동일한 패러다임에 기반하고 있고 상호융합은 매우 자명한 것이라는 생각이 잘못되었다는 점에 착안하고 있다. 본 논문은 진정으로 통합된 지속가능한 연구틀이 정립되기 위해서는 두 혁명 각각이 새로운 지향점을 향해 변모되어야만 한다고 주장한다. 즉, 공간데이터분석(SDA)은 좀 더 접근가능하고 좀 더 적용가능한 방향으로 지향될 필요가 있고, GIS는 체계(systems)로서가 아닌 과학(science)으로서의 성격을 강화함으로써 기술적인 측면을 벗어나 지리정보를 다루는 과정에서 발생하는 개념적이고 분석적인 측면에 집중할 필요가 있다. 이러한 관점에서, GIS 환경하에서 보다 GIS-친화적인 공간데이터분석을 수행하는 것을 '공간데이터분석-중심의 지리정보과학(SDA-centered GIScience)' 이라 규정할 수 있다. 제시된 '공간적 연관 측정치(SAM)에 기반한 ESDA-GIS 연구틀(SAM-based ESDA-GIS framework)' 은 '공간데이터분석-중심의 지리정보과학' 의 실행가능성을 논증하고 있다. 그 연구틀 속에서 연구자는 국지적 통계치를 이용한 다양한 ESDA 방법들을 이용함으로써 공간적 의존성과 공간적 이질성을 효과적으로 탐색할 수 있게 된다.

주요어: 계량혁명, GIS혁명, 지리정보과학, 공간적 연관 측정치, 탐색적 공간데이터분석

I. Introduction: Feeling the Generation Gap

About 55 years, according to Baker and Boots (2005), have passed since the quantitative revolution touched down on and started to empower the discipline of geography. The revolution has been 'recollected' (Billinge et al., 1984) and 'remodeled' (Macmillan, 1989). As the overall discipline, however, has increasingly been saturated by anti-positivist movements such as hermeneutic and critical geogra-

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phies since the early 1970 (Unwin, 1992; Johnston, 1997), positivist geography in general and quantitative geography in particular started to loose its predominant status in the discipline and at least to descend from its apex, allowing for somewhat unpleasant contest of multiple paradigms. About a generation later, geography came to witness another revolution which had been conditioned by the advent of 'information society' and 'microelectronic revolution', the GIS revolution.

It might seem very clear to some people that the two revolutions are epistemologically equivalent: the latter is the legitimate successor of the former; thus the latter can be seen as a "positivist geography's great revenge" (Taylor, 211) or a Trojan horse with which the former attempts to recover the glorious status in its heyday (Taylor and Johnston, 1995). As can be seen from the debates between GIS scholars and critical human geographers since the early 1990s (for a summary, see Schuurman, 2000; Cho, 2002), GIS is alleged to be nothing but a more sophisticated version of spatial science paradigm in (human) geography that the quantitative revolution has been believed to establish.

Aside from the methodological homology, the two revolutions share several properties in a practical sense. First, both of them were initiated and guided by developments in other fields especially in terms of their fundamentals, although softer for the former, and harder for the latter. Second, both of them, due to the nature of revolution, rapidly escalated to the paramount position in the discipline. This can be evidenced by the distribution of memberships among specialty groups in the Association of the American Geographers or other countries' associations. Since the early 1990s, GIS has become a predominant sub-field within the discipline. Third, both of them called for a profound change in research practice: a GIS program is clamed to be a generic research platform as a statistical package previously was; ArcView is doing what SPSS was doing. Fourth, both of them attempted to standardize all the social sciences with their overarching methodologies, which was more evident for the first revolution, but have increasingly been observable in the GIS revolution (e.g., Goodchild and Jenelle, 2004; Okebe, 2006; Steinberg & Steinberg, 2006). Fifth, both of them were holistic in nature, possibly making a positive contribution to bridging human geography and physical geography.

The alleged homology, however, has not always been agreed. In a philosophical sense, Sheppard (2001) contends that neither quantitative geography nor GIS necessarily needs to be positivist. Further, Openshaw (1998: 320) argues that the connection is not so much a reality as an afterthought. Both commentators seem to emphasize that the advent of the GIS revolution is fundamentally conditioned by socio-economic shift towards a more quantitative, digital world.

In a practical sense, there might be several dissimilarities between the revolutions. First, geography was involved in the GIS revolution in much earlier stage than it was in the quantitative revolution, such that there was no controversy on *exceptionalism*. Second, the visibility of geography as a discipline was *hoped* in the first revolution, while it was actually *resulted* in the second revolution (Brown, 2000). Third, the GIS revolution was much less bloody than its predecessor, mainly because it had already had a large number of latent advocates, some of which were obviously descendants of the first revolution. Fourth, whereas the quantitative revolution deployed in a diffusive fashion, the GIS revolution seems to be evolving in a somewhat monopolistic fashion. Originated from the Washing school led by Garrison, the quantitative revolution extended out mainly into the Midwest, resulting in several additional schools (see Barnes, 2001; 2004). In contrast, GIS revolution, in my mind, has given birth to at most a couple of predominant schools during the similar period of time, including the School of UC

Santa Barbara. It may be understandable because the GIS revolution is much more capital-intensive than the previous one so that funding allocation may have been more selective.

This review paper is based on the realization that the relationships between quantitative geography, or SDA (spatial data analysis), and GIS are not so simple as one might think they are; even though GIS inherits much from quantitative geography, the relationships have not always been either straightforward or harmonious. Furthermore, the alleged promise of cross-fertilization can happen only when each side is edified to establish an integrative, sustainable research framework. In this sense, this paper is concerned with: (1) identifying what makes it difficult to integrate SDA and GIS and examining what should be done in each side; (2) conceptualizing an 'SDA-centered GIScience' as an integrative scheme and proposing a 'SAM-based ESDA-GIS Framework' to demonstrate the viability of the particular GIScience.

II. Edifying the Revolutions for an Integration

1. Uneasy Coupling

Throughout the paper, SDA is used to refer to recent developments in quantitative geography or more broadly defined field, *spatial analysis* (Berry & Marble, 1968). Thus, it is true that "the origins of SDA lie in the development of quantitative geography (Fischer, 1999:285)", but SDA has strongly been influenced by more statistically informed methodologies, a set of which might be called *spatial statistics*. According to Anselin and Griffith (1988), the real exposure of geography to spatial statistics was achieved by the work of Cliff and Ord (1973; revised in 1981), which Getis (1999: 241) regards as having opened "the door to a new era in spatial statistics." What makes the book really important is the fact that it enhanced quantitative geography *qualitatively* from a simple application of general statistical techniques to spatial data or a descriptive or semi-inferential level to a full-fledged inferential level.

There might be some sources for which the encounter of SDA with GIS has not been as easy as one might expect. First, "it is not necessary to use a GIS to perform spatial analysis and that integrating the two will not necessarily lead to any greater insights into geographical theory" (Fotheringham, 1992: 1675-6; Fotheringham and Charlton, 1994: 316). Accordingly, we need to acknowledge that the following question should always be asked: "Under what circumstances is a problem better solved using a package that identifies itself as a GIS, or using a statistical package, or a mathematical package, or a scientific visualization package?" (Goodchild and Longley, 1999: 571).

Second, GIS may have absorbed many of latent spatial data analysts. As Fotheringham et al. (2000: 2) argue, "GIS has tended to displace quantitative geography as the paramount area in which students are provided with all-important job-related skills." GIS as a sub-field of geography has accommodated graduate students who would have been in SDA. All these things seem to mirror the recent fate of *Geographical Analysis*. The citation impact factor for the journal is lower than when it was in infancy (O'Kelly, 1999), and it has suffered from new journals focused on GIS topics (Golledge, 1999), such as *International Journal of Geographical Information Science* and possibly *Journal of Geographical Systems* and *Transactions in GIS*.

Third, the relationship between SDA and GIS is not lateral, but in some sense, the formal is subordinate to the latter. Since GIS has increasingly become a general purpose platform (Haining et al., 2000), GIS helps SDA gain more audience if they are integrated (Goodchild et al., 1992; Fotheringham, 1993; Goodchild, 2000). This is congruent with an observation that, in some sense, the advent and development of GIS have contributed to revival or popularity of SDA (Goodchild, 1996; Unwin, 1996). Unwin (1996:540) contends that "largely as a result of the growth of GIS, spatial analysis is back on the research agenda" and Goodchild and Longley (1999:567) even argue that "the relationship between spatial analysis and GIS is analogous to that between statistics and the statistical packages."

Lastly, an abrupt and inadvertent shift from SDA to GIS or even to GIS-SDA interface may result in *de-skilling* within quantitative geography or overall geography. Longley (2000:39) argues that "the intellectual focus can change from identifying the message of spatial analysis to mastering the command structure of a particular software medium ... paradoxically, the upsurge in interest in GIS may actually accelerate de-skilling within the discipline of geography." All these things acknowledge potential difficulties in bridging the two revolutions and the need for a third-party solution beyond a mechanical coupling.

2. Edifying SDA: Making It More GIS-friendly

The term of SDA has increasingly gained popularity over quantitative geography or spatial analysis. This is not simply because 'data-driven' research practices have become more common, but because quantitative geography has qualitatively evolved to "reach a stage of maturity in which its practitioners are nor longer primarily importers of other disciplines' techniques but are mainly exporters of novel ideas about the analysis of spatial data" (Fotheringham et al., 2000, xii; Longley, 2000: 38-39). SDA appreciates the particular nature of spatial data and attempts to spatialize general statistical methods by recognizing that regular statistical assumptions seldom hold for spatial data (Lee, 2001b). It might be ironic that the more advanced SDA, the more difficult the integration. Three things may be responsible for this situation.

First, the term of SDA is hard to define. People easily get confused SDA with other similar terms; spatial statistics, spatial statistical analysis, statistical spatial analysis, spatial statistical data analysis, quantitative geography, spatial manipulation, spatial modeling, geocomputation, and GIS analysis. Even though they overlap on many of their contents, and are exchangeable in practice, an inadvertent mixture in using terms may prevent researchers from positing their research adequately with proper references. For example, Fischer (1999) sees spatial analysis and SDA exchangeable, but Haining (1994) makes a clear distinction between them (SDA is one of three components of spatial analysis); similarly, O'Sullivan and Unwin (2003: 2) see SDA as one of four components of spatial analysis along with spatial data manipulation, spatial statistical analysis, and spatial modeling; Bailey (1994) sees statistical spatial analysis different from spatial analysis; Fotheringham et al. (2000) see quantitative geography and spatial data analysis identical; Griffith and Layne (1999) regard spatial statistical data analysis exchangeable with spatial statistics; Upton and Fingleton (1985), Haining (1990; 2003), and Bailey and Gatrell (1995) seem to consider SDA to be identical to spatial statistics.

Further, between two different reviews in the same book, one on spatial statistics (Getis, 1999) and the other on spatial (data) analysis (Fischer, 1999), one may not recognize a significant difference. As Goodchild et al. (1992:410) point out, spatial statistics or SDA "remains a comparatively obscure field," and "there is no easy way of organizing or codifying it." The identity and status of SDA in geography is still equivocal. A more serious problem in terminology comes from an observation that spatial analysis in quantitative geography is not equivalent to that in GIS. In general, spatial analysis in GIS has been used to indicate spatial data manipulation including vector-based geoprocessing and raster-based overlay operations. A more equivocal term, GIS analysis, seems to substantively overlap with SDA (see ESRI, 2005).

Second, SDA is too difficult even for those who have identified themselves as quantitative geographers. Currently available textbooks on SDA (e.g., Cliff and Ord, 1981; Upton and Fingleton, 1985; Anselin, 1988; Griffith, 1988; Haining, 1990; Bailey and Gatrell, 1995; Fotheringham et al., 2000; Haining, 2003) are far beyond traditional statistics-for-geographers type books (e.g., Clark and Hosking, 1986) and more spatially informed books (e.g., Unwin, 1981). More statistics-driven books (Ripley, 1981; Cressie, 1993; Banerjee et al., 2004; Schabenberger and Gotway, 2005) are also far beyond traditional references from general statistics. In an educational sense, it is even more demanding to achieve a certain level of proficiency in SDA, because additional time should be devoted solely to SDA; there is no way to get to SDA without getting to general statistics (Boots, 2000:19; O'Kelly, 2000:26). Further, it should be noted that understanding basic notions in SDA is one thing, applying them to substantive research topics is another (O'Kelly, 2000:26). As Goodchild et al. (1992:411) correctly point out, spatial statistics or SDA "might be accused of emphasizing mathematical sophistication at the expense of practicality." A confession from a spatial statistician sounds interesting and plausible (Boots, 2000:19); "I also feel that we should be less elitist and more tolerant in the way we present our material. ... I'm not advocating that we lower our standards but that we change our emphasis, at least as far as textbooks are concerned." It seems to me that SDA is difficult to teach as well as to be taught in the current geography.

Third, there are just few software packages which are available in implementing a variety of techniques in SDA. They are not only limited in number and functionality, but also less user-friendly than software for general statistics. Indeed, there is no such a thing as full-fledged software for SDA like SPSS for general statistics (Getis, 1999; Boots, 2000). This situation significantly prevents researchers from actively applying SDA to their empirical research topics.

The three obstacles outlined above directly dictate what should be done to foster scholarly applications of SDA and hence to edify SDA in order to devise an integrative SDA-GIS interface. First, some issues relating to SDA should be clarified especially in comparison with quantitative geography: why we need SDA rather than traditional quantitative geography; what are the scope and contents of SDA in comparison with quantitative geography; how SDA is related especially to spatial manipulation or GIS analysis. Second, more easily readable textbooks with a plenty of application examples are necessary; they should contain a well-designed sequence of instructional modules for SDA where general statistics and SDA are interwoven in a spiral or alternate fashion. Some books may be seen as falling into this category (e.g., Griffith and Layne, 1999; O'Sullivan and Unwin, 2003; ESRI, 2005; Wong and Lee, 2005). Third, more comprehensive and user-friendly packages for SDA are needed. This is not an easy task, mainly because marketplace logic does not seem to favor it as can be seen in the lack of SDA functionalities in GIS programs (Fotheringham, 1991; Goodchild, 1992; Goodchild et al., 1992). It is obviously discouraging that developing an implementation platform is often in hands of GIS vendors (ESRI's ArcGIS9 now includes a module for SDA, Spatial Statistics Toolbox). It is more so since an integration of SDA and GIS has increasingly become necessary. It is fortunate to see some progresses regarding this in recent years (Anselin et al., 2004; Anselin, 2005; Wong and Lee, 2005; Anselin et al., 2006).

3. Edifying GIS: Migrating from GISystems to GIScience

GIS also contains obstacles towards integration. There is an unpleasant truth that GIS is far beyond geography; Longley (2000: 39) contends that "geography has never been central to the development of GIS" and that "geographers have actually played a negligible role in the development of most proprietary systems." The alleged affiliation of geography with GIS might not even exist. This situation has been precipitated by rapidly growing GIS industry and its predominance in tool-making and solution provision over academia, especially less-technical disciplines such as geography. In regard to this, I would argue that GIS needs to migrate from GIS as systems (GISystems) to GIS as science (GIScience).

Goodchild (1992: 43-44) makes a crucial distinction between GIScience and GISystems, and contends that "the handling of spatial information with GIS technology presents a range of intellectual and scientific challenges of much greater breadth than the phrase 'spatial data handling' implies — in fact, a geographical information science" and argues that "geographical information systems are a tool for geographical information science, which will in turn lead to their eventual improvement". Longley et al. (2005) identifies "GIScience as the set of fundamental organizing principles and methods of analysis that arise from the use of GISystems." In the same vein, Mark (2003) sees GIScience as the storehouse of knowledge that is implemented in GISystems and makes the tools of GIS possible.

GIScience is concerned with fundamental issues that arise in dealing with geospatial data. Goodchild (1992) once listed the content of GIScience: (1) data collection and measurement; (2) data capture; (3) spatial statistics; (4) data modeling and theories of spatial data; (5) data structures, algorithms and processes; (6) display; (7) analytical tools; (8) institutional, managerial and ethical issues. Similarly, UCGIS (University Consortium for Geographic Information Science) has identified 10 "long-term research challenges" representing a consensus on the most important long-term components of the GIScience research agenda (McMaster and Usery, 2005): (1) spatial ontologies; (2) geographic presentation; (3) spatial data acquisition and integration; (4) scale; (5) spatial cognition; (6) space and space/time analysis and modeling; (7) uncertainty in geographic information; (8) visualization; (9) GIS and society; (10) geographic information engineering.

Marble (2000: 32) contends, echoing Goodchild's suggestion migrating to GIScience, that "the recent rise of GIScience as an integrative concept covering both GIS and spatial analysis certainly works in favor of a broadly based view of spatial analysis and places us in a better position to move rapidly and effectively toward a closer integration of GIS technology and spatial analysis." Goodchild and Haining (2004: 364) further argue that "the evolution of GIScience owes much to developments in GIS and the field of SDA." All these conceptualizations imply that we need to retreat much of the discipline's intellectual resource from technical aspects of GIS including the design of GI systems and software architecture, and to bring them back to the implementation and sophistication of geographical inquiries with substantive research objectives in an integrative environment.

SDA and GIS *in* geography have been and will be shifting to a part of GIScience where a group of disciplines with *spatial* interest is intensively interacting, making a new kind of division of labor, and driven by new leaders. I argue that geography in general will be able to take a full advantage of new GIScience environment by establishing a sustainable SDA-GIS interface, because "geographers have largely been passive observers of the development of proprietary GIS, yet it is in the use of GIS as a tool for spatial analysis in the digital age that geographers are likely to demonstrate their worthiness in terms of cumulative academic activity" (Longley, 2000:40-41).

III. Integrating the Revolutions

1. Conceptualizing an SDA-centered GIScience

Some benefits of coupling SDA with GIS have been identified. First, SDA needs a data management and manipulation system which deals with spatial data *spatially* (Unwin, 1996); not only attributes of but also topological relationships among spatial observations are effectively input, stored, retrieved, and analyzed (Fischer and Nijkamp, 1992; Goodchild et al., 1992; Bailey, 1994; Haining et al., 2000). A suitable GIS data model should support a full range of SDA (Goodchild, 1987; Fischer and Nijkamp, 1992): (1) operations requiring access only to the attributes; (2) operations requiring access to both attributes and locational information; (3) operations creating object pairs from one or more classes of objects; (4) operations analyzing attributes of object-pairs (spatial autocorrelation); (5) operations requiring access to attributes and locational information for more than one class of objects or object-pairs (spatial interaction modeling); (6) operations creating a new class of objects from an existing class (generation of Thiessen polygons from points or buffer polygons around line segments).

Second, in relation to first, GIS may allow researchers to explore nature of the spatial units necessary to SDA. This is related to the modifiable areal unit problem (MAUP; among others, Openshaw, 1984; Fotheringham and Wong, 1991) and regionalization or (re)districting (among others, Openshaw, 1996). Further, various measurement problems endemic to spatial data are associated with the nature of spatial units, or mismatch between the scale of the spatial unit of observation and the phenomenon of interest (Anselin and Griffith, 1988; Anselin, 1990; Anselin and Getis, 1992). The research on these aspects of spatial data would be conducted in a GIS environment by utilizing various geoprocessing functionalities in GIS.

Third, the display capability of GIS will allow the user greater interaction with the data both in exploratory and confirmatory modes (Goodchild et al., 1992; Fotheringham, 1993; Bailey, 1994; Haining et al., 2000). This aspect is crucial since one of the major aims of SDA is to detect spatial patterns by using various visualizing techniques. Fourth, in a more practical sense, GIS has become a general purpose platform (Haining et al., 2000), and thus GIS may help SDA gain more audience if they are integrated (Goodchild et al., 1992; Fotheringham, 1993; Goodchild, 2000). Indeed, SDA needs GIS more than the latter does the former.

Rooted in the rationales of integrating SDA and GIS presented above, I define an 'SDA-centered GIScience' as an edified or softened SDA conducted in a GIS environment; a GIS-friendly SDA. This is congruent with the sixth research challenge identified by USCIS, that is, space and space/time analysis and modeling. As pointed out, GIS needs to migrate from GISystems to GIScience to place conceptual and analytical aspects of handling geographic information on its center, and SDA needs to become more accessible, applicable, and, thus, GIS-friendly. At issue now is what should be done to make GIS so. The concept of ESDA and local statistics will play a pivotal role.

2. ESDA, CSDA, and GIS

SDA may be divided into three categories; exploratory spatial data analysis (ESDA), confirmatory spatial data analysis (CSDA), and prescriptive spatial data analysis (PSDA) (Unwin, 1996: 510). Tasks of SDA may include, according to Fischer (1999: 284): (1) detection of patterns in spatial data; (2) exploration and modeling of relationships between such patterns; (3) enhanced understanding of the processes that might be responsible for the observed patterns; and (4) improved ability to predict and control events arising in geographical space. It seems that (1) and a half of (2) pertain to ESDA, the other half of (2) and (3) to CSDA, and (4) to PSDA. The distinction between ESDA and CSDA has been based on a dichotomy between data-driven and model-driven (Anselin, 1990; Openshaw, 1990; Anselin and Getis, 1992), and sometimes between inductive and deductive (Openshaw, 1990). According to Haining and his associates (Haining, 1990; Haining et al., 1998; 2000), ESDA is the extension of exploratory data analysis (EDA), and its aims are descriptive, seeking to detect patterns in spatial data, to formulate hypotheses, and to assess statistical models for spatial data. In contrast, CSDA is the extension of confirmatory data analysis (CDA), and its aims include testing hypotheses and fitting models that are explicitly spatial in the sense that spatial dependence is incorporated in the model specification.

It should be noted, however, that the distinction between ESDA and CSDA is often blurred (Anselin and Getis, 1992; Bailey, 1994). Especially, it would be more so if a distinction between pre-confirmatory ESDA (before hypothesis formulation) and post-confirmatory ESDA (after hypothesis formulation) is introduced (Fotheringham and Charlton, 1994). For example, hypothesis testing on LISA, as an important source for ESDA, has always been an issue (Anselin, 1995; Ord and Getis, 1995; Bao and Henry, 1996).

I suggest, nevertheless, that the distinction is still of value, and ESDA is more needed than CSDA. There are two reasons. First, ESDA is more congruent with the nature of spatial data, i.e., spatial dependence, spatial heterogeneity, and spatial outliers. These spatial effects are simply *implicated* in CSDA. Some CSDA techniques such as spatial autoregressive models (Anselin, 1988) and spatial ANOVA (Griffith, 1992) may alleviate the effects in model specifications, but do not provide a way of revealing and exploring them for further insights. Second, ESDA is more congruent with current research platform, i.e., GIS. Since one of the major aims of ESDA is to detect spatial patterns by using visualization techniques, ESDA can take more advantage of GIS's capabilities in visualization and spatial data mining (Fotheringham and Charlton 1994).

According to Bailey (1994: 21), the value of GIS to SDA is: (1) flexible ability to geographically visualize both raw and derived data; (2) provision of flexible spatial functions for editing, transforming, aggregating and selecting both raw and derived data; and (3) easy access to spatial relationships between entities in the study area. All these benefits from integration between GIS and SDA more pertain to ESDA. In a practical sense, the only thing that CSDA needs from GIS is the spatial weights matrix. Here, discussions on which SDA functions are more relevant to GIS environments may provide a good foundation. The 10 GISable SDA techniques proposed by Openshaw (1990) and advocated later on (Fischer and Nijkamp, 1992; Bailey, 1994; Openshaw and Clarke, 1996; Unwin, 1996) are more related to ESDA. Openshaw and Clarke (1996:32) contend that "future GISable spatial analysis methods will be essentially descriptive, exploratory, and probably not inferential in a traditional spatial hypothesis testing sense." It should be noted that although the integration of SDA and GIS does not always substantially enhance researchers' abilities examining geographical inquiries, "*under certain circumstances*, the integration ... will have a reasonable high probability of producing insights that would otherwise be missed" (Fotheringham, 1992:1675-6; Fotheringham and Charlton, 1994:316). I suggest that the circumstances are more likely to happen to ESDA than to CSDA.

ESDA inherits many properties from EDA that can be defined as "detective work" (Tukey, 1977:1) and "an intermediate or soft statistics between descriptive and inferential or hard statistics" (Good, 1983:291), and a bundle of statistical and graphical techniques that enhance a researcher's intuition into data by utilizing a variety of visual representations. EDA techniques require relatively few, and weaker, assumptions and are resistant to outliers or atypical observations (Tukey, 1977; Good, 1983). Some major concepts of EDA, such as brushing, conditioning, and spinning have been translated into the context of spatial data. For example, brushing techniques are to make connections among graphs and data tables such that one selection of point(s) in a window should simultaneously induce a selection for the corresponding data point(s) in other windows (Becker and Cleveland, 1987). The technique was translated into 'geographical brushing' (Monmonier, 1989) or 'spatial windowing' (Fotheringham and Charlton, 1994) where a map window is connected to graph and data windows such that any selection in the map window makes subsequent selections in other windows, and vice versa. This technique has played a central role in conceptualizing and implementing ESDA (among others, Cook et al., 1997; Dykes, 1997; Symanzik et al., 1998).

Other graphical techniques, such as box plot, qq plot, trellis graph, Chernoff faces plot, Tukey's star diagram, scatterplot matrix, and biplot, has been advised for spatial data. As mentioned before, I more focus on ESDA techniques based on spatial statistics, because EDA techniques are basically aspatial, and their translations to spatial data are far from a true 'spatial' EDA (Anselin and Getis, 1992:25). Here I define ESDA, following Anselin (1994; 1998), as "a collection of techniques to describe and visualize spatial distributions, identify atypical locations or spatial outliers, discover patterns of spatial association, clusters or hot spots, and suggest spatial regimes or other forms of spatial heterogeneity".

Several ESDA frameworks for a GIS environment have been proposed (Openshaw, 1990; Goodchild et al., 1992; Fotheringham and Charlton, 1994; Openshaw and Clarke, 1996; Anselin, 1998; Wise et al., 1999). Among them, I choose Anselin's framework (Anselin, 1998:81 Table 5.1). He divides tasks for ESDA into four categories: (1) visualizing spatial distribution; (2) visualizing spatial association; (3) local spatial association; (4) multivariate spatial association, and then allocates relevant ESDA techniques to each. These ESDA techniques include some geostatistical techniques such as variogram (Cressie, 1993), variogram cloud (Cressie, 1993; Majure and Cressie, 1997), pocket plots (Cressie, 1993), variogram boxplot (Majure and Cressie, 1997), spatial lag scatterplot (Cressie, 1993; Majure and Cressie, 1997), and some lattice techniques such as spatial lag scatterplot (Fotheringham and Charlton, 1994), spatial lag pie/bar charts (Anselin, 1994; Anselin and Bao, 1997), Moran scatterplot and scatterplot map (Anselin, 1994; 1995; Anselin and Bao, 1997), local Moran boxplot (Anselin, 1995), LISA local Moran map and Moran significance map (Anselin, 1995; 2000).

Albeit the prevalence of ESDA over CSDA, however, we still need to maintain a large picture of SDA-GIS integration in which CSDA also plays a substantial role. For example, Griffith (1993) proposes a more CSDA-oriented integration scheme where there are three major functions: (1) OLS; (2) spatial autocorrelation test for residuals; (3) spatial autoregressive models. We need to explore not only raw data or preliminarily processed second data such as local Moran's I_i (pre-confirmatory) but also bi-product of CSDA such as regression residuals. With respect to this, I would agree to a 4-module model suggested by Anselin and Getis (1992) as a broader integration scheme, where four components are interwoven: (1) data selection (flexible clustering and aggregation algorithms); (2) data manipulation (creation or smoothing of surface or the partition of data units into polygons); (3) exploratory analysis; (4) confirmatory analysis.

3. 'Local Turn' in SDA and Spatial Association Measures

The importance of local statistics is straightforwardly derived from limitations of global measures, or parameters. Global spatial measures, from spatial autocorrelation coefficients to regression parameters, are based on an assumption of spatial stationarity (Anselin, 1996; Unwin, 1996; Anselin and Bao, 1997; Fotheringham, 1997). According to Fotheringham (2000:71), "the *raison d'etre* for the development of local statistics is the low probability in many situations that the 'average' results obtained form the analysis of a spatial data set drawn from a broad region apply equally to all parts of that region, the assumption of traditional global statistics." It is ironic that, albeit a strong tradition of areal differentiation, quantitative geography has focused on spatial similarities rather than spatial differences, global generalities rather than local exceptions, and 'whole-map' values rather than mappable statistics (Fotheringham, 2000).

In conjunction with ESDA, major objectives of local statistics include: (1) identifying atypical locations (spatial clusters); (2) discovering significant local spatial association (spatial clusters or hot spots); (3) detecting local pockets of non-stationarity (spatial regimes) (Anselin, 1995; 1999; Getis and Ord, 1996). These are correspondent to what Fischer (1999:285) refers to as "spatial dependence and heterogeneity descriptors". In addition, the integration of GIS and ESDA obviously favors local statistics rather than global ones (Openshaw, 1990; Openshaw and Clarke, 1996; Anselin, 1996). Anselin (1996:113) points out that "the focus of ESDA techniques used in conjunction with a GIS should be on measuring and displaying *local* patterns of spatial association, on indicating local non-stationarity, on discovering *islands* of spatial heterogeneity and so on."

Trends toward local statistics are not confined to SAMs (spatial association measures) (see Fotheringham and Brunsdon, 1999). For example, place-specific distance parameters in spatial interaction models can be seen as local statistics (Fotheringham, 1981; Stillwell, 1991; Lee, 2001a). However, I here focus on local SAMs. In a univariate situations, some local SAMs have been proposed, Getis-Ord G_i and G_i^* (Getis and Ord 1992; Ord and Getis 1995), and local Moran's I_i, and Geary's c_i (Anselin 1995), and collectively construct a class of LISA (Local Indicators of Spatial Association) (Anselin 1995; Getis and Ord 1996). Anselin (1996) subsequently developed Moran scatterplot and related mapping techniques for local Moran's I_i (Anselin 1996). ESDA techniques based on univariate SAMs have extensively been applied to a variety of research topics. Lee (2004) recently proposed a new global measure, S, which can easily be decomposed into its local counterpart, S_i.

Obviously, local statistics for ESDA is not confined to univariate SAMs. In bivariate situations, Cross-Moran has been formulated (Wartenberg, 1985) and illustrated (Griffith, 1993; 1995; Griffith and Layner, 1999). Hubert and his associates developed a nonparametric bivariate spatial association measures (Hubert and Golledge, 1982; Hubert et al., 1985). Lee (2001b) proposed a global bivariate SAM for gauging bivariate spatial dependence by integrating Pearson's correlation coefficient and Moran's index and provided a significance testing procedure for the measure (Lee, 2004). Furthermore, Lee (2006) successfully shows that global bivariate SAMs can be decomposed into local statistics and demonstrates that a bundle of ESDA techniques utilizing local bivariate SAMs can be developed such as local-L scatterplot maps and

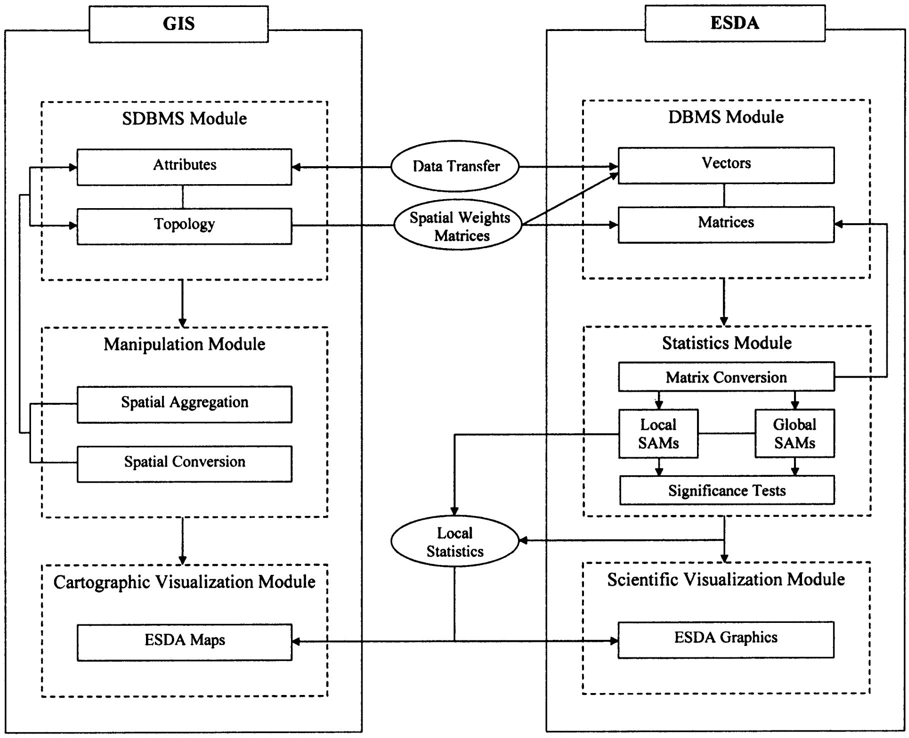

Fig. 1. A SAM-based ESDA-GIS Framework

local-L significance maps. Boots (2003) proposed a procedure for extending the notion of local statistics for categorical spatial data, and GWR (geographically weighted regression) can be seen as a method of providing multivariate local SAMs (among others, Fotheringham et al., 2000).

4. A SAM-based ESDA-GIS Framework and Implementation Issues

An ESDA-GIS framework based on SAMs is largely characterized by a continuous interaction between GIS and ESDA techniques (Figure 1). First, an SDBMS (*Spatial* Database Management System) module in GIS provides information on topological relationships among observations. The information could take a form of either vectors or matrices. A vector format such as sparse contiguity matrices (GAL) or sparse general weights matrices (GWT) (Anselin and Bao, 1996) can be transformed to a matrix format by way of a matrix conversion function in a statistics module of ESDA. Second, attributes associated with spatial entities can be exported and imported between GIS and ESDA by way of a data transfer protocol. A DBMS (Database Management System) in an object-oriented ESDA program can store and manipulate matrices along with other forms of data such as multi-layered arrays and lists. Third, a manipulation module in GIS accomplishes spatial aggregation and spatial conversion that transforms dimensions of spatial entities, e.g., creating centroids from polygons or constructing Voronoi polygons from points. These procedures restructure topological relationships among spatial objects and possibly change their attributes. Fourth, an ESDA computes SAMs and carries out significance tests. Fifth, local SAMs are exported to a scientific visualization module in an ESDA as well as a cartographic visualization module in a GIS. In the former, various ESDA graphics such as scatterplot, boxplot, etc. and, in the latter, local SAMs are mapped to allow for exploration of spatial patterns.

Recent efforts to integrate univariate SMAs with GIS platforms can be seen as good examples of an ESDA-GIS framework. How to integrate GIS and ESDA has been an issue. The first way is to make a module for local SAMs in aspatial statistical packages using script languages without any direct connection to a GIS. For example, Bivand and Gebhardt (2000), and Bivand (2006) developed a bundle for SDA in *R* language. The second way is to use stand-alone ESDA. For example, stand-alone programs implement local SAMs (among others, CrimeStat (Levine, 2004; 2006) and GeoDa (Anselin, 2005; Anselin et al., 2006)). The third way is to customize GIS programs by developing script codes for local statistics, without connection to statistical programs or languages. One of the most comprehensive endeavors has been done by Wong and Lee (2005); they developed a set of ArcView extensions using Avenue script language. The fourth way is to construct an ESDA-GIS platform that connects GIS and some other programs, usually statistical, by means of RPC (Remote Procedure Calls for UNIX), DDE (Dynamic Data Exchange for Window), or ActiveX for Microsoft Windows environment. In the context of local SAMs, several programs have been developed including SpaceStat-ArcView (Anselin and Bao, 2000), R-GRASS (Bivand 2000), SAGE-ARC/INFO (Haining et al., 2000), S-Plus-ArcView (Kaluzny et al., 1998; Bao et al., 2000), and MicroSoft Access-MapObjects (Zhang and Griffith, 2000).

One crucial implementation issue is raised. In situations where a researcher develops a set of statistical and graphical techniques and wants to connect with a GIS program for visualizing and exploring the mappable results, which way could be most viable? This is extremely important, because "ESDA ought to concern itself with the implementation of algorithms, not just their elaboration and the purchase of products claiming to include them" (Bivand, 1998:500). It seems untenable to completely depend on a GIS so that new algorithms are made available by way of a script language the GIS provides, mainly because the GIS script language is not effective for intensive computations and quality-graphics. It also seems cumbersome to build a completely new platform for ESDA-GIS integration, not only because it is not technically easy, but because it may prevent researchers from continuously updating functions and from taking advantage of other integrations which already contain a number of functions. It is also recognized that languages for developing statistical algorithms are interpreted such as *Java*, *S*, and *R*, rather than complied, such as *C* and *Fortran*, because the former more allows researchers to interact with data and prototype new algorithms (Bivand 1996; 1998; Dykes 1998).

Ⅳ. Concluding Remarks

This paper shows that seemingly straightforward relationships between SDA and GIS are rather complicated, and indicates that the alleged promise of cross-fertilization can happen under *certain circumstances*: on the one hand, SDA needs to become more accessible, applicable, and GIS-friendly; on the other hand, GIS needs to be rendered more science-like, rather than technology-like by means of migrating to GIScience in which geographers harness GISystems to conduct more conceptually driven tasks and produce more value-added research outputs through SDA. An SDA rendered more GIS-friendly and practiced in a GIS environment can be seen as an 'SDA-centered GIScience'. A 'SAM-based ESDA-GIS framework' is proposed to demonstrate the viability of the SDA-centered GIScience. Within the framework, GIS takes advantage of ESDA's statistical integrity and computational efficiency, and ESDA takes advantage of

GIS's spatial data management systems and visualization capabilities. Local SAMs and associated ESDA techniques are expected to allow researchers to effectively investigate spatial dependence and heterogeneity.

The SDA-centered GIScience postulated in this paper could make the discipline of geography advantaged over, or at least differentiated from, others in the GIScience village in terms of specialty, or at least division of labor. Berry (2004:444) once raised a question when comparing Berry and Marble's 1968 book, *Spatial Analysis: A Reader in Statistical Geography*, with Goodchild and Janelle's 2004 book, *Spatially Integrated Social Science*: "Will the convergence of new data and methods, together with an emergent cooperation that transcends traditional disciplinary boundaries in new and perhaps lasting ways, provide the necessary and sufficient conditions for both conceptual growth and more powerful practical applications?" My answer would be that yes, it will, but only when geographers continue to elaborate on the SDA-centered GIScience and, thus, to maximize their potentials.

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