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Spatial analysis: retrospect and prospect

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This chapter briefly reviews spatial analysis as a technology for analysing spatially referenced data. Spatial data analysis techniques are important and are becoming even more so as the supply of spatial data increases. Novel new modes of computation, known collectively as 'computational intelligence technologies' will meet some of the new analysis needs that have been stimulated by GIS. Computational intelligence technologies in general and neural networks in particular provide novel, sophisticated, and interesting models and methods which are potentially applicable to a wide range of applications. They are thus seen as the way forward to analyse the data-rich environments of contemporary GIS.

1 INTRODUCTION

Spatial analysis is a technology which typically requires two types of information about spatial objects: attribute and locational information. The scope of discussion here will be restricted to methods and techniques for spatial data analysis (SDA), often referred to as spatial analysis in the strict sense. Smoothing techniques such as areal interpolation (Flowerdew and Green 1991), Kriging (Isaaks and Srivastava 1989), and kernel smoothing methods (Silverman 1986) as well as (locational and attribute) error assessment (Goodchild and Gopal 1989) and the modifiable areal unit problem (Openshaw and Alvanides, Chapter 18; Fotheringham and Wong 1991; Openshaw 1984) are precluded from the discussion, even though they are often fundamental steps and problems in spatial analysis. These issues are addressed in part by other authors in this volume (e.g. Martin, Chapter 6; Openshaw and Alvanides, Chapter 18; Goodchild and Longley, Chapter 40).

The chapter is organised into six sections. It is useful to begin by trying to understand the salient features which make spatial analysis special and different from other forms of data analysis (section 2). Section 3 briefly deals with the development of SDA and describes some significant achievements to date. This is followed by a discussion of Openshaw's (1994a) basic rules for identifying future 'GISable' spatial analysis technology (section 4). Leading from this, section 5 argues for a very different non-conventional style of approach based upon novel modes of computation – which are collectively known as 'computational intelligence' (CI) technologies – as laying the foundations for a new generation of useful and more powerful SDA tools relevant to data-rich spatial data environments. In particular, neural networks, the single most important component of CI-driven spatial analysis, are seen to offer spatial analysts rich and interesting classes of novel data driven non-linear models, and are deemed to be applicable to a wide range of application domains. The potential of this approach is exemplified in two classical spatial analytic tasks: spatial interaction modelling and pattern classification (section 6). In the concluding section some major aspects of this new paradigm are summarised and directions for further research are outlined.

2 WHAT MAKES SPATIAL DATA ANALYSIS SPECIAL?

Given the diversity of analytical perspectives within GIS it is difficult to define SDA as anything more specific than a body of methods and techniques for analysing 'events' at a variety of spatial scales, the results of which depend upon the spatial arrangement of the 'events' (Goodchild et al 1992; Haining 1994). 'Events' may be represented as point, line, or area 'objects' or 'spatial primitives' which are located in geographical space and possess a set of (one or more) other attributes. Location, topology, spatial arrangement, distance, and spatial interaction become the focus of attention in SDA activities. The outcomes of analysis are: detection of patterns in spatial data; exploration and modelling of relationships between such patterns; enhanced understanding of the processes that might be responsible for the observed patterns; and improved ability to predict and control events arising in geographical space. It is the explicitly spatial focus of spatial analysis that distinguishes SDA from other forms of data analysis (Goodchild et al 1992).

It follows that two different types of information are integral to SDA:

- *Locational* (geometric/topological) information about the spatial objects of concern which are generally described by means of their position on a map or using geographical coordinate systems. The spatial objects utilised in most spatial analyses are statistical areas such as census tracts, or points which are sampled from continuous geographical space (Martin, Chapter 6). For some types of spatial analysis it is common practice to represent areas by points (2-dimensional discrete representation of space).
- *Attribute* information about the spatial objects of interest. Two types of attributes may be distinguished: primary attributes (e.g. socioeconomic characteristics, physical properties); and secondary attributes of, or relations between, spatial objects (e.g. flows of information, capital, goods, or people).

SDA employs a wide range of tools ranging from spatial autocorrelation measures, through nearest neighbour methods, *K*-functions, spatial classification and regionalisation methods, to spatial extensions of conventional statistical techniques such as regression models. In principle, we may distinguish between those SDA techniques that use locational information alone and those that use both locational and attribute information. The first class of techniques is essentially concerned with the analysis of spatial distributions (Longley and Batty 1996) and includes techniques such as point pattern analysis (Goodchild et al 1992). The second class includes techniques such as spatial regression models, and utilises both locational and attribute data in order to assess the spatial variation in attribute measurements. This class may be further disaggregated into techniques and methods that deal with primary attributes (interval and/or categorical scale) and those that deal with secondary attributes (relations). The latter includes spatial interaction models, interregional input–output accounting systems of various kinds, and log-linear models: all of these generally rely on 2-dimensional discrete, rather than continuous, geographical spaces.

The crucial role of geographical location of objects, both in an absolute and a relative sense (spatial arrangement), has profound implications for the way in which they can be analysed (Anselin and Getis 1993). In fact, location leads to two different types of spatial effects: *spatial dependence* (often referred to as spatial autocorrelation) and *spatial heterogeneity*. The first directly results from Tobler's (1979) 'First Law of Geography' where 'everything is related to everything else, but near things are more related than distant things'. Thus, spatial dependence implies that the data for particular spatial units are related and similar to data for other nearby spatial units (Getis 1992). Spatial dependence caused by a variety of measurement problems (e.g. the arbitrary delineation of spatial units of observation, the problem of spatial aggregation, the presence of spatial externalities, and spillover effects) poses particular challenges for conventional statistical analysis since this assumes that units of observation are statistically independent of one another (Anselin and Getis 1993; Griffith 1993). The second and equally important spatial effect – spatial heterogeneity or non-stationarity – is related to spatial differentiation which follows from the intrinsic uniqueness of each location, as is evident in spatial regimes for variables, functional forms, or model coefficients (Anselin 1994a). These special features of spatial data render classical statistical methods unreliable unless they have been modified to accommodate the spatial problems at hand. The complications are similar to those found in time series analysis but are exacerbated by the multi-directional, 2-dimensional nature of dependence in space rather than uni-directional nature in time (Griffith 1993).

3 SPATIAL DATA ANALYSIS: ORIGINS AND PROGRESS

The origins of SDA lie in the development of quantitative geography and regional science, and date back to the early 1960s. The use of quantitative (mainly statistical) methods and techniques to analyse the pattern and form of geographical objects (points, lines, areas, and surfaces: Martin, Chapter 6) depicted on maps or defined by coordinates in 2- or 3-dimensional space characterised this early research. Later on, more emphasis was placed on the inherent properties of geographical space, on spatial choice processes, and the spatial-temporal evolution of complex spatial systems.

Many of the SDA techniques were developed in the 1960s and 1970s, in an era of limited computing power, small datasets, and rudimentary computer graphics. Today, as a consequence, current implementations take only limited advantage of the data storage, retrieval, and visualisation capabilities of GIS. Early attempts to implement SDA techniques in a computational environment relied on source code programming, especially FORTRAN. The 1970s saw the advent of statistical software packages such as BMDP, SPSS, and SAS, which soon became the primary applications medium, even although these packages were, and are still, based on statistical techniques which are fundamentally non-spatial in nature. Even today, much SDA activity remains embedded in the aspatial environment of software packages such as SAS, Minitab, Systat, SPSS, S-Plus, and GLIM (Goodchild et al 1992).

In the early days of SDA there was strong momentum behind the *spatial geometric view* with its strong emphasis on point pattern analysis, quadrat analysis, and nearest neighbour methods (Dacey 1960; Getis 1964; Haggett et al 1977; Rogers 1965). This approach used locational data only and attempted to describe the spatial patterning of point objects (events) by comparing observed patterns with those that might theoretically be expected from various normative models, especially those based upon spatial randomness. More recently, geographers (e.g. Getis, Chapter 16; Getis 1983) have realised that better descriptions of point patterns may be obtained by using *second-order* methods, that is methods which describe the relative positioning of pairs of points (Diggle 1983). One such method is to compute a (multivariate) K-function (Ripley 1977) which examines all inter-point distances rather than just those separating nearest neighbours. A comparison of the observed K-function with those derived from possible explanatory models (e.g. those based upon the Poisson model of spatial randomness) over the study area permits assessment of whether the observed occurrences are likely to have arisen from the processes underlying such models (Getis and Boots 1978). By extension, such SDA tools are now available to 'explain' one pattern of particular interest in terms of others (in the multivariate case), as well as to deal with situations involving space-time patterns.

The interest in point pattern analysis was complemented by the *application of standard statistical techniques* to spatial data (Berry and Marble 1968; Haggett 1965; King 1969). In particular, spatial analysts have used the general linear model (e.g. multiple regression analysis), factor and principal components analysis, regional taxonomic methods (spatial classification and regionalisation), multidimensional scaling, discriminant analysis, and trend surface analysis. Only a small number of these SDA tools (notably regionalisation methods with spatial contiguity constraints) were actually developed from first principles within the spatial sciences rather than being based on methods and techniques adapted from other disciplines. One consequence has been that very few SDA techniques have taken into account the special characteristics of spatial data when invoking statistical assumptions, particularly when modelling using statistical packages. Increasing awareness of the problems caused by spatial heterogeneity and dependence, and their effects upon the validity of conventional statistical tools, has led to the development of a large body of methods and techniques (e.g. Anselin and Griffith 1988).

Despite the very large number of rather diverse contributions three major areas can be identified where significant progress has been made in the last decades (see also Getis, Chapter 16):

- *Spatial dependence and heterogeneity descriptors*. The problem of spatial heterogeneity and dependence has received substantial attention in recent times (Cliff and Ord 1981). Spatial analysts concerned with spatial dependence now have a number of tools available. Important measures include Moran's I and Geary's c (Cliff and Ord 1981), semi-variogram parameters, and generalised measures of spatial autocorrelation.

Such measures are of use in a general exploratory sense to summarise the overall existence of a stable pattern of spatial dependence in attribute data, to establish the validity of various stationarity assumptions prior to modelling, and to identify possible forms of a spatial model for the data. They are extremely useful for small datasets, but only of very limited use in the context of large and very large GIS datasets where several regimes of spatial association might be present (Anselin 1997a). It is only very recently that a focus on detecting local rather than global *patterns of association* has been developed to provide a more appropriate perspective. Examples of these descriptors are the distance-based *G*-statistics of Getis and Ord (1992) which can easily be implemented into a GIS-framework (Anselin et al 1993; Ding and Fotheringham 1992). The idea behind these descriptors has been extended to a general class of 'local indicators of spatial analysis' (termed LISA: Anselin, Chapter 17; Anselin 1995).

- *Spatial regression modelling*. In essence, spatial regression models may be viewed as spatial extensions to the familiar family of standard elementary linear regression models for non-spatially related cross-sectional data. This extension is typically achieved by means of a (N x N) matrix of spatial weights (typically a first-order binary contiguity matrix) and a spatial autoregressive structure for the error terms, where N denotes the number of observations (spatial units). N is usually quite small and thus represents only a coarse level of spatial resolution. This has significant implications for the correct specification, estimation, and testing of spatial linear regression models. Following the pioneering work of Getis and Boots (1978), Paelinck and Klaassen (1979), Cliff and Ord (1981) among others, considerable progress has been made in various directions: the refinement of the original framework of spatial linear process models, with a special focus on estimation and testing (the development of new and alternative tests and estimators for various types of spatial linear regression models), the development of more complex models that incorporate different contributions of spatial dependence and heterogeneity, and extensions from a purely cross-sectional to a space–time context. This progress is manifest in a series of recent monographs and edited volumes on spatial statistics and spatial econometrics by Upton and Fingleton (1985), Anselin (1988), Griffith (1988), Arbia (1989), and Cressie (1993) among others, but its dissemination into practice has been hampered by the lack of readily available software (Anselin and Hudak 1992).
- *Discrete spatial data analysis*. The mainstream tradition in SDA has been focused on aggregated spatial data. One area where scholarly interest has been growing in the last two decades is the area of discrete or categorical data analysis (Wrigley 1985). Logistic/logit regression models and (quasi) log-linear models for spatial contingency tables (Aufhauser and Fischer 1985) are the primary workhorses of discrete SDA. The family of statistical models used for discrete SDA is a part of Nelder and Wedderburn's (1972) unified family of generalised linear models, in which a response variable is assumed to come from the exponential family of probability distributions (with the normal, Poisson, binomial, and multinomial distributions).

In spite of these various technical advances, the flurry of results on methods and techniques in SDA has had only limited impact outside the research community. To a large extent this state of affairs is attributable to the lack of readily available software that incorporates explicitly spatial tests and estimators. Currently, none of the popular statistical or econometric packages includes any tools for spatial data analysis, and the only generally available program that performs a range of spatial statistical techniques is Anselin's SpaceStat (1992; Anselin, Chapter 17). The same holds true to a large extent for commercial GIS. Consequently, the actual application of appropriate spatial data analytic techniques has been very limited, even within the academic community of geographers and regional scientists. In contrast (and as documented throughout these volumes) there has been recent and very rapid growth in the availability and richness of spatial data as a consequence of the GIS data revolution, making the somewhat esoteric area of SDA of considerable potential interest. The momentum behind developments in GIS, however, is not the academic arena with its theoretical and methodological interests in knowledge acquisition, but rather the concern to analyse spatial databases for a variety of applied purposes.

4 THE NEW ANALYSIS NEEDS – OPENSHAW'S CRITERIA FOR IDENTIFYING FUTURE SDA TECHNOLOGY

The next few years seem set to provide a unique opportunity for spatial analysts to enter a new era in the development of novel SDA styles. New analysis needs are being created and stimulated as a by-product of developments in GIS technology. GIS is creating extremely data rich and multi-domain, but theory poor and hypothesis-free, environments which are different from those within which computational SDA techniques have hitherto been applied.

While there is a general consensus that the lack of SDA functionalities in current GIS seriously limit the usefulness of GIS as a research tool to analyse spatial data and relationships (Anselin and Getis 1993; Fischer and Nijkamp 1992; Goodchild 1987; Openshaw 1991), there is little agreement about the kinds of SDA techniques and methods that are most relevant to GIS environments. Openshaw (1991, 1994f) and Openshaw and Alvanides (Chapter 18) suggest several criteria that aim to distinguish between 'GISable' and 'GIS-irrelevant' technology. These relevancy criteria provide a useful guide to the new analysis needs, without specifying in detail how such SDA methods might be developed. The most important criteria for 'relevance' are:

- A GISable SDA tool should be able to handle *large* and *very large numbers* (from a few tens to millions) of *spatial objects* without difficult and thus meet the large-scale data processing needs in GIS.
- GIS relevant SDA techniques should be sensitive to the *special nature* of spatial information.
- The most useful GISable SDA techniques and models will be *frame independent* (i.e. invariant under different spatial partitionings of a study region).
- GIS relevant SDA should be a *safe technology* (i.e. the results should be reliable, robust, resilient, error and noise resistant, and not based in any important way on standard distributions).
- GISable SDA techniques should be *useful in an applied sense* (i.e. they should focus upon spatial analysis tasks that are relevant to GIS environments).
- The results of SDA operations should be *mappable* in order to afford understanding and insight, since GIS is a highly visual and graphics-oriented technology.

These criteria make it apparent that future GISable spatial analysis technology will be *data driven* rather than theory driven in nature, and essentially *exploratory* rather than inferential in a conventional spatial hypothesis-testing sense. There is a clear need for a quantitative exploratory style of spatial analysis which can complement the map-oriented nature of GIS. Exploratory spatial data analysis (ESDA; Anselin, Chapter 17), a spatial extension of mainstream exploratory data analysis, provides a useful means of generating insights into (global and local) patterns and associations within spatial datasets. The search process is controlled by the user in a highly interactive graphical environment as, for example, in Regard (Unwin 1993). The use of ESDA techniques, however, is generally restricted to expert users interacting with the data displays and statistical diagnostics to explore spatial information, and to fairly simple low dimensional datasets.

In view of these limitations, it becomes evident that we urgently need novel exploration tools which are sufficiently automated and powerful to cope with the data richness-related complexity of exploratory spatial analysis of large (multiple gigabyte) datasets (Openshaw 1995). The need is for tools that intelligently allow the user to sift through large quantities of spatial data, to simplify multivariate data, and efficiently and comprehensively to explore for patterns and relationships against a background of data uncertainty and noise.

From this perspective the question of how to link SDA technology and GIS (Anselin and Getis 1993; Fischer et al 1996; Goodchild et al 1992) becomes less important than the need to rethink spatial analysis technology fundamentally, to adopt the most useful and relevant technologies for solving problems in new data-rich environments, and to demonstrate the utility of novel approaches to spatial analysis (Openshaw and Fischer 1995).

5 COMPUTATIONAL INTELLIGENCE – A NEW PARADIGM FOR SPATIAL ANALYSIS

Novel modes of computation which are collectively known as CI-technologies hold some promise to meet the needs of SDA in data-rich environments. Following Bezdek (1994) we use the term 'computational intelligence' in the sense that the lowest-level forms of intelligence stem from the capacity to process numerical (low-level) data, without explicitly using knowledge in an artificial intelligence sense. CI tolerates imprecision and uncertainty in large-scale real-world problems in order to achieve tractability, robustness, computational adaptivity, low cost, real-time speed approaching human-like turnaround and error rates which approximate to human performance.

Artificial life, evolutionary computation, and neural networks are the major representative components in this arena. Artificial life is a methodological approach incorporating evolutionary principles: it is based on population rather than individual simulation, simple rather than complex specifications, bottom-up rather than top-down modelling, and local rather than global control (Langton 1989). It has great potential to develop novel exploratory approaches capable of efficiently and comprehensively exploring large spatial databases for patterns and relationships, as illustrated in Openshaw (1994e). Evolutionary computation (genetic algorithms, evolutionary programming, and evolutionary strategy) derives from biology and has proved its merit in treating hard optimisation problems where classical optimisation algorithms (e.g. hill climbers and simplex) and less classical ones (e.g. simulated annealing) tend to be inappropriate. Evolutionary computation might be adopted in SDA, for example to improve the quality of results of spatial optimisation problems (e.g. optimal sizing: Birkin et al 1995), route choice, and zone design problems.

No doubt, CI is currently best suited to systems which can efficiently process information in a massively parallel way and which can 'learn' by adjusting certain parameters. This neural network view is extremely attractive in a world where information abounds, as in the case of large spatial databases. Neural networks are likely to become the single most important component of a CI-driven SDA program (Fischer 1997). The recent re-emergence of neural-network-based approaches has been accomplished by a massive expansion of research, spanning a range of scientific disciplines – perhaps wider than any other contemporary intellectual endeavour. Much of the recent interest of computational geographers in neural network modelling (e.g. Leung 1997; Openshaw 1993) stems from the growing realisation of the limitations of conventional tools as vehicles for exploring patterns and relationships in GIS and remote-sensing environments and from the consequent hope that these limitations may be overcome by judicious use of neural net approaches.

Neural networks (connectionist models) are parallel distributed information processing structures consisting of simple, but generally non-linear processing elements (which can possess a local memory and can carry out localised information processing operations with adaptative capabilities), massively interconnected via unidirectional signal conduction paths called connections. Each connection has a weight associated with it that specifies the strength of this link. Each processing element (PE) can receive any number of incoming connections and has a single output connection which can branch into copies to form multiple output connections, where each carries the same signal. The information processing active within each PE can be defined arbitrarily with the restriction that it has to be completely local – that is, it has to depend only on the current values of the input signals arriving at the PE and on values stored in the PE's local memory (Hecht-Nielsen 1990). Characteristically, two mathematical functions are active at each PE. The first integrates the connection weights with the inputs arriving via the incoming connections which impinge upon the PE. Each PE then typically applies a transfer (activation) function to the value of the integrator function and produces its output signal. A common choice is the logistic function in the case of continuous network inputs (see Fischer 1995, 1997).

Although a vast variety of neural network models exist, and more continue to appear as research continues, many of them have common topological characteristics, PE properties, and training (learning) heuristics. Three basic entities characterise a neural network (Fischer and Gopal 1993):

- the network topology or interconnection of its PEs (called the neural networks architecture);
- the characteristics of its PEs;
- the method of determining the weights at the connections (called the training or learning strategy).

Different interconnection strategies lead to different types of neural net architectures (e.g. feedforward versus recurrent) which require different learning (training) strategies. At the most fundamental level two categories of training may be distinguished, namely supervised and unsupervised. In supervised learning the network is trained on a training set consisting of a sequence of input and target output data. Training is accomplished by adjusting the network weights so as to minimise the difference between the desired and actual network outputs. Weight adjustment is based on the definition of a suitable error function, which is then minimised with respect to the weights and biases in the network using a suitable algorithm (e.g. gradient descent or global optimisation). Alternatively, unsupervised learning (also called self-organisation) requires only input data in order to train the network. During the training process the network weights are adjusted so that similar inputs produce similar outputs. This is accomplished by a training algorithm that extracts statistical regularities from the training set, representing them as the values of network weights (Fischer and Gopal 1994b; Fischer 1995). Prior knowledge may be used to specify the properties of the network learning methods. Bootstrap techniques, for example, may be used for estimating the bias of network parameters.

Multilayer feedforward networks (perceptrons and radial basis function networks) have emerged as the most attractive neural network architecture for various spatial analysis tasks (Fischer and Gopal 1994a; Gopal and Fischer 1996, 1997; Leung 1997). Analytical results show that two-layer (one hidden layer) feedforward networks are very capable of approximating arbitrary mappings in the presence of noise. However, they do not provide more than very general guidance on how this can be achieved, and what guidance they do offer suggests that network training will be difficult. Consequently, there is an urgent need to develop application domain-specific methodologies which provide more specific guidelines for judicious use of neural network approaches in SDA.

One critical issue for a successful application of neural-network-based spatial analysis is the complex relationship between learning (training) and generalisation. It is important to stress that the ultimate goal of network training is not to create an exact representation of the training data itself, but rather to build a model of the process which generates the data in order to achieve a good generalisation (out-of-sample) performance of the model. One method of optimising the generalisation performance of a model is to control its effective complexity where complexity is measured in terms of network parameters.

The attraction of neural-network-based SDA essentially stems from the following features:

- representational flexibility and freedom from linear model design constraints;
- inbuilt ability (via net representation and training) to incorporate rather than ignore the special nature of spatial data;
- robustness and fault tolerance to deal with noisy data and missing or fuzzy information;
- efficiency of large spatial datasets analysis, raising the prospect of being able to process finer resolution data or to carry out real-time analysis;
- inbuilt capability to adapt the connection weights to changes in the surrounding environment (learning);
- improved generalisation (out-of-sample performance) capabilities;
- potential to improve the quality of results by reducing the number of rigid assumptions and shortcuts introduced by conventional methodologies.

6 APPLICATION DOMAINS AND EXAMPLES OF NEURAL-NETWORK-BASED SPATIAL ANALYSIS

Neural network models in general, and feedforward neural network models in particular, can provide novel, elegant, and extremely valuable classes of mathematical tools for SDA, based on sound theoretical concepts. They may be viewed as non-linear extensions of conventional spatial statistical models such as regression models, spatial interaction models, linear discriminant functions, and pattern recognition techniques (Fischer and Gopal 1994a; Fischer et al 1997). They are particularly appropriate to two major domains (Fischer 1994):

- as *universal function approximators* in spatial regression, spatial interaction modelling, spatial choice, and space–time series analysis;
- as *pattern recognisers and classifiers* of large datasets (e.g. census small area statistics, high-resolution remote sensing data).

Feedforward neural network model building may be considered as a three-stage process, as outlined in Fischer and Gopal (1994a) and applied to telecom traffic modelling by Gopal and Fischer (1996):

- identification of a specific model from a family of two-layer feedforward networks which are

characterised by specific types of non-linear processing elements;
- estimation of the network parameters of the selected neural network model and the model optimisation (using regularisation theory, network pruning, or cross-validation) for the given training set;
- testing and evaluating the out-of-sample (generalisation) performance of the model.

There is little doubt that neural pattern classifiers have an important role to play in high dimensional problems of pattern recognition and classification of massive quantities of data, for example associated with national classifications based on census small area statistics or with spectral pattern classification problems using RS satellite imagery. For example, Fischer and Gopal (1996) illustrate the virtues of NN classification *vis à vis* its conventional ML counterpart in a pixel-by-pixel supervised spectral pattern classification of a Landsat-5 Thematic Mapper image of Vienna. The task of discriminating between *a priori* defined urban land cover categories is challenging because urban areas comprise a complex spatial assemblage of disparate land-cover types – including built structures, numerous vegetation types, bare soil and water bodies – each of which has different spectral reflectance characteristics. However, the results suggest that neural network classifiers in general and a fuzzy ARTMAP classifier in particular are very powerful tools for classifying remotely-sensed imagery if non-linearity is encountered in the dataset. Indeed in the Vienna application it has an outstanding out-of-sample classification accuracy of 99.26 per cent on the pixels testing dataset. This error rate is less than 1/15 that of the two-layer perception, 1/20 that of the Gaussian maximum likelihood classifier and 1/30 that of the radial basis function network. Inspection of the classification error matrices reveals that the fuzzy ARTMAP classifier accommodates more easily a heterogeneous class label such as 'densely built-up residential areas' to produce a visually and numerically correct urban land cover map, even given smaller numbers of training pixels. In particular the normal maximum likelihood classifier tends to be sensitive to the purity of land cover signatures and performs poorly if they are not pure. Another serious problem with the normal classifier is its long processing time if RS data of a large area are to be analysed – which is a common feature in GIS environments. This problem will be exacerbated given anticipated increases in data volumes from planned multichannel satellites (Barnsley, Chapter 32; Dowman, Chapter 31).

7 CONCLUSIONS AND PROSPECTS

GIS technology has already greatly increased the remit of SDA. Conventional SDA tools are generally not sufficiently powerful to cope with the new analysis needs. SDA is entering a new era of data-driven exploratory searches for patterns and relationships. CI technologies in general and neural networks in particular provide an interesting and powerful paradigm to meet the new challenges, yet one that is likely to evolve slowly rather than instate radical change within a short timeframe. The driving forces behind this change are the large amounts of GIS-based spatial data that are now available, the availability of attractive and novel CI tools, the rapid growth in computational power (especially that delivered through massively parallel computers), and the new emphasis on exploratory data analysis and modelling.

Neural networks provide not only novel and extremely valuable classes of data-driven mathematical tools for a series of spatial analysis tasks, but also an appropriate framework for re-engineering our well-established SDA techniques to meet the new large-scale data processing needs in GIS. Application of neural network models to spatial datasets holds the potential for fundamental advances in empirical understanding across a broad spectrum of application fields in spatial analysis. To realise these advances, it is important to adopt a principled rather than an ad hoc approach where spatial statistics and neural network modelling have to work together. The most important challenges in the next years will be twofold: first, to develop specific methodologies for particular application domains; second, to gain deeper theoretical insights into the complex relationship between learning and generalisation. These are of critical importance for the success of real-world applications.

The mystique and metaphorical jargon promulgated by the field may have the effect of lessening the amount of serious attention given to the new neural networks paradigm. Nevertheless many aspects of the study of neural networks lend themselves to rigorous mathematical analysis, and this provides a sound foundation on which to base a study of the capabilities and limitations of neural network systems and applications. Casting the analysis in the universal language of mathematics makes it possible to dispel much of the mystique (White 1992). A start has been made for a neural-network-based SDA, but much remains to be done.

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