*Meta*space: From a Model of Spatial Contiguity to the Conceptualization of Space in Geo-Analyses

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Abstract

Admittedly the most crucial and the most neglected aspect of the spatial regression analysis, spatial contiguity remains an ambiguous concept that is largely dependent on the type of spatial units used and the characteristics of each application. The application of regression analysis to spatial data raises computational as well as conceptual issues. Computational issues consist in statistical inefficiency, which is introduced in the model through the property of spatial dependence, inherent to spatial data. The solution of the statistical inefficiency requires the specification of a spatial autocorrelation model, to which an endogenous approach is proposed. Despite its technical simplicity, the method encompasses conceptual implications that impact on the underlying conceptualization of space: *meta*space emerges as a relative in a conscious effort of the human brain of conceptualizing space according to its analytical needs. *Meta*space is populated with *meta*entities: geometric primitives and their attributes; understanding its properties is fundamental, because *meta*space is the realm of spatial analysis, GIS, and geocomputation.
Keywords: *Meta*Space, relative space, spatial contiguity, spatial analysis, GIS

1 Introduction

Spatial regression analysis is a flexible tool that can serve to study diverse problems. Two applications are used as examples throughout the paper. The two examples have been chosen for the diversity of their scope and of the issues they arise. The first example refers to an environmental problem; the second is a socio-economic application.

Environmental Case: The Venetian Lagoon (Italy) Clams. Chemical pollution in the past decades has induced contamination in the Venetian lagoon sediment. This is viewed as an ecosystem stressor. Pollutants in the sediments (heavy metals

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and organic compounds) tend to biocumulate throughout the trophic chain; this might cause a stress on the ecosystem, especially in the organisms living in the sediment. Some of these organisms, e.g. clams, are an economic resource. Specifically, the Venetian Lagoon is the main producer in Europe of clams (tapes Philippinarum): the pollutant biocumulation might cause severe damage to the fishing industry (Bertazzon *et al*., 2000).

Socio-Economic Case: The Alberta (Canada) Ski Resorts. A noticeable number of minor ski resorts in the province are located off the Rocky Mountains. The analysis aims at identifying factors that may have influenced the location of ski resorts and the growth of their capacity. The Alberta ski industry is viewed as a demand/supply system. The system is considered to be demand-driven: the supply (resorts and their capacity) are stimulated by localised demand, represented by population, income, and demographics: the location and growth of ski resorts is a response to a demand for recreation expressed by local population (Bertazzon, 1998).

2 Spatial Regression Analysis

The objective of the analysis is to establish a functional relationship among the objects or events under consideration. In the case of spatial regression analysis such objects are located in space. The aim of the method is to describe, analyse, estimate, and predict the variable of interest. In the general case of multivariate regression, a dependent variable (interest variable) is expressed as a function of a set on explanatory (independent) variables (Eq. 1).

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k + \varepsilon \qquad (1)$$

In the case of the Venetian Lagoon Clams the content of mercury (Hg) in clams (c) is a function of the content of mercury in the sediment (s), among other explanatory variables:

$$Hg_c = \boldsymbol{f}(Hg_s) \textit{ or } \quad Hg_c = \beta_0 + \beta_1 Hg_s + \ldots + \beta_k x_k + \varepsilon \qquad (2)$$

In the Alberta Ski Resorts case the location of ski resorts (SR) is a function of the location of the population (Pop), among other explanatory variables:

$$SR = \boldsymbol{f}(Pop) \text{ or } \quad SR = \beta_0 + \beta_1 Pop + \ldots + \beta_k x_k + \varepsilon \qquad (3)$$

In the classical regression model (Eq. 1), *y* and the k *x* variables are vectors of observed values of the dependent and explanatory variables: in the clam model (Eq. 2), y represents a series of observations on the content of mercury in clams; in the ski resort model (Eq. 3) x1 represents a series of observations on the Alberta population. The vector $\beta = [\beta_0\ \beta_1\ \ldots\ \beta_k]$ represents the set of coefficients, or functional links between each explanatory variable and the dependent variable (Eq. 1). The ε vector is the error, or regression residual. Each ε_i represents the difference between the observed value of y_i and the value estimated by the function [x] * [β]. The crucial step for analyzing and predicting the interest variable is the estimation of each β parameter, which will be subsequently replaced in the formula (Eq. 1) to produce the analytical results. The classical estimation method is known as OLS (Ordinary Least Squares), and consists in minimizing the squared error vector ε. Calculating the first and second order conditions for a minimum for $\varepsilon'\varepsilon$, the OLS estimator is a combination of the observed X and Y series:

$$\beta_{OLS} = (X'X)^{-1} (X'Y) \tag{4}$$

The OLS method relies on a number of assumptions (Johnston 1984), that guarantee the optimality of the estimates. Particularly, the error vector ε should be *identically* and *independently distributed* (i.i.d.) or

$$\varepsilon \sim N (0, \Sigma^2) \tag{5}$$

Under these conditions, the estimator β_{OLS} is B.L.U.E., or the Best Linear Unbiased Estimator.

The crucial property of β_{OLS} in *spatial* regression analysis is the *variance* of the estimator, and specifically the assumption of an *independent* distribution. Under this assumption the variance of the vector ε can be expressed as a single parameter, σ^2, multiplied by the identity matrix:

$$\Sigma^2 = \sigma^2 I \tag{6}$$

Only under the assumption of an independent distribution of the vector ε, is the estimator β_{OLS} guaranteed to have minimum variance, or to be the BEST in the class of linear unbiased estimators: the one with the minimum variance in its class. The property of minimum variance, guaranteed by the Gauss-Markov theorem, implies *efficiency* of the estimator.

3 Space, Time, and their (Computational) Properties

Space and time are often given joint consideration in conceptual terms, whether they are considered objective properties of the world or convenient constructions of the human brain (Couclelis, 1999; Gatrell, 1983). Despite this frequent joint consideration, space and time display very different computational properties.

Time. Time flows within one dimension and in one direction: from past, through present, to future[1]. Different instants can be ordered unambiguously following the time-direction, along the *timeline*. Time is conventionally stamped with standard units (minutes, hours, weeks, years). For centuries calendars and clocks have shaped the lives of human beings. Calendars and clocks also shape the records of human life and history: the city-state of Athens, in 5th century B. C. had

[1] These statements are valid for common experience, at “human scale”, i.e., singularities of time and space are not considered (Hawking, 1988).

a magistrate, the *Eponym Archon*, whose main role was to name after himself the year of his office!

Space. Space is, in its simplest definition, bi-dimensional. If a location s_0 is considered, different locations can be located North, South, East or West of s_0, and in all possible intermediate directions. Space does not flow, it lies, and no *space-line* is given. Locations *cannot* be organized according to some "natural order". The ordering of spatial observations requires a set of strong and arbitrary simplifications, such as the assumption of a bi-dimensional space; the choice of *two* conventional directions, such as East-West and North-South; and possibly the choice of a conventional *zero*, such as the intersection between the Equator and the Greenwich Meridian. Space is *not* conventionally stamped with standard units[2]. Artificial units can be superimposed on space, but objects and events do not normally occur and are not commonly recorded according to such rasters. Even though it is possible to associate objects and events with a particular cell on a raster, this is not the way they are recorded: Meridians and parallels, in common experience, are only referred to in determining the borders of 'no fly zones'[3], and earlier in this paper reference was made to the city of Athens in the fifth century BC, not to the city at 38 N and 24 E in its classic period!

3.1 Time Series vs. Spatial Series

Classical regression analysis is typically applied to several types of a-spatial data, particularly to temporal data, or time series, for which a number of statistical routines have been devised and refined over the past decades[4]. Spatial regression analysis is a relatively younger technique, and most problems posed by the use of spatial data are, to date, unsolved.

Time. Given the uni-dimensionality and uni-directionality of time, and its conventional subdivision in standard units, *time series* can be unequivocally defined. In a time series observations are regularly spaced[5], and unambiguously ordered in the single dimension and along the single direction of time. A *time series* is formed by two components: the temporal feature is the reference to one of the standard units in which the timeline is subdivided. The attribute feature is the value of the observed variable (e. g. the value of the Dow-Johns index, the temperature at a sampling station). When regression analysis is applied to time series, the assumption of independent distribution of the error vector *can* be met.

Space. Due to the multidimensionality of space, to its lack of a natural direction and order, and to the general unavailability of regularly spaced data, spatial series *cannot* be built in analogy with time series. Unlike in time series, in spatial series a bi-univocal correspondence between standard units and events is hardly

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[2] The location of objects and events is normally referred in terms of countries, cities, or morphologic systems, *not* in terms of their coordinates.

[3] Navigation in fact, unlike everyday experience, relies upon this raster.

[4] A considerable contribution has been made by the field of econometrics.

[5] Taken at subsequent units, i.e. every hour, every week, etc.

possible, not simply because of recording issues. Not only is space generally conceptualized as a bi-dimensional plan, but objects lying on it are similarly conceptualized as geometric primitives: points, lines, and polygons[6]. Lines, and particularly polygons vary in shape and size within a single spatial series, leading to the property known as spatial heterogeneity (Anselin, 1988). Like time series, spatial series are made of two components: a locational feature and an attribute feature. *Un*like time series, the locational feature is not a standard unit of space. And this is due to the way in which spatial items are recorded more than to the way in which they occur[7].

3.2 Spatial Dependence

Waldo Tobler (1979) referred as *the first law of geography* to his proposition that "Everything is related to everything else, but near things are more related than distant things." What the first law of geography expresses (rather informally) is the property known as *spatial dependence*. More formally, Anselin (1988) defines it as "the existence of a functional relationship between what happens at one point in space and what happens elsewhere", or:

$$y_i = f\ (y_1, y_2, \ldots, y_N) \tag{7}$$

Eq. 7 is the formal expression of a *spatial process*. Owing to the generality of Anselin's expression, the effect of distance is not as openly stated as in the second part of Tobler's proposition, but spatial processes tend to display a spatial range, and the relationship expressed in Eq. 7 can have different sign and varying strength (Ripley, 1981). In other words, *what happens at one point in space* can affect positively or negatively *what happens elsewhere*, and the strength of such an effect can vary. Empirical evidence, as well as qualitative and quantitative analyses tend to confirm in the most diverse instances the validity of Tobler's first law of geography, the property that the analytical tradition within geography acknowledges as the *condicio sine qua non* for any spatial analysis (Haggett et al., 1977). While viewed by geographers as the benign property that *allows for* the implementation of spatial analysis, spatial dependence is symmetrically viewed by non-geographers as the unfortunate feature that *imposes* spatial analysis. Thus in such fields as spatial regression, strongly rooted in traditionally non-spatial fields, it is perceived as a cumbersome complication that, affecting some key statistical properties, threatens the effectiveness of robust, long-established techniques (Anselin, 1988; Griffith and Layne, 1999). Spatial dependence is composed of two elements: location and attribute. Location information refers to spatial objects, or

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[6] Along the time line every event in a series can be alternatively conceptualized as a point or a segment, but it does in any case correspond to the standard unit segment of reference.

[7] Obviously most temporal events do not occur regularly in standard units, but that is the way they are recorded.

locational units, such as census districts or weather stations, typically represented by points, areas, or lattices. Attribute information refers to the observed features, or variables, of those spatial units, such as population or rainfall. In the spatial analysis context, the most delicate aspect of the model is the locational component.

Spatial dependence can be observed in a data-set, and measured by the statistical index of *spatial autocorrelation*, perhaps the only index that explicitly takes into account locational features and attribute features (Goodchild, 1987), and can help determine the sign and extent of such dependence. Spatial autocorrelation observed in a data set is generally the indication of a spatial process, involving those or other variables[8]; unfortunately spatial autocorrelation provides no indication of the spatial process that *causes* the dependence.

3.3 Spatial Dependence in Regression Analysis

Spatial dependence implies, also intuitively, some redundancy of information: this renders standard regression methods inefficient. Formally, the presence of spatial *dependence* in a data set violates th hypothesis of *independence* in the error distribution; hence the OLS estimator is no longer the Best estimator, the one with minimum variance, in the class of linear, unbiased estimators (Johnston, 1984), and the property of efficiency is no longer guaranteed. In the presence of spatial dependence the OLS estimator is still unbiased, but the violation of the efficiency property renders it not only unreliable, but potentially misleading. The dependence among observations introduces non-null values of the cross products, or covariances, and the variance matrix (Eq. (6)), takes the form of Eq. (8), where the diagonal identity matrix I is replaced by the full matrix Ω.

$$\Sigma^2 = \sigma^2 \Omega \tag{8}$$

Eq. (8) is the expression of the variance-covariance matrix in the presence of autocorrelated error: the correlations ω_{ij} in the matrix result from the dependence among observations, and can be interpreted as the effect of spatial dependence, or the result of the spatial process for each pair of observations. The entire Ω matrix is thus the expression of the spatial process(es) at work. It should thus be clear that, while disconcerting from the statistical standpoint, this is the crucial, and most distinctive component of a *spatial* regression model.

Within regression analysis the standard solution to an autocorrelated error is known as GLS or Generalized Least Squares method (Johnston, 1984), and consists in creating an inverse of the Ω matrix (Eq. 9) and introducing it in the calculation of the OLS estimator (Eq. 4) which thus becomes β_{GLS}, as shown in Eq. 9, where the inverse matrix restores the variance matrix to its optimal properties (Johnston, 1984).

[8] Goodchild (1987) refers to the example of Italian immigrants settling near other Italians in London (Ontario), where the apparent correlation may simply indicate a different spatial process, such as the concentration of a certain type of jobs.

$$\beta_{GLS} = (X' \Omega^{-1} X)^{-1} (X' \Omega^{-1} Y) \quad (9)$$

Statistically, the GLS solution is flawless: the cause of efficiency is surgically removed, restoring the optimality of the estimates. In the case of *spatial* regression, the cause of inefficiency is spatial dependence, the most fundamental property of any spatial process: its surgical removal is not a *geographically* flawless solution.

4 Conceptual Issues in Spatially Autocorrelated Models

In time series analysis, the GLS solution is conceptually acceptable, but in spatial series analysis, where it represents spatial processes, the solution is unsatisfactory: ridding the model of its inefficiency corresponds to ridding it of its spatial component. If the matrix Ω the spatial dependence in the data, building an inverse of the matrix Ω removes, along with the inefficiency, the entire spatial component of the data. The focus of the analysis should then be shifted just to the matrix Ω. "Building an inverse of the matrix Ω" means specifying a spatial autocorrelation model. Ideally, this should lead to understanding the spatial process(es) at work. Even though spatial processes have received a considerable attention in the literature (Ripley, 1981), statistical indices, such as spatial autocorrelation, can hardly explain anything beyond the sign and spatial extent of the correlation. Despite these limitations, the statistical approach (spatial autocorrelation index) is retains many conceptual and operational merits.

4.1 Spatial Autocorrelation Model

As spatial dependence is comprised of two components, so must be the autocorrelation model. Location and attribute are explicitly accounted for in the Ω^{-1} matrix:

$$\Omega^{-1} = W * C \quad (10)$$

Where w (weight) represents the locational feature, and c the attribute feature. While c expresses the sign and value of the dependency, the locational feature expresses its spatial extent, or range. The locational feature, w, can thus be interpreted as an attempt to interpret the concepts of *near* and *distant* in Tobler's law, or to define the properties of the spatial process. Defining an appropriate matrix w for the spatial weights, is a way of addressing these questions. W is known, technically, as a contiguity matrix. In its simplest specification it is a binary structure, designed specifically to separate what is near from what is distant. Some more complex specifications include various types of weights to increase or decrease the effect of such *nearness*[9]. The locational component is

[9] *Farness* is obviously not weighted, having a 0 value in the basic specification.

modelled through such matrix, whose role is to define which units are, and which ones are not contiguous, or near. Despite its crucial role in spatial regression analysis, the contiguity matrix has received proportionally very little attention in the literature (Griffith and Layne, 1999), yet its importance is widely acknoledged. Any application of spatial regression analysis relies on some ambiguous, largely artificial, often application-specific definition of contiguity. Despite all their limitations, such definitions do retain a crucial merit: they are solely based on locational features, on a single metric (most often the Euclidean one) in absolute[10] space, within which they are consistently developed. Still, it is just such merit that introduces most of the ambiguity and prevents the formulation of a uniform criterion to define contiguity beyond the specificity of single applications. In applied analysis, in the interest of analytical results, it is crucial that the extent of spatial dependence be specified to a high level of accuracy, and possibly unambiguously. Yet to date, due to a number of technical problems, any such determination, general and applicable to different cases is far from being achieved, and when it is determined for single phenomena, based on their unique features, it still lacks the property of unambiguousness (Anselin, 1988)[11].

4.2 Contiguity Matrix

Due to its ambiguousness, highlighted by Anselin (1988), there are several practical possibilities of defining contiguity. Conceptual differences depend on the approach taken, but the most basic differences are due to the type of locational data at hand: there are typically two alternatives. For area units, contiguity is typically based on shared borders, as shown in Fig. 1(a). The criterion is, in general, applicable only to area data ; it is fairly unambiguous, in that it depends on the topology of the data; it also allows for the definition of several orders of contiguity (Fig. 1(a)). In most applied cases the spatial units are artificial (sampling points, census districts), hence the definition of contiguity depends solely on the topological properties of artificial objects. The criterion can be considered endogenous, but, considering the overwhelming importance of the topological properties, it should more appropriate be defined structural.

The alternative is the definition of a threshold distance, as exemplified in This criterion is applicable to any kind of spatial data (area, point, line, or lattice data). It is *not un*ambiguous, since the threshold must be determined from some *external* criterion: the approach is, therefore, exogenous.

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[10] It is the classical conceptualization of space, representable by Euclidean geometry in a Cartesian frame (Couclelis 1999).

[11] Recent computational, or rather geocomputational advances do not seem yet to address the conceptual issues involved (Anselin, 1998).

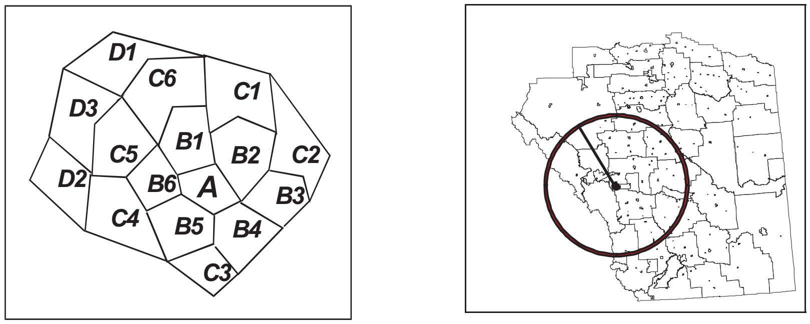

Fig. 1. Continuity based on (a) Shared borders; (b) Threshold Distance

Even though the two definitions of contiguity present some considerable differences, they have important elements in common. Particularly: in both cases the demarcation between near and distant is only determined by the locational feature. Due to this properties, both measures of contiguity may be defined locational. This characteristic has important consequences on the specification of a spatial dependence model: Tobler's law states that "*near things are more related than distant things*",it does not state that more related things are nearer then less related things…. This is the criterion used by the two measures of contiguity: some things are more related *because* they are near; . In Eq. 10 the w element is set equal to 1 or to 0 by the topology. And this 1 or 0 weights the attribute feature: consequently, in the model, only near things can be related! Especially in light of this Solomonic effect, crucial questions arise, such as: what measure of distance is appropriate, and what distance is relevant, in determine contiguity? Can there be aa single answer for any application? Even though specific applications may require different measures of distance, is it possible to find at least a standard criterion as a general guideline?

4.3 *Ad hoc* measure of contiguity in the Alberta ski resort application.

In the Alberta ski resorts case study, population, income, and other demographic data are attributes of census units in the province. Supply variables (lift, hour capacity, price, etc.) are consistently attributed to the census units of pertinence[12]. Census units provide an irrelevant, if not misleading, base for locational contiguity. With border-based contiguity, when a large area is considered and different orders of contiguity are introduced, topological contiguity becomes increasingly irrelevant. A census tract in fact is not necessarily near a ski resort because it is contiguous to it within the fifth order (Fig. 1(b)). Threshold distance contiguity presents some advantages, but the result is still ambiguous, particularly in a mountain region. For this case study, a distance measure based on traveling time was introduced, and based on it, three orders of contiguity were defined:

[12] Alternatively, they could have been considered as point values.

1^{st} order contiguity: if the census unit - resort distance allows for a half-day ski trip;
2^{nd} order contiguity: if the census unit - resort distance allows for a day ski trip;
3^{rd} order contiguity: if the census unit - resort distance allows for a weekend ski trip.

The definition of day-trips is conceptually appropriate for a tourism model, and it can be referred to a network distance (Bertazzon, 1998). This criterion is an example of an exogenously defined distance model: not only does it require an external, a priori knowledge of the phenomenon under exam, but this choice does not find any justification within the spatial regression model.

4.4 Endogenous Approach to Contiguity

The problem with the specificity of such solutions as the trip-length lies not only in the need for external knowledge, and in the need to "start it all over again" for each new application, but also in the fact that in some cases *ad hoc* measures may not be known, or not available. For all these reasons, and because of the dissatisfaction associated with the need for an external solution to an essential component of the spatial regression model, the question arises, whether it would be possible to follow a standard criterion to defining contiguity: an explicit, endogenous model of spatial autocorrelation. The natural solution, comes from the statistical routines that deal with spatial autocorrelation, i.e. semivariogram or correlogram. The semivariogram will be considered. The empirical variogram provides a description of how the data are related (correlated) with distance.

$$\gamma (h) = 1 / (2 |N(h)|) \Sigma_{N(h)} (z_i - z_j)^2 \qquad (11)$$

Where N(h) is the set of all pair-wise Euclidean distances i-j=h, and z_i , z_j are the values of the variable at each pair of locations (MathSoft, 1996). The crucial parameter in the present analysis is the *range* value: the distance (if any) at which data are no longer autocorrelated. The range value is not infrequently used to determine *endogenously* the threshold for distance-based contiguity.

The semivariogram is an explicit model of spatial autocorrelation. Even though its calculation is not strictly required by spatial regression analysis, it can be considered endogenous to the model, in that it uses the same data or raw variables, and no *a priori* choice is required. The endogenousness of the approach is very important in that it keeps the whole problem, and its solution, within one single conceptual framework; yet the most radical difference, conceptually, between this the topological approach, is, beyond its endogeneousness, the role taken by *relatedness* and *nearness* in each case. While in the topologically based contiguity (be it border or distance based) it is the locational feature to drive the determination of relatedness, in this approach, it is *both* locational and attribute feature that determine *jointly* the autocorrelation model, and hence the contiguity matrix. The distance element, or the h interval, enters as a measurement unit, but is evaluated by the γ function *in conjunction* with the attribute correlation, and based on the pattern of γ, function of z *and* h, the range is calculated and the threshold determined. In the topological model, things are related *because* they are near, and *only* near things can be related. The semivariogram model considers *both* relatedness and nearness, location and attribute. The endogenous process from location and attribute data to the estimation of the spatial regression coefficient is summarized in Fig. 2.

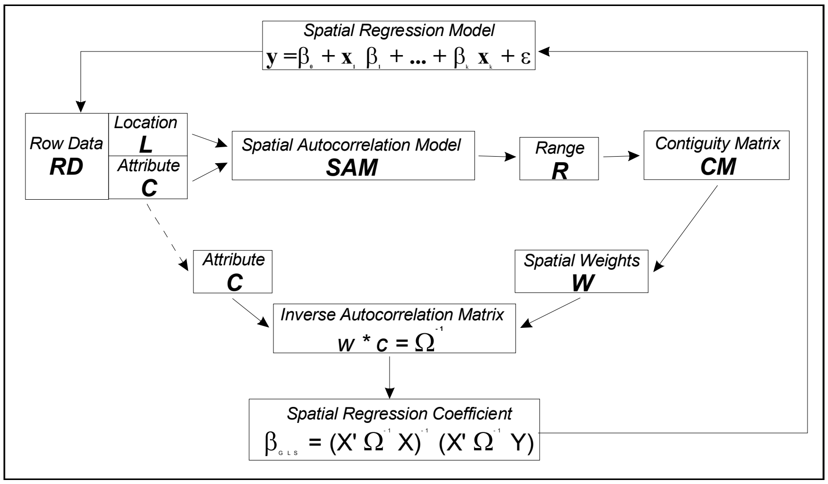

Fig. 2. Endogenous Approach to Contiguity.

As shown in Fig. 2, applying the endogenous approach, through the use of a spatial autocorrelation model (SAM), i.e. the semivariogram, the entire analysis is conducted within one consistent framework.

Before discussing the conceptual implication of the endogenous approach, a few comments should conclude the case studies referred to throughout this paper. The endogenous approach was used in the clam example, where no other exogenous model was available; based on this, regression coefficients were calculated, producing a satisfactory goodness of fit (Bertazzon *et al*, 2000). For the Alberta case, the trip-length criterion proved to be the most appropriate choice (Bertazzon, 1998).

5 METASPACE

Absolute, or Newtonian space, is conceptualized as a neutral container of things and events (Couclelis 1999); thus things and events can be assigned coordinates and represented by Euclidean geometry in a Cartesian frame. Opposed to this traditional view is the conceptualization of relative space, defined as *a space emerging out of the relationships among things* (Gatrell, 1983).

5.1 Endogenous Contiguity Model as the Creation of a Relative Space

Based on Gatrell's definition, the endogenous approach to spatial contiguity can be seen exactly as the construction of a relative space. The process described in Fig. 2 forms a sub-procedure in which *a new space emerges out of the relationships of proximity and relatedness among a set of things*. According to this interpretation, during the process occurs a shift not between spaces, but between conceptualizations of space. This conceptual shift involves a number of implications. The definition of a relative space implies the dissolution of distance into a relationship, so that the spatial coordinates of locational units become attributes, not dissimilar from any other attribute of those units. As Gatrell (1983) notes, the concept of relative space is more general and empirically more useful than the concept of absolute space, for two reasons: first, by referring to a 'relation' we are envisaging many ways in which the spatial separation of objects can be described. Second, we do not require the relation to be something with the properties of distance (so-called 'metric properties'). This conceptualization of space opens a path towards alternative definitions of contiguity, independent on topology and [Euclidean] distance. Such solutions as the trip-length, previously considered *a priory* and exogenous, could be absorbed within the endogenous process through a relative, more general definition of contiguity. Border and threshold criteria could be replaced by more relevant relatedness measures. Relative space provides a conceptual framework to define rigorously the endogenous approach to the definition of spatial contiguity. Within this framework the approach possesses general validity, is consistent, and is unambiguous: the method therefore does provide a single criterion, if not a standard procedure for virtually any application. In absolute space the method would be spurious, as attribute features would be used to define spatial contiguity in locational terms; the contradiction is resolved in relative space, where both locational and attribute properties belong to the same conceptual plane. The flexibility of relative space allows for diverse conceptualizations of spatial separation, more general than traditional metrics.

5.2 Relative Space as a *Meta*Space

The conceptual shift from absolute space to a particular relative space poses some issues regarding the properties of such space and objects in it. Intriguing is the ontological status of a space (relative) that "emerges out of the relationships among things". If the very existence of such space is subordinate to the existence of those objects and relationships, what is the ontology of a space affected by a subordination condition? Traditionally the ontological question about space revolves around the question whether space (as well as time) is an objective property of the world, or a construct of the human brain - the Kantian *synthetic a priori* (Couclelis, 1999). Defining it as a Kantian space, or a construct of the human brain, leads to a logical contradiction, even before the ontological question is raised: this space cannot be an *a priori* -i.e. before experience- category, since it is subordinate to the existence of objects and their relationships, unless those objects and relationships can conceivably exist *a priori*. Even admitting the existence of *a priori* objects and relationships, relative space emerges out of those objects and relationships (Gatrell, 1983): it is therefore configured as a *meta*[13]category, perhaps ontologically nested in the a priori universe, but mediated: a *meta*space. The alternative conceptualization of space (and time) as an objective property of the world would lead to the same conclusion: the existence (ontological status) of relative space as an objective property of the world is not necessarily rejected, but its emergence from objects and relationships confers it a status of *meta*category. If the Kantian definition of space is a *synthetic a priori* (Couclelis, 1999), this relative space, a *meta*space emerging from within and interest of spatial analysis, should be defined as *an analytical a posteriori*.

Objects and relationships provide the foundation for the emergence of relative space, but as a consequence of the conceptual shift to *meta*space, their nature and properties are also affected. Objects and relationships of absolute space are geometric primitives with their attributes in *meta*space. *Meta*space emerges out of the set of objects being analysed and the relationship defined as spatial dependence, a relationship in turn rooted in the locational and attribute features of those objects. Defined and measured in Newtonian space, locational properties dissolve into relative, a-locational properties, not dissimilar from any other attribute property, in the shift to relative space. The dissolution of absolute location into an a-locational attribute transforms the contiguity relationship into an (a-locational) proximity. The very relationship of spatial dependence is configured as a multi-correlation among a-locational attributes.

*Meta*space is a conscious effort of the human brain of conceptualizing space according to some specific analytical needs: it plays the role of a laboratory where analyses and predictions about the world are performed, i.e., where knowledge is acquired. Fundamental questions arise therefore also with respect to its logic, physics, and epistemology: How does *meta*space work? What are the rules that govern it? The mechanisms that make it function? How can knowledge be acquired and transferred within it and about it?

How does *meta*space relate to absolute space? The comparison is not between two alternative physical spaces, but between two alternative conceptualizations of space. If *meta*space is a laboratory for the acquisition of knowledge, assessing the relevance of that knowledge to "the real world" is the most fundamental question about *meta*space. In order to address it, it is necessary to comprehend the relationships between ontology, epistemology, physics and logic of *meta*space to those of absolute space.

The absolute space of daily experience is populated with people, objects, and events. *Meta*space is populated with *meta*entities: geometric primitives and their attributes. Spatial analysis, GIS, geocomputation deal only with *meta*entities in *meta*space: all the questions raised in this section are about their ability to deal with people and our world.

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[13] The Greek preposition μετα - "meta" means *after*,*beyond*.

6 Conclusion

The analysis of spatial contiguity and its conceptual implications has lead to the specification of an endogenous approach, and, in turn, to the proposition of a relative space, emerging from the properties of relatedness and nearness of spatial data. Such space is configured as a *meta*space, an *a posteriori* analytical conceptualization of space where spatial analysis is performed. Beyond absolute space, *meta*space is the space populated by geometrical primitives and attributes, the laboratory where knowledge is acquired about our world. Understanding the ontology, epistemology, logic, and physics of *meta*space is understanding the relevance of spatial analysis, GIS, and geocomputation to people in their world.

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