Non-Toblerian Geographical Spaces

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Abstract. This work introduces the concept of 'non-Toblerian geographical spaces', where anisotropic and action-at-a-distance relations are relevant. Non-Toblerian spaces arise often in cases of rapid change caused by human actions, and we argue that these cases are becoming more frequent due to globalization and to the growing integration of markets. The current generation of GIS does not handle such spaces properly. This paper provides practical and theoretical evidence on the commonness of non-Toblerian spaces. We argue that some relevant critiques on the limits of GIS made by postmodern thinkers can be addressed by adopting a generalized measure of proximity. The paper also discusses the *Generalized Proximity Matrix (GPM)*, a tool for representing non-Toblerian spaces, focusing on its use for dynamical spatial modelling. The GPM allows GIS to provide a flexible support for proximity measures, and thus support modelling in non-Toblerian spaces.

Keywords: Spatial relations, dynamical spatial modelling, spaces of places, spaces of fluxes.

1 Introduction

Spatial relations are a fundamental part of applications that use geographical information systems, as we use these relations to make queries and perform operations on geospatial objects. Finding out a formal way to specify topological spatial relations [1] was an important step in developing a common set of GIS-related standards [2]. Within the domain of spatial relations, the notion of *proximity* is especially important. Many spatial operations and spatial models depend on representations of *proximity* that provide a practical application of Tobler's [3] principle (*"the first law of geography: everything is related to everything else, but near things are more related than distant things").* In our common-sense use of GIS [4], the notion of proximity is associated to point-set topological predicates [1] and to isotropic distances in Euclidean space. Spatial analysis properties such as autocorrelation, used in geostatistics [5] and area analysis [6], rely on Euclidean distances or topological relations. These methods have brought about notable progress in spatial analysis, with applications in disciplines such as public health, public security, spatial econometrics, and social inequality analysis [7-9].

Despite these successes, there is increasing evidence about many problems that cannot be solved effectively using the conventional definitions of *proximity*. As we argue in the present paper, many human-built spaces have a strong tendency toward anisotropy, where some directions prevail over others. The rapid land changes common in the world´s developing nations are influenced by relations that act at a distance, such as connections to markets [10]. We need to represent such spaces if we are to capture relations that consider how today's global economic forces influence local actions. In this perspective, this paper proposes that GIS should adopt a *flexible notion of proximity* for spaces where anisotropic and action-at-a-distance relations are relevant. We call such spaces "*non-Toblerian*", by analogy to Waldo Tobler's "first law of geography". In non-Toblerian geographical spaces, proximity is not measured by topological relations or by Euclidean distances, but it is a singular property of each spatial object from that space. For each spatial object, we need to find out its proximity relation to all other objects in the same space. This relation will depend on the underlying social relations that have created the objects in this space. By making proximity into a flexible and individual relation between objects, we will be able to represent much richer problems using GIS.

Strictly speaking, Tobler´s "first law of geography" continues to be valid in spaces that use a flexible definition of proximity. We chose to call such spaces '*non-Toblerian*' to honour Waldo Tobler´s insights, which have led to much significant work on GIScience and to highlight that such spaces need a flexible definition of *proximity*. In this paper, we provide practical and theoretical evidence on the commonness of non-Toblerian spaces. We also argue that some relevant critiques on the limits of GIS made by postmodern geographers [11] can be addressed by developing models on such spaces. The paper also discusses the *Generalized Proximity Matrix (GPM)*, a tool for representing non-Toblerian spaces, focusing on its use for dynamical spatial modelling. This paper follows from earlier works by the authors, including a first definition of the GPM [12] and its use for multiscale modelling [13] [14]. The authors have tested the ideas described here using the TerraLib open source GIS library [15] and the TerraME spatial dynamical modelling environment [16].

2 Why Many Human-built Spaces are Non-Toblerian

There are many cases where action-at-a-distance relations define how humans occupy space. When people move into a region, they create and use access routes. A new road will attract new occupants to its surroundings, be it in urban expansion areas or in rural domain. The resulting patterns are not isotropic, since they follow preferential paths set by the transport network. Consider land changes in the state of Rondonia, part of the Amazon rainforest in Brazil, a case well-documented by remote sensing data [17], and shown in Figure 1. Systematic cutting of the forest vegetation starts along roads and then fans out to create the "fishbone" pattern shown in the eastern half of the 1986 image. In the Brazilian Amazonia, there are many fishbone patterns associated with planned settlements, created by the Brazilian government in a centrally planned design. From the main road, shown in Figure 1 (top left), the planners created a network of side roads and settled poor people from other regions of Brazil. Deforestation along the expanding network of highways and local roads created a ‘fishbone’ pattern. Such colonization projects had no consideration for environmental constraints and landscape characteristics of each region [18].

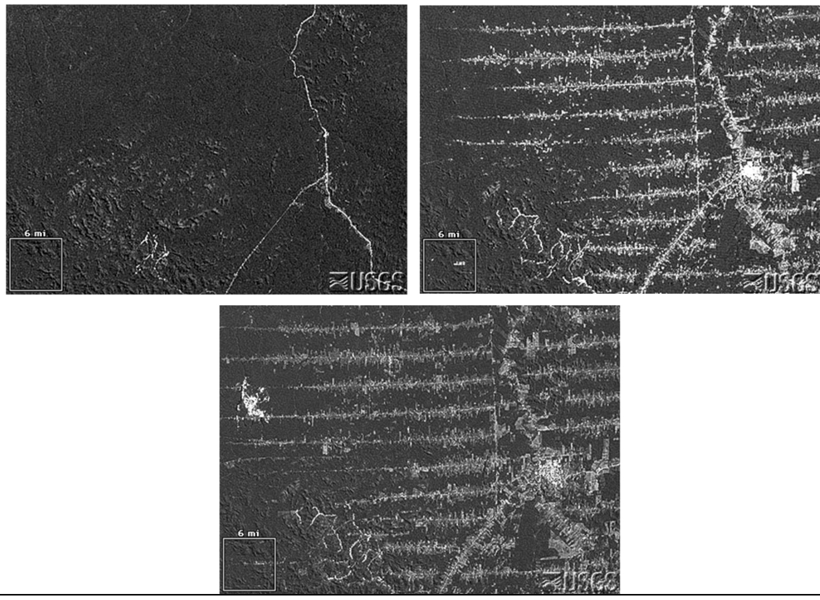


Fig.1. Human occupation in Rondonia, Brazil, as shown in LANDSAT images. Top left: image from 1975; top right: image from 1986; bottom: image from 1992 (source: USGS).

A second example concerns urban chance in Riyadh, Saudi Arabia´s capital, shown in Figure 2. From the 1970s to the 1990s, Riyadh´s population grew from about a half million to almost two million. The city grew through migration from rural areas. In the mid-1970s Riyadh's population was increasing by 10 per cent a year, a growth supported by the increase of oil revenues. The government built new roads leading to the city, which led to a pattern of occupation induced by the transport network.

Fig.2. Urban expansion in Riyadh, South Africa, as shown in LANDSAT images. Left: image from 1972; right: image from 1990 (source: USGS).

The Rondonia and Riyadh cases are examples of a more general scientific question of how human relations evolve in space and how this evolution depends on the pathways and routes for humans to occupy space. Usually, when changes in geographical space depend on networks and routes, a non-Toblerian space emerges as a result. Thus we need a theory to explain how non-Toblerian geographical spaces emerge. We consider that *social network theory* is a good candidate for providing such explanations.

Social network theory deals with analysing the interplays between individuals or groups, and actors at different levels of analysis. The regularities and patterns of such interactions shape these networks [19, 20]. An important part of social network theory concerns the analysis of properties of empirical data for issues such as collaboration networks, disease spreading, and innovation diffusion. Most of this data has a spatial part. Indeed, one of the important pioneering works on both social networks and time geography was Hägerstrand´s work in the diffusion of innovations [21]. There are now many techniques for analysing social network data [19, 22, 23], which allow calculation and comparison of structural and spatial properties. Increasingly, the GIS community is interested in the connections between networks and other spatial forms of representations [24]. In a recent survey of the relations between social science and GIScience, Goodchild et al. [7] stressed the need to build direct spatial expression of networks and expressed interest in creating synergies between the two fields.

As well as analysing empirical data, an important branch of social network theory considers the questions of how do networked patterns arise. In connection to their work on scale-free networks, Barabasi and Albert [25] propose a theory on how social networks emerge. They consider that most real networks have *preferential attachment*. That is, given an existing route inside the Amazon forest as shown in Figure 1, it is much more likely that new settlements will emerge close to that route than in other places of the same regions. In turn, these settlements induce building new roads, which in turn create conditions for newcomers to occupy the regions following the road pattern. Thus, networks have a constraining effect on how geographical space is occupied and have a cascading effect on shaping the spatial patterns. Such effects are more noticeable in cases of fast land change, such as the

Rondonia and Riyadh examples, but to a lesser extent influence all human-built spaces.

The result of the *preferential attachment* effect is a strong dependence between the individual or groups present on the space. As shown by Barabasi and Albert [25], the extreme form of preferential attachment leads to a scale-free network described by an exponential distribution, as with the World Wide Web [26]. Even in less extreme cases, preferential attachment leads to spaces where the spatial relations are strongly anisotropic, thus needing new methods for calculating proximity. In the most general case, all individual spatial relations need to be calculated separately. In this paper, we discuss a method for general expression of proximity relations in non-Toblerian spaces, called the *Generalized Proximity Matrix (GPM).* Before that, we propose to examine some GIS critiques by postmodern geographers, since we consider the theory of non-Toblerian space can answer some of those criticisms.

3. Non-Toblerian Spaces as a Response to Postmodern Views of Space

One of the most contentious issues for setting up GIScience as an academic discipline has been the criticism raised at geographic information systems by the so-called ‘postmodern’ geographers [27]. Much of this criticism was ideological, including accusations of ‘links between GIS and imperialism’ [11]. In this section, we shall not consider such extreme criticisms, but will examine some issues raised by postmodern thinkers which we consider relevant to our discussion. To this end, we consider how writings of two leading scholars (David Harvey and Manuel Castells) have influenced us to propose the notion of non-Toblerian spaces as a response to their views on the new spaces created by globalization.

In his book *“The Condition of Postmodernity”* [28], David Harvey makes an analysis of the new relations of production in today's society. For Harvey, the most important cultural change in recent years has been caused by the ‘compression of space-time’. He notes that from the 16th century to the 19th century the average speed of the sailing ships was 20 km/h. From the mid-19th century onwards, the steam locomotive reached 100 km/h. In the 20th century, jet aircrafts reached 800 km/h. Today, with telecommunications and the Web, we can exchange documents and hold meetings with people in other places in the world at the same time. According to Harvey, the compression of space-time is an essential part of new forms of capitalist production, where the financial capital gains autonomy from the industrial capital and from governments. International flows of resources are reshaping geographical space in a way unprecedented in history. Harvey´s idea of the ‘compression of space-time’ points out the traditional way of expressing spatial relations between geospatial objects (properties such as Euclidean distance) captures only local effects. Strictly Euclidean geographical spaces do not represent the social and economic phenomena of our time.

A second relevant author is Manuel Castells, who in his book "The Rise of the Network Society" [29] coined the notion of *'space of flows'* in contrast to the traditional geographical space, which he calls *'space of places'*. In a space of flows, connections happen in real-time across large distances. This space is shaped by the flows of information, people and goods. Castells [29] writes:

"Our societies are constructed around flows: flows of capital, flows of information, flows of technology, flows of organizational interactions, flows of images, sounds and symbols. (…) Thus, I propose the idea that there is a new spatial form characteristic of social practices that dominate and shape the network society: the space of flows. The space of flows is the material organization of time-sharing social practices that work through flows. By flows I understand purposeful, repetitive, programmable sequences of exchange and interaction between physically disjointed positions held by social actors. (p.412)"

For Castells, the *'space of places'* is the spatial arrangement formed by adjoining locations, whose spatial relations are defined by the everyday logic of neighbourhoods. The traditional city in Europe and the US has been built as a *'space of places'*. However, the *'space of flows'* is increasingly determinant on the power relations and on the trade of goods and services. As Castells put is, the conflicts between the *'space of places'* and the *'space of flows'* creates *"a structural schizophrenia between two spatial logics that threatens to breaks down communication channels in society"* [29].

The idea of 'non-Toblerian spaces' and its associated tools (as discussed below) is a way to represent the 'compression of space-time' and the 'space of flows' in the traditional 'space of places' handled by a GIS. The idea is to represent how the flows influence the relations between the geographical objects. This is especially relevant for uses such as dynamical modelling and multiscale modelling, as shown in the next sections.

4. Tools for Representing Non-Toblerian Spaces

Considering the key role of proximity in spatial modelling, a GIS should provide a consistent way to express spatial non-isotropy for different types of spatial functions. In [12], we introduced the idea of a *Generalized Proximity Matrix (GPM)*, a matrix whose elements express both *absolute space* relations such as Euclidean distance or and *relative space* relations such as network connection. Using the GPM, two geographic objects (e.g., municipalities) could be "near" each other if they are connected through a transport or telecommunication network, even their absolute locations are thousands of kilometres apart. The GPM allows extending techniques such as spatial analysis, map algebra, and cellular automata to incorporate relations on relative space. Thus, it provides a new way for exploring complex spatial patterns and non-local relations in spatial statistics. In what follows, we extend the GPM as defined in [12] to provide a general way of expressing proximity relations.

4.1 Definition of the GPM

Consider a set $\mathtt{O}$ of geographical objects with geometrical representations defined over $\Re^2$. Examples of representation of such objects include: (a) regions defined closed polygons; (b) cellular automata organized as sets of cells, whose boundaries are the edges of each cell; (c) point locations in two-dimensional space. Given two objects $\mathtt{o_i}$ and $\mathtt{o_j}$ belonging to $\mathtt{O}$, we refer to the *proximity relation* between $\mathtt{o_i}$ and $\mathtt{o_j}$ by $\mathtt{w_{ij}}$. The GPM is a set of triples [$(\mathtt{o_i},\ \mathtt{o_j},\ \mathtt{w_{ij}})$], where each pair of objects is associated to a proximity measure. The GPM records if (and how much) two objects in $\mathtt{O}$ are near to each other, according to different types of *absolute* and *relative* space criteria. It is an extension to the traditional definition of the spatial weights matrix $\mathtt{W}$ [30] to include a generic definition of proximity. In this section, we describe the basic notions of GPM considering objects of the same type (e.g., two farmers, two grid cells) represented at the same spatial scale. In Section 5 we discuss multiscale relations. Figure 3 shows some alternative criteria for building the *proximity* between pairs of objects in $\mathtt{O}$.

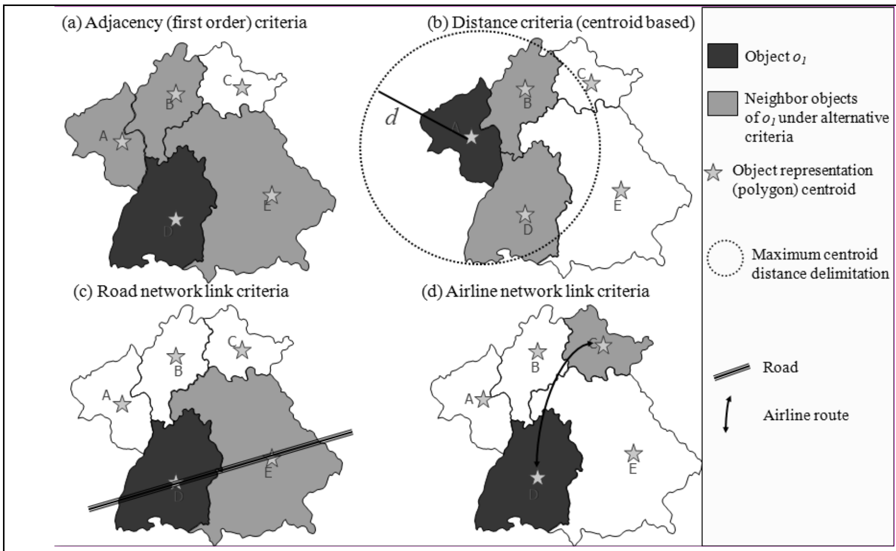


Fig. 3– Alternative criteria for calculation of proximity combining absolute and relative space relations.

Conventionally, GIS applications use topological adjacency and Euclidian distances (Figures 3.a and 3.b) to define proximity relations. In these cases, computing the spatial weights matrix $\mathtt{W}$ depends only on *absolute space* relations, as in the definitions below:

- $\mathtt{w_{ij}} = 1$, if $\mathtt{o_i}$ is next to $\mathtt{o_j}$; $\mathtt{w_{ij}} = 0$, otherwise. (1)
- $\mathtt{w_{ij}} = 1$, if $\mathtt{distance}(\mathtt{o_i},\ \mathtt{o_j}) < \delta$; $\mathtt{w_{ij}} = 0$, otherwise. (2)
- $\mathtt{w_{ij}} = 1/\mathtt{distance}^2(\mathtt{o_i},\ \mathtt{o_j})$; $\mathtt{w_{ij}} = 0$, if $\mathtt{i == j}$. (3)

Spatial weights may just mark the existence of a certain relation (as in equation 1 or 2), or quantify the strength of the relation (as in equation 3). A simple example of the GPM is shown in Figure 4, where the weights use the topological adjacency condition for the objects shown in Figure 3.a (equation 1).

	A	**B**	**C**	**D**	**E**
A	0	1	0	1	0
B	1	0	1	1	1
C	0	1	0	0	1
D	1	1	0	0	1
E	0	1	1	1	0

Fig. 4 – Spatial weights matrix for objects of Figure 3 under adjacency condition

Alternatively, we could define the GPM using the relations shown in Figures 3.c and 3.d, using the road network or the airline routes. The resulting matrix would express proximity relations induced by these networks. Thus, the GPM expresses proximity relations by combining different neighbourhood conceptions which include: (a) topological relations on point sets (Egenhofer operators); (b) network connectivity, both physical (e.g., roads) and logical (e.g., trade fluxes); (c) vicinity in cell spaces and grids. The underlying idea behind the GPM arose in the GIScience literature in previous papers, such as the geoalgebra of Takeyama and Couclelis [31] and the graph cellular automata of O'Sullivan [32]. We now show the GPM is a generalization of these previous works, providing a general way for expressing proximity.

Couclelis [33] proposes the notion of *proximal space*, which aims to combine the ideas of absolute space and relative space. To capture relations in proximal space, Couclelis [33] uses a *relational map*. Given a set of spatial objects O, a relational map R_i for object o_i is the set of all objects that influence it. The set of all relational maps for all spatial objects is the *metarelational map*. The geoalgebra proposed by Takeyama and Couclelis [31] uses the *metarelational map* to extend traditional map algebra functions over the proximal space, and thus capture spatial relations that act at a distance. Takeyama and Couclelis' [31] *metarelational map* is a GPM whose all weights are either 0 or 1. Thus, the *geoalgebra* of Takeyama and Couclelis [31] can be expressed by functions that use the GPM to compute its results, as shown in [12]. Since the weights of the GPM are general and not limited to 0 or 1, it follows the GPM is a generalization of Couclelis' work.

Other recent proposal is the idea of graph-CA[34]. A graph-CA is a relaxation of conventional cellular automata (CA) that uses a directed graph to define cell neighbourhoods. Each cell c_i of the CA is associated to a vertex v_i and each edge of the graph represents a connection between two cells c_i and c_j. The *graph-CA* model [34] is as a special case of a GPM-based CA, where the weights are 1 (one) for cells connected by a graph and 0 (zero) otherwise. Therefore, any CA whose neighbourhood relations use a GPM will support the graph-CA model.

4.2 Calculation of the GPM combining absolute and relative space relations: an example

To calculate the GPM considering relative space relations, we need an extra data set: a network N that provides the connectivity information. The network N provides information about physical links (roads and rivers) and logical links (airline routes, market chains), which connect objects in O, as Figures 3.c and 3.d show. We want the proximity matrix to express information such as: *Are these cities connected though the airlines network? Are two frontier areas in the Amazon inserted in the same productive chain?* More broadly, we can apply the same idea to objects of different types represented at different scales (see Section 5.2). For instance: *Is this Indian reservation connected to mining areas trough the roads network? Are these cities connected to export facilities through the transport network?*

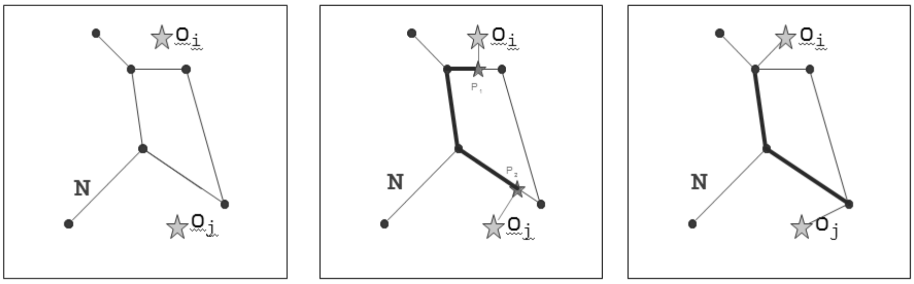
There are many possibilities for computing a GPM combining absolute and relative space criteria. In what follows, we consider the case where its weights w_{ij} combine two measures in a linear fashion:

$$w_{ij} = \alpha * prox\_abs\ (o_i,\ o_j) + \beta * prox\_rel\ (o_i,\ o_j) \qquad (4)$$

The first term, prox_abs, is an absolute space relation, which we calculate using topological or Euclidean distance measures, as in equations (1) and (2). The second term, prox_rel, expresses the relations on the relative space. The weights α and β mark the relative importance attached to absolute and relative space relations. To calculate prox_rel, we distinguish between two types of networks. The first type includes *closed networks*, whose entrances and exits are restricted to its nodes. Examples are railroads, highways, telecommunication networks, banking networks, and productive chains. The second type comprises *open networks,* in which any location can be used as an entrance or an exit. Examples are transport networks such as small roads and rivers. Besides its edges and nodes, the network N must provide information on the cost of traversing each edge. For example, in road networks this cost may represent distances (in metres, for example) or travel time (in hours). Figure 5 shows graphically how to calculate prox_rel for closed and open networks.

For open and closed networks, a simple way to calculate $prox\_rel(o_i,\ o_j)$ is as follows:

1. For each object in o_i, calculate the nearest entry point e_i in network N. In an open network, e_i can be any point inside an edge. In a closed network, e_i is necessarily one of the nodes.
2. For each object in o_j, calculate the nearest entry point e_j in network N (the same rule above applies for both open and closed networks).
3. Calculate the cost of the traversal from e_i to e_j ($ncost_{ij}$) using network analysis operators.
4. Calculate the cost of reaching e_i from o_i ($cost_i$), and to e_j from o_j to ($cost_j$).
5. Calculate $prox\_rel\ (o_i,\ o_j)$ using $cost_i$, $cost_j$ and $ncost_{ij}$,.



(a) Objects to be linked through network N | (b) Open Network linkage from O_i to O_j | (c) Closed Network linkage from O_i to O_j

Fig. 5. Schematic representation of an algorithm for proximity measurement in open networks.

The values of $\mathtt{cost}_i$, $\mathtt{cost}_j$ and $\mathtt{ncost}_{ij}$ depend on the network type. Defining $\mathtt{prox\_rel}(o_i, o_j)$ depends on the network cost unit (meters, hours, amount of service, etc.) and on the application needs. A specific formula has to be chosen in each case. An example of such formulas is

$$\mathtt{prox\_rel}(o_i, o_j) = a/(\mathtt{cost}_i)^2 + b/(\mathtt{cost}_j)^2 + c/(\mathtt{ncost}_{ij})^2 \qquad (5)$$

The methods discussed in this section are one possible way to calculate the GPM, given a set of objects O and a network N. We could apply other case-specific rules. For example, given a road network, one can define that objects are not linked to the network if they are more than a 100 km away from the closest entry point. In general, for each application, there will be a suitable way of computing the GPM, dictated by the particular properties of the non-toblerian space. Our experience [13] [14] points out the method discussed here provides a reasonable first guess. In the next section, we show these ideas in practice on dynamical modelling applications.

5 Dynamical Modelling in Non-Toblerian Spaces

5.1 Using the GPM with Cellular Automata

The GPM is applicable in many different types of spatial analysis and spatial modelling functions, providing a means to explore complex spatial patterns and non-local relations. We now consider some of its uses. One case where the issue of spatial anisotropy is important is when using cellular automata (CA) for spatial dynamical modelling. CAs have been used in the last two decades for simulation of urban and environmental models. They are popular largely because they are tractable, but contain enough complexity to simulate surprising and novel change as reflected in emergent phenomena [35]. Early proposals for use of CA in spatial modelling stressed their pedagogic use in showing how global patterns emerge from local actions. For realistic geographical models, the basic CA principles are too constrained to be useful, a fact which led to proposals for extending the basic CA model [36].

Carneiro et al. [14] propose an extension of the CA model called *Irregular Cellular Space (ICS).* In the ICS model, there is no fixed geometry for the space representation and the cellular space is an arbitrary arrangement of cells. An ICS geometrical representation may vary from a regular grid of same size squared cells to an irregular set of points, lines, polygons, nodes and arcs, pixels, or even voxels. ICS spatial relations use GPMs allowing representing non-homogenous spaces where the spatial proximity relations are non-stationary and anisotropic. Carneiro et al. [14] implemented the ICS model in TerraME, an environmental modelling software platform [16]. To show the possible uses of an ICS, we built a simple cellular automata model that aims to reproduce fishbone deforestation patterns in Rondonia, Brazil, a case discussed in Section 2. The model takes as a starting point an area with forest where a road has been built. We then consider three cases:

1. Deforestation growing from the main road, based on a Moore neighbourhood, in which each cell has nine neighbours, all equally related. The GPM is constant for all objects and considers only its 3 x 3 neighbours.
2. Deforestation growing from the main road and from a network of secondary roads, where the GPM uses only the *relative distance* from the road network.
3. Deforestation growing from the main road and from a network of secondary roads, where the GPM uses both the *absolute* and *relative distances* from the road network.

The transition rule is simple, since this is an illustrative example. For each year of simulation, a cell that contains forest and has two or more deforested neighbours has a 20% chance of also being deforested. Figure 6 shows the results. Sequence A shows the simulation using isotropic neighbourhoods. Sequence B uses anisotropic neighbourhood relations using a GPM that considers only relations in relative space. Sequence C uses a GPM that considers anisotropic neighbourhood relations using both relative and absolute distances. The starting point is data from 1975, where the road was first opened and the first settlements were created. We then show simulated results for six year intervals (1980 and 1986). Comparing Figure 1 (actual fishbone patterns) with Figure 6 (simulated fishbone patterns), it is clear the GPM that combines absolute and relative space relations (sequence C below) provides a much better simulation.

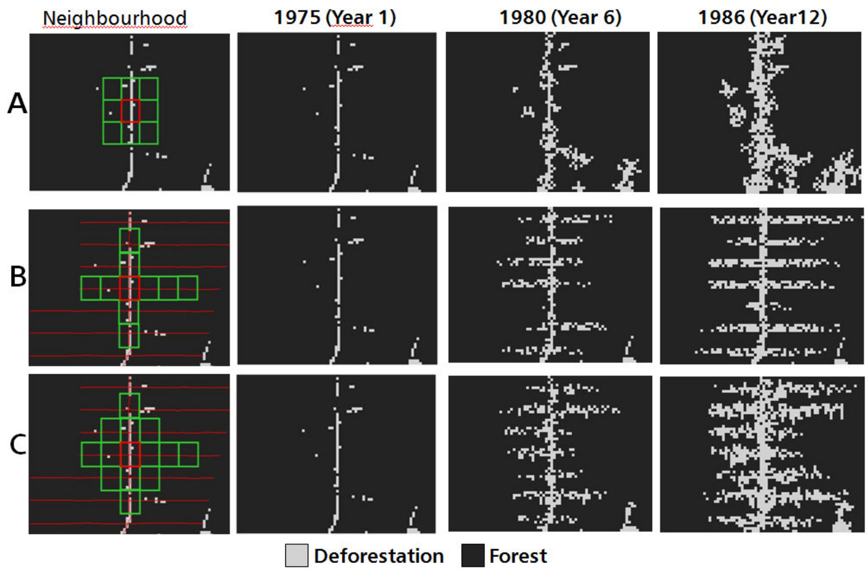


Figure 6. Alternative results of GPM-based CA for simulating fishbone patterns in Rondonia, Brazil (compare with Figure 1 above).

5.2 Using the GPM in Multiscale land change models

A land change model projects the expected changes in land use and land cover in a region. Models can also project the impact of policy changes on the current land use trajectory [37]. This needs the clear differentiation between spatial determinants of change. We need to distinguish local *proximate causes* linked to land use changes (soil type and distance to roads, for instance) from *underlying driving forces* that work at higher hierarchical levels, including macroeconomic changes and policy changes [38]. Local land changes are thus linked to trade flows. Globalization connects places of consumption to remote places of production, and thus land systems cannot be adequately understood without knowing their linkages to decisions and structures made elsewhere. In this sense, understanding the role of networks is essential to understanding land change[39]. Such networks can be physical, such as roads, or logical, such as market chains, linking a certain location to distant consumption or influential sites.

Flows of resources, information, and people are essential parts of non-Toblerian spaces, and land change models should capture them. These flows are represented by networks which link processes that act on different scales [12, 39, 40]. Efficient representation of such flows with geometries of the absolute space is essential to achieve a realistic perspective of spatial relations, and to support efficient land-change models [28]. As an example, consider how market connections influence deforestation in the Amazonia rainforest. Take figure 7, which shows the main road network and the most important national markets in Brazil (left) and the current deforestation in the Amazon rainforest (right).

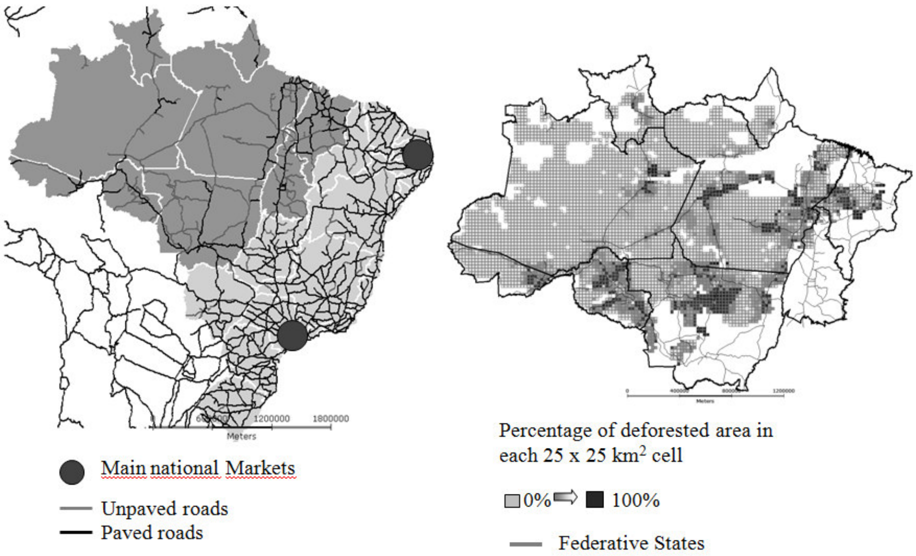


Fig. 7. Example of multiscale network based relation: (a) Roads network and main markets in Brazil (Amazonia shown in dark grey area); (b) 25 x 25 km2 cells showing deforestation in Amazonia.

Different flows connect the region to distant places of consumption, influencing the land use system in diverse ways. Timber, grain and beef products from Amazonia are mostly sold to the South-east and North-east of Brazil, as Figure 7 points out. Incorporating such diverse connections in land change models is essential to improve our understanding on how the land use system works, and to envisage future scenarios for the region. To capture such complex relations, we extended the GPM to allow spatial relations between different types of objects possibly across different geographical scales. We consider set O_1 of geographical objects with geometrical representations defined over a subset $S_1 \subset \Re^2$, and another set O_2 of geographical objects with geometrical representations defined over another subset $S_2 \subset \Re^2$. The GPM uses the relative space relation $\texttt{prox\_rel}(o_i, o_j)$ described in Section 4.3, except that now $o_i \in O_1$ and $o_j \in O_2$. Figure 8 shows this multiscale relation.

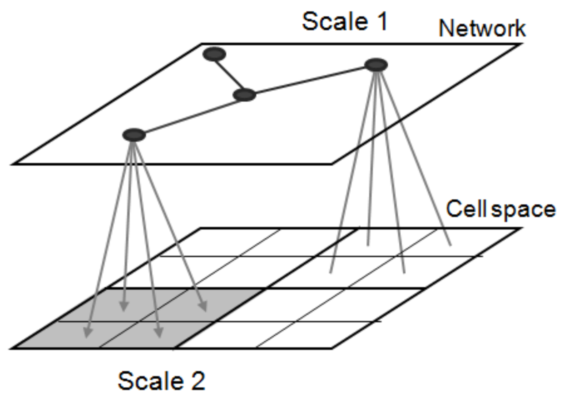


Fig. 8. Example of how a GPM is built in a multiscale based relation. Objects in a network (scale 1) are connected to objects in a cell space (scale 2).

In [13] and [41], we discuss the use of multiscale relations. We developed a land change model which relates 25 x 25 km^2 cells to the two main places of consumption at the national scale (São Paulo and North-east) through the roads network, as shown in Figure 7. We used an *open network* strategy to build the GPM. The network cost is the arc's length (in meters) for paved roads, and the double of the length to non-paved roads (under the assumption they double travelling time). The GPM we built includes a *2:n* relation from the two markets to every cell, and an *n:2* relation from every cell to the two markets. Both directions are useful in land change models. For example, we used the market-to-cells relation to establish links between São Paulo and Amazonia. We included a rule in the model to cause cells in Amazonia to change as a result of a policy changes in São Paulo. This change in the market conditions can be an incentive (demand increase) or a restriction (need of certification). The land-change model developed in [41] uses an *n:2* relation (from cells-to-markets) and employs the GPM to calculate the connectivity of each cell to any of the markets. Each cell receives a new attribute (*connection to markets*) whose value is the minimum weight associated to it in the GPM according to the road network. If road conditions change, the variable is recomputed. Figure 10 shows the connection to markets in 2000 and the projected 2010 connectivity, assuming some roads are to be paved in the period.

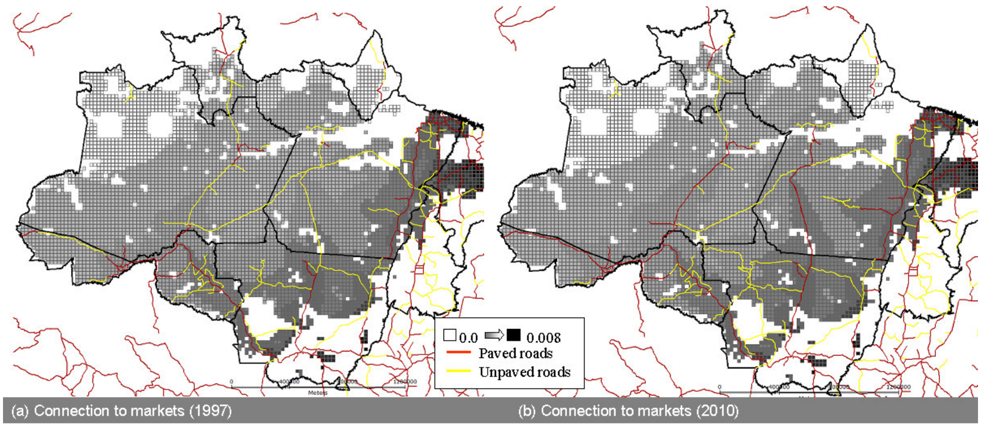


Fig. 10. Cells (25 x 25 km^2) representing the connection to markets in Amazonia, built using a network-based multiscale spatial relation: (a) in 1997; (b) in 2010 (paving some roads). The darker cells are more connected to markets. Source: Aguiar [41].

6. Conclusions

This paper discusses geographical spaces whose spatial relations are strongly anisotropic or influenced by actions at a distance, and calls them "non-Toblerian spaces". We consider that non-Toblerian spaces arise often in cases of rapid change caused by human actions, and we argue that these cases are becoming more frequent due to globalization and to the growing integration of markets. Traditional GIS does not capture such relations, since it relies on spatial relations based on topological operators and Euclidean distances. The authors consider that to be general, a GIS has to provide a flexible notion of proximity, expressed in a different way for all pairs of spatial objects. To support this flexibility, the authors propose the idea of a GPM (Generalized Proximity Matrix). The paper shows how to calculate the GPM and provides examples of its use for dynamical spatial modelling and multiscale modelling.

One of the interesting properties of non-Toblerian spaces and associated tools such as the GPM is that they provide a way for GIS applications to respond to the challenges of modelling complex problems in a globalized world. Such problems have been outlined by postmodern thinkers such as Manuel Castells, which contrasts the *'space of places'* of a typical GIS to the *'space of fluxes'* induced by today´s networked society. Using the GPM provides GIS applications with a powerful tool to represent both the *'space of places'* and the *'space of fluxes'* and their relations.

In theory, all spatial analysis methods could be rewritten to use the GPM. Since it is also an extension of the spatial weights matrix used in spatial analysis, the GPM is also a useful tool in spatial statistics. Given the benefits of using a flexible definition of proximity, GIS designers should consider the design of GIS where all spatial analytical functions can use flexible neighbourhood definitions such as the GPM. However, the GPM adds a layer of complexity to the application, since it has to be computed carefully for all objects. This added complexity is significant, since the expert often has to make subjective choices for calculating proximity relations in non-Toblerian spaces. Ideally, the GPM would be available as an optional tool, to be used when the problem defies solution using conventional measures of proximity. Devising semi-automatic tools for computing and using the GPM in different cases is one of challenges they authors have been working on. We are working to provide a flexible open source software where the ideas of GPM and non-Toblerian spaces can be experimented by the GIScience community.

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References

1. Egenhofer, M., Franzosa, R.: Point-Set Topological Spatial Relations. International Journal of Geographical Information Systems **5** (1991) 161-174
2. OGC: OpenGIS Simple Features Specification for SQL. Open GIS Consortium, Boston (1998)
3. Tobler, W.: A Computer Movie Simulating Urban Growth in the Detroit Region. Economic Geography **46** (1970) 234-240
4. Egenhofer, M., Mark, D.: Naive Geography. In: Frank, A., Kuhn, W. (eds.): Spatial Information Theory—A Theoretical Basis for GIS, International Conference COSIT '95, Semmering, Austria, Vol. 988. Springer-Verlag, Berlin (1995) 1-15
5. Goovaerts, P.: Geostatistics for Natural Resources Evaluation. Oxford Univ. Press, New York (1997)
6. Anselin, L.: Local indicators of spatial association - LISA. Geographical Analysis **27** (1995) 91-115
7. Goodchild, M., Anselin, L., Applebaum, R., Harthorn, B.: Toward Spatially Integrated Social Science. International Regional Science Review **23** (2000) 139-159
8. Feitosa, F., Camara, G., Monteiro, A.M., Koschitzki, T., Silva, M.S.: Global and Local Spatial Indices of Urban Segregation. International Journal of Geographical Information Science **21** (2007) 299-323
9. Anselin, L., Syabri, I., Kho, Y.: GeoDa: An Introduction to Spatial Data Analysis. Geographical Analysis **38** (2006) 5-22
10. Câmara, G., Aguiar, A.P., Escada, M.I., Amaral, S., Carneiro, T., Monteiro, A.M., Araújo, R., Vieira, I., Becker, B.: Amazon Deforestation Models. Science **307** (2005) 1043-1044
11. Schuurman, N.: Trouble in the heartland: GIS and its critics in the 1990s. Progress in Human Geography **24** (2000) 569

12. Aguiar, A., Câmara, G., Cartaxo., R.: Modeling Spatial Relations by Generalized Proximity Matrices. V Brazilian Symposium in Geoinformatics - GeoInfo 2003, Campos do Jordão, SP, Brazil (2003)
13. Moreira, E., Aguiar, A.P., Costa, S., Câmara, G.: Spatial relations across scales in land change models. In: Vinhas, L. (ed.): X Brazilian Symposium on Geoinformatics, GeoInfo 2008. SBC, Rio de Janeiro (2008)
14. Carneiro, T., Câmara, G., Maretto, R.: Irregular Cellular Spaces: Supporting Realistic Spatial Dynamic Modeling using Geographical Databases. In: Vinhas, L. (ed.): X Brazilian Symposium on Geoinformatics, GeoInfo 2008. SBC, Rio de Janeiro (2008)
15. Câmara, G., Vinhas, L., Ferreira, K., Queiroz, G., Souza, R.C.M., Monteiro, A.M., Carvalho, M.T., Casanova, M.A., Freitas, U.M.: TerraLib: An open-source GIS library for large-scale environmental and socio-economic applications. In: Hall, B., Leahy, M. (eds.): Open Source Approaches to Spatial Data Handling. Springer (ISBN 978-3-540-74830-4), Berlin (2008) 247-270
16. Carneiro, T.: Nested-CA: a foundation for multiscale modeling of land use and land change. PhD Thesis in Computer Science (avaliable at www.dpi.inpe.br/gilberto/teses/nested_ca.pdf). Computer Science Department, Vol. Doctorate Thesis in Computer Science. INPE, Sao Jose dos Campos (2006)
17. Alves, D.S., Pereira, J.L.G., de Sousa, C.L., Soares, J.V., Yamaguchi, F.: Characterizing landscape changes in Central Rondônia using Landsat TM imagery. International Journal of Remote Sensing **20** (1999) 2877-2882
18. Batistella, M., Robeson, S., Moran, E.: Settlement design, forest fragmentation, and landscape change in Rondônia, Amazônia. Photogrammetric Engineering and Remote Sensing **69** (2003) 805-812
19. Scott, J.: Social network analysis: A handbook. Sage (2000)
20. Strogatz, S.: Exploring complex networks. Nature **410** (2001) 268-276
21. Hägerstrand, T.: Innovation Diffusion as a Spatial Process. The University of Chicago Press, Chicago, IL (1967)
22. Wasserman, S., Faust, K.: Social network analysis: Methods and applications. Cambridge University Press (1994)
23. Carrington, P., Scott, J., Wasserman, S.: Models and methods in social network analysis. Cambridge University Press (2005)
24. Liben-Nowell, D., Novak, J., Kumar, R., Raghavan, P., Tomkins, A.: Geographic routing in social networks. Proceedings of the National Academy of Sciences **102** (2005) 11623-11628
25. Barabasi, A., Albert, R.: Emergence of scaling in random networks. Science **286** (1999) 509
26. Albert, R., Jeong, H., Barabasi, A.: Diameter of the world wide web. Nature **401** (1999) 130-131
27. Schuurman, N.: Critical GIS: Theorizing an emerging science. Cartographica **36** (1999) 1-108
28. Harvey, D.: The Condition of Postmodernity. Basil Blackwell, London (1989)
29. Castells, M.: The Rise of the Network Society. Blackwell Publishers, Oxford (1996)

30. Anselin, L.: Interactive techniques and Exploratory Spatial Data Analysis. In: Longley, P., Goodchild, M., Maguire, D., Rhind, D. (eds.): Geographical Information Systems: principles, techniques, management and applications. Geoinformation International, Cambridge (1999)
31. Takeyama, M., Couclelis, H.: Map Dynamics: Integrating Cellular Automata and GIS through Geo-Algebra. International Journal of Geographical Information Systems **11** (1997) 73-91
32. O'Sullivan, D.: Exploring spatial process dynamics using irregular graph-based cellular automaton models. Geographical Analysis **33** (2001) 1-18
33. Couclelis, H.: From Cellular Automata to Urban Models: New Principles for Model Development and Implementation. Environment and Planning B: Planning and Design **24** (1997) 165-174
34. O'Sullivan, D.: Graph-cellular automata: a generalised discrete urban and regional model. Environment and Planning B: Planning and Design **28** (2001) 687-705
35. Batty, M.: GeoComputation Using Cellular Automata. In: Openshaw, S., Abrahart, R.J. (eds.): GeoComputation. Taylor&Francis, London (2000) 95-126
36. Couclelis, H.: Cellular Worlds: A Framework for Modeling Micro-Macro Dynamics. Environment and Planning A **17** (1985) 585-596
37. Pijanowskia, B.C., Brownb, D.G., Shellitoc, B.A., Manik, G.A.: Using neural networks and GIS to forecast land use changes: a Land Transformation Model. Computers, Environment and Urban Systems **26** (2002) 553–575
38. Veldkamp, A., Lambin, E.F.: Predicting land-use change. Agriculture Ecosystems & Environment **85** (2001) 1-6
39. Verburg, P.H., Schot, P.P., Dijst, M.J., Veldkamp, A.: Land use change modelling: current practice and research priorities. GeoJournal **61** (2004) 309-324
40. Verburg, P.H., Kok, K., Pontius Jr, R.G., Veldkamp, A.: Modeling Land-Use and Land-Cover Change. In: Lambin, E., Geist, H. (eds.): Land-use and land-cover change: local processes and global impacts. Springer, Berlin (2006)
41. Aguiar, A.P.D.: Modeling Land Use Change in the Brazilian Amazon: Exploring Intra-Regional Heterogeneity. PhD Thesis, Remote Sensing Program, Vol. PhD. INPE, Sao Jose dos Campos (2006)