The Near-Decomposability Paradigm Re-Interpreted for Place-Based GIS

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We hypothesize that humans tend to think in objects while nature can be interpreted as gradients of matter and processes. Such gradients can be steep, like the borders between water and land or between forest and pasture. But objects and decomposing complexity call for a scale. For place-based GIS, the scale issue and the ability of handling multiple scales are even more crucial than for classic GIS. We argue that the paradigm of near-decomposability of systems can play an important role in GIScience research and for the foundation of place-based GIS.

Keywords: hierarchical patch dynamics paradigm; object-based image analysis; scale detection; Brownian motion; Wiener process

1 Introduction

1.1 Motivation

Geographic information systems (GISs) were originally designed to digitally represent physical entities, such as roads, buildings, parcels, or trees. Through increased modelling capacities, GISs were soon used to address invisible or not directly mappable information, such as suitability zones or potential maps. Over the years, we have witnessed frequent attempts of place-based investigations into human phenomena in the humanities and social sciences, but short literature searches on Google Scholar and Scopus reveal that this notion has only recently transgressed into geographic information science (GIScience), and only a small fraction of the GIS-relevant literature (most likely less than 0.1 per cent) deal with human-centred and philosophical notions of place.

The workshop Platial'18[1] calls for "platial" analyses. In previous work, the authors of this article have been criticized that "platial" is not a proper English word. We will, therefore, not use this term as such but will address the workshop questions accordingly. We will focus on what objects are and will link the GIScience notion of objects to the near-decomposability paradigm and to the hierarchical patch dynamics (HPD) paradigm, to find out if such methodologies can substantiate a multi-scale object centred methodology for place-based GIS.

1.2 Hierarchy Theory

According to Nobel prize laureate Herbert Simon, basically all viable systems, whether physical, social, biological, or artificial, have a near-decomposable architecture. They are organized into hierarchical layers of parts, sub-parts of parts, parts of sub-parts, and so on, in such a way that interactions between elements belonging to the same parts are much more common than interactions between elements belonging to different parts (Egidi and Marengo, 2004). To exemplify this notion, Simon uses the

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often-cited example of the two watchmakers who each have to build a watch out of 1000 pieces. One watchmaker assembles all pieces, one after the other, and has to start from scratch if he is disturbed in the process and forced to put the watch down, causing the pieces to fall apart. The other watchmaker designed his watches so that he could put together sub-assemblies of about ten components each, and each sub-assembly could be put down without falling apart. Ten of these sub-assemblies could be put together to make a larger sub-assembly, and ten of the larger sub-assemblies constituted the whole watch. This second, hierarchically structured strategy turns out to be more successful. Simon concludes that systems that are near-decomposable are much less vulnerable than systems that are not, as disturbances are more likely to remain confined to specific subcomponents. Near-decomposable systems limit interactions and information flows among different parts of the system and are, thus, better able to keep damaging events confined to sub-parts. While there is a large body of literature that utilizes, adopts, or criticizes the work of Simon and others in the fields of economics and operations research, there is surprisingly little evidence in GIScience literature. Here, instead of efficiency and stability of systems, the focus is on the spatial organization of systems.

In ecology and landscape ecology, hierarchy theory has been translated into a powerful way of dealing explicitly with spatial heterogeneity and has emerged as a unifying concept across different fields of earth sciences. Wu (1999) suggested the integration between hierarchy theory and patch dynamics through the emergence of the hierarchical patch dynamics paradigm (HPD) and laid a theoretical framework for a theory-driven break down of ecological complexity through a hierarchical scaling strategy. Most of the systems we examine in ecology and environmental science are characterized by organized complexity (Allen and Starr, 1982). On one hand, these systems have more components than analytical mathematics can handle; on the other hand, the use of traditional statistical methods cannot be justified because of the inadequate number, and the non-random behaviour, of components. Wu (1999), drawing on the concept of flux rates in hierarchy, suggests that ecological systems are near-complete-decomposable (or near-decomposable) systems because of their loose vertical and horizontal coupling in structure and function.

1.3 Object-Based Image Analysis

Blaschke (2010) summarized the utilization of multi-scale image segmentation methods in an attempt to bridge remote sensing and GIS functionality for the classification of remote sensing imagery while building on earlier work related to landscape ecology (Burnett and Blaschke, 2003). Image segmentation is a good example of how to spatially decompose complexity. Resulting objects at a certain scale are believed to have less internal heterogeneity concerning one or several parameters as compared to the adjacent areas. Tiede (2014) demonstrated that this concept can also be applied to non-image data. Despite its proven application to non-image data, this field is currently called (geographic) object based image analysis (OBIA/GEOBIA), see Blaschke et al. (2014).

1.4 Translating Concepts Between Disciplines

We want to transfer some elementary OBIA concepts to place-based GIS research. First, we need to expand the term “heterogeneity” from the original values created by sensors to encompass all kind of intensities of matter, processes, or interaction and their respective intensities. Here, by again referring to Simon, we may assume that for a more “intense” interaction the behaviour of one component depends more closely on the behaviour of other components belonging to the same part than on components belonging to other parts (i. e., objects vs neighbouring objects). This defines a near-decomposable system: individuals within a hierarchical subunit have closer, more widespread, more intense, and more frequent interactions than individuals belonging to different subunits. But a similar architecture can also be found in most complex artefacts, which consist of assembling parts and components that, in turn, can be assemblies of other parts and components, and so on, or in software (with the use of subroutines, particularly in object-oriented programming, Egidi and Marengo 2004).

2 Methodology

2.1 GIScience Objectification

Humans embrace natural complexity via abstraction. Our limited sensual and mental facilities cannot assimilate the whole. The challenge we face is how to leverage the strengths of abstraction by objectification (upon which so much of GI infrastructure is based) while learning from the concept of ecosystems as mobile expanses of flux, of complexes of material or energy gradients. We believe that decomposition allows us to grasp more of natural complexity. Burnett and Blaschke (2002) contrasted the nature of objects with gradients found in nature and addressed less anthropomorphically rendered "objects", such as the margins of semi-natural forests and meadows. GIScience scholars deal with spatial objects but less often with gradients.

Without going into detail, we may refer to earlier work on the dichotomy of the vector and the raster domains in GIScience (see, e. g., Kemp (1996)). For simplicity's sake, we may assume that space is most often manipulated, conceptually and in GI tool development, as complexes of objects – or as raster data. One efficacy of the object paradigm is obvious: one can *do* things with a partitioned space, e. g., a landscape that one cannot do with an un-partitioned space. Measuring the perimeter-to-area ratio of a forest patch, for instance, may provide insight into the nesting requirements of a particular bird species. However, as Burnett and Blaschke (2002) point out, there exists a paradox when many attributes used to define objects are derived explicitly from the placement of the object's boundary itself. That raises the question of which comes first, the object or its boundary? If boundaries are not "real", what alternatives do we have? While this is already difficult in the spatial domain – despite significant progress over the last fifteen years or so – it is even more ambiguous when dealing with place.

2.2 GIScience Partitioning of Space

Objectification requires spatial (and spatio-temporal) discretization. For a discussion on fiat vs bona fide objects, we refer to Smith and Varzi (2000). Any discretization of space may be likened to cutting with a double-edged blade. But dissection space is not an end in itself. Even post-dissection the partitioned space is doable today. In fact, in OBIA, objects are increasingly over-segmented to build complex objects from segments which may be regarded as object candidates (Burnett and Blaschke, 2003). It is well understood that in ecosystems, the structure or "gradients" that we observe are evocations of self-organized thermodynamically open systems (Müller, 1998). Goodchild et al. (1994) noted that there are many ways of representing a field as a collection of discrete objects. Objects in GI systems are simply the human discretization of near-decomposable hierarchical structures, and we lose sight of their "not-object" nature at our peril. The challenge is now to transfer these concepts to place-based (platial) GIS.

As stated at the beginning, in GIS we store information about the gradients that *define* apparent objects. This is made easier by the observation that gradients, though ubiquitous in nature, are not randomly distributed. We can draw upon the power of hierarchy theory (Koestler, 1967; O'Neill et al., 1986; Simon, 1969, 1977), a dialect of general systems theory (Bertalanffy, 1969), and identify holon (Janus-faced, near-decomposable elements) boundaries by characterizing the structure of the system at higher and lower levels.

It is difficult to classify hierarchies because their composite holons tend to overlap (Koestler, 1967). Koestler proposes a rough classification where structural hierarchies emphasize the spatial aspect of the system (a structure of the spatial domain or physical space itself), whereas functional hierarchies consider a process as another aspect. We seek a spatial partitioning schema that explicitly incorporates hierarchy and functional relationships. OBIA is somewhat successful in this respect (Blaschke et al., 2014). The artefacts that are manipulated in these software environments are, as we propose, closer to the holons found in nature; they are objects but can also be "not-objects" (Burnett and Blaschke, 2002).

2.3 Mathematical Foundations

Also, for place-based GIS, mathematical models are needed that can be adjusted to multiple scales. Especially at the nano and microscale, a discrete and stochastic description of processes is key, e. g., in

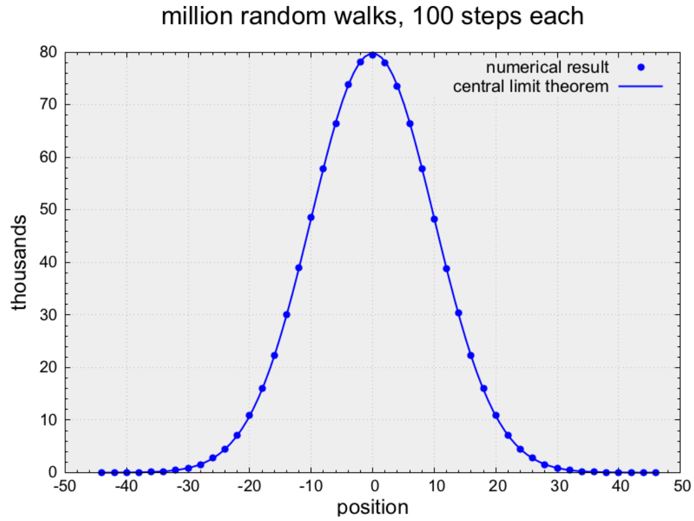

Figure 1: Central Limit

molecular and cellular biology or in nanophysics of materials and fluids. Because the dynamics and the properties of macroscopic systems must be understood, controlled, or even designed, the models on different scales have to be linked, and the information produced on the various levels has to be transferred. Finding transmission conditions in a computable way is an important goal for mathematics and computational sciences. We suggest to join analytic and computational bridging of scales, also taking into account hardware developments that can account for multi-scale and parallel structures. We argue that there are two principal ways of bridging scales analytically and computationally:

1. Symmetry concept. If different outcomes are equivalent, they should have the same probability.
2. Universality. Many random microscopic subsystems interact with each other. They may all look similar and may interact with each other to produce a larger outcome (an example is the central limit theorem).

Central Limit. The central limit theorem is a probability concept. The average distribution of a large number of identically distributed and independent variables is approximately normal. When certain conditions are fulfilled, and the number of iterations on independent variables is large enough, each of these variables will have a well-defined variance along with a well-defined expected value. Then, an approximately normally distributed function will result, as depicted in Figure 1.

Brownian Motion and Wiener Process. Brownian motion process, or *Brownian motion*, usually describes the physical process of movements originally observed by Robert Brown, who discovered the movement of tiny particles suspended in a liquid. It is a continuous-time stochastic process with independent, stationary increments and represents the motion of a point whose successive displacements are random and independent as well as statistically identical over different time intervals of the same length. Einstein considered the possibility that formalizing Brownian motion could support the idea that molecules existed. In mathematics, Brownian motion is described by the *Wiener process*, a continuous-time stochastic process named after Norbert Wiener. The Wiener process can be constructed as the scaling limit of a random walk or other discrete-time stochastic processes with stationary independent increments. Like the random walk, the Wiener process is recurrent in one or two dimensions (meaning that it returns almost surely to any fixed neighbourhood of the origin infinitely often). Unlike the random walk, it is scale invariant.

2.4 Utilizing Brownian Motion and the Wiener Process for Scale Detection

In computer vision, scientists developed multi-scale algorithms for the selection of salient regions (e. g., Kadir and Brady 2001). Such scale space-based approaches propose that saliency is defined in terms of local signal complexity based on the Shannon entropy of local image descriptors. The applicability of

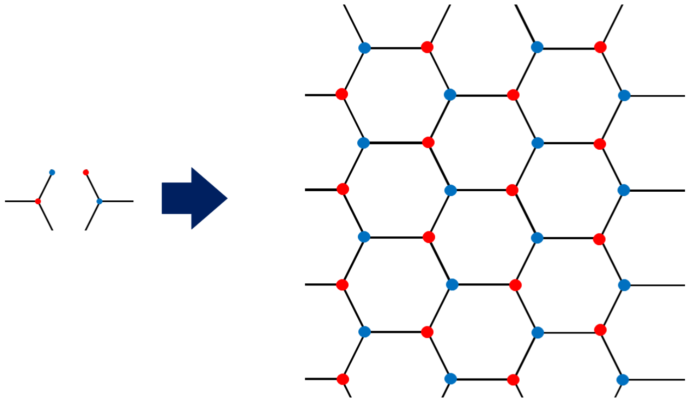

Figure 2: Two-dimensional analogue of random walk (Hairer, 2018)

this low-level approach has been demonstrated for several image processing problems. There are, of course, dozens of other scale selection frameworks in computer vision, some of which focus on saliency of points or pixels. Several computer vision approaches utilize a probabilistic localized scale selection principle, e. g., based on maximum likelihood estimation under a Brownian image model. Most of these methods aim to identify an “intrinsic” or “appropriate” scale for local image structures. Blaschke and Hay (2001) applied a *linear scale-space framework* from computer vision to automatically analyse real-world structures at multiple scales in a satellite image. They showed that when there is no a priori information about these structures, appropriate scale(s) for an analysis may be identified by applying Gaussian filters to an image at a range of kernel sizes resulting in a scale-space cube or “stack”, where each layer in the stack represents convolution at a specific scale. While some non-linearity situations could be identified through this “stack of scales”, the authors could not provide a mathematically sound foundation for the detection of such non-linearities.

We aim to transfer some basic and widely acknowledged methods from mathematics and from computer vision to scale detection problems in GIScience. The simulation of a two-dimensional random walk is presented in Figure 2. At a very low scale, a random function is assumed:

$$h\colon \text{Grid} \longrightarrow \mathbb{Z} \qquad \text{such that} \qquad |h(x) - h(y)| = 1 \text{ for } x \sim y.$$

This means the next value is always either the previous value plus one or the previous value minus one. Alternatively, if one selects the value of any point, it will be assigned to a value from any existing neighbour and the difference will always be one. The random function results in a two-dimensional graph such as a honeycomb graph. The large amounts of the grids in Figure 2 results from universe object mechanism presented in Figure 3a. The simulation of an infinitely large grid is called a free field (Figure 3b), which is actually not a random function but a random distribution. As the free field is infinitely large, it should converge to something, i. e., a Gaussian generalized function following the equation

$$Eh(x) \cdot h(y) = -\log|x - y|,$$

where E denotes the expected value operator. But this is not proven yet. For the full paper, we shall verify whether the planar Gaussian free field can serve as a universal scaling limit for spatial scaling models, similarly to Brownian motion, which is the scaling limit of a wide range of discrete random walk models.

It is not possible to evaluate individual points in the free field. When looking up the image very closely one can see in the light coloured region a lot of dark spots and, likewise, dark regions contain light points, whereby the colour is just the value of the function. An increasing image resolution yields more and more points in the light region and the value increasingly fluctuates without converging to anything tangible. However, a value converges to a limited interval. Therefore, if we look at a little circle instead of the value of a point, we can find an average value. Then, this average value can converge to a limit by increasing the resolution or scale, respectively. We should, therefore, refer the free field to random distribution rather than to random function. The free field behaves like a function but cannot be evaluated at the level of individual points. But the free field is still an object that has a

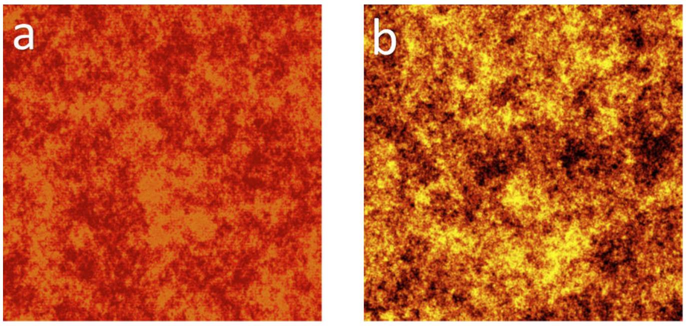

Figure 3: Simulations of Brownian Motion. (a) very large amounts of the grids, (b) infinitely large amounts of grids (free field)

description similar to the Brownian motion which is described by Gaussian distribution (Bell curve, see Figure 1). In the full version of this paper, we shall explain that this is relevant to place-based GIS for finding non-linearities of scaling and, under assumptions, defining appropriate scales.

2.5 Crossover Regimes

Let us take a "free model" according to the Gaussian universality classes and then perturb it a little bit. The models will look similar but if we zoom out, differences become visible. Therefore, bearing in mind the application for place-based GIS, what we can describe mathematically is the transition at which point to start a crossover from one universality class to another one. This transition can be approximated mathematically by normal form equations. We utilise (a) the Kardar-Parisi-Zhang (KPZ; Diehl et al. 2017) and, (b) the dynamic ϕ_d^4 model. These equations are used to investigate the dynamic scaling of growth processes (Sasamoto and Spohn, 2010). Recently, the KPZ equation has been considered to be a natural model for one-dimensional motion in the crossover regime (Hairer, 2015). However, the dynamic ϕ_d^4 model is for two or three dimensions. To explain large scale behaviours, both equations KPZ and ϕ_d^4 were experimentally evaluated for physical phenomena and, in particular, for the macroscopic behaviour of critical systems (Chandra and Weber, 2015). If we look at both equations in the right way, they can be considered as smooth. This means, when we measure the regularity, we are looking for how well we can approximate the function by polynomials (Hairer, 2015). As we restricted the KPZ to be one-dimensional, the spatial variable x can only take on values from a one-dimensional space (Chandra and Weber, 2015). Moreover, h is our random function and ϵ represents space-time white noise, which is a quite irregular random distribution. Thus, the KPZ equation can be defined as:

$$\partial_t = \partial_x^2 h + (\partial_x h)^2 + \epsilon \qquad (kpz, d = 1).$$

For the dynamic ϕ_d^4 model, the spatial variable x takes values in two or three-dimensional spaces. The ϵ is the same as in the KPZ. The Gaussian free field can be assumed as a Gaussian random field on $\phi: R^d \to R$, which is actually a distribution and not a function. For the dynamic ϕ_d^4 model we can then assume

$$\partial_t \phi = \Delta\phi + c_1\phi - c_2\phi^3 + \epsilon \qquad (\phi_d^4, d = 2,3)$$

3 Conclusion and Outlook

We hypothesized – and will explicate further in the full version of this manuscript – that humans are programmed to grasp complexity through objects. We have referred to a particular GIScience methodology (OBIA) to decompose complexity as well as to the near-decomposability paradigm and some mathematical concepts. We conclude that GIScience needs to incorporate mathematical models to develop its theory and methodology further as exemplified with multi-scale handling. Still, some of the briefly illustrated concepts, in particular, two-dimensional fractional Brownian motion, are difficult to understand and to be utilized, both conceptually and computationally.

We believe that OBIA can serve as a methodology for place-based GIS, particularly when taking it out of the image processing domain, as illustrated by Tiede (2014) for an alternative overlay methodology. OBIA is less dependent on segmentation as one may think. There is never a perfect solution to segmentation. We argue to implement a flexible, yet theory-driven approach to build image objects on demand based on image primitives (segments). We suggest that generating a structural hierarchy needs to be followed by building a corresponding object-relation hierarchy. Some of such hierarchies can be derived directly from multi-scale image analysis (semantic rules can be created using sub/super-object spectral and spatial information such as neighbourhood, shape, size, compactness, etc.), but others must originate from expert knowledge, machine learning, or mathematical models. Expert knowledge will undoubtedly be incomplete; however, it allows us to partition space based on a spatial semantic network. By using fuzzy rules, we can deal with transition zones or gradients and move towards the incorporation of place as rule-based multi-scale objects and their relationships.

Notes

1. http://platial18.platialscience.net

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