Non-linear behaviour, emergence, and complexity in geographical systems

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1. Introduction

Non-linear dynamics and complexity are increasingly discussed in the broader scientific literature (e.g. Horgan, 1995). These works have generated a diversity of terms including complexity science, complexity theory, non-linear dynamical systems, self-organisation and chaos. These terms are now being increasingly applied and framed within a geographical context (see Manson, 2001; O'Sullivan, 2004; Batty and Torrens, 2005; O'Sullivan *et al*. 2006). The associated movement towards the application of non-linear dynamical theory to spatial systems creates both opportunities and constraints for the researcher. Successful identification of non-linearity can enhance prediction, understanding and explanation in geographical systems; however, the identification of non-linear interactions in geographical systems is not a trivial task.

The aims of this paper are twofold: first we will provide a general discussion of what it means to have a "complex" system. Secondly, we will discuss the methodologies that may shed light on the type and nature of such non-linear and complex behaviour. The full paper will present a typology of the potential sources of complexity.

2. Complexity, emergence, and non-linearity

The term "complexity" is often used ambiguously to refer to either a property of form or process; "complex system" is more pragmatically used to refer to systems which display complexity of either form or form and process. Systems are usually considered to display a complex *form* if they have dynamically-converged on a semi-structured organisation. In addition, systems are considered to involve complex *processes* if they display some (ill-defined) number of relationships that are characteristic of systems that generate complex forms. One class of such relationships is non-linear interactions.

In general, non-linear components lead to non-linear systems. A non-linear component is defined by the absence of a constant arithmetic relationship between its inputs and outputs as the inputs change. A non-linear system is a linkage of two or more components for which the outputs of the components in series are not the same as the arithmetic sum of the components treated separately. Consider, for example, the following two systems, made from the same components, but with different architectures (Figure 1):

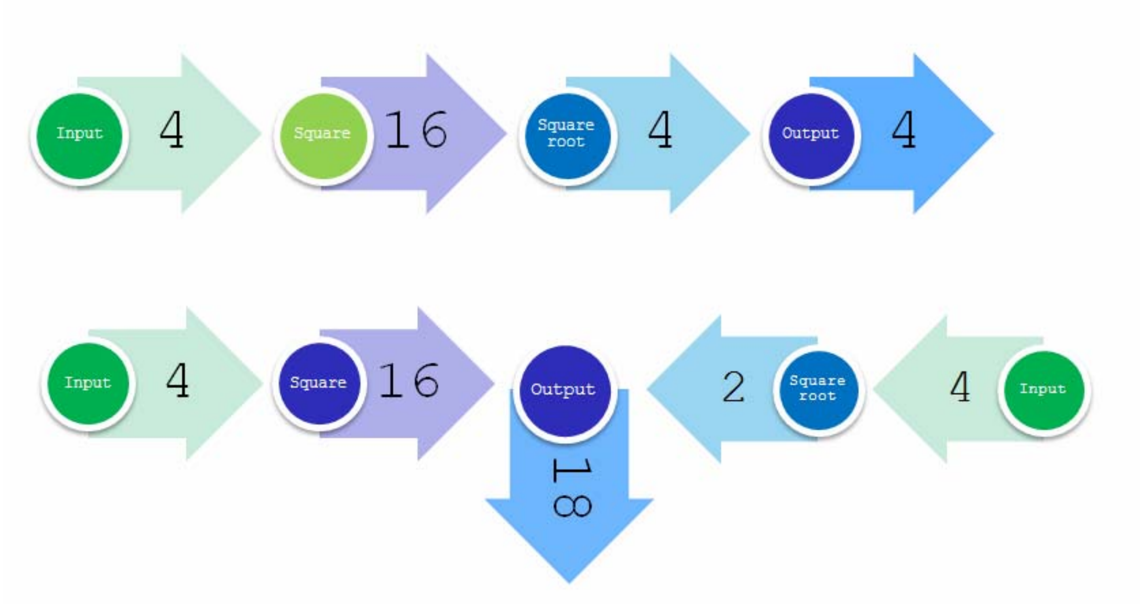

Figure 1. Example showing a system (top) in which the output is not just equal to the sum of the components' outputs (bottom).

Emergence can be defined as "an unforeseen occurrence; a state of things unexpectedly arising" (OED, 2007). Non-linear systems, in which there is a complicated relationship between inputs and outputs, are plainly capable of generating such unexpected patterns. Often, simple behaviours at the component-scale generate complicated patterns at the system-scale, or vice versa. Emergence highlights a key characteristic of complex forms: it is extremely difficult to track the dynamics generating these patterns.

The relationships between complexity, non-linearity and emergence will be furthered discussed in the full paper.

2. Example: Social systems as complex systems

Social systems are highly elaborate consolidations containing a nearly unlimited number of components (people, organisations, places) linked by both linear and non-linear relationships involving the transfer of objects (information, resources) on trajectories in both space and time. The interactions of these components form the building blocks of social processes such as migration, urbanisation and the development of social structure. These processes are constantly changing and evolving over time in reaction to internal and external influences. Furthermore, social systems are typified by exhibiting a combination of chaotic and self-organising behaviours at a variety of scales. Systemic changes may be gradual, incremental or discontinuous, and evolutionary or spontaneous. Equally the result of such changes may be of great significance to some or all of the components, or none at all. They may propagate other changes, or be dampened without trace. Table 1 presents a complex systems view of the development of the social structure of a neighbourhood.

Characteristic of complex system	**Example (Emergence of social structure)**
Large number of entities, interacting dynamically (i.e. spatially and temporally).	Collection of individuals (e.g. neighbourhood) interacting spatially and temporally.
Diverse interaction possibly involving both human and non-human entities (e.g. environment).	Information exchanged between individuals as well as interactions between individuals and local facilities. Social capital and thus structure emerges as a result of this.
Each individual is ignorant of the behaviour of the system as a whole; therefore, the system cannot be understood by summing or averaging the behaviour of individual components; system wide properties emerge.	Individuals act in own interest or that of their immediate social group without perfect knowledge of more distance individuals or the system-level dynamics.
Interactions are non-linear.	Action of an individual (random or otherwise) can have a great impact on the structure of the system.

Table 1. The main features of a complex system applied to the emergence of a social structure.

5. Methods for studying non-linearity, emergence, and complexity in social systems

When studying non-linearity, emergence and complexity, Social systems have particular problems. There are not generally composed of identical components, and there tend to be large numbers of components interacting in a dynamically constructed network. This makes the analytic techniques of traditional non-linear research largely inapplicable, leaving inductive techniques or modelling as our only available options.

In general we can identify the following categories of social-science studies:

- Studies identifying simple behaviours from simple data and then using these to build models of non-linear, emergent, or complex systems.

- Studies identifying simple and/or complex behaviour from complex data and then using these to build models of non-linear, emergent, or complex systems.

The former are considerably more frequent than the latter, reflecting a general absence of both techniques to deal with data-led understanding of complex systems, and information on those techniques that already exist. It is clear that considerable efforts are needed to improve the inductive investigation of complex, emergent and non-linear social systems at a variety of scales.

Systems that are as complex as geographical systems require methodologies that can handle individual non-linear behaviour. The traditional treatment of non-linear behaviour/complexity in geography is the aggregation of individuals into groups, and the accompanying statistical treatment of these groups. These techniques are being increasingly viewed as outdated, in particular due to their inability to detail the effects of small-scale and individual level histories, interactions, or even, in any realistic sense, behaviour. We must therefore look for new methodologies from other disciplines; for example, the modelling of interactions through the plotting of components against each other in phase-space would allow for understanding of the development of form over time and the recognition of interaction patterns.

At a larger scale, interactions between individuals build up into networks. It is not at all clear what the important scales are for any given system, or how we might examine the issue. One metric might be, for example, the size of the minimum sub-graph which exhibits an emergent behaviour. Exploring the behaviour of systems through perturbation and forced bifurcation can contribute towards understanding both the causes and consequences of non-linear complexity within social systems. Furthermore, as Heppenstall and Ross (2007) have demonstrated, using and adapting methods such as recurrence plots for visualising and quantifying hidden structures in spatial data holds great promise.

Diffusion of some of the more "novel" techniques into geography is already taking place; one of the more prominent paradigms to impact on geography in the last 5 years is agent-based modelling (ABM). This technique allows us to model at an individual level; however, issues surrounding validation, verification and how to analyse and visualise potential non-linear interactions still remain. Individual-based modelling allows cross-scale analysis of systems by taking individual-scale behaviour and seeing if it generates the patterns seen at the larger scale. Calibrated models allow some degree of inductive investigation, and this is likely to be particularly true where calibration is achieved using heuristic-based exploration of the system's solution space, as the path taken by the exploration might reveal stabilities inherent within the system (e.g. Kim, 2005). Largely, however, the inductive analysis of models suffers the same issues as the inductive analysis of real systems, the only advantage being that the individual-scale is completely delimited.

At the global level, there are a number of measures that might quantify the "complexity" of a system (e.g. Shiner *et al.*, 1999). Unlike emergence, there is no concrete notion of what the subjective category "complexity" refers to, so it seems unlikely there will ever be a well-formed statistic of this type. However, such statistics do provide a qualitative indication of system complexity which can be used to justify further investigation and provide a metric of *some* system state which can be used in scaled investigations.

Table 2 presents a categorisation of selected techniques that are currently available for the exploration of non-linear behaviour; methods have been selected as examples for each category (this list is not meant to be a definitive catalogue of all techniques, merely a representative sample).

Class of method	**Technique**
Spatio-temporal modelling	Agent-based modelling; Spatial interaction model
Temporal modelling (time-series)	ARMA; Regression modelling; Bayesian models; Survival analysis
AI/CI/machine learning/data mining methods	Clustering and cluster discovery; Neural networks; Genetic algorithms; Fuzzy logic
Network theory	Spatial interaction models
Statistical physics / Non-linear dynamics	Phase diagrams; Forced Bifurcation or Perturbation; Recurrence plots; Complexity measures
Individual-based modelling	Cellular automata; Microsimulation; Agent-based modelling
Optimisation	Genetic algorithms; Simulated annealing

Table 2. Classification of methods that can help identify and model non-linear behaviour.

5. Conclusion

Recent advances in computational power have given geographers an increased understanding of the importance of small-scale individual-level dynamics and their effect on larger-scale complex system dynamics. The systems that we study are far more complicated than the typical geographer's toolbox will allow us to peer into. We are still largely reliant on "traditional" models that lack the ability to detail the effects of small-scale and individual level histories, interactions, or even, in any realistic sense, behaviour.

This paper will outline the nature of the difficulties ahead, and indicate some of the techniques that may be brought to bear on the problem. By understanding the role that non-linearity, emergence and complexity have to play in the relationships and structures within real systems, our understanding of the fundamental geographical processes can be enhanced. It is noted that not all non-linear systems are complicated; indeed many are both simple and predictable. However, identification of non-linear relationships can open new avenues of understanding for both social scientists and geographers.

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