Analyzing Social-Ecological Systems:

Linking Resilience, Network theory, and Agent Based Modelling

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Abstract:

The past decade has seen an increase in interdisciplinary science and in the analysis of Social-Ecological Systems (SES). The study of the complex interactions between humans and nature is central to the understanding of our planet's state and to plan for the future. This thesis develops a systemic approach that uses network theoretical tools to analyze structural properties, agent based models to simulate dynamics of a system, and a resilience framework to analyze, conceptualize and discuss the results given by the theoretical models. A combination of models and techniques drawn from different disciplines is synthesised in order to develop a uniform set of tools which is effective for a structural analysis of SES.

The first step in this research integrates network and resilience theory, and builds a theoretical model that analyzes how landscapes' structural properties affect the dynamics of a simple predator-prey system. The second step builds upon the first and introduces a "managing institution" that is able to alter the landscapes' structural properties according to pre-determined rules. It analyzes how human intervention influences the landscape network of a given system and how these properties influence the predator-prey system under study. The third step in this work constructs a model that analyzes management communities' interactions. The model aims to uncover the relationship between authority and management path homogenization, which influences the ability of the social system to proactively build resilience.

Methods, techniques used, and the models presented in this thesis can prove extremely useful as a first assessment of a SES resilience. They potentially assist policymakers to make more informed decisions based on a combination of empirical experience and computer assisted reasoning. Moreover, this research contributes towards a theoretical understanding of the complex evolutionary mechanisms that govern a SES.

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It is usually thought that a PhD is the work of a single person. I do think that this is only partially true, as many people have helped me shaping thoughts, methods, and techniques at the basis of this work and by supporting me during these last three and a half years. I am afraid I may forget some people who supported me in many different ways, thus I would like to thank all those whose help, advice, and discussion time allowed me to complete this thesis. Thank you all, from the bottom of my heart, Thank you.

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1 Introduction

The world is becoming increasingly complex and interlinked due to globalization and the advancements of technologies. Ecological degradation, conflicts, persistent poverty and hunger are all signs of an increasingly unstable world. The inter-linkages existing between the social and the ecological system are important as the two systems depend on one another. The social system is build and shaped by relations happening within the system. Social variables, interacting with each-other, may shape the ecological system in which they are embedded and vice-versa (e.g. the food crisis, that is, the sharp increase in staple food prices experienced in 2007, highlights the interconnectedness of the social system with the ecological system)

In this context "linear thinking" has proved to be inadequate. New practical approaches to assess the capabilities of societies to adapt and transform themselves in an ongoing changing environment need to be undertaken. In order to explain the increasing complexity and interrelations, the concept of ecological resilience, first introduced by Holling, has been extended in order to combine ecological and social systems by scholars of different disciplines (most of the literature deals with social ecological system abbreviated to SES). Resilience is a fundamental feature of most SES as it denotes the amount of external and internal shocks that a SES can undergo without being totally disrupted. Its study, embracing the methods and tools of the so-called "science of complexity", can prove of paramount importance in the understanding of a system's behaviour. The concept of resilience is based on non-equilibrium dynamics and is crucial for the comprehension of weaknesses, strength, and recovery capacity of a given site. For example, think of the recovery of the tourism industry after the Asian Tsunami, the recovery of the economy after 9/11, the impacts of intensive agriculture on water sources, and the impacts of energy on the economy.

However, the complexities and the interrelations occurring in a SES call for a definition of a different (new), formalized theoretical framework. To serve this purpose best, the tools and the definitions provided by the study of networks should be integrated in resilience thinking. Representing complex systems with a network (nodes attached to each other through edges) allows an understanding of the network resilience erosion of various systems at various temporal and spatial scales. Resilience of a SES viewed from a network perspective may help to explain which actions should be undertaken in order to "plan" and "adapt" in a sustainable way. The relation between networks and resilience could be identified through specific metrics that enable a redefinition of resilience concepts from a network perspective and may give rise to a network-resilience theory allowing a better understanding of sustainable development, adaptation and of the transformations occurring throughout the world today. In other words, a network resilience theory will improve the understanding of SES by looking at individual SES subsystems (of a given spatial territory) and hence feeding back on where the weaknesses and the strength of a SES lies. In an interconnected and interdependent world, this different approach to resilience can provide useful insights on how to enhance the adaptability of societies to climate change and other external shocks, whether natural or anthropogenic in nature.

1.1 Research questions and objectives

In order to integrate network methods and resilience thinking, there is a need to introduce both theories. Subsequently, it will be discussed how the two can be integrated and why a structural approach (i.e. network approach) is useful in helping to assess the resilience of the system. Thus, the central/main research questions to which this thesis wants to provide an answer are the following:

1. Is it possible and to integrate resilience principles and network theory, and if yes, how?
2. How do the dynamics of a system unfold and how are they influenced by the structural properties of the system?

The first question relates to the feasibility of integrating network methods in resilience thinking (see Chapters 3, 4, and 5). The second main research question pertains to the feasibility of measuring the influence of different structural properties on the resilience of a system, while taking dynamics into account (see Chapters 5, 6, 7, and 8). The second question is closely related to the first but it also encompasses the concept of network adaptability to internal or external disturbance.

The questions outlined above need to be answered not only conceptually, but there is also a need for a more formalized, numerically simulated, approach to network resilience in order to better comprehend an evolving social-ecological system. The creation of an algorithm representing the main features of a SES could give useful insights on its evolution, its strengths and weaknesses.

1.2 Thesis Outline

The thesis is organized as follows.

Chapter 2 justifies how resilience of SES is assessed. More precisely, the chapter first frames the research in a broader epistemological view, then looks at the definition of complex adaptive systems and comments on the availability (and suitability) of tools to analyse such systems in order to accomplish the objectives of this thesis.

Chapters 3, 4, and 5 present the main theoretical background and methods used in order to build the theoretical models reported in Chapters 6, 7, and 8. More specifically, Chapter 3 is an overview on network theory. In Chapter 3, terminology regarding network theoretical tools is first defined. Second, the most commonly used network metrics are presented in detail, as well as the characteristics of network classes such as random, small world, scale-free and regular networks are described. Finally, the chapter looks at how network theoretical tools have been applied so far, with particular focus on ecological networks.

Chapter 4 is an overview of the resilience framework. The first part of the chapter is concerned with defining resilience and liking social and ecological resilience, thus shifting the focus of the analysis from a single system (social or ecological) to a combination of the two: Social-Ecological System. The main resilience concepts are then described in detail as well as the difficulties encountered in applying resilience concepts in the field.

Chapter 5 describes a first possible integration of network theoretical tools in the broader resilience framework. It introduces simulations and agent based models, methods used in subsequent chapters (i.e. Chapters 6, 7, and 8). Agent based models are further analyzed pointing out strength and weaknesses of this approach to modelling complex systems. Moreover, the chapter presents possible advantages and limitations of a case study in relation to the thesis objectives. Section 5.2 of this chapter is based on Baggio (2011).

As previously mentioned, Chapter 6 presents a first theoretical model that deals with a simple landscape viewed as a network in which predators and prey interact. Predator-prey is the simplest possible food web and has been chosen to not over-complicate the model so as to focus on how the network structure and connectivity properties influence the "resilience" of the system. Here resilience is specifically defined as the amount of connectivity disturbances that a simple system (such as the one represented by the model) can absorb while maintaining coexistence of predators and prey. The model presented in Chapter 6 hence aims to represent a rather simple ecological system. Chapter 6 further develops analysis presented in a paper published in Landscape Ecology (Baggio et al. 2011), where the first author (i.e. the author of this thesis) has designed the research, coded the model, analyzed the model and wrote the paper. Kehinde Salau assisted the author in coding the model, Michael Schoon assisted the author in writing the paper and Marco Janssen and Orjan Bodin have helped the author with the research design and reviewing the paper.

Chapter 7 builds on Chapter 6 adding management interaction to the system analyzed. Thus, it incorporates an agent that represents a social system, allowing for the construction of a simplified SES. The objective of Chapter 7 is to understand the impacts of simple management strategies within a complex system, by looking at how different management strategies give rise to diverse landscape structures.

Moreover, the chapter looks at possible feedbacks existing between social actors (such as managers) and the ecological system Chapter further develops analysis presented in a paper at NAACSOS (Baggio et al. 2009) where the first author (i.e. the author of this thesis) has designed the research, coded the model, analyzed the model and wrote the paper. Kehinde Salau has helped the author in revising and coding the model, Michael Schoon assisted the author in writing the paper and Marco Janssen reviewed the paper and the research design.

Chapter 8 focuses more on the social aspects of the system, presenting a model that looks at how authority influences the heterogeneity of management strategies. Diversity in the range of management strategies is needed in order to foster a resilient SES. High homogenization is responsible for narrowing the windows of opportunity for experimentation and innovation that often allow a SES to adapt and transform in the face of potential internal and external disturbances.

Chapter 9 outlines and discusses conclusions from each model concentrating on how structural properties are able to indicate a possible enhancement or erosion of the resilience of a SES. Moreover, it brings the three models together from a theoretical point of view, and gives an overlook of different possible avenues that can further enhance our understanding of SESs (e.g. by linking models, experiments and case studies).

2 Justifying the approach

This chapter is concerned with the justification of the approach chosen throughout the research. In particular, section 2.1 explains the epistemological point of view of the author regarding this research. Section 2.1.1 looks at how it is possible to acquire knowledge of a real system, while section 2.1.2 explains the usefulness of the practice of analogy. Finally, section 2.1.3 clarifies the suitability of the methodological approach chosen in view of the nature of the research undertaken.

The second part of the chapter presents the justification of using network methods rather then other complex-system analysis tools. Section 2.2 defines complex adaptive systems (CAS) by outlining their main characterizing features. Section 2.2.1 gives a brief overview of the tools used to analyze complex adaptive systems: non-linear dynamics, statistical mechanics or physics and networks. A more comprehensive review of the science of networks is given throughout Chapter 3.

2.1 An epistemological point of view

The methodological approaches adopted are clearly influenced by one’s own viewpoints and convictions. There is still much interest in the way knowledge is acquired, a research question studied in philosophy for more than 2000 years dating back as far as Plato, Socrates and before. It is beyond the scope of this thesis to dwell into the debate, since it is not the main object of this field of study, but my viewpoint on how knowledge could and should be achieved is briefly explained. Although the importance of an epistemological frame in which research should be embedded is recognised, this frame is not considered to provide any strict guideline. Finding reasonable explanation of the phenomena under study is, in my opinion, the crucial aspect of a researcher and of this research.

In recent years a number of concepts and techniques derived from physics have been applied in different fields such as biology, economy, sociology, ecology. Network theory is one notable example of techniques derived from physics and applied elsewhere (see Barabási and Bonabeau (2003) and Watts (2004) for non-mathematical reviews and Chapter 3). However, the idea of applying instruments that derive from physics and mathematics to other disciplines is far from new. Indeed, Hobbes' work *The Leviathan* (1651) attempts to use Galilean laws of motion to derive an ideal configuration of society; Hume's *An Enquiry Concerning Human Understanding* (1748) hoped to build a science of society that was a reflection of Newton's theories of the solar system.

However, the work presented in this thesis does not mechanically apply physical laws and theorems to the object of the research, but it makes the best possible use of the knowledge that is available in order to build specific methods aimed at understanding the actual and predicted performance of a system. In order to reach a reasonable understanding of a system, a set of initial conditions and a series of agent based models (explained in section 5.2) are built and analyzed so as to derive possible future behaviours of such system. At a later stage, understanding the system could contribute to identify the correspondence between adopted choices and outcomes, allowing reasonable forecasts of future behaviour.

As Einstein points out, mathematical constructs come first, and it is only after these constructs are built and conclusions are drawn deductively that it is possible to confront these conclusions with reality (van Gigch, 2002a). Once, confronted with the real world, mathematical constructions can be accepted, modified or rejected. In other words, formulated theories should be empirically tested so as to reject or modify parts which fail to represent a reality (Popper, 1959). Today it is better to refer to computational models, rather than mathematical constructions, as uncertainty and the importance of agents in the social science and particles in quantum mechanics have led scholars to re-think ways of modelling reality (for in depth information on agent based modelling and simulations refer to section 5.2). This new type of modelling is the product of the aforementioned testing of theoretical constructions; in fact the axiomatic base of models is inadequate to explain the complexity of real world phenomenon (Henrickson & McKelvey, 2002).

Majorana (1942) draws a parallel between physics (i.e. quantum mechanics) and social sciences. In particular, in quantum mechanics there is no fatal succession of phenomena (e.g. no pure/strong determinism), but there exists a probability of consequences. Moreover, this probability (or statistical character) is not dependent on the uncertainty resulting from a voluntary action, but it is an intrinsic quality of the system. This leads also to a "lack of objectiveness in the description of phenomena" (Mantegna, 2005: 139) since

> the result of any measure seems, […], to be concerned with the state where the system is led during the same measurement rather than the undetectable state in which the system was before the perturbation.

According to Majorana's reasoning there is scope to use statistical mechanics (in the case of this research, network theoretical techniques as explained throughout Chapter 3) methods and tools in social sciences. Always according to Majorana and as reported by Mantegna (2005: 140):

> the statistical laws of social sciences might increase their function, since their function is not only of empirically establishing the resultant of a great number of unknown causes, but, above all, it is to provide an immediate and concrete evidence of reality. The interpretation of this evidence requires a special skill, which is an important support of the art of government.

Generally speaking, theories fit in a general framework (following the paradigms discussed in Kuhn (1962)), that is applied until better alternatives are found or until their inefficiency is proved. Although this framework can be falsified, it is under its "shield" that a research is often set up (Lakatos, 1974). This shield provides core principles that allow the researcher to not have to continually defend them. In other words, core paradigms are changed only if empirical evidence clearly shows that they are false statements or completely inefficient (Lakatos, 1974). However, it is also possible that core paradigms might change due to conceptual problems that could arise (i.e. problems of internal/external consistency or discrepancies with traditions in other/our fields) rather than for their empirical invalidity. The research tradition or framework used defines the characteristics considered problematic (i.e. conceptual and quantification aspects) as well as the method/s which is/are to be used to deal with these problems (Laudan, 1977). Therefore, progress in science occurs either by investigating the real world empirically, by abstracting features and representing reality through models (section 2.1.1), or when it is possible to increase the applicability of existing theories through the use of analogy, concept explained in section 2.1.2. The use of analogy follows the saying: *"Pluralitas non est ponenda sine necessitate"*[1].

2.1.1 Acquiring knowledge of the Real World:

The process of acquiring knowledge is a long debated issue in philosophy. Aristotle and the Stoics thought that a real system should be studied through four different aspects, namely *physica* (*aisthêsis* for the Stoics), i.e. the study through observation of perceivable quantities (e.g. the five senses); *logica* (*logos*), or reasoning, thus formulation of theories (e.g. mathematical constructions or computational models); *ethica* (*arètê*), or the norms in which the real system are embedded (e.g. values and norms); *politica* (*hormê*), or dealing with the actions that shape and are shaped by the real system (e.g. action research) (Nijland, 2002). Hence, knowledge is not only acquired via feedbacks occurring between deductive reasoning and empirical testing (as in Figure 2-1A), but also from two other components that might as well be equally important: action (*politica*) and the model of values (*ethica*) (as shown in Figure 2-1B).

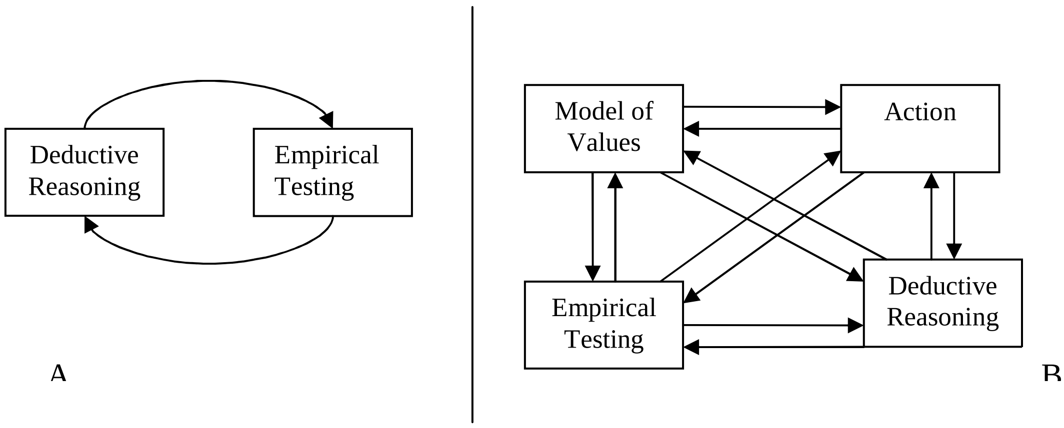


Figure 2-1 Interrelation between cognitive acts
Without (A) and with (B) action and model of values; arrows indicate the relations between the "domains" (adapted from: Nijland, 2002).

[1] Entities should not be multiplied unnecessarily (sentence attributed to Ockham (1284-1347)).

According to Figure 2-1 and to a more constructivist perspective, reason alone can not provide us with an objective knowledge of the real world (i.e. absolute, objective Truth does not exist), but experience based activities are equally important (van Gigch, 2002b). Moreover, actions undertaken and the model of values to which a researcher and the object/subject of the research refer to, interact with reason and empirical testing in improving knowledge. For example, as van Gigch states (2002b), management science has tried to formalize the decision making processes, often making tied assumption on the model of values (e.g. greed) and on the influences of actions, thus not looking at action and values so as to take into account clients-recipients relations. However, as Nijland (2002) points out, an unarticulated holistic approach is not useful; "a longitudinal, interdisciplinary, participatory but quantitative social-system analysis" is preferred (Nijland, 2002: 212). The four aspects of cognition are more or less important depending on the methodology used (e.g. observation in statistical analysis, reasoning in simulation of system dynamics) (Nijland, 2002).

Since the aim of this research is to integrate network theoretical tools (Chapter 3) and resilience thinking (Chapter 4), the theoretical aspects are prevalent. Therefore, the approach used in this research concentrates on the aspects relating to reason. Although the importance of integrating reasoning with the other aspects of cognition is recognised, at this stage focussing on the *logos* is thought to be the best way to undertake this research. The starting point is given by the problems arising in "measuring resilience" (Carpenter et al., 2001) (see Chapter 4), and an abstract selection of the fundamental variables that are thought to drive a system's resilience is performed. These fundamental variables are used in order to construct and simulate a theoretical model. Future stages of the work might as well include the empirical testing of the model and how values and action can influence and are influenced by it.

2.1.2 Analogy: a way of integrating different disciplines

Analogies are useful when the objective is to compare an unfamiliar system with one that is better known. In particular, according to Maxwell (Turner, 1955), analogies generate science through the transferring of a mathematical problem's solution from one branch of science to another (e.g. from physics to social sciences), and through the fact that, making an analogy more complete might develop into a "new theoretical and experimental inquiry" (Turner, 1955: 234). The use of analogy helps with the identification of mathematic formulations of relations and actions, since they are transferred from familiar system to unfamiliar ones: analogies extend a line of reasoning of a known field to an unknown one.

When it is possible to establish some similarities between different phenomena, it is also possible that a common law or principle exists. This line of reasoning could lead in the right direction, especially if similarities exist not only between attributes of two phenomena but also between the functions of the elements or the structure of different systems. The usefulness of analogy depends on whether consequences can be tested or observed and then passed from one more familiar system to a rather unfamiliar one (Gentner, 1983). A mathematical model might be constructed if it is possible to reproduce structural relations from a better known environment. Although analogies have to be used with caution, in order to avoid the possibility of abuses (Daniel, 1955), Nagel (1961) claims that theories should show at least a formal analogy to already familiar (existing) constructed systems in order to understand how to apply it to concrete problems.

It is also worth mentioning the difference that exists between analogy and homology, since often the definitions of the two terms overlap and are not clear. Following Fitch (2000: 229, Box 1):

> homology is the relationship of any two characters that have descended, usually with divergence, from a common ancestral character and analogy is the relationship of any two character that have descended convergently from unrelated ancestors.

Homology means similarity attributable to common origin, while analogy might be interpreted as similarity attributable to common evolution[2]. As for the research undertaken, it is referred to homology if two different systems have a set of empirically tested correspondence of properties and mechanisms. Homology is rarely used as it is not easy to find different complex systems with an exact correspondence of empirically tested properties and mechanism. Analogy is used to better illustrate certain aspects of the work, since it has been shown that analogies can lead to the development of new fields of inquiry (see for example: Majorana, 1942; Mantegna, 2005; Turner, 1955).

2.1.3 Thesis Approach

There are numerous papers dealing with epistemological issues comparing or trying to integrate methodologies and approaches in social and natural sciences (Nijland, 2002; van Gigch, 2002a, 2002b). Thus, a structural approach, using the tools of network theory (explained in Chapter 3), could give useful and new insights on how coupled SESs behave. Clearly, this approach and this work is centred on the "reasoning" chapter of Nijland (2002) tetrahedron of knowledge acquisition (depicted in Figure 2-1B) as elucidated in section 2.1.1, and once a computational (or agent based) model is constructed, there will be a need for empirically verifying these model, and to look at the different context (model of values) and different management (action) that will affect and will be affected by the models itself.

The role of this thesis is to explain, rather than predict, systems' strengths and weaknesses, since social systems might be inherently impossible to predict, as pointed out by Bernstein et al. (2000). Since SES are open systems, problems of replicability or applicability may arise, but these issues may be raised and addressed once a first set of coherent and logical arguments are put in place (i.e. the aim of this research). Further, the key purpose of this research is not to assess the behaviour of single actors (e.g. individuals), that is inherently very difficult or impossible to predict, but in the behaviour of a SES on the aggregate, starting from single

[2] Here evolution is intended in its general meaning (e.g. not biological evolution).

heterogeneous agents interacting between themselves. Thus the objective is to understand if and how regularities may emerge from the behaviour of single actors (Majorana, 1942). In this perspective, the building of a coherent theory might be useful in order to explain if and how different structures influence the dynamics of a SES, so as to assess the resilience of a given SES.

To conclude, the final aim of this thesis is to integrate network methods in resilience thinking, so as to analyze the resilience of an SES from a structural perspective. In this context SESs are approached from a network point of view, trying to capture only the most important properties of single nodes (e.g. individuals, species etc.) and their interactions (e.g. edges that connect two nodes) in a dynamic setting. I am aware that I will not find any absolute or objective “Truth”; however, I think that this research will allow a better understanding of SES dynamics, hence an increased verisimilitude of real system representation and possibly the design of policies that are more able to enhance or erode the resilience of a SES.

2.2 Complex Adaptive Systems

It is not easy to define complex adaptive systems (CAS) in an unambiguous way, however, following Levin (2002) a system is characterized as complex and adaptive if a) its components (or agents) are diverse and behave differently, b) these components interact locally (where locally is not necessarily geographically constrained), and c) there is an independent process that is based upon those interactions and that allows for change in the composition/behaviour of components.

The properties of a CAS described above assign to CAS some characterizing features (Levin, 2002; Waldrop, 1992). More precisely, such systems are characterized by:

- *Non-determinism,* since it is impossible to precisely determine the behaviour of CAS; the only predictions that can be made are probabilistic;
- *Presence of feedbacks,* whether positive or negative, loops are present in such systems and the relationships that forms between the components become more important than the component itself;

- *Distributed nature*, hence it becomes very difficult to precisely locate functions and properties;
- *Qualitative difference between larger and slower functions (or cycles) and smaller and faster ones* (Holling, 2001, 2004; Levin, 2002; Waldrop, 1992);
- *Limited decomposability*, as the structure of such systems is studied as a whole. Again, the interactions between the components are a fundamental variable, thus it is very difficult if not impossible, to analyze CAS by decomposing it;
- *Self-similarity*, implies that a system will have the same structures at different scales;
- *Emergence and self-organization*, i.e. universal structures might emerge in CAS as they self-organize, although it is not possible to foresee these by looking at its components.

Interactions between species in an ecosystem, the behaviour of consumers, or people and groups in a community, the stock-market, the immune systems, the river networks, and birds' flying patterns among others, are all examples of CAS. The analysis of CAS, given its peculiarities, calls for a new strategy, in order to make cross-disciplinary comparisons searching for features that are common to different systems in different domains (Lansing, 2003). In particular, different tools have "emerged" in order to try to understand CAS.

2.2.1 Tools for analyzing complex systems

In order to analyze CAS, Amaral and Ottino (2004) identify three main "toolboxes":

- Non-linear dynamics
- Statistical mechanics
- Networks

Non-linear dynamics

Complex adaptive systems are characterized by the non-linearity of the interactions of their components. Although non-linear dynamics and chaos are nowadays part of science (Amaral & Ottino, 2004), it is worth stressing the fact that non-linearity does not imply non-predictability, but rather that deterministic views of the world should be critically examined.

There are a number of mathematical techniques that enable one to deal and to find solutions for systems characterized by non-linear dynamics, however, most of these solutions are obtained through numerical approximations, and thus there is a need of powerful computers that allow nonlinear dynamics to exhibit self-organization and chaos. Since chaotic behaviour often arises from the iteration of simple mathematical equations, it is possible to affirm that chaos suggests that systems that are simple when decomposed, become very complicated when they are treated as a whole. Systems that display such non-linear behaviour are virtually everywhere, examples of which can be the economies, stock markets, population growth, and turbulent fluids.

Statistical mechanics

The origin of statistical mechanics (or physics) at the turn of the 20th century led to a new meaning of prediction, and permitted the introduction of discrete models such as cellular automata and agent-based models (Amaral & Ottino, 2004). Moreover statistical mechanics allows us to reason in terms of ensembles, thus leading the way to conceptualizing “universality” and “scaling” (Amaral & Ottino, 2004).

Thanks to the techniques of statistical mechanics, the availability of data and the use of computers, it has been discovered that many physical systems display universal properties that do not depend on the single components and on the single interactions that exist within a system. Moreover, it can be argued that some universality exists in other complex systems as well (e.g. social, ecological), although exact solutions are very difficult, if possible, to obtain, and most current research use numerical simulations (i.e. see section 5.2) in order to reach probable solutions. Statistical mechanics is also concerned with the idea that there exist a set of relations (*scaling laws*), that could help the understanding of different critical exponents that characterize the behaviour of parameters and functions.

Finally, statistical physics methods introduce discrete models. Discrete, or agent-based modelling has been successful especially in ecology and social sciences (e.g. see section 5.2.1 and 5.2.2 and references therein) (Amaral & Ottino, 2004). This type of modelling is concerned with algorithms (computer programs) rather than equations and allows its components to interact and evolve. More precisely, agents (or basic building blocks) live in a certain environment, and they may possess different characteristics, which can change over time. This type of modelling allows to investigate different scenarios and in some cases this approach has replaced equation based ones (e.g. predator prey models, fire spreading etc.) (Amaral & Ottino, 2004). This thesis makes wide use of agent based models combined with network theoretical tools in order to look at the resilience of SES. Agent based models and simulations are discussed in depth in section 5.2.

Networks

Most systems can be viewed as networks; that is, elements that interact with each other. Networks are described extensively in Chapter 3; here the explanation will be limited to how networks can help us in analyzing complex systems by giving a very simple and hypothetical example. First of all, a definition of a SES is required. Figure 2-2 represents a closed, simplified system. The analysis is based on two different types of agents: ecological and socio-economic ones. In this case, ecological nodes are defined as those nodes that refer to resources that are non-human (abiotic or biotic environment), while socio-economic nodes refer to those that are based on humans. Moreover, the interactions that occur between ecological and socio-economic nodes and between nodes that belong to the same macro-category are analysed.

To begin with, assume a closed, small, geographical space, in which two resources are present (ecological nodes) and two type of organization exist (socio-economic nodes), as shown in Figure 2-2.

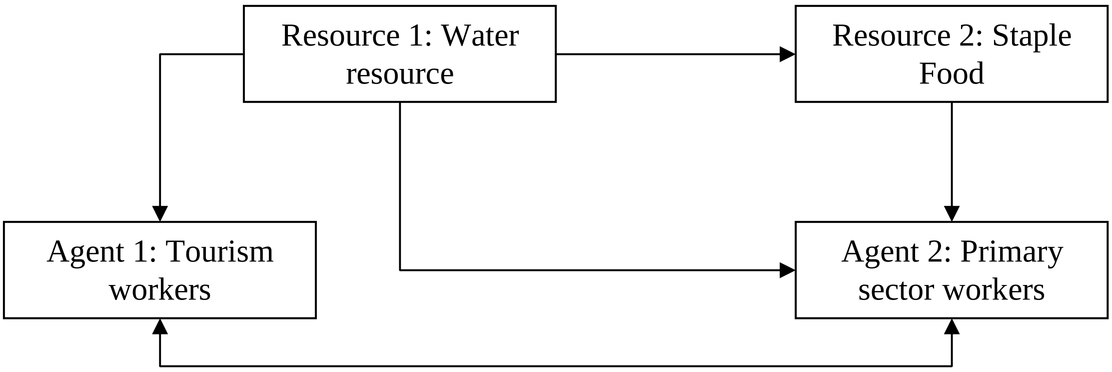


Figure 2-2 Over-simplified interactions in a geographical space
(Own elaboration)

Figure 2-2 can be represented by a network as shown in Figure 2-3:

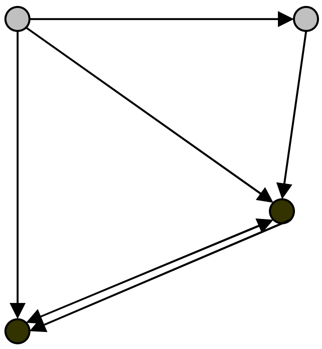


Figure 2-3 Network representation of the simplified system
(Own elaboration)

The network representation is very effective in indicating which relations exist between the different nodes. At this point, the light grey dots represent the ecological agents and the dark grey dots represent the socio-economic ones. Moreover, the connections can be directed (represented by an arrow) or bi-directed (represented by a double arrow). Directed connections symbolize an extraction, type of relationship, that is, a relation that represents a flow of resources from one agent to another. Bi-directed edges symbolize a bargaining (or exchange) type of relation. The network represented in Figure 2-3 can be shown in an evolving setting. After defining the two macro-categories explained in the previous paragraph, it is possible to affirm that, in this example, there exist some agents that are more connected than others.

The dark grey dots are connected by a bi-directed arrow, representing the fact that they both need to interact in order to divide the extraction from the light grey dots (represented by the two directed connections). Moreover, there is an additional extraction type of relationship (single-pointed arrow) also between the two socio-economic nodes, meaning that one of the two nodes needs exclusively "something" from the other. As it is shown, even in this over-simplified example, the collapse of one dot can lead to the collapse of the entire system (Figure 2-4, moving clockwise from graphs A to D):

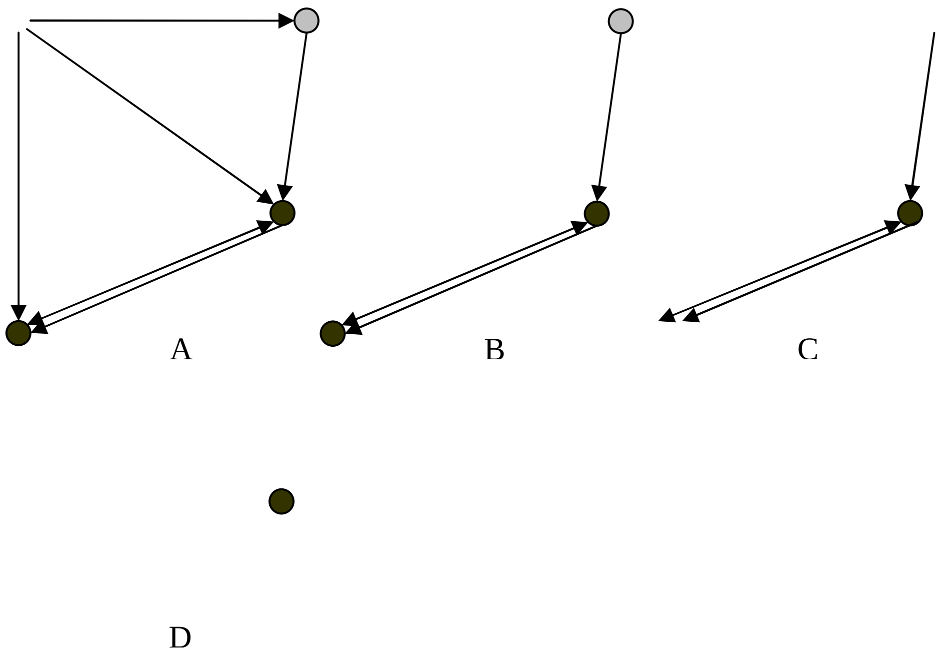


Figure 2-4 Effects of the removal of the most connected node in time (Own elaboration)

Figure 2-4 graphically explains the effects of the removal of one ecological agent. In this case, in which we simulate a close system with only two resources and two agents, the main resource dries out (A); this leads to the disappearance of the extraction connections that connect to the second ecological dot and to the socio-economic ones (B); since the dried out ecological node is crucial, as it is the only input for the survival of the other two nodes, the latter also "disappear" (C). The process described in (B) repeats itself creating a cascading effect, which will lead to the disappearance of the remaining edges and to the collapse of the whole system (D).

It is possible to reproduce a more realistic system by giving characteristics and behaviour rules to single nodes and edges (or relation between nodes) existing in the system represented by a network. In other words, it is possible, and possibly better, to integrate network theoretical tools with agent based modelling, thus allowing for pre-determined actions and dynamics to unfold upon an identified network. Chapters 6, 7, and 8 propose three different theoretical models that look simultaneously at dynamics that unfold on a network so as to look at how structural properties affect the resilience of a SES.

3 Network theory

This chapter resumes section 2.2.1 and expands, introduces, explains, and defines the terminology that refers to science of networks (graphs) (section 3.1). Secondly it deals with the measures that are commonly used to statically characterize a network (section 3.2) and metrics widely used in social network analysis (section 3.2.1). Section 3.3 introduces different classes of networks, based on previous definitions and measurements. More precisely it defines regular networks (3.3.1), random graphs (3.3.2), small worlds (3.3.3), scale-free networks (3.3.4), and introduces the concept of modularity (3.3.5). Section 3.4 reviews the main studies dealing with real network and reports the main findings. A particular focus is given to ecological networks (food webs) characterizing them as transportation networks (3.4.1). Finally a brief summary of what has been explained in the whole chapter (3.5) is provided.

I am aware that networks are used across different disciplines, but, since the objective is to integrate it with Socio-Ecological System (SES) resilience there is a need to use an unambiguous terminology. Hence, I will not adopt sociological definitions, but rather a more mathematical one. I refer to nodes and edges, and not to actors and ties; to adjacency matrices and not to socio-matrices, to clustering coefficient and average shortest path length, rather than to fraction of transitive triples and characteristic path length. The terms just mentioned are defined and explained in detail in the first two sections of this chapter (i.e. sections 3.1 and 3.2), but listing the terms that I will use and their counterparts in sociology enhances communication across disciplines.

3.1 Network Structure

Networks can be considered as a tool to analyse and abstractly represent complex systems. A network can be thought of as a set of *nodes* connected through *edges* as shown in Figure 3-1:

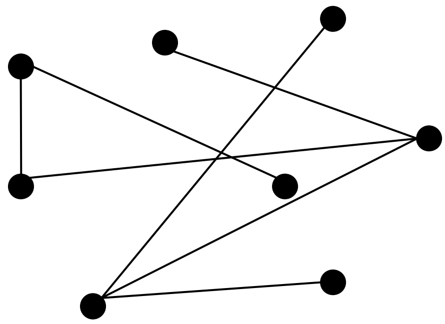


Figure 3-1 Network representation
The black dots are called nodes, while the lines connecting any pair of nodes are called edges (Own elaboration).

Network theory (here also called graph theory) dates its conceptual origins back to the 1730s thanks to Euler (1736); but the starting point of modern graph theory is considered to be the work of two Hungarian mathematicians on random graphs (Erdős & Rényi, 1959, 1960). The terminology and definitions used in this chapter follow the work of Börner et.al (2007), integrated by authors that have extensively written on networks measures and terminology (Albert & Barabási, 2002; Amaral & Ottino, 2004; Barabási & Bonabeau, 2003; Börner et al., 2007; da Fontoura Costa et al., 2007; Dorogovtsev & Mendes, 2002; Newman, 2003b; Strogatz, 2001; Wang & Chen, 2003; Watts, 2004).

As explained above, a network is a set of nodes connected through edges. Following a more rigorous definition it is possible to say that a *graph (network) G* is defined by a non-empty set of nodes $V = \{v_1, ..., v_n\}$ and a non-empty set of edges $E = \{(v_1, u_1), ..., (v_i, u_j)\}$: *G = (V, E)*. The total number of nodes in the graph of the set *V* is represented by *N*, while the total number of edges in the network of the set *E* is represented by *M*. The *i-th* node of the set *V* can be connected to the *j-th* node through an edge; that is, an edge connects a pair *(i, j)* of nodes. If an edge belonging to *E* connects a pair of nodes *(i, j)*, *i* and *j* are said to be *neighbours*.

Networks can be undirected or directed. *Undirected graphs* have edges that connect a pair of nodes in a transitive fashion (that is, edges that connect node *i* to node *j* and vice-versa), while *directed graphs* are composed only by directed edges connecting a pair of nodes in a given direction. *Undirected edges* (or edges) are normally represented by a straight line or a double arrow line, while *directed edges* are normally represented by an arrow indicating the direction of the relation between a pair of nodes. Figure 3-2 gives a graphical representation of an undirected and a directed graph:

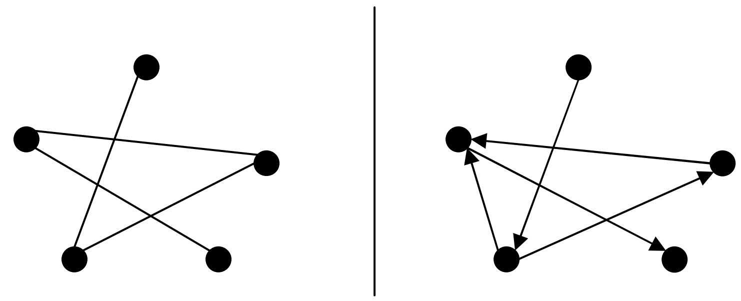


Figure 3-2 Undirected Network (right) and a Directed Network (left)
Undirected edges (right) and directed edges (left) (Own elaboration).

Networks can also be weighted. Real networks display a wide heterogeneity when it comes to assess the strength of the relations that exist between nodes. Weighted networks can be directed or undirected. Figure 3-3 displays an example of a weighted undirected graph.

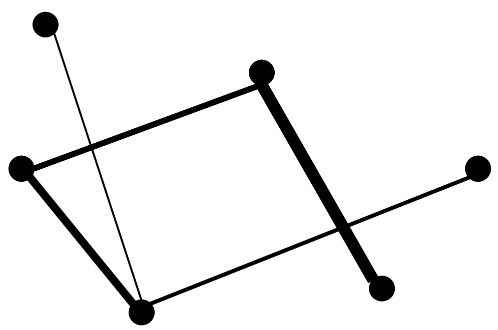


Figure 3-3 Weighted network
The strength of the edges is given by the thickness of the line (Own elaboration).

To be more rigorous, in weighted networks each edge *(i, j)* is associated with a weight w_{ij} (also be called the *weight of an edge*). Having defined the weight of an edge, it is possible to define the *strength of node i* (s_i) as the sum of the weights of its edges: $s_i = \sum_j w_{ij}$. Weighted networks clearly provide more information upon the graph, since they combine topological information with quantitative measures.

Independently from whether weights or edges directions have been defined, a network is termed connected if no isolated nodes exist. A *giant component* can be defined as the largest connected part of a network.

In a network, sub-graphs may be defined. Sub-graphs' properties in random graphs were first extensively studied by Erdős and Rényi (1959). A *sub-graph* is a graph whose nodes and edges are all also nodes and edges of a larger network. Formally a sub-graph can be defined as follows: consider a graph $G = (V, E)$, then a sub-graph $G_1 = (V_1, E_1)$ of G is a sub-graph of G if and only if all the nodes of V_1 belong to V and all the edges of E_1 belong to E.

The simplest types of sub-graphs are called *trees*, *cycles* and *complete sub-graphs*. The notations used by Albert and Barábasi (2002) are used to formally assess the order and the property of sub-graphs. Trees are hierarchical graphs in which every node has only one node from which it originates (also called parent node). The order of the tree is defined by the number of nodes that composes it, as shown in Figure 3-4: a tree of order k has k nodes and $k-1$ edges.

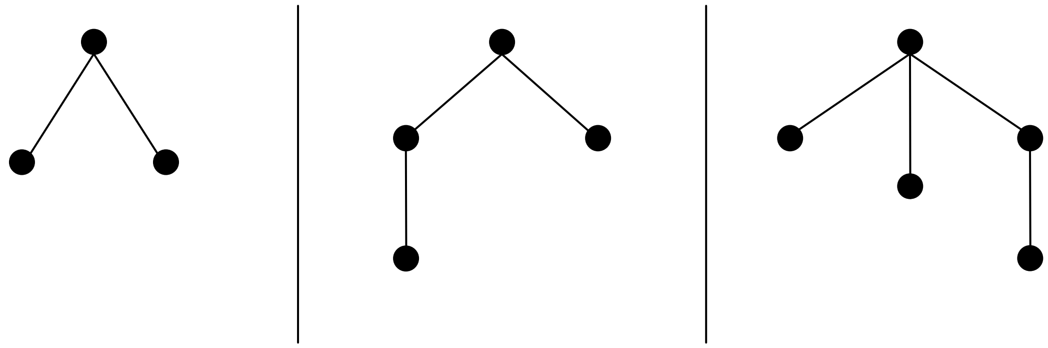


Figure 3-4 Trees
Tree of order 3 (left), a tree of order 4 (centre), and a tree of order 5 (right) (Own elaboration).

Cycles are closed loops in which every two consecutive edges have one node in common. The node needs to belong exclusively to the consecutive edges. The order of the cycle is again defined by the number of nodes; more precisely, a cycle of order k has k nodes and k edges, as shown in Figure 3-5:

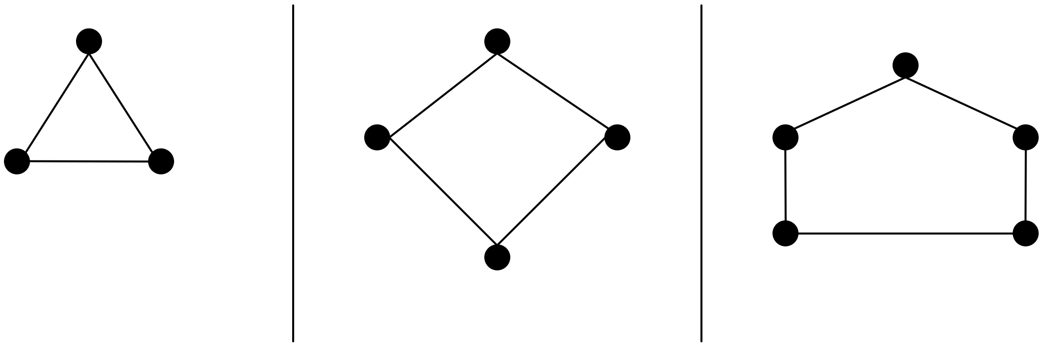


Figure 3-5 Cycles
Cycle of order 3 (left), a cycle of order 4 (centre), and a cycle of order 5 (right) (Own elaboration).

Complete sub-graphs are sub-graphs that are fully connected. The order of complete sub-graphs is again given by the number of nodes that compose the sub-network. In other words, a complete sub-graph of order k has k nodes and $k(k\text{-}1)/2$ edges ($k(k\text{-}1)/2$ is the maximum number of edges in a graph if every pair of nodes is connected through one edge and node do not have edges that lead to themselves), as shown in Figure 3-6:

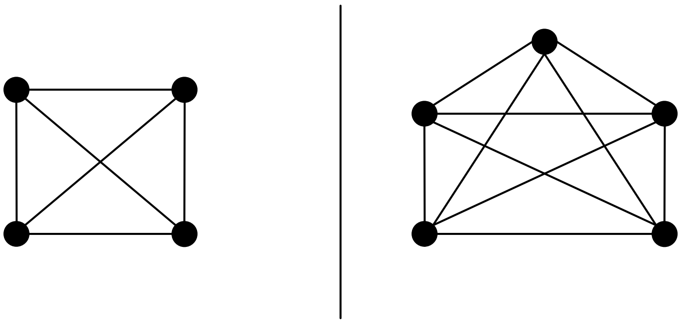


Figure 3-6 Complete sub-graphs
Complete sub-graph of order 4 (left) and order 5 (right)
(Own elaboration).

As explained in the previous paragraph, the maximum number of edges that exist in a graph is given by $k(k\text{-}1)/2$. A graph can not contain self-referring edges (*loops*) or multiple edges that connect a pair of nodes. If a graph contains loops or multiple edges, it is called *multi-graph*. Figure 3-7 shows multiple edges and loops.

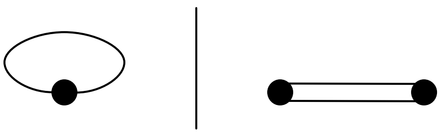


Figure 3-7 Loop (right) and multiple edges connecting a pair of nodes (left)
(Own elaboration).

Last but not least, the definition of a bipartite-graph is given. A bipartite graph is a graph in which two different set of nodes co-exist. In the case of this work, social and ecological node will be represented as two different sets. Hence, it is possible to define a bipartite-graph as *G=(Vse+Vec, E)*, where *Vse* is the non-empty set of social nodes, *Vec* is the non-empty set of ecological nodes, and *E* is the non-empty set of edges. An example of a bipartite-graph is shown in Figure 3-8:

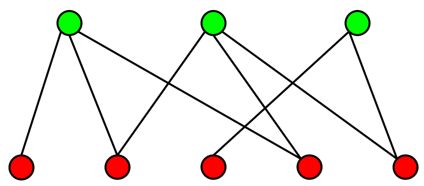
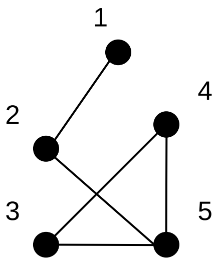
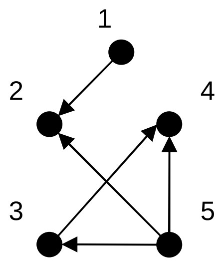


Figure 3-8 Bipartite-graph representation
Only the relations between the two different sets of nodes are represented (here socio-economic nodes in dark-grey and ecological nodes in light-grey) (Own elaboration).

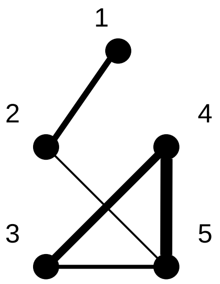
Graphs and networks can be represented graphically (as shown so far) or as a matrix. The matrix that defines a network is also called *adjacency matrix*. The adjacency matrix is a square matrix in which values are 1 if a connection exists between the nodes to which the cell refers (interception of column and row), and 0 if the two nodes are not connected. Formalizing: the adjacency matrix $A_{ij} = \{a_{ij}\}$ is a $N \times N$ matrix defined such as $a_{ij} = 1$ if $i, j \in E$ and $a_{ij} = 0$ if $i, j \notin E$. If the matrix is representing an undirected graph, then it will be symmetric as $a_{ij} = a_{ji}$. If the adjacency matrix is representing a directed graph, then there is the possibility that the matrix is asymmetric; i.e. $a_{ij} \neq a_{ji}$. Finally, if the adjacency matrix is representing a weighted graph, than the matrix is not represented by $a_{ij}, a_{ji} = 1,0$ but by the strength of the edges: w_{ij}, w_{ji}, whose value is given by the strength of the connection between node i and node j (and vice-versa). Figure 3-9 depicts the adjacent matrix for undirected, directed, unweighted and weighted graphs:



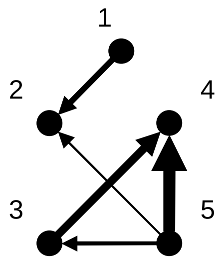
	1	2	3	4	5
1	0	1	0	0	0
2	1	0	0	0	1
3	0	0	0	1	1
4	0	0	1	0	1
5	0	1	1	1	0



	1	2	3	4	5
1	0	1	0	0	0
2	0	0	0	0	0
3	0	0	0	1	0
4	0	0	0	0	0
5	0	1	1	1	0



	1	2	3	4	5
1	0	3	0	0	0
2	3	0	0	0	1
3	0	0	0	4	2
4	0	0	4	0	5
5	0	1	2	5	0



	1	2	3	4	5
1	0	3	0	0	0
2	0	0	0	0	0
3	0	0	0	4	0
4	0	0	0	0	0
5	0	1	2	5	0

Figure 3-9 Networks and their adjacency matrices
Undirected (top-left), directed (top-right), weighted undirected (bottom-left) and weighted directed (bottom-right) graph representation with their respective adjacency matrix. Note how the matrix is symmetric when the graphs are undirected, asymmetric when directed. Moreover, the weights are represented by the thickness of the line and weights are given arbitrarily on a scale from 1 to 5 (1 the weakest, 5 the strongest) (Own elaboration).

3.2 Network Measures

So far, section 3.1 has dealt with different structures that highlight certain properties of a whole network. This section introduces the measures that are commonly used in order to statically characterize a network's topology.

This section starts by defining local measures. Local measures are those metrics that refer to a single node or to a pair of nodes. As explained before, a network is a set of nodes connected through edges. If it is possible to reach a node from another node then an "ideal" walk on certain edges is carried out. If the walk connects a pair of nodes, this walk will have a finite distance. Moreover, in graph theory the walk is defined as *path*. Formally, a path $P_{i,j}$ that connects node *i* to *j* is defined as an ordered sequence of *n+1* nodes and *n* edges that will connect *i* and *j*; the length of the path $P_{i,j}$ is equal to *n*.

Now, it is possible to define the nearest neighbours of a node keeping in mind what a path is. In this context it is possible to affirm that the nearest neighbours of a node are those nodes that are reachable in a unit path length. In other words, the nearest neighbour of node *i* are those nodes whose $P_{i,\, z}$ = 1, where z represent any node in the unitary distance.

When referring to length or distance between two nodes in an unweighted network only the *geodesic* distance between the two is taken into account. The geodesic distance is unitary (or its length is equal to one) if node *i* and *j* are connected through an edge, independently from the actual physical distance that may exist between the nodes as shown Figure 3-10. In case of weighted networks, the distance may as well be calculated as the sum of the weights of the edges that it is necessary to bypass in order to reach node *j* from node *i*.

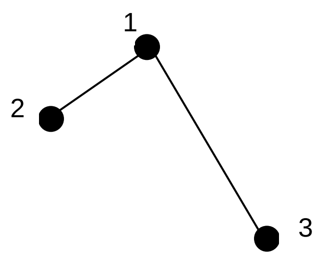


Figure 3-10 Geodesic distance
In an undirected graph, the geodesic distance between nodes 1,2 and 1,3 is equal to 1, while the physical distance is different (being distance 1,2<distance 1,3) (Own elaboration).

Given the definitions above, it is possible to define the *shortest path length* ($\ell_{i,j}$) as the shortest geodesic path that is exist from node *i* to node *j*; if nodes are connected through directed edges, then $\ell_{i,j} \neq \ell_{j,i}$. The *diameter* (*D*) of a network is then defined as the *maximum shortest path* length in a graph. In other words, the diameter of a network is the maximum of the shortest path lengths that exist in a network: *max* $(\ell_{i,j})$ where *i* and *j* represent any pair of nodes existing in the graph.

The *average shortest path length* ($\langle \ell \rangle$) of a network is, as the name suggests, the mean value of $\ell_{i,j}$ over all possible pairs of nodes *i*, *j* that exist in a network. Formally: $\sum \ell_{i,j} \big/ N_{i,j}$ where $N_{i,j}$ is equal to the number of all the possible pair of nodes.

Making use of the definition of *path*, it is also possible to define *reachability*. Reachability can be defined as the possibility of reaching node *j* starting from node *i*, irrespective of the number of edges and nodes that it is needed to bypass. In Figure 3-11, for example, all nodes are reachable in the undirected network, while in the directed graph, if we start from node 2 no node is reachable, while if we start from node 1, only nodes 2, 3, and 4 are reachable.

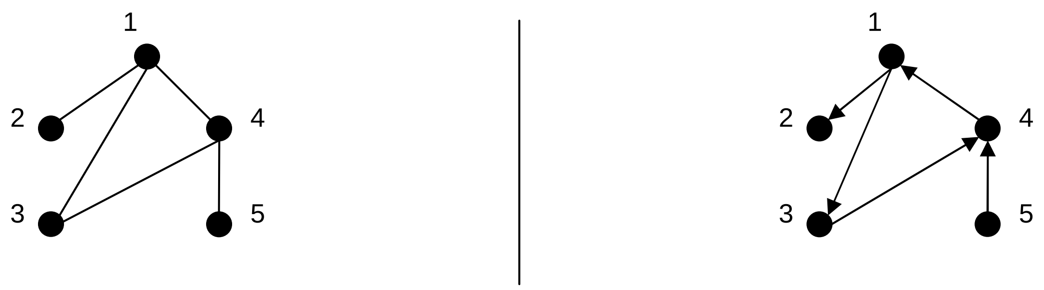


Figure 3-11 Undirected (left) and Directed (right) graph (Own elaboration).

Another important measure that characterizes a node is the number of edges that are linked to it. The number of edges that are connected to a node is also called the *node degree* (or the degree *k* of node *i*: k_i). The average degree of a network is then the sum of the node's degrees divided by the number of nodes that exist in the network: i. e. $\langle k \rangle = \sum k_i \big/ N$. The degree of a network can also be defined as the number of the nearest neighbours of a node. In undirected graphs, the definition given above holds perfectly. In directed graphs, it is possible to differentiate the in-degree of a node *i* ($k_{in,i}$) and the out-degree of a node *i* ($k_{out,i}$).

The in-degree represent the incoming edges that are connected to node *i*, while the out-degree measures the number of edges outgoing edges from a node *i*. Figure 3-11 graphically shows the definition of degree, and the nearest neighbours of a given node. More precisely, referring to Figure 3-11: $k_1 = k_4 = 3$; $k_3 = 2$; $k_2 = k_5 = 1$; for the undirected graph. Moreover, the nearest neighbours of node 1 are nodes 2, 4 and 3. As for the directed graph, the in-degree of a node is separated from its out-degree, hence: $k_{in,1} = 1$, $k_{out,1} = 2$; $k_{in,2} = 1$, $k_{out,2} = 0$; $k_{in,3} = 1$, $k_{out,3} = 1$; $k_{in,4} = 2$, $k_{out,4} = 1$; $k_{in,5} = 0$, $k_{out,5} = 1$. In the directed graph it is also possible to define the nearest neighbours in two ways; the nearest neighbour from which node 1 can be reached is node 4, while the nearest neighbours that can be reached from node 1 are nodes 2 and 3. Clearly, the higher the degree of a node, the more that node will be important for the network structure (Albert & Barabási, 2002; Barabási & Bonabeau, 2003; Dorogovtsev & Mendes, 2002).

When not all nodes in a network have the same degree, then it may be interesting to study how wide is the node *degree distribution* ($P(k)$) (Albert & Barabási, 2002). The degree distribution in undirected graphs is the probability that node i will have degree (or number of edges) k. In directed graph we need to differentiate the in-degree distribution and the out-degree distribution.

Another measure that is widely used to characterize a network topology is the *clustering coefficient* of node i (C_i). The clustering coefficient can be thought of as a way to determine how many nearest neighbours of node i are also nearest neighbours to each other. More precisely, if we select a node i with degree k_i, then the maximum number of edges between the nodes connected to node i will be equal to $k_i(k_i - 1)/2$, and the actual number of edges between the k_i nodes will be equal to E_i; thus the clustering coefficient of node i, C_i, can be defined as the ratio between the maximum number of edges and the actual number of edges: $C_i = {}^{2E_i}\!/_{k_i(k_i - 1)}$.

After defining the clustering coefficient of a given node, it is possible to define the average clustering coefficient C. The average clustering coefficient is defined as the average value of the nodes clustering coefficient (C_i) over the possible N nodes: $C = \sum_i C_i \big/ N$.

There are other numerous metrics found to characterize a network's topological properties.. Amongst them it is worth to highlight the concepts of global and local efficiency. *Global and local efficiency* are measures introduced by Latora and Marchiori (2001). The efficiency measure is built upon the assumption that the network transmits information and that there is hence a scope to explore how well its nodes can interact locally and globally (Crucitti et al., 2004; Latora & Marchiori, 2001). Unlike the average shortest path length, that is reasonable for the connected component of a network, or for completely connected networks, the global efficiency is well-defined even for unconnected networks (Crucitti et al., 2004; Latora & Marchiori, 2001).

More precisely, the efficiency in communication between a pair of nodes i, j can be defined as being inversely proportional with respect to the shortest path; i.e. $\varepsilon_{ij} = \frac{1}{d_{ij}}$ for every pair of nodes i, j. If there is no path that connects nodes i, j, $d_{ij} = +\infty$ thus $\varepsilon_{ij} = 0$. Given the definition of efficient communication it is possible to define the global efficiency as the average efficiency of the network (Latora & Marchiori, 2001). Formalizing:

$$E(G) = \frac{\sum_{i \neq j \in G} \varepsilon_{ij}}{N(N-1)} = \frac{1}{N(n-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}}.$$

In order to allow comparisons of the efficiency $E(G)$ across different networks, $E(G)$ is normalized considering the case in which a network with the same number of nodes is fully connected; that is, *E(G)* is normalized by $\frac{N(N-1)}{2}$ edges, case in which communication is most efficient. Thus $0 \leq E(G) \leq 1$ being $E(G) = 1$ only if the network is fully connected. $E(G)$ is the global efficiency of the network: $E(G) \equiv E_{glob}$.

If the global efficiency is the average efficiency of the network, it is possible to think at the local efficiency as the average efficiency of sub-graphs. In mathematical notation, that is: $E_{loc} = \frac{1}{N}\sum_{i \in G} E(G_i)$, where G_i is the sub-network of the neighbours of node i.

Another important characteristic of complex networks is assortativity. *Assortativity* is a measure that allow us to understand if the network displays a positive correlation between the degree of its nodes and the probability that they are attached to one another: a node with high degree will preferentially attach itself to a node of a high degree as well (Newman, 2002, 2003a). In other words, assortativity refers to the fact that similar nodes tend to connect with each other.

A simple way to measure assortativity is by using the Pearson correlation coefficient between the degree k of a given pair of nodes (e.g. i, j) (Newman, 2002): $r \propto \overline{k_i k_j} - \overline{k_i} * \overline{k_j}$. When $r > 0$ the network is considered to display assortative mixing; when $r < 0$ the network displays disassortativity and when $r = 0$ the network does not display assortativity (or disassortativity).

An example of an assortative network will be a social network in which people tend to connect with those that have similar characteristics (e.g. income, age, sex, race, type of work etc.); on the contrary, if people tend to connect with those that have different characteristics, then the network will display disassortative mixing (Newman, 2003a). An important characteristic to take into account is the degree of a node. If the network displays assortative mixing, then high degree nodes will prefer to attach to other high degree nodes. Vice versa, if the network displays disassortative mixing, high degree nodes will preferentially connect to low degree nodes. Most social networks seem to display assortative mixing, while most technological and biological networks tend to display disassortative mixing (Newman, 2002, 2003a).

3.2.1 Social Networks metrics

Social network analysis has developed its own terminology. Nonetheless, social network analysis focuses on different measures than those described above. In particular, the concept of *centrality* of a network node with respect to others is considered. There are numerous measures of centrality (Hanneman & Riddle, 2005), but it is possible to group each measure into two broad categories: local measures and global measures.

Local centrality can be thought of as a measure of how well a node is connected to its neighbours; a node degree refers to the simplest local measure of a node centrality.

Global centrality takes the whole network structure into account in order to determine the importance of a node with respect to the entire graph. There exist two common measures that are used to compute global centrality: *closeness centrality* and *betweenness centrality* (Börner et al., 2007).

Closeness centrality is used to calculate the geodesic distance between different nodes. A node is globally central if it constitutes a neighbour to many other nodes. In other words the shorter the path between node *i* and other nodes, the higher the centrality of node *i*. Formalizing:

$$Cc(i) = \frac{1}{\sum_{j=1}^{n} P_{i,j}}.$$

Betweenness centrality describes the importance of a node in a network based on the flow it can control. In other words the importance of a node is given by its uniqueness. As an example it is possible to think at two different communities that speak different languages (hence facing communication barriers). A problem arises when the two communities need to talk to each other, and there is only one person who is able to communicate effectively with both communities. The node that represents this individual will have a high betweenness centrality. More precisely the betweenness b of node i can be formalized as follows:

$b_i = \sum \frac{L_{h,i,j}}{L_{h,j}}$ where $L_{h,j}$ represents the total number of shortest path from h to j and $L_{h,i,j}$ represents the number of those paths that will pass through node i, It is also possible to characterize the betweenness distribution. More specifically, it is possible to compute the probability distribution $P(b)$ that a node has betweenness b. Finally, it is also possible to calculate edge betweenness (b_e). Edge betweenness has the same meaning of node betweenness and is calculated as follows: $b_e = \sum \frac{L_{h,e,j}}{L_{h,j}}$ where $L_{h,j}$ represents the total number of shortest path from h to j and $L_{h,e,j}$ represents the number of those paths that will pass through edge e.

Since both measures (Cc and b) depend on the size of the network, both measures are normally standardized in order to allow comparisons. More precisely, closeness centrality is divided by N-1 and betweenness centrality is divided by $(N-1)(N-2)$.

Another measure that may be of interest is the so called distribution of node distances. According to Börner et al. (2007), it is possible to characterize two main measures of node distances. The first being simply the probability distribution of finding two nodes separated by a distance ℓ. The second indicator is called the *average mass* of a graph, since it involves computing how many nodes it is possible to find within a distance less or equal to ℓ. Thus, if we define the average mass of a graph as $M(\ell)$, then at $\ell = 0$ average mass includes only the starting node, hence $M(0) = 1$; if $\ell = 1$ than $M(1) = 1 + k$ (that is, the starting node plus its nearest neighbours) and so on.

Since the objective of the thesis is to look at structural properties of networks whose nodes represent social components (human) and ecological components of a SES, at this point, there is no need to go beyond the formal description of the most important measures that will be used throughout the thesis.

3.3 Network Classes

The characterization of the structural properties of a network is usually defined by its connectivity properties (in simple words, how nodes and edges are formed and attached to each other) (Albert & Barabási, 2002; Amaral & Ottino, 2004; Barabási & Bonabeau, 2003; Dorogovtsev & Mendes, 2002; Strogatz, 2001; Watts, 2004). In the previous sections (i.e. sections 3.1 and 3.2) structural properties and measures commonly used to define connectivity properties have been characterized. This section defines four major categories of *network classes*. A network class is an ensemble of networks that share the same properties, mainly with respect to their degree distribution function, average clustering coefficient, and average shortest path length.

Four network classes are widely reviewed in the literature according to their statistical properties: regular networks, random graphs, small worlds, and scale-free networks (Albert & Barabási, 2002; Amaral & Ottino, 2004; Barabási & Bonabeau, 2003; Börner et al., 2007; Dorogovtsev & Mendes, 2002; Erdős & Rényi, 1959, 1960; Newman, 2003b; Strogatz, 2001; Wang & Chen, 2003; Watts, 2004).

3.3.1 Regular Networks

As intuition suggests, regular networks display the smallest average path length and the highest clustering coefficient. Regular network have N nodes and $N(N-1)/2$ edges. Regular networks do not appear in real-world. Nonetheless they may be useful to study a particular case of a regular graph, the so called *regular lattice*. The regular lattice is a model in which every node *i* is connected only to *k* of its neighbours. The term "lattice" as explained by Wang and Chen (2003) could suggest a two-dimensional (*d=2*) square grid, but the most simple lattice is uni-dimensional and can be represented by a row or a ring. This type of network is highly clustered, being $C_{REG} = 3/4$, while the average path length tends to infinity as $N \to \infty$.

3.3.2 Random Graphs

Erdös and Rényi (1959; 1960) were the first to study the statistical properties of random graphs (thus also called ER model). Since their pioneering work, random graphs have been widely studied in graph theory (Bollobás, 1985). This section looks at random graphs describing the properties that are more important from a "complex network" point of view.

First of all, an informal definition of random graph (random network) is provided. As described by Erdös and Rényi (1959), imagine N buttons scattered randomly on the floor, if one ties two buttons randomly together with probability p, one will end up with a random graph with on average $p * N(N-1)/2$ edges distributed randomly (Albert & Barabási, 2002; Dorogovtsev & Mendes, 2002; Erdős & Rényi, 1959, 1960; Strogatz, 2001). Random graphs described in this section have a fixed number of nodes, while the number of edges varies according to the probability of edge existence (p in the previous paragraph) (Dorogovtsev & Mendes, 2002) as shown in Figure 3-12.

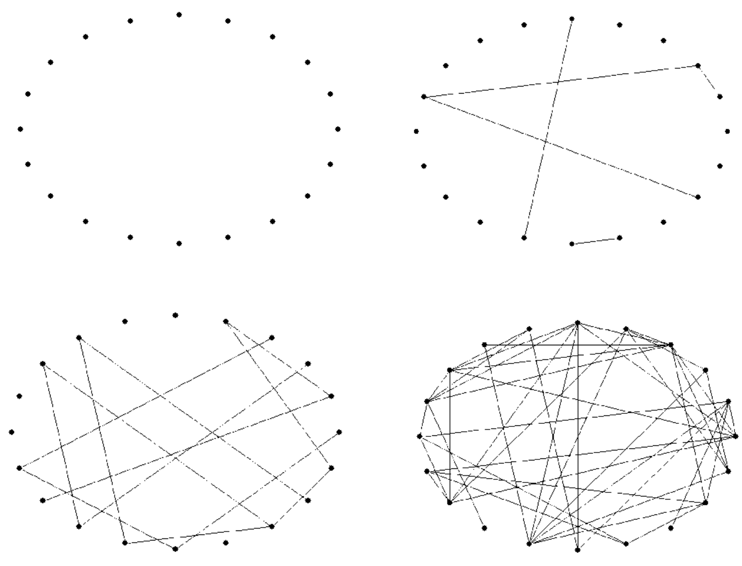


Figure 3-12 E-R (random) graph
N=20 and different probability of nodes being connected: from 0 (top-left), 0.05 (top-right), 0.1 (bottom-left), 0.25 (bottom-right) (Own elaboration).

Moreover, random graphs are characterized by the following average shortest path length: $\langle \ell_{ER} \rangle = \ln(N)/\ln(pN) \equiv \ln(N)/\ln(\langle k \rangle)$, that is, the average shortest path length increases as the natural logarithm of *N* for large *N*.

As explained section 3.2 on network measures, the clustering coefficient is a way to answer the following question: how many nearest neighbours of node *i* are also nearest neighbours to each other? In random graph, the probability that two of the nearest neighbours of node *i* are also nearest neighbours to each other is equal to *p*. Thus, the clustering coefficient of a random graph scales according to 1/*N*. More precisely: $C_{ER} = p = \langle k \rangle / N$.

Erdös and Rényi were also the first to study the maximum and minimum node degree in a random graph (Erdős & Rényi, 1959). The random graph degree distribution approaches a Poisson distribution for large *N* (Albert & Barabási, 2002; Dorogovtsev & Mendes, 2002). As explained above, a random graph contains $p * N(N-1)/2$ edges on average. Furthermore, the degree distribution is binomial (thus it approaches a Poisson distribution for large *N*): $P_{ER}(k) = \binom{N-1}{k} p^k (1-p)^{N-1-k}$, i.e. the average degree will then be equal to $p * (N-1)$. As mentioned above, for large *N* the degree distribution of a random graph can be thought of as a Poisson distribution, hence: $P_{ER}(k) = e^{-\langle k \rangle} \langle k \rangle^k / k!$, where the expected value and variance are equal to $\langle k \rangle$ (see Figure 3-13).

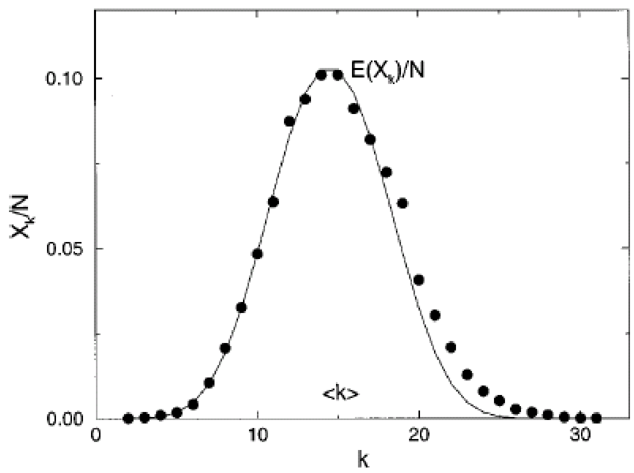


Figure 3-13 Degree distribution of a random graph
p=0.0015 and N=10000 (dots) compared to a Poisson distribution (line), where *k* is the degree and <*k*> is the average degree and y axis represent probability of finding a node with degree *k* (after Albert & Barabási, 2002).

Thus, it is possible to define a random graph as any graph whose degree distribution follows a Poisson. This peculiar distribution of node degree in random graph means that although edges are placed randomly, the resulting network is rather homogeneous, with most of the nodes having the same degree, while the distribution rapidly decays for large and small degrees (Dorogovtsev & Mendes, 2002).

3.3.3 Small-World Networks

Watts and Strogatz (1998) discovered that some real networks can not be classified as completely random graphs nor regular graphs. Thus, they thought of a model that could preserve important characteristics of both random and regular graphs.

The original small-world (SW) network can be thought of as the result of the lattice example described above. In this case, Watts and Strogatz represented a regular uniform and one-dimensional (represented by a ring) lattice, where every node i is connected to K nearest neighbours. From the regular lattice, then, every edge is rewired with a probability p. The higher the p parameter, the more the graph will resemble a random graph. Thus small-world graph can be defined as a class of graph that is neither completely ordered nor completely random, but somewhere in between.

The original model by Watts and Strogatz (1998) can also be obtained by adding new edges between the nodes of the lattice. In this case, node *i* and *j*, where *j* is not one of the nearest neighbours of *i*, are connected through an edge with probability ϕ. As shown in Figure 3-14, increasing ϕ has a very similar effect on the regular lattice as when increasing *p* in the rewiring small-world.

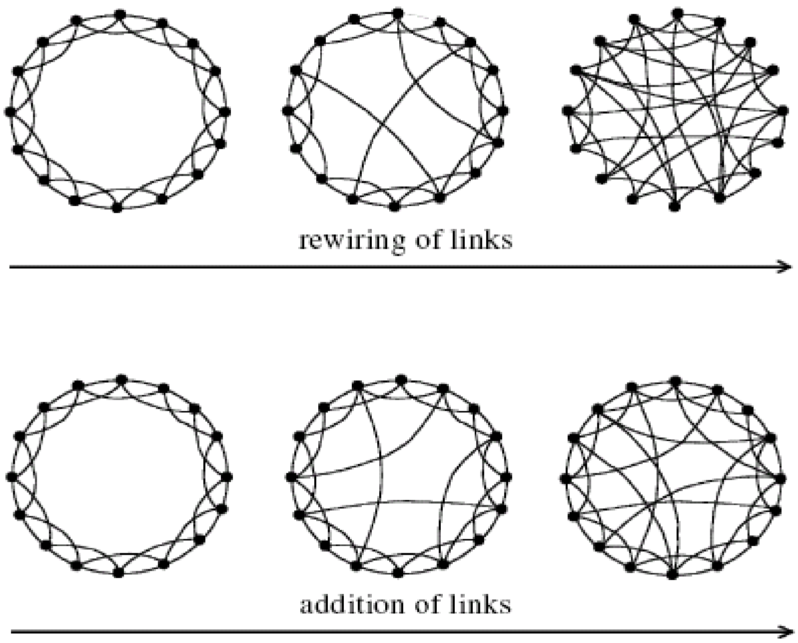
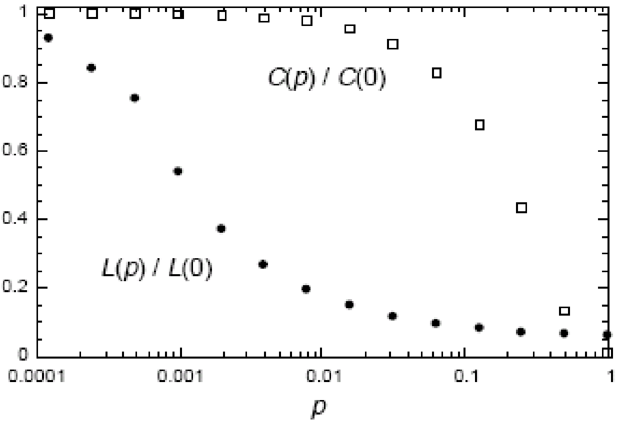


Figure 3-14 Generation of small-world networks
Rewiring edges (top) or addition of edges (bottom). In both cases the generation starts with a regular graph (left), as edges are rewired (top) or added (bottom) the graph becomes a small world (centre); continuing the process of rewiring edges (top) or addition of edges (bottom) leads to a random graph (right) (after Dorogovtsev & Mendes, 2002)

SW graphs can be positioned somewhere between random graphs and regular graphs, with regard to two measures explained in section 3.2. A regular lattice will display long average path length, scaling $\langle \ell_{REG} \rangle$ as N, while at the same time, it will be highly clustered, with C_{REG} independent of scale and equal to $3/4$ for large k. On the contrary, random graphs (ER-type) display a short average path length and $\langle \ell_{ER} \rangle$ scales as $\ln(N)$ (as explained in section 3.3.2), while they do not display a high clustering coefficient, scaling C_{ER} as $1/N$.



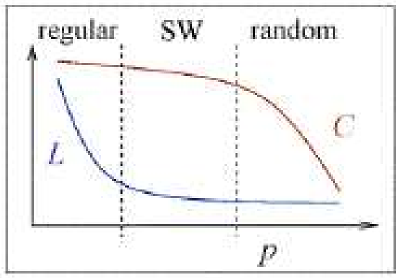


Figure 3-15 Average shortest path length and clustering coefficient in Small World networks Normalized shortest path length (here L) and clustering coefficient (C) as a function of p (rewiring probability) for the SW graph with *N*=10000 and <*k*>=10 (after Watts & Strogatz, 1998)

As depicted by Figure 3-14 and Figure 3-15, and as explained above, there is an abrupt change in the average path length that occurs for a given value of *p*. Thus, it is of interest to identify the value of *p* at which this transition occurs independent from the network size N. Since there is a size N^*, such as if $N < N^*, \langle \ell_{SW} \rangle \propto N$, but if $N > N^*, \langle \ell_{SW} \rangle \propto \ln(N)$ then p is dependent upon the system size. In other words, $\langle \ell_{SW} \rangle$ does not start to decrease until $p \geq NK$, at least one shortcut has to exist.

The clustering coefficient is slightly different in the case of the rewiring small-world graph or in the case of the edge addition small-world graph. More precisely:

- The clustering coefficient for the rewiring version is:
$$C_{SWR} = \frac{3(K-1)}{2(2K-1)}(1-p)^3;$$
- The clustering coefficient for the addition version is:
$$C_{SWA} = \frac{3(K-1)}{2(2K-1)+4Kp(p+2)}.$$

As Newman (2003b) points out, the degree distribution of small-world network does not approximate reality very well. This difference between the small-world degree distribution and the degrees distributions seen in real networks derives from the construction process of the small-world network. Moreover, SW degree distribution is calculated differently, whether it refers to the rewiring or the adding edge version of the model (with the latter simpler to calculate analytically).

If *p=0* than the degree distribution will be a vertical line to $\langle k \rangle$ (such as the degree distribution of a regular lattice) as shown in Figure 3-16:

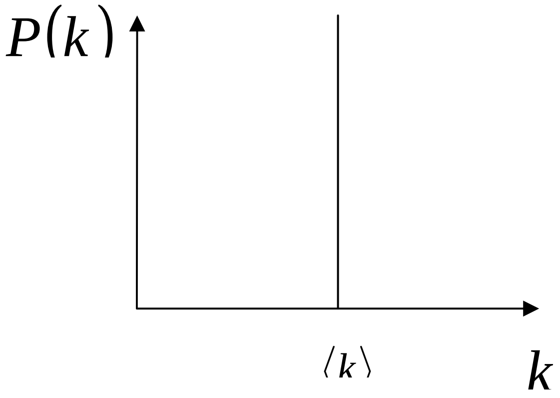


Figure 3-16 Regular lattice degree distribution
where <*k*> is average degree, and *P(k)* the proability of finding a node with degree *k*, being k the degree of a node (Own elaboration).

In the adding edges case, each node has at least a degree equal to 2*K*, plus a binomially distributed number of shortcuts, thus it is possible to affirm that the probability *P(k)* of having degree *k* is equal to:

$$P(k) = \binom{N}{k-2K}\left[\frac{2Kp}{N}\right]^{i-2K}\left[1-\frac{2Kp}{N}\right]^{N-i+2K}$$

for $K \geq 2K$ and $P(k) = 0$ for $k < 2K$.

In the rewiring edges case, for $p > 0$ each node will still retain at least *K/*2 edges after the rewiring process is complete. Following Barrat and Weigt (2000) the degree distribution in the rewiring case can be formalized as follows:

$$P(k) = \sum_{n=0}^{\min(k-K,K)} \binom{K}{n}(1-p)^n\, p^{K-n}\,\frac{(pK)^{k-K-n}}{(k-K-n)!}e^{-pK}$$

for $k \geq K$ and $P(k) = 0$ for $k < K$.

The resulting degree distribution is a rather homogeneous one, similar to the degree distribution of a random graph (Poisson), with a peak and an exponential decay as shown in Figure 3-17. Moreover, Figure 3-17 shows how small-world networks are rather homogeneous, with the majority of nodes having the same degree (as the peak at $\langle k \rangle = K$ suggests).

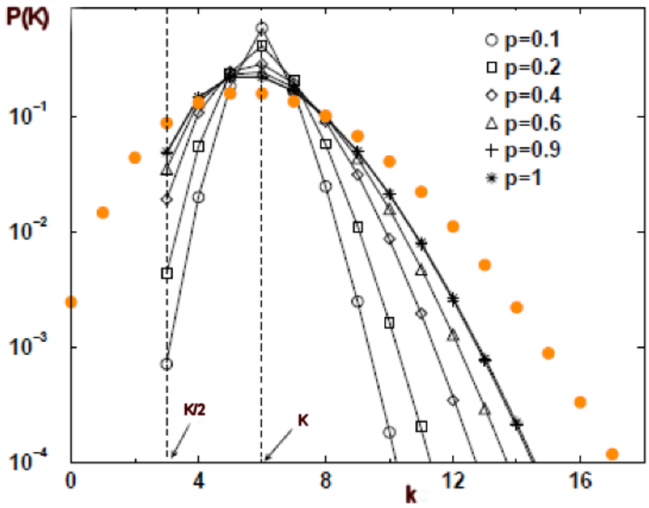


Figure 3-17 Degree distribution of the small-world network
Rewiring edges for K=3, different levels of p and N=1000; full circles represent the corresponding ER graph. *k* = degree of node *i* and *P(k)* = probability of finding a node with degree *k* (after: Barrat & Weigt, 2000).

3.3.4 Scale-Free Networks

ER graphs and SW networks have similar degree distributions, that is, both classes of networks peak at a certain value $\langle k \rangle$ and then they decay exponentially (as depicted in Figure 3-13 and Figure 3-17).

However, in real networks, nodes and edges are not randomly assigned, but the way they behave and attach follows specific rules. One of these rules can be classified as *preferential attachment*: new nodes will connect to the already most connected nodes in the network. Preferential attachment can also be thought of as popularity is attractive (or the rich get richer).

Barábasi and Albert (1999) construct a model (BA) that is capable of reproducing the preferential attachment behaviour. Moreover, the BA model differs with respect to ER and SW in the fact that it is a dynamic model; hence, it looks at the evolution of a network, assuming that the topology of a network can be explained by its evolution through time. More precisely the BA model is based upon the application of two rules, which are considered key features of networks that are built on real data.

- **Growth**: starting with a small number of nodes N_0, at every time step one new node is added and connected to *n* already existing nodes, being $n < N_0$;
- **Preferential attachment**: the probability Π that a new node will attach to an already existing node depends on the degree *k* of the already existing node *i*: $\Pi(k_i) = \frac{k_i}{\sum_j k_j}$.

After a certain time interval *t*, the network constructed following the rules defined here, will have $N = t + N_0$ nodes and kt edges (Figure 3-18 shows the evolution and construction of such a scale-free network).

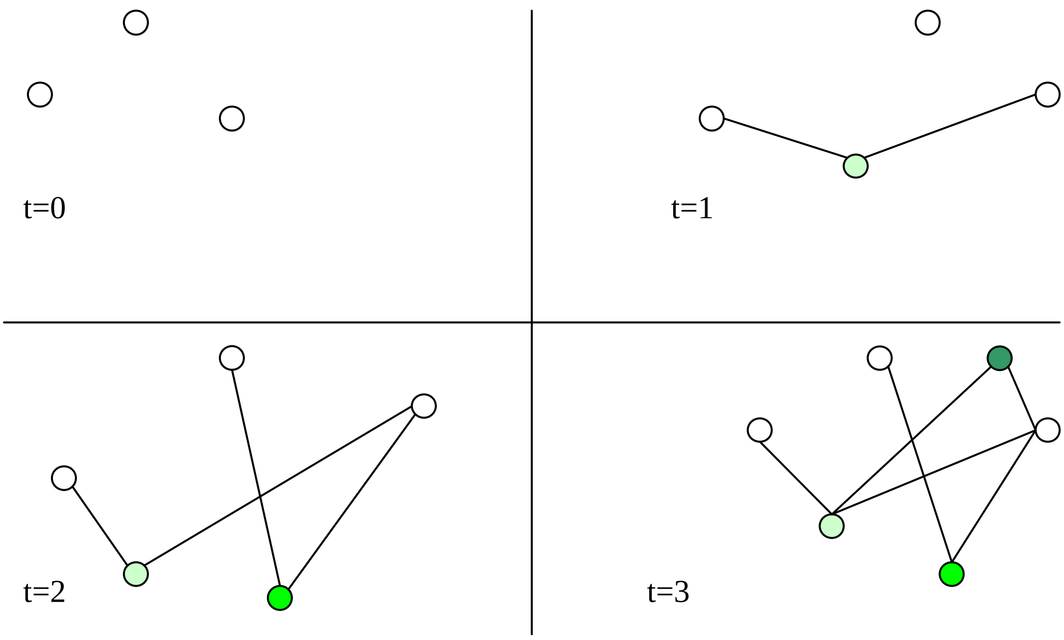


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Figure 3-18 Evolution of a the BA model
Starting with $N_0=3$ number of nodes, at each time step a new node is added as well as $k<N_0=2$ number of edges, new nodes attach according to the preferential attachment rule (Own elaboration).

Numerical simulations show how the BA model evolves into a scale invariant state (thus the name Scale-Free) where the probability of finding a node with degree *k* follows a power law with exponent γ_{BA} equal to 3: i.e. for large N, $P(k) \propto k^{-3}$.

Figure 3-19 depicts numerical simulations for the BA model with different starting number of nodes.

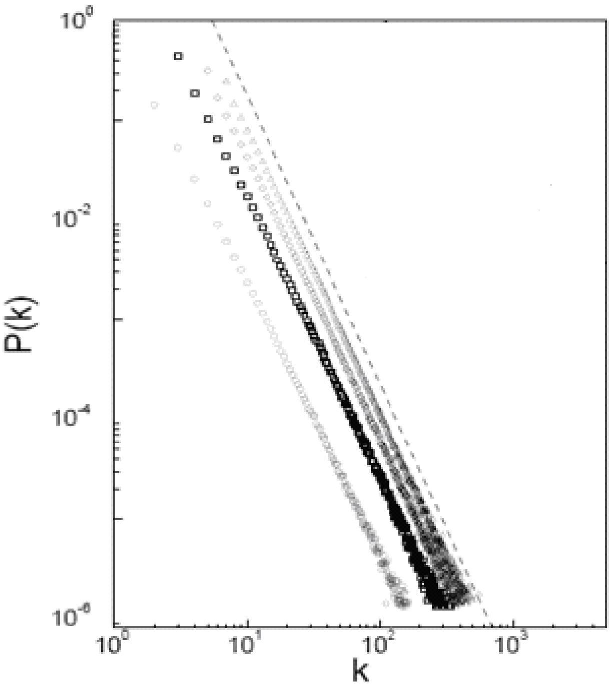


Figure 3-19 Numerical simulation of the BA model
Where $N=N_0+t$=300,000 and N_0 differs, being 1 (circles), 3 (squares), 5 (diamonds), 7 (triangles). Being *k* the degree of node *i* and *P(k)* the probability of finding a node with degree *k* (after Barabási et al., 1999).

The average path length of the BA model is smaller compared to that of a random graph (ER), as shown in Figure 3-20. More precisely, the average path length of the BA network increases with respect to the logarithm of *N*, with the best fit assuming the following form: $\langle \ell_{BA} \rangle = A \ln(N - B) + C$.

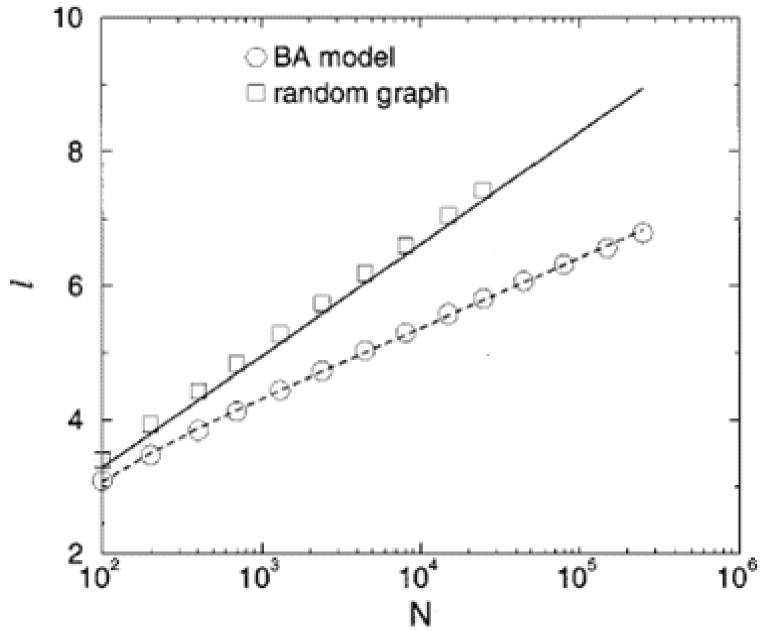


Figure 3-20 ER (random graph) and BA model average path length (*l*)
The network having <*k*>=*4* and being of the same size *N* (after Albert & Barabási, 2002).

The fact that the BA model has a smaller average path length than that of a random graph ER indicates the higher efficiency of the Scale-Free topology compared with the random graph topology when nodes are hit by random errors (see section5.1 for more information on errors and attacks effect on different network topologies). The clustering coefficient has been widely investigated for Small-Worlds and Random Graphs; there is no analytical formulation of *C* for the BA model. However, Albert and Barabási (2002) show that the clustering coefficient of a BA network will be of the following form: $C_{BA} \propto N^{-0.75}$, which is higher than the clustering coefficient of a random graph (being $C_{ER} \propto N^{-1}$) as shown in Figure 3-21.

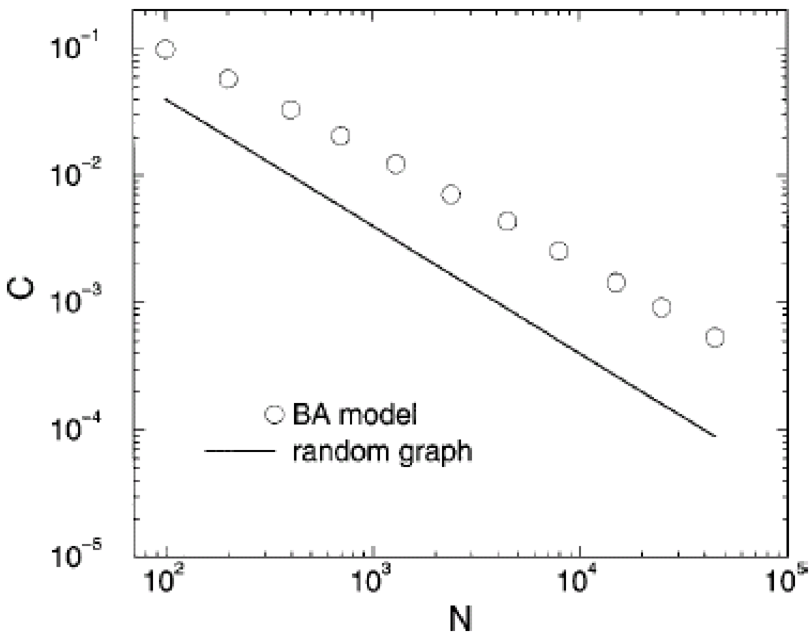


Figure 3-21 Clustering coefficient (*C*) of the BA model and the ER graph
Note how the two clustering coefficient diverge when *N* (size of the network) increases (after Albert & Barabási, 2002).

Another important property of the BA model is that its node degrees are correlated. This result is the outcome of the construction of the network (that evolves) and is a feature that is not present in random graphs (where node degrees are uncorrelated). In other words, if nodes that have degree k and nodes that have degree l are taken into account, then the number of pairs connected with degrees k and l will be n_{kl}. Since $n_{kl} \neq n_k n_l$, correlations do exist (in random networks $n_{kl} = n_k n_l$). It is important to know that this correlation arises spontaneously, but are nevertheless non-trivial (due to the dynamical process that generates the BA network).

3.3.5 Modularity

All the network classes described in section 3.3 can have different characteristics based on the metrics portrayed in section 3.2. Another characteristic of complex networks is modularity. Modularity or community structure seems to be a common feature of many different networks (Newman, 2006; Newman & Girvan, 2004). A modular structure refers to a network whose nodes are densely connected within a specific group and loosely connected to nodes belonging to other groups. Figure 3-22 graphically displays a modular network.

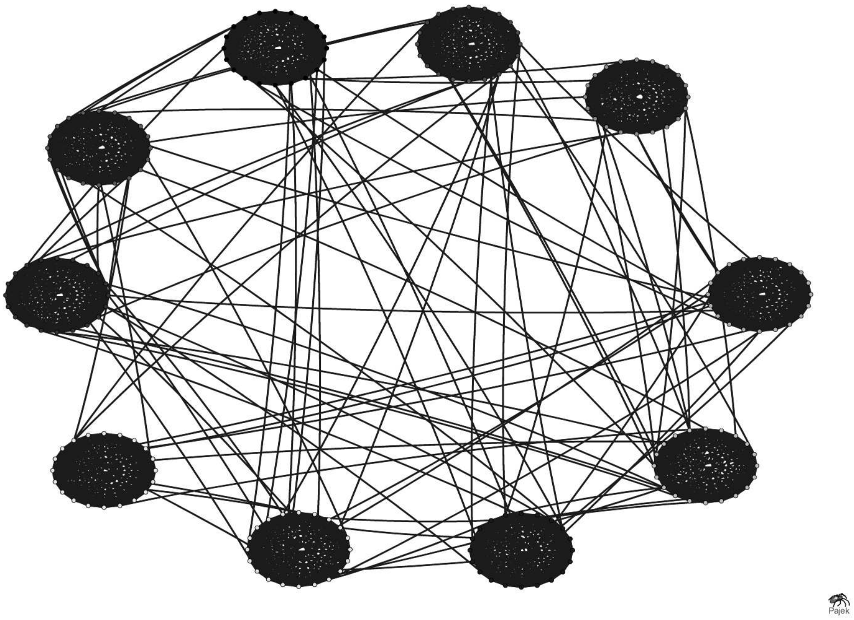


Figure 3-22 Modular network with 10 communities (Own elaboration)

Discovering the best possible partition of a network across communities is a non-trivial problem. There is a need to balance accuracy and computational limits given by present-day possibilities (and costs). Newman and Girvan (2004) propose the following algorithm in order to detect community structures (or modules) in complex networks:

1. The betweenness scores for all edges in the network is calculated (i.e. refer to section 3.2.1 for detailed information on betweenness).
2. The edge with the highest betweenness score is removed from the network; if two or more edges have the same highest score, one edge will be randomly chosen and removed.
3. Repeat steps 1 and 2.

This algorithm allows defining different modules existing in a network and introduces a new network metric: the *modularity index* (Newman & Girvan, 2004).

The modularity index is a measure that allows the comparison of different network partitionings. Formalizing, Q being the modularity index:

$Q = \frac{1}{2M}\sum_{ij}\left(a_{ij} - \frac{k_i k_j}{2M}\right)\delta_{c_i,c_j}$, where c_i represent the community to which node i belongs and δ_{c_i,c_j} is the Kronecker delta function taking value 1 if nodes i and j belong to the same community, and 0 otherwise. M represents the total number of edges in the network and a_{ij} represents the network's adjacency matrix (see section 3.1).

To this point , this chapter introduced and described network structures and the most common metrics used in the literature. Moreover, a brief classification of networks based on certain metrics is given. The next section of this chapter characterizes real networks as found in the literature and reports their main metrics.

3.4 Real Networks

In the previous sections of this chapter, the main measures used to topologically characterize a network have been explained, and four models that are often used to classify a graph have been presented: regular, random (ER), small-world (SW) and scale free (SF). This section summarizes a sample of networks studied, giving a central role to ecological networks (more precisely, food webs).

The increased use of complex network tools is largely attributed to the growing interest in complexity issues since the turn of the last decade, thus the will to go beyond reductionism and understand organizing principles of complex systems accompanied by the increase in computing power and the possibility of accessing large databases. This led to the study of the first real world networks (Albert & Barabási, 2002; Dorogovtsev & Mendes, 2002).

Since 1999 a number of real networks have been analysed (see the reviews of Albert & Barabási, 2002; Caldarelli, 2007; Dorogovtsev & Mendes, 2002; Newman, 2003b; Watts, 2004). Some of the most meticulously studied large networks are: the World

Wide Web, the citation of academic papers and the scientific collaboration networks. This is also due to the availability of data and the small relative cost of obtaining them.

At present, the World Wide Web represents the largest network on which information is available. The WWW network is defined as a graph whose nodes are the web pages and whose edges are the hyperlinks connecting two web pages. It is a directed network; thus, it has an in-degree distribution and an out-degree distribution. At first, as explained in Barabási and Albert (Albert & Barabási, 2002; Barabási & Albert, 1999), scholars were expecting the WWW to follow a Poisson distribution, hence behaving as a random graph. However, they soon discovered that the WWW was following a power law degree distribution, thus resembling what has been classified as a scale-free network. Table 3-1 gives an overview of the studies that refer to the World Wide Web.

Table 3-1 World Wide Web based networks

Network	N	$\langle k \rangle$	γ_{out}	γ_{in}	$\langle \ell \rangle$	C
WWW	325729	4.51	2.45	2.10	11.20	
WWW (Altavista)	203549	10.46	2.70	2.10	16.18	
WWW pages (nd.edu)	269504	5.55	2.40	2.10	11.27	0.29
WWW, site level	153127	35.21		1.94	3.10	0.11

Notes: The table reports their size (*N*), the average degree ($\langle k \rangle$) the in and out degree exponent of the power law distribution (γ_{in} and γ_{out}), the average path length ($\langle \ell \rangle$) and the clustering coefficient (C) (adapted from: Albert & Barabási, 2002; Dorogovtsev & Mendes, 2002; Newman, 2003b).

In citation networks, academic papers represent the nodes of the network and citation to other papers represents the edges. This type of network excludes or renders highly improbable the appearance of loops, since it is very unlikely to cite papers that are still not published (with the citation of forthcoming papers as an exception). Collaboration on scientific papers is another well studied network. Here, nodes are represented by authors and an edge is formed when two authors collaborate on a paper. This type of network is often limited to authors that pertain to a certain "literature" (e.g. medline, biology, mathematic, physics and so on). Table 3-2 gives an overview of citation and collaboration networks that have been analysed in the literature.

Table 3-2 Co-authorship and citation based networks

Network	N	$\langle k \rangle$	γ	$\langle \ell \rangle$	C
SPIRES co-authorship	56 627	173.0	1.2	4.0	0.73
Biology co-authorship	1 520 251	15.5		4.9	0.60
Neuroscience co-authorship	209 293	11.5	2.1	6.0	0.59
Math. co-authorship	70 975	3.9	2.5	9.5	0.76
LANL co-authorship	52 909	9.7		5.9	0.43
Citation	783 339	8.6	3.0		

Notes: The table reports their size (*N*), the average degree ($\langle k \rangle$) the degree exponent of the power law distribution (γ), the average path length ($\langle \ell \rangle$) and the clustering coefficient (C) (adapted from: Albert & Barabási, 2002; Dorogovtsev & Mendes, 2002; Newman, 2003b).

Networks have also been analysed in different context such as biology (e.g. protein and neural networks) and linguistics (e.g. words that appear in the same sentence). Networks examining the structure of boards of directors have also been studied, where every director is a node and an edge is formed when two directors sit on the same board. Finally, other types of networks such as the network of sexual contact and of telephone or e-mail exchange have been analyzed. Table 3-3 gives a summary of these studies.

Table 3-3 Other networks

Network	N	$\langle k \rangle$	γ	γ_{out}	γ_{in}	$\langle \ell \rangle$	C
Caenorhabditis elegans	282	14.0				2.65	0.28
Escherichia coli (metabolic)	778	7.4	2.2			3.20	
Metabolic network	765	9.6	2.2			2.56	0.67
Protein interactions	2115	2.1	2.4			6.80	0.07
Saccharomyces cerevisiae	1870	2.4		2.4	2.4		
Word co-occurrence	460902	70.1				2.67	0.44
Words Roget's Thesaurus	1022	5.0				4.87	0.15
Words, synonyms	22 311	13.5	2.8			4.50	0.70
Film actors	449 913	113.4	2.3			3.48	0.78
Company directors	7 673	14.4				4.60	0.88
E-mail messages	59 912	1.4		2.0	1.5	4.95	0.16
E-mail address books	16 881	3.4				5.22	0.13
Phone call	533106	3.2		2.1	2.1		
Sexual contacts	2 810			3.4	3.4	3.20	

Notes: The table reports their size (*N*), the average degree ($\langle k \rangle$) the in and out degree exponent of the power law distribution (γ_{in} and γ_{out}) or the degree distribution if the network is undirected (γ), the average path length ($\langle \ell \rangle$) and the clustering coefficient (C) (adapted from: Albert & Barabási, 2002; Dorogovtsev & Mendes, 2002; Newman, 2003b).

3.4.1 Ecological Networks: Food Webs

Although ecological networks resemble topological characteristics of other networks (Dunne et al., 2002a, 2002b), recent development points at treating them as transportation networks (Caldarelli, 2007; Garlaschelli, 2004; Garlaschelli et al., 2003). In other words, ecological networks are represented as the structure on which other dynamics unfold.

Ecological networks, more precisely food webs, require the detection of the predator-prey relationships of every species with all others present in the designed study area. This predator-prey relationship may as well be represented by a network whose nodes are species and whose directed edges are predator-prey relations.

Theoretically, in order to properly describe an ecological system it would be crucial to know the amount of predation as well, but, since this information requires extensive field work it is usually overlooked by most food webs studies. Although the nodes of a food web usually represent different species, recent studies prefer to design ecological networks whose nodes represent trophic species (Caldarelli, 2007; Dunne et al., 2002a, 2002b; Garlaschelli, 2004; Garlaschelli et al., 2003; Williams & Martinez, 2000). Trophic species are defined as a group of species that are functionally equivalent, that is, that share the same set of prey and predators[3].

A food web shapes and is shaped by the environment. Simple organisms such as bacteria and plants form the basis of a food-web, and for this reason they are also called *basal* (species that have no prey). Basal species have to convert the flow of resources that comes from the environment into a flow of resources for *intermediate* species (species that have preys and predators) that in turn will transform more resources in order to sustain *top* species (species that have no predators). Figure 3-23 graphically represents such relations.

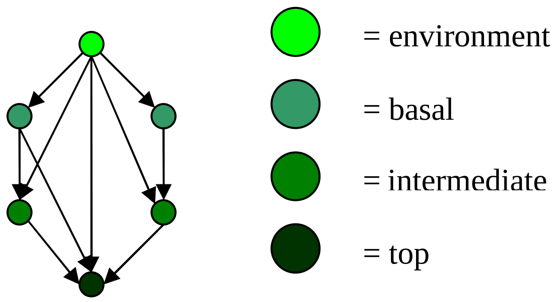


Figure 3-23 Food-web graphic representation
The flow of resources is represented by the directed edges while nodes represent trhophic species (Own elaboration).

The flow of resources is the crucial element in a food web, and the ecological network can be thought of as a transportation network in which resources are transferred from the environment up to top species (Garlaschelli, 2004; Garlaschelli et al., 2003). According to Dunne et al. (2002a; 2002b) *connectance* (also called *edge density*) plays a crucial role in assessing the robustness of a food web. Connectance can be defined as the number of edges (predations) that are present in an ecological network with respect to the maximum number of possible edges (predations).

[3] From here on, for brevity the word species refers to trophic species unless other specified.

Formally: $c = m/n(n-1)$, where $m =$ the number of edges that exist in the web and $n(n-1) =$ the number of possible edges (hence for big enough n, $c \cong m/n^2$).

Recent studies that depict food webs as transportation networks have led to the discovery of scale-invariance of the system (Garlaschelli, 2004; Garlaschelli et al., 2003). Moreover, depending on the graphical representation of the transportation network it is possible to assess the efficiency of the food web, with a star-like network appearing as the most efficient and the chain-like network as the least efficient (see Figure 3-24).

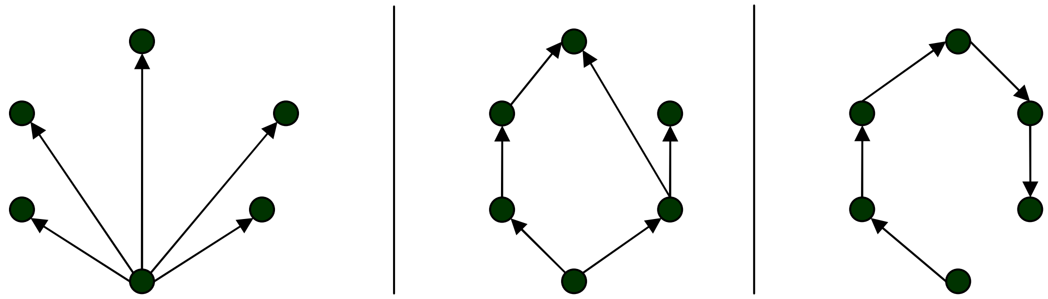


Figure 3-24 Food webs as transportation networks
From the most efficient (star-like at the left) to the least efficient type (chain-like at the right), (Own elaboration).

Furthermore, it is possible to associate the star-like and the chain-like topology of a food web to an "efficiency exponent" η; with $\eta = 1$ attributed to the most efficient network (shown at the left in Figure 3-24) and $\eta = 2$ to the most inefficient network (shown at the right in Figure 3-24) (Garlaschelli, 2004; Garlaschelli et al., 2003). Table 3-4 reports the main food-webs studied so far with the most important measures used to characterize them.

Table 3-4 Food-webs

Food web	N	c	$\langle \ell \rangle$	C	η
Bridge Brook Lake	25	0.171	1.85	0.16	
Skipwith Pond	25	0.315	1.33	0.33	1.13
Coachella Valley	29	0.312	1.42	0.43	1.13
Chesapeake Bay	31	0.071	2.65	0.09	
St Martin Island	42	0.116	1.88	0.14	1.16
St Marks Seagrass	48	0.096	2.04	0.14	1.16
Grassland	63	0.026	3.74	0.11	1.15
Silwood Park	81	0.030	3.11	0.12	1.13
Ythan Estuary[1]	83	0.057	2.20	0.16	1.13
Scotch Broom	85	0.031	3.11	0.12	
Little Rock Lake	93	0.118	1.89	0.25	1.13
Canton Creek	102	0.067	2.27	0.02	
Stony Stream	109	0.070	2.31	0.03	
Ythan Estuary[2]	124	0.038	2.34	0.15	1.13
El Verde Rainforest	155	0.063	2.20	0.12	
Lake Tahoe	172	0.131	1.81	0.14	
Mirror Lake	172	0.146	1.76	0.14	

Notes: Where possible, for every food web the number of trophic species (size N), connectance (c), average path length ($\langle \ell \rangle$), clustering coefficient (C) and the efficiency exponent (η) are reported. Ythan Estuary is reported without (1) and with (2) parasites (adapted from: Dunne et al., 2002a; Garlaschelli, 2004)

3.5 Concluding Remarks

This chapter has introduced one of the tools and techniques that will be used at a later stage in order to assess the resilience of a system. First of all the structure of networks has been explained and some definitions of network structures have been presented (e.g. sub-graphs, trees, cycles, complete sub-graphs).

The most commonly used measures have been introduced so as to characterize the topological features of a network (e.g. global efficiency, local efficiency, degree, degree distribution, closeness centrality etc). Finally, the interdisciplinary character of network theory has been demonstrated by looking at how networks have been applied in very different domains. Section 3.4 has shown how network theoretical tools have been used in different disciplines that go from biology to ecology, from economics to sociology, highlighting food webs as transportation networks. Given the use of network approaches in such different disciplines, the use of network metrics appears to be a promising avenue for characterizing CAS, such as SES from a structural perspective. Network theoretical tools need to be used in conjunction with a framework that allows us to explicitly incorporate SES characteristics. Network theoretical tools embedded in a resilience framework (explained in Chapter 4) will be used to assess SES resilience in subsequent chapters of this work (i.e. Chapters 6, 7, and 8).

4 Resilience Theory

This chapter centres on the concept of resilience, so as to put in context the methodological tools that will be used as the analysis proceeds (i.e. chapters 6, 7, and 8). Section 4.1 defines resilience and justifies the linkages that exist between the social and the ecological systems. Section 4.1.1 reports the main methods used and the theoretical advancements made in resilience theory (i.e. adaptive cycle and panarchy). Section 4.1.2 introduces the peculiarities of humans and how they can influence ecological systems.

Section 4.2 glances upon the several attempts made to measure resilience across different disciplines. Section 4.2.1 shows the importance of human interactions with the ecological system using the framework of Anderies et al. (2004). Finally, section 4.3 summarizes the main characteristics of the resilience theoretical framework in relation to thiw work, and gives brief concluding remarks on the importance of resilience for the analysis of a SES.

4.1 Linking Social and Ecological Resilience

Resilience is the ability of a SES to absorb disturbance and re-organize while undergoing change, so as to still retain essentially the same functions, structures, identity and feedbacks (Walker et al., 2004).

The definition above has evolved from the original one introduced by Holling in the early 1970's when equilibrium thinking was still the most important way to look at a system. In his seminal paper, Holling (1973: 17) defines resilience "as the ability of an ecological system to return to an equilibrium state after a temporary disturbance". Resilience as defined by Walker et al. (2004) can be thought of as the synthesis between Gunderson and Holling definition of resilience given in 2002 (Gunderson & Holling, 2002) and the operational definition given by Carpenter et al. (2001). Specifically resilience refers both to the amount of disturbances that a system can undergo while maintaining its original functions and controls (Gunderson & Holling, 2002)[4], as well as to the extent to which a SES is able to self-organize, learn and adapt (Carpenter et al., 2001) [5].

The resilience definition used is based on non-equilibrium and accommodates the need to be "integrative" (i.e. using a systemic approach) in order to understand any SES. That is, it goes beyond reductionism and looks at how a system behaves as a whole. It is not possible to look at single and separated causation relation, as it is important to look for and understand multiple causes that are at least partially interlinked with each other. Furthermore, it is crucial to incorporate uncertainty, and base decisions upon multiple hypotheses, and not upon the testing (approve/reject) of a single one (Holling, 1998).

Since the resilience concept embraces uncertainty and multiple hypotheses, the interaction between humans and nature (characterized by uncertainty, surprises and multiple possible explanations) becomes central in order to be able to give a reasonable explanation of a SES. Moreover, it is accepted that production/consumption and well-being do not only depend on the social system, but also on the ecological system in which they are embedded (Arrow et al., 1996; Olsson et al., 2004; Scoones, 1999; Walker et al., 2002).

According to Scoones (1999) the ecological system is the result of the interaction between itself and the social system, more precisely the ecological system affect the social one, which in return impacts upon the ecological system as shown in Figure 4-1.

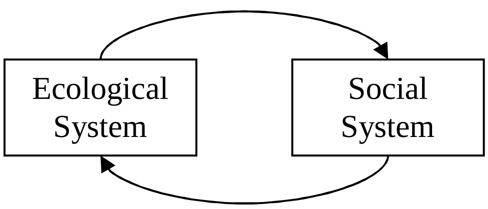


Figure 4-1 Interaction between social and ecological systems (Own elaboration).

[4] i.e. a measure of the system's ability to cope with unexpected/unpredictable events (Holling, 2001).
[5] For in depth information on the various definition of resilience used in the literature, please refer to (Brand & Jax., 2007).

Therefore, a specific SES is the result of a context specific history of (inter)actions occurring between humans and the environment (Scoones, 1999), hence the importance of linking social issues to ecological issues. It is then possible to define a spatial system[6] consisting of two major components: humans and nature (i.e. social system and ecological system). Thus, resilience is a characteristic of the whole system (social AND ecological) and the interactions and processes that exist between and within the two system are fundamental for its assessment.

It is worth recalling that resilience is the ability of a system to absorb disturbance and re-organize while undergoing change so as to still retain essentially the same function, structure, identity and feedbacks (Walker et al., 2004). Given the interlinkages that exist between the social and the ecological system, it is possible to argue that social and ecological resilience are strictly related. According to Adger (2000) the link that exists between the social and the ecological system is stronger the more a community is resource dependent. Therefore, the resilience of an SES will depend on the biodiversity of the ecosystem among other ecological variables, and on the institutional rules and the means of production that are present in the social system. The stronger the resource dependency of a given community, the stronger the relation between social and ecological resilience will be. Thus it is possible to say that for many predominantly rural societies, social relations are mainly shaped by the local environment in which they are embedded. Such communities are not able or do not have the possibility to substitute natural for man-made capital. This reasoning leads to assert the importance of enhancing the resilience of a SES. From this point of view the resilience of a system is a vital component of sustainable development and sustainable resource utilization (Adger, 2000).

[6] Here a spatial system refers to any territorial space where there exist nature and human interaction (directly or indirectly). To some degree a spatial system can be defined as any region or territory on earth. The boundaries will be artificial in any case.

4.1.1 From Adaptive Cycles to Panarchy

Starting from the original definition of resilience in 1973, and proceeding to the most recent definition given by Walker et al. (Holling, 1973; Walker et al., 2004), it is possible to affirm that the complexity of SES does not rely upon the random interaction of a great number of elements, but, most likely, on the interlinkages that occur between a small set of controlling variables (Holling, 2001, 2004). Amaral and Ottino (2004: 148) define *complex adaptive system* as follows:

> A complex system is a system with a large number of elements, building blocks or agents, capable of interacting with each other and with their environment. The interaction between elements may occur only with immediate neighbours or with distant ones; the agents can be all identical or different; they may move in space or occupy fixed positions, and can be in one of two states or of multiple states. The common characteristic of all complex systems is that they display organization without any external organizing principle being applied. The whole is much more that the sum of its parts.

According to Holling (2004) and to the definition above, self-organization is crucial, and is achieved thanks to a small set of controlling variables interacting with each other. These interactions are the drivers of the complexity, the adaptability and the transformability of a SES. The evolution of these key interconnected elements can be represented by an *adaptive cycle*.

The adaptive cycle is an abstract construction in which four stages are represented. A system does not follow the four stages linearly, but it can jump from one phase to another, forward or backwards. The four phases are defined as: growth, accumulation, restructuring, renewal and they can be divided into two main parts: a front-loop of growth (or exploitation) (r) and accumulation (or conservation) (K) and a back-loop of novelty (or release or creative destruction) (Ω) and renewal (or reorganization) (α). The front-loop is generally more predictable and less characterized by uncertainties and surprise (thus more stable), while the back loop is generally less predictable or unpredictable and is characterized by a higher degree of surprise and uncertainty (thus more unstable). Figure 4-2 represents the adaptive cycle. It is important to stress again that the succession is not linear, but a system can jump from one phase to another independently of the arrows shown in Figure 4-2. It is also worth noting that accumulation refers to accumulation of resources that can be either desirable or not (e.g. phosphates accumulation in soil due to fertilizers).

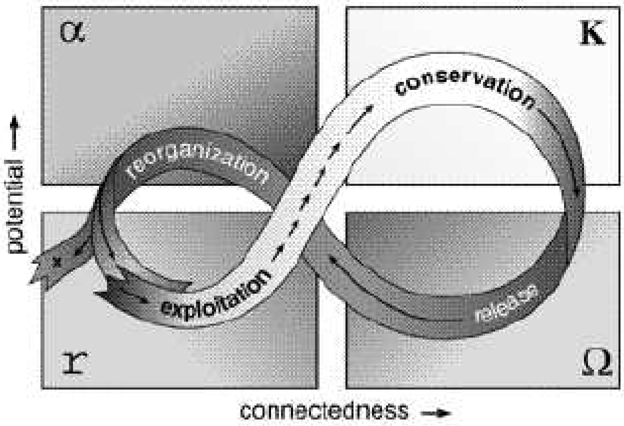


Figure 4-2 Adaptive cycle representation
Arrows on the loops indicate the succession of stages (after: Gunderson & Holling, 2002).

Three main dimensions allow the definition of the different stages of the adaptive cycle: potential, connectedness and resilience; in other words: the capacity of the system to accumulate and use resources, the increase of the rigidity of connections and the capacity of the system to absorb shocks. Figure 4-2 represents the adaptive cycle on a plane: the axis of "resilience" is not shown. If the third axis is added and the cycle is projected in a three dimensional space, it is possible to observe how resilience increases or decreases depending on the phase of the cycle (as shown in Figure 4-3).

More precisely, in this thesis, the most important relationship is the one occurring between connectedness and resilience: as connectedness increases, the resilience of the system seems to decrease. Connectedness can be thought of a measure of the rigidities of a system. A rigid (highly connected) system undermines the ability to respond (adapt effectively, or maintain controls and functions) to surprise and uncertainty, since the flexibility and learning from different experiences is crucial for maintaining a system in a desirable state. For example, one may think of connectedness as wires between two objects. At first, an increase in connectedness renders the two objects more stable, thus enhancing their state, but if the number of wires keep increasing, than eventually the two objects will be unable to move. In this case, a shock affecting one of the two objects will transmit entirely to the other, favouring a “cascading” collapse.

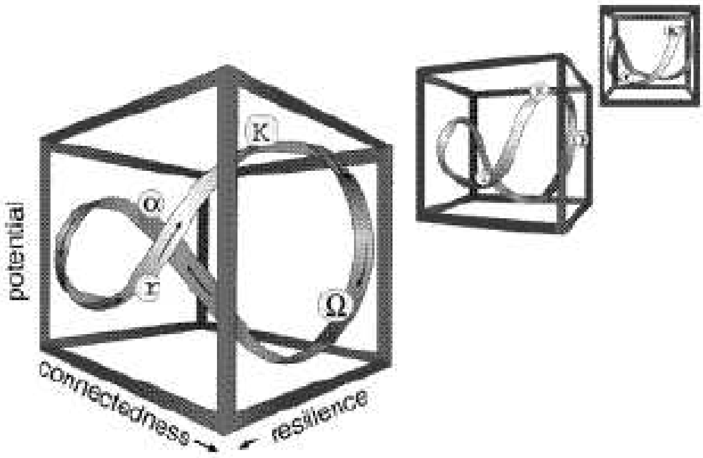


Figure 4-3 Adaptive cycle projected in a three dimensional space (after: Holling & Gunderson, 2001).

The Lake Mendoza case study (Carpenter et al., 2001) is reported as an example to facilitate the understanding of the adaptive cycle. Since the object of the example is a lake, it is possible to affirm that the management will attempt to keep the lake in its desirable state of clear water versus the undesirable state of turbid water (from here on: clear state and turbid state). According to Carpenter et al. (2001) Lake Mendoza in Wisconsin is an example of a slow change from the clear state to the turbid state. The lake was characterized by a first front loop of growth and accumulation (from r to K) when the first settlers came in the 1840’s. Agricultural production did not increase much, but population did, as well as the human-produced waste. After World War II, an increase in agricultural production as well as urbanization in the area triggered a sharp decrease (collapse) in water quality (with the lake being now in the Ω phase as a result).

Given the situation, the proposed solution favoured the diversion of sewage effluents from the lake (phase α, reorganization and experimentation of new ways). Unfortunately, when completed, the diversion did not improve the water condition of the lake, since what was saved from sewage was added to the lake as increase in fertilizer use. The spread of bacteria created public nuisance and lowered even more the water quality of the lake, hence returning rapidly to another Ω phase. Since the failure of the sewage effluent diversion, managers of the lake thought of another way to tackle the continuing decrease of water quality, hence initiating another set of policies aimed to restore/increase water quality in Lake Mendoza (another α phase), but due to low participation of the most affected interest groups (social problem), this possible remedy produce limited results, leading to another Ω phase. Again, a new set of possible solutions was put in place (this time bio-manipulation) initiating a new reorganization (α) phase, and for the fourth time, the policies in place did not result in the desired outcome. Hence, nowadays a new set of policies is tried, although the effects can still not be ascertained. Figure 4-4 summarizes the adaptive management cycles of Lake Mendoza:

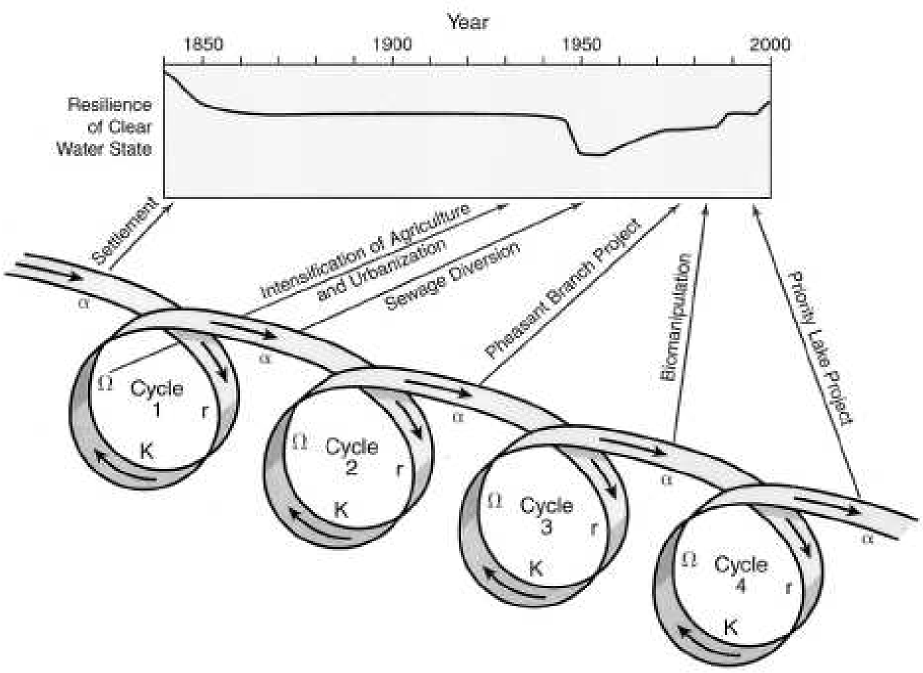


Figure 4-4 Adaptive cycle representation of management of Lake Mendoza (after: Carpenter et al., 2001).

From Figure 4-4 it would seem that the stages of the adaptive cycle are subsequent to one another, but again, it is important to remind that the phases of the adaptive cycle do not follow any order by definition (Walker et al., 2004): its stages are by no means intended to be fixed and regular. Systems can move forward, or go back from one phase to another, may even jump certain stages, but most importantly, cycles occur at a number of different scales, hence cross-scale interactions are crucial in determining the dynamics of a SES (Walker et al., 2004).

SES are characterized by multiple cross-scale interactions, involving high levels of uncertainty and possible surprises. In addition, cross-scale interactions are, according to the resilience perspective, what defines a SES multi-stable behaviour (Folke, 2006); that is, SES can have multiple stabilities in the same basin of attraction (as explained in section 4.1.2). Therefore cross-scale interactions may be the reason why policies that seem to be appropriately targeted for a single issue do not succeed, as these kind of policies fails to address other levels of the system. Cross-scale interaction can be divided into two main categories as shown in Figure 4-5:

- Time interactions: policies and actions implemented today may have undesired consequences in the future and may be limited by actions and policies implemented in the past.
- Space interactions: policies and actions at the local level may be influenced or may influence unintentionally policies and actions taken at a higher level (e.g. local actions are influenced and may influence county policies and actions that influence or are influenced by national policies and action).

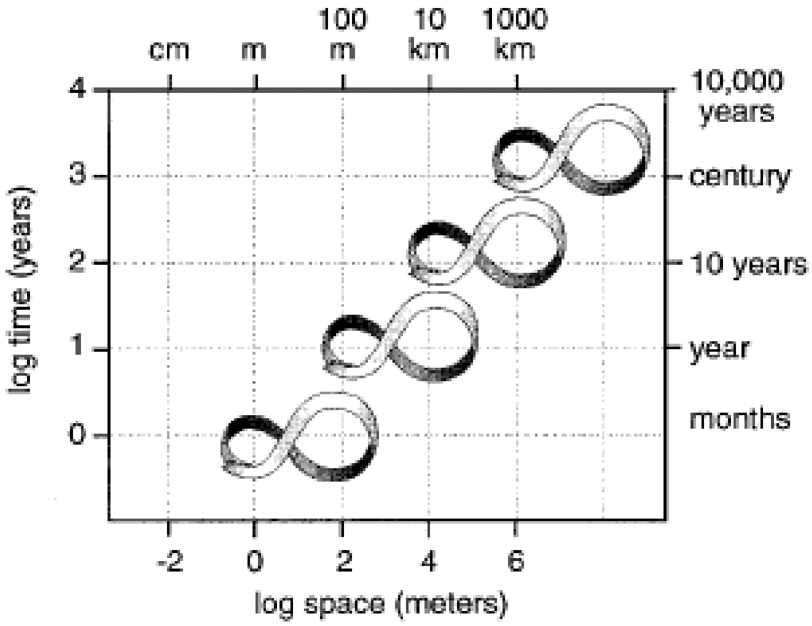


Figure 4-5 Stylized Panarchy
(after: Holling, 2001)

In this context, *Panarchy* may be defined as the whole of the hierarchical levels (i.e. the whole of the different time and space scales), where each level is characterised by an adaptive cycle. More precisely, the concept of Panarchy combines the hierarchical structure of systems evolving from small and fast systems, such as individual choice or a leaf of a tree, to large and slow systems, such as social embedded institutions or a whole forest. This nested structure exchanges renewal and conservation thanks to two processes, called revolt (e.g. dramatic changes, such as a fire or a disease), and remember (e.g. rebuilding based on past history, as in the case of unused seeds or embedded institutions). Smaller and faster systems affect larger and slower ones through the revolt element, while larger and slower systems have an impact on smaller and faster ones through the remember element as shown in Figure 4-6. Although the representation of the connections existing between different levels is far from complete, as multiple linkages between different phases of each level may exist, the two described above (revolt from smaller Ω to larger K and remember from bigger K to smaller α) may be crucial for the understanding of a system (Holling, 2001, 2004).

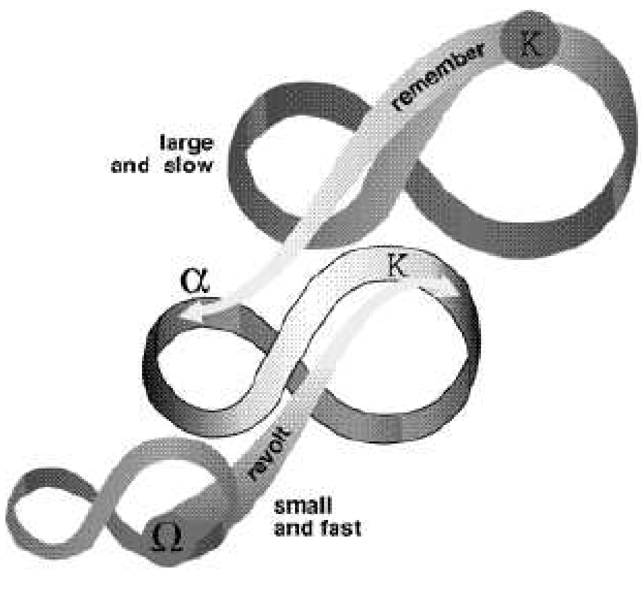


Figure 4-6 Panarchy: small and fast vs slow and big
How smaller and faster cycles are influenced and influence slower and bigger cycles in the Panarchy context (after: Gunderson & Holling, 2002)

To explain the Panarchy nature of SES it is possible to think of the management of a particular rural area where a policy to enhance agricultural production is put in place. The policy aims at incentivizing the use of fertilizers. Fertilizers will increase agricultural production, but an extensive use may actually reduce soil capacity (increasing the phosphate present in the soil), this leading, in the long run, to an actual decrease of ecosystem resilience, and eventually affecting in an undesired way the agricultural production at a different time scale (e.g. in the long run). In the context of the lake example proposed above, one may think of an increase in fertilizer use due to prior policies designed to improve agricultural production. The increased use of fertilization introduces phosphates into the soil, and from there into the lake, eventually creating the conditions for a transition from a clear state to a turbid state (Elmqvist et al., 2003; Folke et al., 2004).

According to the adaptive cycle and Panarchy of SES, human history exhibits non-regular changes but rather disruptions that are spasmodic and catastrophic (e.g. the collapse of the Western Roman Empire, the French and the Soviet Revolution) followed by a long period of development (Holling, 2001). More precisely, it is possible to affirm that two main trends have been observed in the history of SES:

- Levels of Panarchy are added over time: an increase in the complexity of societies and differentiation of species in an ecosystem (e.g. from the tribal organization to the nation states, from unicellular organisms to mammals).
- Changes from one regime to another are rapid and discontinuous, often non-predictable and surprise-generators.

Discontinuous and unpredictable shifts may be the result of small changes and shocks that accumulate throughout the various levels of the Panarchy. In particular, an abrupt shift of a system (collapse) could happen when the adaptive cycle at various levels finds itself in the Ω phase (Holling, 2001, 2004; Holling & Gunderson, 2001). To clarify this concept, a very simplified example is presented. Recall the previous example of Lake Mendoza and think of two groups deriving their livelihoods from local resources: farmers and fishermen. Moreover, for the sake of simplicity, let us assume that both groups are educated and fully informed on the state of the lake and the amount of phosphates that will cause a shift of the lake from a clear to a turbid state. Let us further assume that the regional government decides to increase agricultural production, thus incentivizing the use of fertilizers (that contain phosphates). We also assume that these incentives, if used, will provoke a regime shift and both, farmers and fishermen are aware of such consequences. What will happen in this hypothetical situation? Since the key objective is to define Panarchy, let us depict only two different scenarios:

- The two groups have created a joint institution to manage the local lake and surroundings in order to enhance the standards of living of the community(social system in K phase). In this case, it may well be the case that farmers renounce to introduce more phosphate into the soil and the lake.
- There is civil unrest and the two groups are in conflict (social system in Ω phase). In this context, the farmers may welcome the new set of policies and increase fertilizer use. The lake shifts to a turbid state and the fishermen are forced to leave the lake (which may also lead to a “cultural” change, in the case of fishermen losing indigenous knowledge in the long run).

4.1.2 Introducing interactions with and within humans

As the example above reveals, the interactions of humans with one another and the environment in which they are embedded is fundamental for the resilience of a SES. Moreover, collapse is often triggered by events that are almost non-predictable[7]. How can humans then adapt to this uncertainty and surprise state that characterises the world in which they live?

Humans have the ability to foresee and intentionally pursue different paths of SES management. As the management of Lake Mendoza has demonstrated, humans are able to adopt strategies based on their experience, and based on an envisioned specific objective. Moreover, they are able to select those strategies that they deeme to be the most appropriate one. The social system is also able to learn from prior

[7] In the example given in section 4.1.1, information will be very limited, not permitting a clear cut decision even to the joint institution, leading to multiple different possible outcomes.

knowledge and to experiment new ways (or management paths) so as to achieve desired outcomes. However, as the same example shows, the ability to foresee and to intentionally manipulate certain aspects of a SES does not always lead to the desired result. Since the knowledge of a panarchical adaptive system (as a SES is) can never be complete, one should always plan for the possibility that uncertain and extreme events may happen. Social-Ecological systems are characterized by a high level of uncertainty and surprise; policies that are designed in order to optimise one scenario (or one possible foreseen future) could result in worsening the situation, since predictions often fail to materialise. Thus, it is worth to implement policies that can be robust across multiple scenarios (alternative possible foreseen futures), and that can enhance the resilience of the overall SES (Bankes, 2002). Furthermore, as Alfred Marshall pointed out more than a century ago, optimising one scenario is a useful solution only in the short run and when the system is fairly stable (i.e. institutions, culture, politics, and general economic conditions) (Foster, 2005), and this is not clearly the case in the present world and for most if not all of the SES.

Another characteristic that can be thought quite peculiar in humans is communication. More precisely, humans are capable of communicating ideas and experiences. Communication plays a crucial role in the development of feasible and flexible strategies necessary to manage adaptively (or co-manage adaptively) SES. In this context a very interesting result has been discovered through simulations (Bodin & Norberg, 2005): if the social network (or network of relations) is over-connected, the flexibility of the system is reduced and the whole community behaves as a single entity, hence not allowing for experimentation and reducing the resilience of the overall SES. However, relations and communication can foster (if not locked-in) flexibility and new ideas, as well as inform learning. In the the Lake Mendoza example, communicating past experiences allowed managers to experiment with new management paths (strategies) that could have produced better results. Moreover, they preserved prior knowledge and increased their experience in resource management.

Finally, the third main characteristic that differentiate humans is technology. Technology amplifies the actions undertaken and permits a wider range of possibilities. To return to the Lake Mendoza example, technological advances have given the possibility to divert sewage, and to bio-manipulate the lake. Clearly, technology can also be a drawback, as it has been the case for fishing industry in the North Sea, where new ways of fishing have almost fully depleted the stocks of cod.

Summarizing, it is possible to affirm that human (inter)actions strongly influence the resilience of a SES. It is possible to assume that the resilience of a system is the result of four crucial aspects, with the first three applicable to every level of the panarchy. The four aspects are defined as in Walker et al. (2004: 2-3):

- Latitude: the maximum amount a system can be changed before losing its ability to recover (before crossing a threshold which, if breached, makes recovery difficult or impossible).
- Resistance: the ease or difficulty of changing the system; how "resistant" it is to being changed.
- Precariousness: how close the current state of the system is to a limit or "threshold."
- Panarchy: because of cross-scale interactions, the resilience of a system at a particular focal scale will depend on the influences from states and dynamics at scales above and below. For example, external oppressive politics, invasions, market shifts, or global climate change can trigger local surprises and regime shifts.

Social actors (humans) of a SES can influence the *latitude*, the *resistance* and the *precariousness* of the system. More accurately, Walker et al. (2004) redefine the four crucial aspects of resilience from a different perspective. In the context set by Walker et al. (2004) a system tends to move toward a basin of attraction. Besides, there may be more than one basin of attraction depending on the initial conditions and the position of a system. To explain: think of a basin of attraction as a bowl, and the system as a ball that continuously moves inside the bowl (assuming hence a non-stop movement, so that no single equilibrium is reached). Now, assume that there may be more than one bowl and the ball can, driven by internal and external factors, jump from one bowl to the other. Different bowls represent different basins of attraction as depicted in Figure 4-7 and Figure 4-8.

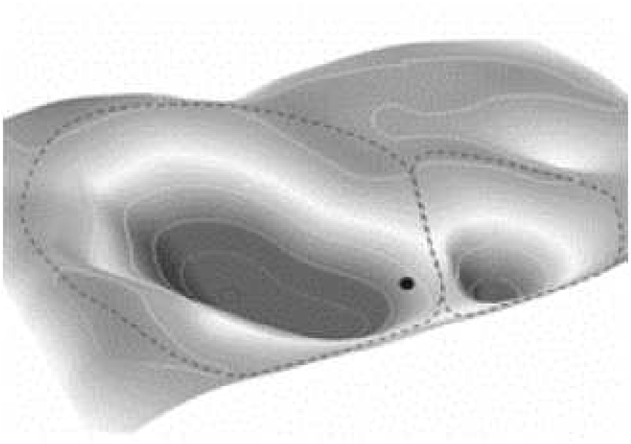


Figure 4-7 Basin of attraction representation
The dashed line representing the different bowl's boundaries and the black dot representing the ball (as described above) (after: Walker et al., 2004).

After defining the concept of basin of attraction, it is possible to redefine the four aspects of resilience as follows (the four characteristics are also shown in Figure 4-8) (Walker et al., 2004):

- *Latitude* (L): the width of the basin of attraction (of the bowl); as latitude increases, the resilience of the system also increases as it is more likely that the ball (system state) will remain in the basin of attraction: a greater number of states can be achieved without crossing any threshold.
- *Resistance* (R): the depth of the basin of attraction (of the bowl); as the resistance increases, greater magnitude of disturbance is required for our ball (system state) to cross the threshold and moving to another basin of attraction.
- *Precariousness* (Pr): how near is the system (our ball) to the boundary of the basin of attraction in which it moves. The more the system is precarious, the more it will be position itself near the threshold.
- *Panarchy*: how the three attributes/characteristics above are influenced by cross-scale interaction. That is, how slower and bigger system influence/are influenced by our ball and how our ball influences/is influenced by faster and smaller system.

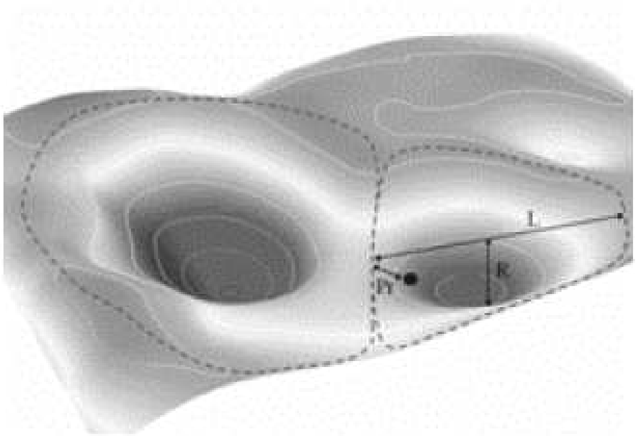


Figure 4-8 Representation of the four crucial aspect of resilience
L being latitude, R being resistance, Pr being precariousness as described above. The dashed line represent the threshold between the different basin of attraction (after: Walker et al., 2004)

Given the definitions above, it can be claimed that humans are capable, given their unique features, to alter the basin of attraction in which their SES is embedded. Communication fosters new ideas, or preserves tested ideas and allows for experimentation or neglect experimentation, while the ability to predict and take action based on prior information can better or worsen their situation. Technology enables to alter the movement of the system and the basin of attraction. However, the limitation and the drawbacks of these characteristics need to be addressed. More precisely, the social system can influence the latitude (widening it or narrowing it), the resistance (making the basin deeper or shallower), and the precariousness (moving the system away or near the threshold line). Two models that deal with the presence of humans and management strategies (or paths) devised for simple SES are presented in Chapters 7 and 8.

4.2 Theory into practice?

As seen in section 4.1.2, humans have unique features that enable them to manage SESs; however, these characteristics are useful to the extent that predictions are accurate and communication is effective and translates into action.

The concept of resilience implies the capacity of absorbing disturbances and reorganization maintaining the same functions, structure and feedbacks while undergoing change (Olsson et al., 2004). Thus, an understanding of the SES is essential, and so is its "measurement". Although there is ongoing research regarding the "measurement" and the adaptive management of SES from a resilience perspective (Anderies et al., 2004; Anderies et al., 2006; Carpenter et al., 2001; Folke et al., 2004; Janssen et al., 2006; Perrings, 1998; Reggiani et al., 2002; Walker et al., 2002), quantitatively assessing resilience remains a very difficult task, due to complications in disentangling interactions within the subsystems and identifying clear causal relationships.

These difficulties are mainly due to the complications arising from the panarchical nature of SESs, and the uncertainty that exists when determining the resistance, the latitude and the precariousness of the basin of attraction in which the system is embedded. In other words, variation in one system affects other systems, often at different spatial and time scales (e.g. fertilizers used in agriculture to enhance the economic system, actually lower the resilience of the ecosystem and, in the long run, of the economic system as well). Actions that may enhance resilience in one system in a certain space at a certain time may lower resilience of that very same system at another space or time scale.

Given these interaction and the complexity of SES, difficulties arise in assessing the build up or erosion of resilience in a quantitative way. Thus, the literature discussing the resilience perspective stresses the importance of adaptive management in order to either prevent an undesirable basin of attraction or move away from an undesired one (Walker et al., 2002). Adaptive management is based on the continuous feedbacks occurring between the social and the ecological system. These feedbacks should enhance the learning and the ability to devise possible alternative future scenarios, maintaining the diversity needed for reorganization (Carpenter et al., 2001; Olsson et al., 2004; Walker et al., 2002). Adaptive management needs to handle the interplay between disturbance and reorganization, stressing adaptive capacity, learning, and possible innovation allowing for cross-scale interaction and uncertainty. Therefore, the management of SES's implies the advancement toward more desirable states in the same basin of attraction, and/or a shift into a more desirable basin of attraction.

4.2.1 Resilience: a first practical definition

As seen throughout this chapter (Chapter 4), a SES is characterized by external (e.g. increased urbanization, regional policy that affect local context etc.) and internal variables (such as farmers, policy entrepreneurs etc.). Although there are different frameworks used to conceptualize resilience, the conceptual framework proposed by Anderies et al. (2004) is used here in order to allow a first working definition of resilience. In order to comprehend the framework, *robustness* of a SES needs to be defined. Robustnass is defined as the maintenance of a system performance under different possible scenarios (different possible and unpredictable external or internal events and uncertainty about the information existing on the system). Thus, according to Anderies et al. (2004) a robust system may not have the most efficient configuration for one possible future (so as to perform at an optimum level), but it will be able to perform in more possible futures, while the most efficient configuration for one future will easily collapse if that one future does not happen (Anderies et al., 2004; Bankes, 2002).

Moreover, this approach is used as the starting point for integrating resilience and network theory in Chapter 5 and subsequent chapters of this thesis (i.e. Chapters 6, 7, and 8). The robustness conceptualization is the one proposed by Anderies et al. (2004) and reported in Figure 4-9.

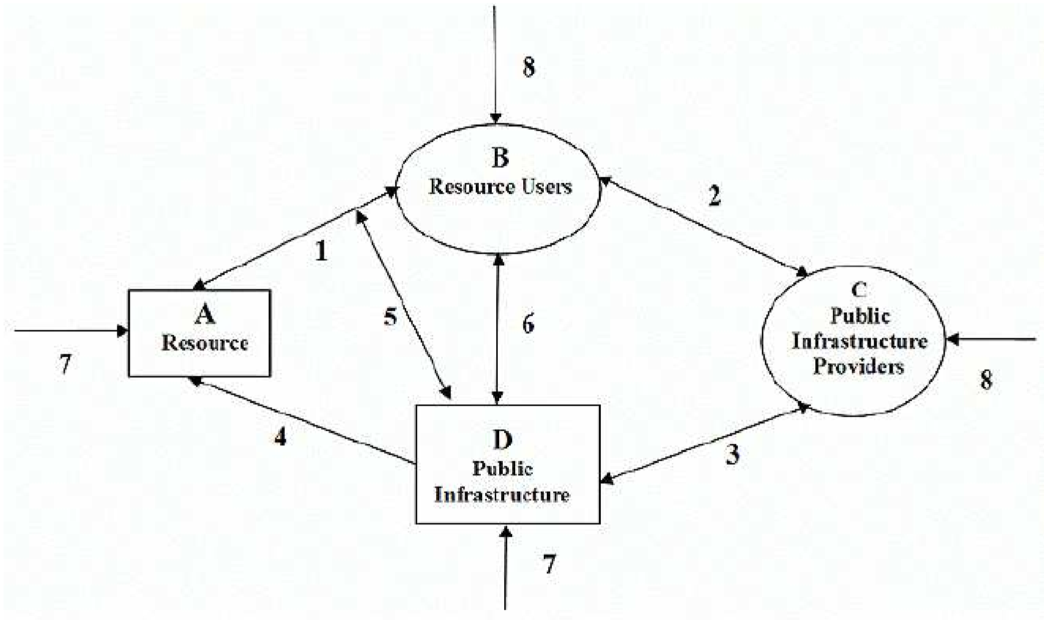


Figure 4-9 SES conceptual framework
as proposed in Anderies et al. (2004), (after: Anderies et al., 2004).

To better illustrate the framework, an example will be provided; specifically we will take into account two systems, one that deals with agriculture and another that deals with fisheries[8]. In the two different contexts just outlined, the elements in Figure 4-9 are described as follows (Anderies et al., 2004):

A. The resource being water supply for irrigation or fishery.
B. The resource users being farmers and fishermen.
C. The public infrastructure providers being the local government (or the farmers and the fishermen themselves, depending on the local context).
D. The public infrastructure being the works for irrigation, dams etc. (i.e. physical capital) or the rules, norms and beliefs that those managing and using the system adopt (i.e. social capital).

These four key elements link with one another as Figure 4-9 depicts. What follows is a possible description of these links keeping in mind the two systems outlined above (Anderies et al., 2004):

[8] For in depth information on the framework here outlined and the potential complication that may arise please refer to the original paper by Anderies et al. (2004).

1. Resource and resource users: water or fish availability. In the case of water, it may be pointed out that availability when needed is more important, than the overall availability irrespective of time. Moreover the link may reveal information regarding the exploitation (use) of the resource and the possible lessons that can be learned from what has been done in the past.
2. Resource users and public infrastructure providers: this link could represent negotiation and/or interest groups, the voting (if the context allows it) or the monitoring of the performance of the providers.
3. Public infrastructure providers and the public infrastructure itself: building the infrastructure needed and their maintenance.
4. Public infrastructure and resource: how the public infrastructure affects the resource (e.g. irrigation is putting water availability at risk? Is the provision of free technology for fishermen putting the fishery stocks at risk?)
5. Public infrastructure and resource dynamics: how infrastructures affect the dynamics that have contributed to create. In other words, it is necessary to look at the feedbacks between public infrastructures and the ecological system (e.g. over-fishing or overuse of water resources due to the infrastructures provided). This link may seem similar to the previous one, but the main feature here has to do with the feedback structure.
6. Public infrastructure and resource users: monitoring resource users (e.g. fishers and farmers). Make sure resource users obey the rules set for the use of the infrastructures provided. Sanctioning (and so enforcement) is also part of this link as well as maintenance and production of the infrastructures themselves.
7. Biophysical external events such as floods, droughts, earthquakes etc.
8. Social external events such as migration, changes in commodity prices, major changes in the political arena, civil war etc.

The framework proposed tries to broadly illustrate the structure of agents and links that exist in a SES. In addition it is possible to give another and more precise definition of what a shift might be when looking at a SES as a single integrated system. In this context, it is important to understand that a resource collapse does not necessarily imply a system collapse; that is, in order for the SES to collapse (change basin of attraction) both, the ecological and the social system need to collapse. If this is not the case, we may simply have a SES closer to the collapse threshold (or nearer to shift to another basin of attraction, as explained by Figure 4-7 and Figure 4-8). In other words, the SES may find itself in a more precarious state being precariousness defined as in section 4.1.2, nevertheless the SES has not yet shifted basin of attraction. To be aware of what a SES collapse (shift) signifies, involves the comprehension of how interactions between and within the different agents of the system affect the overall SES. In other words, it is possible to enhance our understanding of the resilience of a SES by looking at how single agents interact with one another and with the surrounding environment (i.e. refer to Chapters 6, 7, and 8 for a theoretical application of these thoughts).

4.3 Concluding Remarks

This chapter explained what resilience is, and how its definition has evolved. Moreover, it links social and ecological resilience, hence allowing treating a SES as a single system. Section 4.1 introduced and explained the recent advances in resilience theory, particularly focusing on the concept of adaptive cycle and Panarchy. This explanation was facilitated by a practical example (Lake Mendoza).

The features characterizing humans have been described in section 4.1.2. These features have been integrated in a wider SES context so as to explaine how the social system is able to intentionally affect and being affected by the ecological system. The terminology used is borrowed by Walker et al. (2004), and the description of the attributes that can be shaped by social systems has been presented.

Although progress has been made since Holling first introduced the concept (and since scholars first linked social and ecological systems), there is still much ongoing research with regard to ways to understand, conceptualise and measure the resilience of a SES. In this context, the tools used in network theory may be applied successfully to resilience theory, permitting a better visualization and comprehension of a system’s strengths and weaknesses, so as to devise better strategies or management paths that lead to adaptation and/or transformation. The integration between network theoretical tools and the resilience framework, or, in other words how network theoretical tools can be used in order to assess the resilience of a SES, will be the focus of the Chapters 5, 6, 7, and 8.

5 Network-Resilience Integration

Chapters 3 and 4 have introduced network theory and have summarized the main features of resilience thinking. This chapter looks at a first possible network resilience definition (section 5.1). Moreover it gives a brief summary of the different impact that disturbances (namely errors and attacks) have on network topological features. Thus, section 5.1.1 analyzes how errors and attack influence network metrics described throughout Chapter 3, in different network classes, described in section 3.3.

The second part of the chapter (section 5.2) will briefly outline the preferred avenue so as to achieve meaningful insights on how to integrate network metrics and resilience of a SES. At first, section 5.2 provides an introduction and justification of the use of simulations and agent based models, the latter are investigated in section 5.2.1 where they are introduced. Section 5.2.2 outlines important application for Chapters 6, 7 and 8. Section 5.2.3 highlights some of the main issues concerning agent based models. Section 5.2.4 explains how an agent based model might be evaluated and validated. Section 5.2 is a revised version of Baggio (2011).

Section 5.3 examines the possibility of devising a case study as an approach to analyze resilience from a network perspective. Ideally case studies will be used in the future in order to validate the models presented in 6, 7, and 8, However, at this stage of the research a case study is beyond the scope the thesis as first, it is necessary to theoretically advance our knowledge and the understanding of how network metrics influence the resilience of a SES. Finally, a brief summary of the chapter and of the purpose of using theories and methods described here as well as in Chapters 3 and 4 is provided in section 5.4.

5.1 Resilience of a Network

At this stage, a clear definition of network resilience is not available. However, network theory has dealt in depth with the concept of robustness. The robustness of a network is assessed (in network theory) by analyzing the effect of nodes' failures on common network metrics such as *giant connected component* (GCC), clustering coefficient, average shortest path length, global and local efficiency (please refer to sections 3.1, 3.2 and below). Moreover, failures of nodes can be random or targeted as explained in section 5.1.1 (Albert et al. 2000; Crucitti et al. 2004). Robustness has been widely studied on static networks, specifically investigating structural properties of random and scale-free networks (Albert et al. 2000; Crucitti et al. 2004); however, it does not take into account the dynamic processes shaping the evolution of networks and the evolution of processes unfolding upon the networks.

On the other hand, as explained throughout Chapter 4, resilience is an intrinsically dynamic concept, thus the starting point is defining network resilience as the amount of disturbances a network can undergo without being totally disrupted, that is, without breaking down its giant component, while allowing the network to evolve (that is to create or delete nodes and edges). Thus, while robustness refers to semi-static networks, resilience of a network refers to a "robustness" analysis in the case of evolving networks, that is, allowing for a network to change in time by removing, adding edges and nodes.

The giant connected component contains most of the networks' nodes. In network theory giant components are studied in relation with random graphs, since they appear unexpectedly once the *percolation threshold* is reached (Albert & Barabási, 2002; Börner et al., 2007; Caldarelli, 2007; Dorogovtsev & Mendes, 2002; Newman, 2003b). The *percolation threshold* can be thought of as the critical edge-density at which a giant component emerges. A rigorous definition is also provided by Dorogvtsev and Mendes (2002: 1151):

> percolation is a phenomenon determined for structures with well defined metric structure, e.g., regular lattice. In case of

networks […] one can speak about the emergence of a giant component.

Moreover, since an SES can be represented by an undirected or by a directed graph, the structure of the giant component in both cases will be analyzed. First of all[9], it is important to stress that in a directed network the existence of a path from node i to node j does not imply that an inverse path exists. Therefore, what is defined as a giant component in an undirected network is considered a giant weakly connected component (GWCC) of a directed network. To better understand this concept, refer to Figure 5-1. The components not connected to the GWCC (or GCC in undirected networks) are called disconnected components (DC) (as in Figure 5-1).

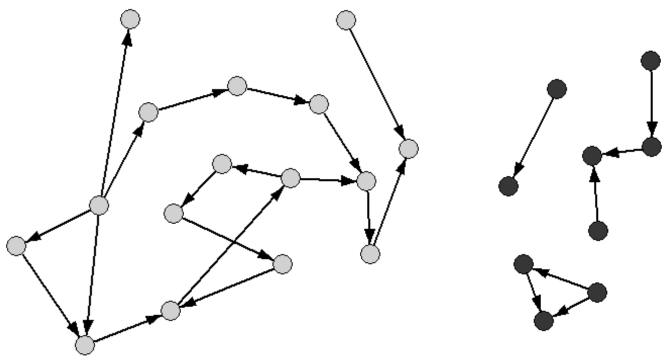


Figure 5-1 Giant connected component (GCC)
Sample network composed by a GWCC (connected light-grey nodes) and DC (disconnected dark-grey nodes) (Own elaboration)

Further, in case of a directed network (a network whose edges are directed) the GWCC can be divided into a giant strongly connected component (GSCC) a giant in-component (GIN), and a giant out-component (GOUT). The GSCC consist of nodes that are joined by directed paths (i.e. every node of the GSCC is reachable by any other node of the GSCC). The GIN consists of nodes from which it is possible to reach the GSCC and the GOUT consists of nodes that can be reached from the GSCC. Finally, the GWCC contains tendrils and tubes. Tendrils are nodes that cannot reach or be reached by the GSCC but are connected to the GOUT or GIN while tubes are nodes that connect GIN and GOUT. Figure 5-2 is built on Figure 5-1 but the GWCC is divided into the components just outlined above.

[9] This section will use the terminology, definitions and acronyms from Börner et al (2007) and from Dorogvtsev and Mendes (2002).

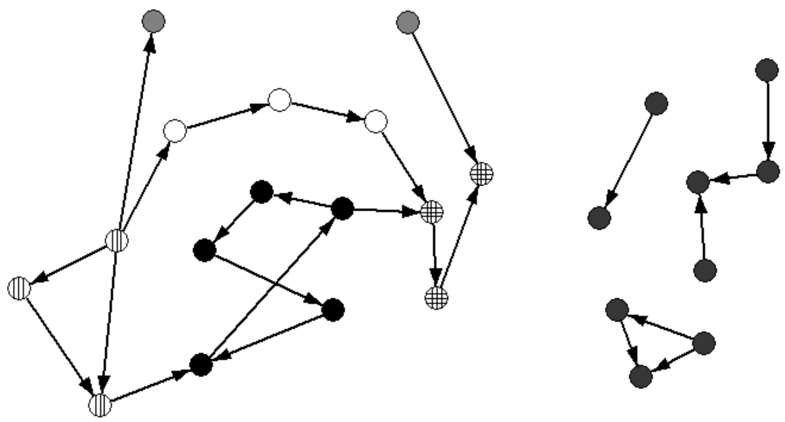


Figure 5-2 Giant connected component of a directed network
Sample network as in Figure 1; the GWCC is divided as follows: GSCC (black nodes), GIN (stripe nodes), GOUT (grid nodes), tendrils (grey nodes), tube (white nodes) and DC (dark-grey nodes); (Own elaboration).

5.1.1 Disturbances and Resilience in a Static Network

Given the starting definition of network resilience it is important to distinguish between two main disturbances that may affect the resilience of a network: errors and attacks. Errors are considered random failures, while attacks are failures that hit specific nodes. Errors and attacks have different effects on the main statistical features of a network depending on its topology (Albert et al., 2000; Crucitti et al., 2004). Random failures and specific failures (i.e. errors and attacks) have been studied in relation to random and scale-free networks. As discussed in sections 3.3.2 and 3.3.4, random graphs are homogeneous while scale-free networks are non-homogeneous as shown in Figure 5-3. In random network most of the nodes have more or less the same degree (i.e. the degree distribution of a random network follows a Poisson distribution). In scale-free networks the majority of the nodes have a low degree; although some nodes have a very high degree (i.e. the degree distribution of a scale-free network follows a power law).

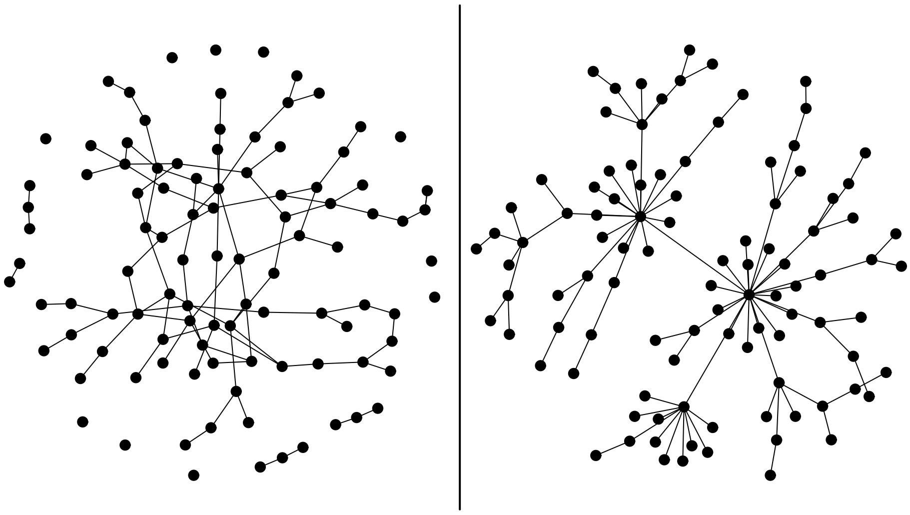


Figure 5-3 Random and Scale-Free network
Random network (left), scale-free network (right) with 100 nodes and 99 edges (Own elaboration).

The degree distribution is found to heavily affect the behaviour of a network when it is hit by random or targeted failures. More precisely, in random graphs there is no appreciable difference between an error and an attack, while on the contrary, scale-free networks seem to be much more robust to errors (thus random failures) rather than to attacks (Albert et al., 2000). This difference in behaviour is intuitively very easy to understand. Since in random networks most of the nodes have the same degree, targeting one of them or eliminating randomly one node does not have any differentiated impact. On the contrary, the degree distribution of scale-free networks follows a power-law and is highly heterogeneous. In scale-free network, as one recalls from section 3.3.4, a high number of nodes has low degree and very few nodes have high degree (as shown in Figure 5-3). Thus, it is intuitive when a random error occurs, there is a high probability that a node with low degree is hit, thus having a low impact on the whole network structure. On the contrary, if an attack on the highly connected nodes takes place, the network will be more easily disrupted, with respect to a comparable random network, as shown in Figure 5-4.

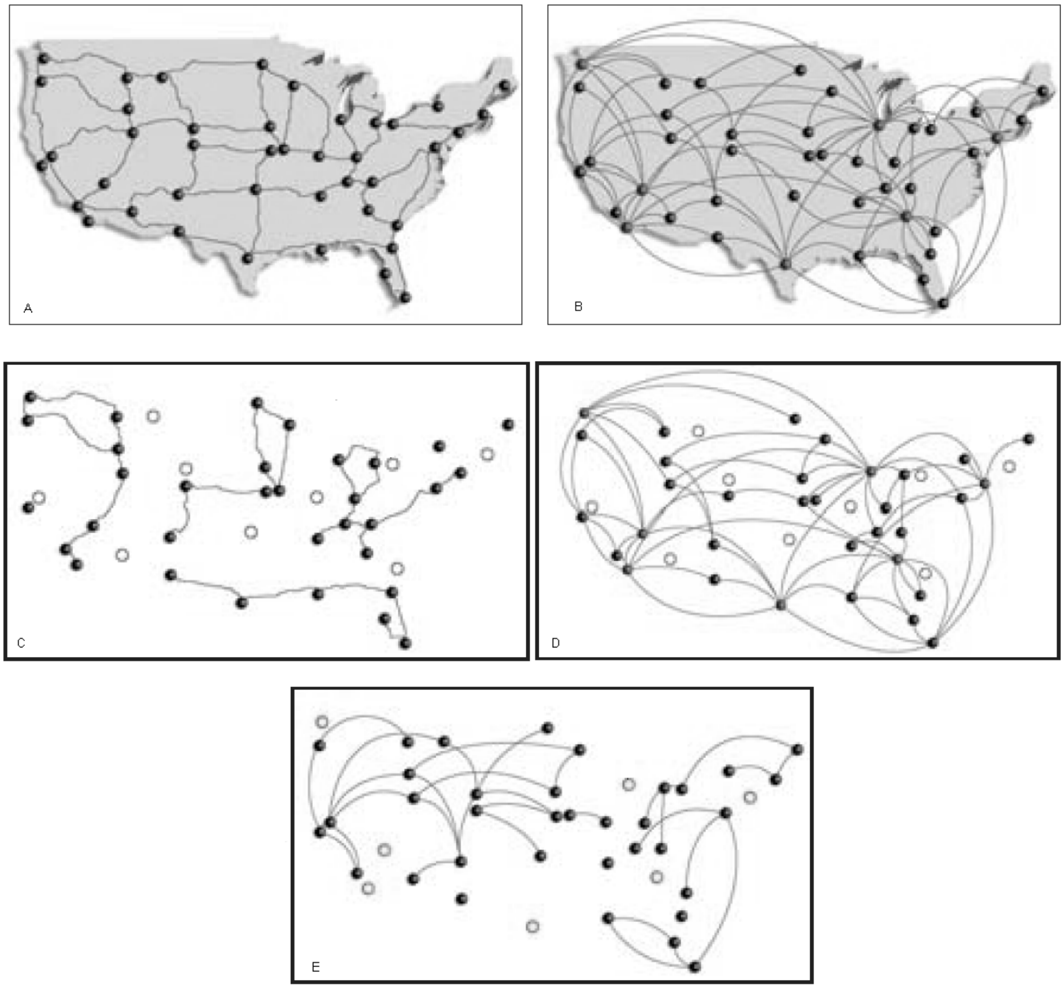


Figure 5-4 Attack and random errors on random and scale free networks
A represents the rail network of the USA (i.e. a random network); B the airport network of the USA (i.e. a scale free network); C shows the effect of random errors on the railway network; D shows the effect of random errors on the airport network; E shows the effect of attacks on the airport network. Attacks and errors have the same effect on random network, thus the attacks for the railway network of the USA are not reported (after: Barabási & Bonabeau, 2003)

Figure 5-5 also looks at the behaviour of a random and a scale-free network when errors and attacks occur, but, the effect of errors and attacks is measured by how they influence the average path length and the relative size of the giant connected component. As Figure 5-5 portrays, the topology of the network clearly influences the robustness of a graph with respect to errors and attacks. Figure 5-5 gives a visual representation of the key argument of this section and of the whole thesis: topology matters. Due to the degree distribution of its nodes, random networks are more susceptible to errors in comparison to scale-free network that are very robust to this kind of failure. On the contrary, scale-free networks are highly vulnerable if the most connected nodes are attacked.

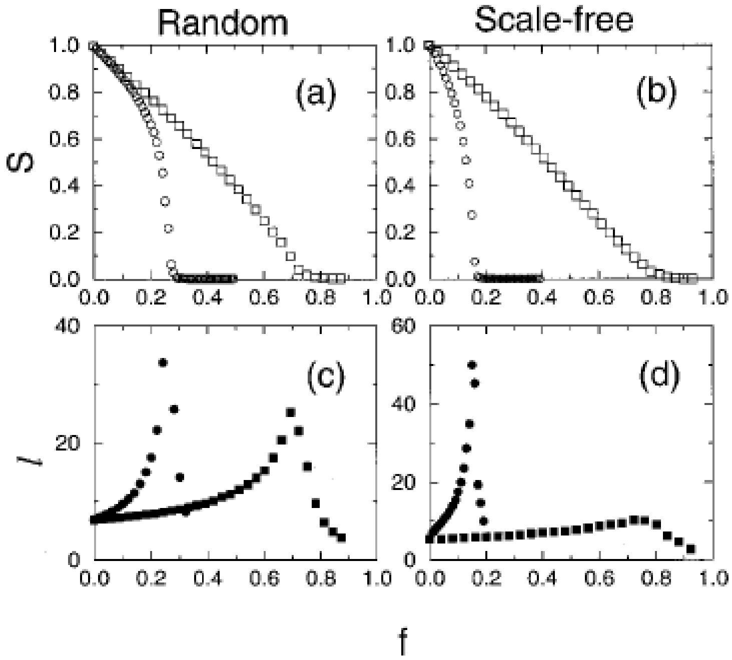


Figure 5-5 Error and attack tolerance
Represent the effect of errors (squares) and attacks (circles) (i.e. *f* represents the fraction of nodes that has failed) on the relative size *S* (a and b) and the average path length *l* (c and d) of the giant connected component of a random graph (a and c) and of a scale-free network (b and d). (after: Albert & Barabási, 2002).

Moreover, it is possible to look at the effects of errors and attacks from an efficiency (global and local as described in section 3.2) point of view. Again, Figure 5-6 clearly shows, the topology of a network plays a significant role with regard to the maintenance of efficiency as defined here. As previously explained, scale-free network are more tolerant to random failures than random graphs, while on the other hand, random network are more tolerant than scale-free network to targeted failures.

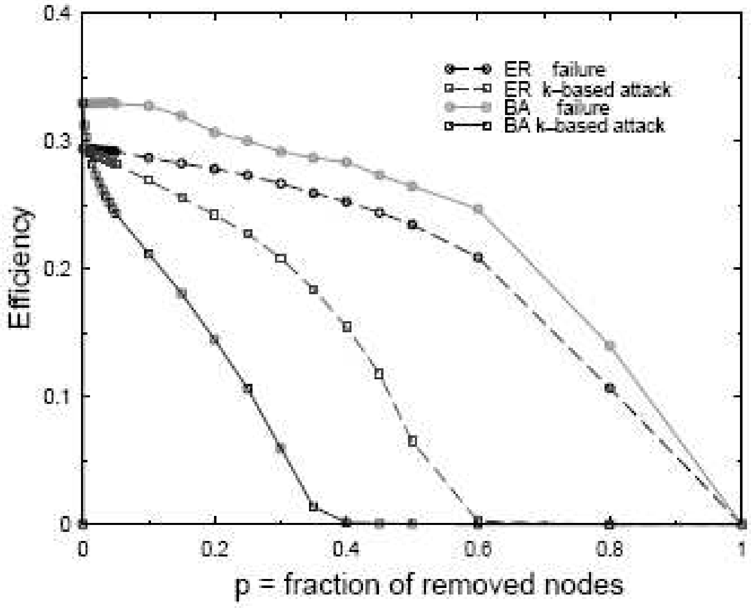


Figure 5-6 Global efficiency of a network with regard to errors and attacks
Errors are considered random failures, while attack target the nodes with highest degree. ER = Random graph as described by Erdős and Rényi (1959; 1960), BA = Scale-free network with preferential attachment as described by Barabási and Albert (1999) (after: Crucitti et al., 2004).

Furthermore, failures influence the average shortest path and the relative size of the giant connected component, and they also shape the efficiency of a network. It is then possible to confirm that designing a topology that is able to tolerate errors and attacks could be a first step in building a SES that is more resilient (i.e. network resilient as defined in section 5.1)

Finally it is worth looking at how assortativity (see section 3.2) influences the resilience of a network. A network that displays assortative mixing will be more tolerant to attacks, since its high degree nodes will be clustered with other high degree nodes, while networks that display disassortative mixing are much more susceptible to attacks (Newman, 2002, 2003a). It is worth remembering that errors and attacks are defined as random and targeted failures. Moreover, it is possible to think of attacks as targeted interventions. In a SES, the social system may decide to intervene locating a particular node of the food web or of the landscape network, and such intervention can be thought of as an attack. Another consequence of the assortativity of a network is the formation of the giant component. In assortative networks[10] the giant component forms more easily than in disassortative networks (Newman, 2002). At the same time, the relative size of an assortative network's giant component is smaller than that of a disassortative network.

5.2 Assessing Resilience: Simulations and Agent-Based Modelling

Social and ecological systems might be inherently impossible to predict (Bernstein et al., 2000) and can be defined as CAS. As already explained in section 2.2, it is not easy to define CAS in an unambiguous way. However, here I summarize the definition reported in section 2.2 and used throughout this work. Following Levin (2002), a system can be defined as a CAS when a certain number of elements - its components - are interacting in interdependent ways. These interactions are typically nonlinear and, although "simple" at a local level, they collectively form a non-predictable set of behaviours and structures at a more macro level (i.e. not derivable as a straightforward composition of the local characteristics, or, the sum is greater/smaller the its parts).

The properties of a CAS described above results in some characterising features (Levin, 2002; Waldrop, 1992) already extensively explained in section 2.2. Here these features are just briefly recalled so as to remember them to the reader:

- *Non-determinism*.
- *Presence of feedbacks.*
- *Distributed nature.*
- *Qualitative difference between larger and slower functions (or cycles) and smaller and faster ones*
- *Limited decomposability.*
- *Self-similarity.*
- *Emergence and self-organisation.*

[10] Assortative network and disassortative network will be used for brevity, although the following terminology is more appropriate: a network that displays assortative/disassortative mixing.

Interactions between species in an ecosystem, the behaviour of consumers, or people and groups in a community, the stock-market, the immune systems, the river networks, and patterns of birds' flight are all examples of complex adaptive systems: in these cases emergent configurations are often not possible to understand via a reductionist analysis. That is, via an approach that reduces a complex system into sub-components, assuming that relations between these sub-components are stable and static. It is counterproductive and can be highly misleading to assume that a complex system is a mere sum of its components.

The study of CAS calls for a new strategy, which makes cross-disciplinary comparisons looking for features that are common to different systems in different domains (Lansing, 2003). CAS differ from systems studied in other disciplines such as classical physics, where success is achieved due to the high power of theoretical predictions, and to the accurate representation of that part of reality that the researcher wants to represent (Henrickson & McKelvey, 2002). When dealing with CAS, it is possible to argue that the role of a model should aid the understanding of the fundamental processes, regularities and universalities that might or might not exist in such systems. Simulations may prove to be the best tool to analyse and understand the complexities of social and ecological systems.

Models are a representation of reality, not reality itself, and modelling is the activity of abstracting from what one considers as fundamental features of a real system for a specific purpose. Models used to represent reality can be a result of different techniques: statistical, mathematical (e.g. differential equations) or simulations. Statistical models are constructed from existing data, thus they might be inherently flawed if we are to model complex systems that display nonlinearities, critical thresholds or sensitive dependence on initial conditions. Statistical models are able to forecast a limited timeframe only if the system that we want to represent is fairly stable (Farmer & Foley, 2009). Moreover, in economics, general equilibrium models are used. Unfortunately, these models assume a predetermined, "perfect" world and hence are not able to display patterns such as those observed in the recent financial and economic crisis (Farmer & Foley, 2009). These models might be appropriate to explain certain outcomes only under a pre-determined, narrow set of conditions, while failing to explain outcomes of complex adaptive systems. Mathematical models can be more complex; however, the complexities existing in social and ecological systems often do not allow for differential equation based models to have exact analytical results, unless the system is greatly simplified by making strong assumptions (e.g. the homogeneity assumption) in order to obtain tractable representations (e.g. the impossibility of finding analytical solutions to the three-body problem, as pointed out by Poincaré (1892-1899)). Following Galan et al. (2009) is possible to describe a formalised model as "mathematically intractable" when, given today's state of mathematics, the model cannot provide solutions or understandable insights of the model's behaviour. In other words, when assumptions and simplifications do not permit a correct representation of the unique features of human behaviour (e.g. reflexivity, learning, heterogeneity of agents etc.) (Henrickson & McKelvey, 2002). Given the adaptiveness and the characteristics of CAS described at the beginning of this section and in section 2.2, it is not possible to model CAS as an entity that passively responds to external forces but rather as an entity that actively responds to external and internal inputs.

Simulations (or computational modelling) can be used to build formal representations of reality (thus a model) without the need for over-simplification or very strong assumptions. They seem a natural candidate for representing complex adaptive systems, while other techniques might be more appropriate in explaining the behaviour of systems that are fairly stable, in which the outcomes are the result of linear combinations of internal relations, rely on equilibrium conditions and focus on universality. In other words, the laws that govern human behaviour are a result of chain path selections, thus inherently different from certain laws physics such as Newton's second law of motion: $F = ma$, where relations are linear and solutions are deterministic.

Simulations imitate processes (Hartmann, 1996) and can be thought of as representations of reality in which it is possible to explore different hypotheses, assumptions and parameters. They provide insights into the world represented through the use of analogy (Peck, 2008). They may be helpful for descriptions, building scenarios or devising new theoretical developments (Garson, 2009;

Hartmann, 1996). Simulations enable us to explore the dynamics of a real process, where it is often not possible to proceed by empirical experiments either because of scale, cost, ethical considerations or theoretical impossibility (e.g. what would have been the response to a policy that has not been implemented but that could have been a possible alternative solution?) (Hartmann, 1996). Simulations are a powerful tool if used correctly, and much effort should be devoted to reflecting upon the assumptions made in order to represent reality. It is crucial to understand the role of assumptions in the model building process. Every equation, parameter, rule, inclusion, or exclusion of variables is based upon certain hypotheses, and a model's validity is as good as its assumptions (Silvert, 2001). Thus, the primary role of a researcher should be the identification and the understanding of the implications of such assumptions. Every model, especially when seeking to represent a CAS, needs to be built through a process of continuous interactions between modellers and researchers or practitioners that deal with empirical issues. It is vital to understand what is happening in the field and how case studies, experiments, and other techniques are employed (Peck, 2008; Silvert, 2001).

5.2.1 Agent Based Models

Agent-based models (ABM) (or individual-based models –IBM- as often called in ecology) allow the simulation of a system from the bottom-up, that is, through an ensemble of individual entities called agents. These behave according to a predetermined set of rules and are subject to defined initial parameter configurations (Bonabeau, 2002; DeAngelis & Mooij, 2005; Macy & Willer, 2002). Agents in the model can represent any scale of social or ecological organisation, from single individuals to institutions, from a single organism to species (Bonabeau, 2002; DeAngelis & Mooij, 2005; Macy & Willer, 2002; Peck, 2008; Srbljinovic & Skunca, 2003). The application of ABM has grown consistently in the last 15 years, both in ecology as well as in social sciences (Breckling et al., 2006; DeAngelis & Mooij, 2005; Macy & Willer, 2002). Human beings as well as the environment in which they live, are complex, non-linear, path-dependent and self-organising (Bonabeau, 2002; DeAngelis & Mooij, 2005; Macy & Willer, 2002). Understanding these dynamics may provide a description of a system not at an averaged aggregate, global level (i.e. using standard analytical techniques) but as an emergent configuration of the interactions between individual agents (Macy & Willer, 2002). Even simple ABM can display complex and surprising behaviour patterns such as Schelling's segregation models (1969; 1971), which provide insightful and novel information on the mechanisms for social groupings (Bonabeau, 2002) as explained below and in Figure 5-8.

Agent based models are widely regarded as an appropriate modelling technique for the study of emergent phenomena and CAS. They do not assume that a system will move towards an equilibrium, although the system modelled might reach one (e.g. segregation in the Shelling model (1971)). In ABMs, at every simulation time-step (i.e. every time the whole iteration process shown in Figure 5-7 is restarted), agents act according to the surrounding environment and take action following the rules defined, thus allowing the discovery of critical thresholds and the emergence of behaviours not easily (or not) inferable when considering single agents. This happens, for example, when interactions between agents are characterised by nonlinearities and thresholds, when agents display memory, path dependence and time-correlations such as with learning and adaptation, when space is explicit and fundamental (e.g. distances and landscape heterogeneity exist) and agents' positions are not fixed (e.g. agents move on an heterogeneous landscape, thus their interaction also depend on their position in time), or when populations are heterogeneous (Bonabeau, 2002; Breckling et al., 2006; DeAngelis & Mooij, 2005; Macy & Willer, 2002). The description of these single agents' characteristics with reference to the whole system can be very difficult to model in an analytical way (Srbljinovic & Skunca, 2003), as the agent behaviour becomes more complex, the complexity of equations increases exponentially leading to their intractability. Moreover, in ABMs stochasticity (i.e. probabilistic behaviour) is not "noise" but is deliberately an inherent component of the model and agents' behaviour (Bonabeau, 2002).

In an ABM setting, agents are programmed in order to obey predetermined rules, to react to certain environmental conditions, to interact with one another, and might even to be able to learn and adapt (Bonabeau, 2002; Gilbert & Terna, 2000). Thus, the modeller needs to define the agents by programming their cognitive abilities and the interactions amongst themselves and with the environment. More precisely, a researcher who uses computer simulated ABM to represent a real system needs to undertake a model-building process that can be delineated in three stages (Galán et al., 2009). First of all, one needs to conceptualise the system that will be represented, thus defining the purpose, the “research question” and identifying the crucial variables of the system and their interrelations. Subsequently, it is necessary to find a set of formal specifications that is able to fully characterise the conceptual model. Finally, the model needs to be coded, implemented and executed (Galán et al., 2009). According to Gilbert and Terna (2000) when the model is iterative, every agent receives input from the environment, processes it, and act (reacts), generating a new input until a pre-determined condition is met (e.g. time limit or all agents find themselves in a given condition). Figure 5-7 graphically represents this process.

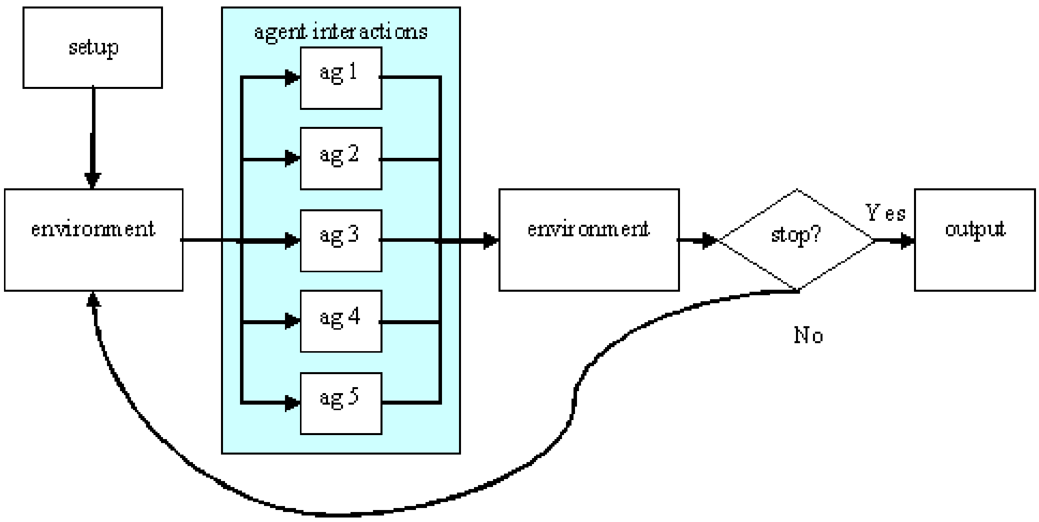


Figure 5-7 Graphical representation of the simulation process
(Own elaboration)

Agent based models can generate series (time series in most cases) of state variables at different scales. The results should be analysed using advanced statistical techniques and tools, since a single simulation run is simply a particular case in the infinite parameter space.

Numerous applications of ABMs exist, especially in social sciences and ecology (Bernardes et al., 2002; Bodin & Norberg, 2005; Cuddington & Yodzis, 2000; Hovel

& Regan, 2008; Nonaka & Holme, 2007; Schelling, 1971; Sznajd-Weron & Sznajd, 2000; Sznajd-Weron & Weron, 2002; Weins, 1997; Wilson, 1998). Section 5.2.2 reports and explains in detail two selected ABM. As an example, consider a model in which a number of agents are spread over a two-dimensional lattice. Each one of them has an opinion which, for the sake of simplicity, can only assume two values. An agent can change her opinion conforming to the one of the four immediate neighbours if all neighbours have identical opinions. Let also assume that these changes happen with a certain probability distribution influenced by an external factor. This is the simple scheme according to Sznajd-Weron and Sznajd (2000), which is based upon a well known model for the magnetization in a material proposed by Ising (1925) (which has become probably the most famous model in the recent history of physics). This simple ABM has raised much attention and many applications have confirmed its validity. For example, it has been used to reproduce distributions of votes in political elections (Bernardes et al., 2002), to infer how strong an advertising campaign has to be in order to help one of two products dominate the whole market (even if the former initially captured a small part of it) (Schulze, 2003), or to simulate price formation in a financial market (Sznajd-Weron & Weron, 2002)

At this point, it is worth to examine in depth a famous example of ABM so as to look at the architecture (or how an ABM may be build). For this purpose, Schelling's model of segregation (Schelling, 1971) re-implemented in NetLogo (Iozzi, 2008; Wilensky, 1997a), can be taken as a first example. Schelling developed two different agent based models in order to explain self-segregation (Schelling, 1969, 1971). The simplest uses a one-dimensional space (a line) in which two types of agents (blue and red, circle and crosses) are randomly placed. Each agent knows her neighbours in a determined region (number of agents left and right from a determined agent). Each agent can be in two different states: happy or unhappy, depending on how many neighbours of the same type she has and an internal parameter that defines a "happiness threshold" (i.e. the percentage of similar agents in the neighbourhood necessary to be happy). If the agent is unhappy, she will move to another empty space. "Happiness" is computed at every time-step and the simulation stops when no more unhappy agents exist. Even with this simple rule, it is possible to discover an interesting emergent behaviour as the population converges and self-segregates, thus having regions populated by one type of agent and regions populated by another. The other model of segregation proposed by Schelling uses a two-dimensional space. Here the neighbourhood is defined using the von Neumann neighbourhood construction (i.e. four cells orthogonally surrounding the cell where the agent is placed). This second model resembles the first as for agents' attributes (happiness thresholds and movement). Again, after a certain number of time-steps the model converges to a state where no unhappy agents exist, and regions of different types of agents are created (thus again, there exist self-segregation and regions of only circles or only crosses appear). The "strength" of self-segregation critically depends on the "happiness threshold" of each agent as shown in Figure 5-8.

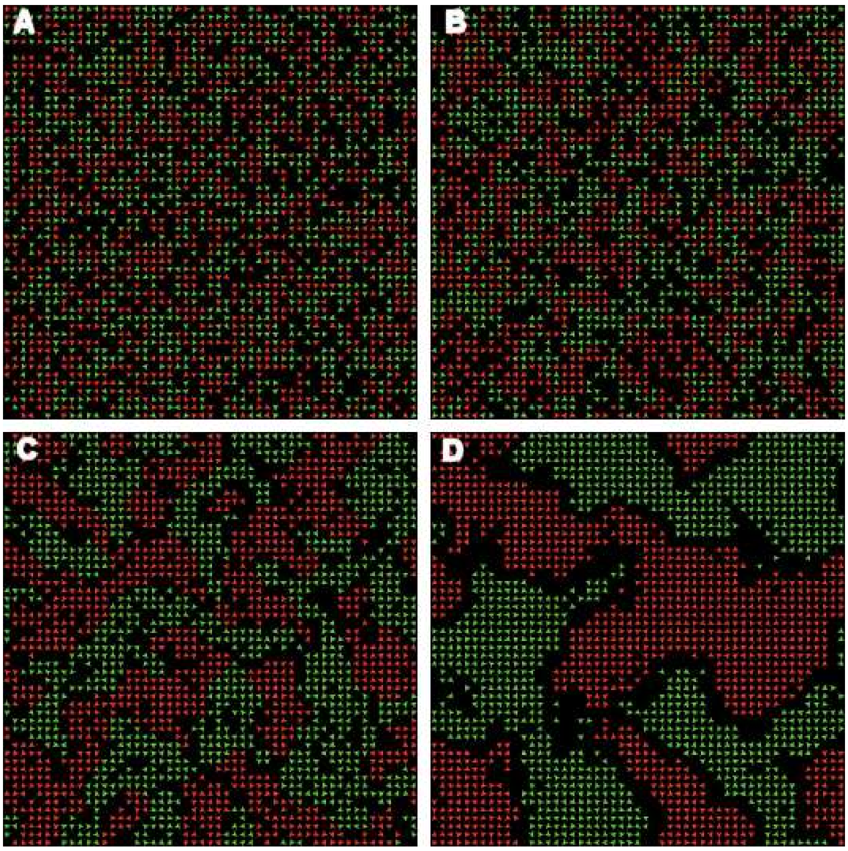


Figure 5-8 Schelling's self-segregation model in NetLogo
Self segregation model as resulted in the NetLogo simulation: 3 different values of "happiness threshold", two types of agents (light grey and dark grey). Figures were generated by using the same random-seed (90) so as to be sure that the differences in the results reported graphically are only effect of the happiness threshold parameter. A represent the initial state, B represent a world in which happiness threshold = 25%, C happiness threshold = 50% and D happiness threshold = 75% (Own elaboration).

More precisely, it is possible to report a pseudo-code that enables a better understanding of the mechanisms involved in the model. In the NetLogo environment (Wilensky, 1999) it is necessary to first setup global variables and variables that will only be property of a certain type of agent. In the example above, global variables are the average similarity and the percentage of unhappy agents. Average similarity is computed by looking at the percentage of agents of the same type (the same colour in our example). Four agent's own variables exist:

1. *happy?* reports whether an agent is happy, thus if the threshold condition is met; happy can assume two values: true or false, being true when an agent is happy and false when an agent is not happy;
2. *similar-nearby* reports how many neighbouring patches are occupied by an agent of the same colour;
3. *other-nearby* reports how many neighbouring patches are occupied by an agent of a different colour;
4. *total-nearby* is the sum of the previous two variables.

Once defined the main variables used or computed by the model, one has to initialise the model (thus performing a setup procedure). It is good practice to reset all variables to zero before the setup. In the setup of the Schelling model it is necessary to input the number of agents that will populate our world. Once the agents are created, they need to be assigned to a specific colour (in the example used, agents are equally split between light grey and dark grey) and also assign them to a location (agents in this case are randomly assigned). If an agent is assigned to a cell where another agent already exists, the agent will try to find another location and will move until she finds an empty cell. When agents have their own colour and are placed on a two dimensional space, it is possible to set the "happiness threshold" variable. In the example proposed, this threshold is equal for all the agents in the model, but it is also possible to assign different happiness thresholds to every agent (this may be an interesting exercise in order to look for possible differences between the original model and the "personalised happiness threshold model").

Once the model is configured, it is possible to start the simulation, thus looking for patterns that emerge during the time-development of the model. In order to run the simulation, at every time-step agents need to perform predetermined tasks. In our example, the simulation stops when all agents are happy (thus $happy? = true \ \ \forall agent$). In case there are unhappy agents, these will move, looking randomly for a new empty cell[11]). Once all the agents have checked if they are happy or not (and in the latter case have moved), global variables and own agent's variable are computed, and the simulation is ready to enter a new time-step. As stated before, the simulation will run until all agents are happy, thus until the variable *happy?* is set to true for every agent.

5.2.2 Selected applications of Agent Based Models

As described in section 5.2.1, ABM have been extensively used in ecology (DeAngelis & Mooij, 2005) and in social sciences, with a particular focus on social dynamics (Castellano et al., 2009). In this section two selected ABM are presented. The two models presented will form the foundations for the ideas and the development of the theoretical work described in subsequent Chapters 6, 7, and 8. First of all, a simple predator-prey model is presented. This model has been implemented in NetLogo (Wilensky, 1997b) and used by Wilson (1998) to compare ABM results with more traditional predator-prey modelling techniques. More precisely, in the ABM presented two type of agents exist: predators and preys. Both types of agent move randomly on a two-dimensional lattice, but are able to move only if the chosen location is not occupied by an agent of the same type. Prey type agents are simpler, as they die only via predation and each prey has a set probability to reproduce (e.g. `prey reproduce if random 100 < prey_reproduce`). Each predator has a handling time. Handling time mimics the handling and eating of the prey by the predator; when the handling time of a predator is greater than zero (*handl > 0*), predators can reproduce. Each predator reproduces with a given probability, similar to prey-type agents. When *handl = 0,* predators look for prey and

[11] For more detailed discussion on problems of random movement and differences between the NetLogo implementation and the original movement described by Schelling see Iozzi (2008).

kill the prey when their location overlaps; once a prey is killed the predator who killed a prey "replenishes" its handling time; the time-step ends and the whole iterative process starts again. Figure 5-9 visualises the graphical interface, where one can easily change predators and prey settings.

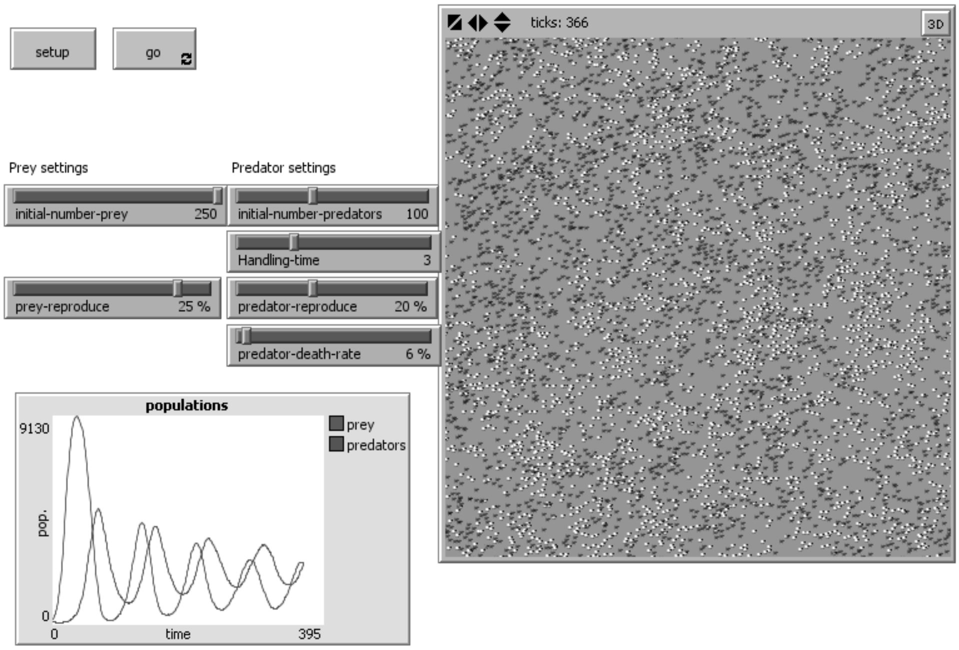


Figure 5-9 Predator-prey model interface
(Own elaboration).

This simple ABM has been used to investigate the effects of parameter changes on predator-prey dynamics and to compare ABM results with other modelling techniques. Nonetheless, referring to the population dynamics' context, the function of such model is, in Wilson's own words (1998: 126), "to bridge the fundamental gap between real biological systems and general population-level models". The use of simulations seems to be fundamental in producing new theoretical insights on complex adaptive systems. Simulations and ABM in particular, seem to be a promising tool, and, as of now, numerous applications have been proposed in ecology (DeAngelis & Mooij, 2005). More precisely ABM models could set the agenda for a new research process exploring learning and evolution issues, which can be better described by rule-based simulations such as ABM than by mathematical models. Evolution dynamics and predator-prey under different modelling assumption are the most prominent candidates of this new research agenda, given that single agent interactions may give rise to emergent behaviour at population and community level, (Cuddington & Yodzis, 2000; Hovel & Regan, 2008; Nonaka & Holme, 2007).

Social science, in particular social dynamics, is another very promising field in which ABM and simulations have been widely used. Opinion dynamics, cultural and language dynamics, crowd behaviour and the formation of hierarchies have been looked through the lenses of simulation and ABM (Castellano et al., 2009). More precisely, here we will concentrate on opinion diffusion following the Deffuant model (Deffuant et al., 2000; Stauffer et al., 2004) and a subsequent modification (Deffuant et al., 2005).

In its original formulation (Deffuant et al., 2000) a population of N agents is considered. These agents are represented by nodes and each node might interact (discuss) with any other neighbouring node[12]. To each node (i) an opinion x_i is assigned. Opinions are randomly chosen in the interval [0, 1]. A determined threshold τ is set. This threshold represents a "maximum distance of opinion"; in other words, if the opinions are too distant, no real discussion is possible, and no change in opinion will occur. The rules of the model are as follows: at each time-step a randomly selected node interacts with one of its first neighbours. Let i and j be two interacting nodes at time *t*. If $\left|x_i(t) - x_j(t)\right| > \tau$ nothing happens, and, as explained above, both agents will retain their own opinions; if $\left|x_i(t) - x_j(t)\right| < \tau$ then the opinions of both agents will start converging. How fast they will converge depends on another parameter *conv*, which lies in the interval [0, 0.5]. More precisely:

$$x_i(t+1) = x_i(t) + conv\left|x_j(t) - x_i(t)\right| \qquad \textbf{[eq. 5-1]}$$

$$x_j(t+1) = x_j(t) + conv\left|x_i(t) - x_j(t)\right| \qquad \textbf{[eq. 5-2]}$$

[12] Terminology refers to Network theory, please refer to Chapter 3 for an in-depth discussion of network theoretical related concepts.

The same dynamics occur in the case when opinions are considered discrete (Stauffer et al., 2004); that is, they do not assume continuous values between two numbers (e.g. 0 and 1), but assume values with intervals (e.g. only integer values such as 1, 2, 3). As briefly explained, the difference lies in the fact that the opinion of each node can take an integer value $s \in Q$, where s is the opinion taken and Q the ensemble of all possible opinions. In this case, the difference with the previous model is that the threshold is also an integer, and that the resulting opinion after a discussion with a neighbouring agent is rounded to the nearest integer.

This model in its continuous form has been used to explain the formation of clusters of people that share the same opinion and the possible polarization of opinions in societies. Clusters of nodes sharing the same opinion form for different values of the "discussion threshold"; polarizing societies happens if $\tau = 0.2$ while homogenisation occurs if $\tau = 0.5$ independently from the convergence parameter $conv$, as shown in Figure 5-10.

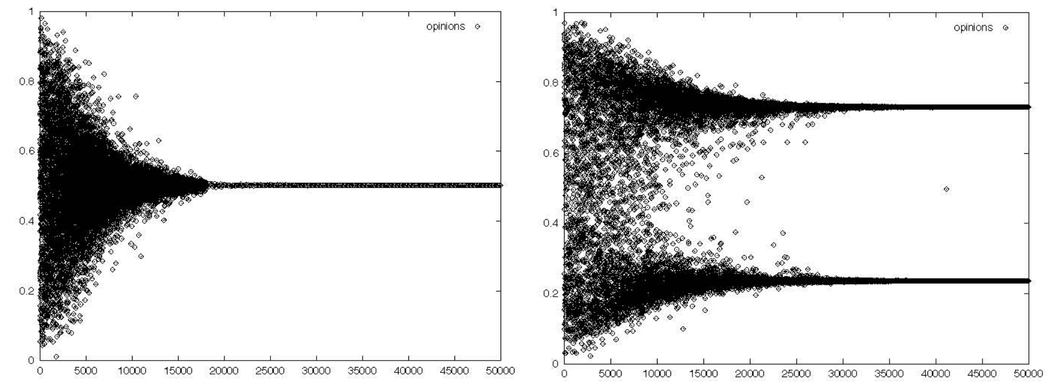


Figure 5-10 Deffuant model results
Opinions convergence when $\tau = 0.5$ (left) and $\tau = 0.2$ (right), N = 1000 and $conv$ = 0.2 (after: Deffuant et al., 2000).

Social dynamics is also a field in which the use of simulations and ABM has proved very promising. Humans are able to learn, adapt and transform their opinion and their strategies according to their social environment. Learning, adaptation and transformation allows emergent behaviour that is not easily (or impossible) to infer by looking at individual interactions or by making strong assumptions about homogeneous mixing and the "average" individual.

5.2.3 Issues with ABMs

Agent based models are often very complicated and hence understanding them in detail can be a quite intricate exercise (Galán et al., 2009). There is scepticism around computational models, as the results might be counterintuitive (though counterintuitive does not necessarily suggest incorrectness). Here, it is worth remembering that the main purpose of simulations and ABMs is to allow for new theoretical developments and advances. If the model is considered plausible (within reason) and coded correctly, even if its results might be counterintuitive, it can still assist in advancing existing theories or deepening our theoretical understanding of the system under study. One risk is that the results might be the consequence of an unknown process inside the "black box" (the computer) used to perform the simulation (Macy & Willer, 2002). The latter can be and has to be tackled by publicising the models and by exposing the models' code to the scientific community so that it will be possible to validate and replicate the results. Moreover, the value of ABMs for theoretical development could be dismissed as "*muddying in the water*", as the number of variables, parameters and their relations may approach the complexity found in the real world (Peck, 2008). It is important to take into account that agent-based models are not a universal solution.

At present day, there is no formal methodological procedure for building an ABM, although there are certainly similarities across all model building methods. The first step that needs to be considered is to make sure that there are no discrepancies between what one thinks the model is representing and what the coded model is actually doing (Galán et al., 2009). More precisely, it is worth taking into account that a model has to serve a purpose, and hence, has to contain the right level of detail. As already noted, a model cannot retain all of the real world's details and it should be a simplified, although meaningful, representation of reality (Axelrod, 1997; Bonabeau, 2002). When constructing a model it is necessary to abstract from the real world, hence in ABMs more than in other modelling techniques it is necessary to refer to practitioners or draw on empirical research or carefully reviewing the existing literature in order to gain insights into processes and fundamental behaviours that characterise single agents and their interrelations. It is important to look for implications, and evaluate that very same model. The absence of a clear research question to answer will render the model less useful in understanding the part of reality under investigation. Thus, assumptions need to be thoroughly identified and the impact of each one of them on the results produced by the model needs to be measured (Galán et al., 2009). Moreover, ABMs should be treated with caution, when looking for the quantitative aspects of the results (Bonabeau, 2002), as the importance and the validity of ABMs relies on their ability to explain different configurations arising from the set of parameters used, and in allowing a (mainly) *qualitative* understanding of the system studied.

ABMs and simulations need to be treated and approached differently from traditional analytical models (Peck, 2008). The most challenging aspect of ABMs resides in a careful understanding and planning of how single agents behave. The choice of the rules that will allow them to interact with the environment and between themselves is a central issue. There is a need for a systematic procedure and it is necessary to avoid assumptions that are not confirmed by "general wisdom" (existing literature, experts assessments etc.). Therefore, as already stressed, a continuous interaction and feedback between researchers and "experts" is necessary, so that it may be possible to shed light over the appropriate parameter space region to explore and the interactions that exist between agents. This will also allow to assess the appropriateness of the model in its different stages (initiation, running, validation) (Farmer & Foley, 2009; Galán et al., 2009; Peck, 2008).

Even when one engages continuously with experts and carefully plans his/her simulation following all good practices possible in the model building process, there is still room for errors and artefacts (Galán et al., 2009). More precisely, errors refer to a disparity between the coded model and the model that the modeller intended to code (e.g. the modeller wants the model to call for taskA before taskB, but the model runs taskB before taskA). It is important to highlight the fact that there is no error if there is no disparity between the actual model and what was meant by the researcher, thus it is not possible to assert that an error exists if the modeller's objectives are not known. Obviously, the modeller's intentions should always be stated in a clear way.

Artefacts, on the other hand, are disparities between the assumptions made by the researcher and thought to be the cause of specific results and what is actually causing them. This might happen as sometimes it is necessary to formulate hypotheses that are not critical for the system's representation but are nevertheless required in order to run the simulation code (e.g. the size of a grid might influence the results although the size is not a one of the critical assumptions of the modelled system). It is important to point out that an artefact ceases to be an artefact as soon as it is discovered, and the cause of the results becomes known. Both errors and artefacts can be avoided. In order to avoid errors, one needs to meticulously check the coding procedure and all its parts in order to make sure that the coded model is performing exactly as it was intended to. Artefacts can be avoided by implementing a model with the same critical hypotheses but with different assumptions, as to control how results are affected. This is a common procedure to assess the validity of the outcomes.

5.2.4 Evaluation of ABM

Validating, verifying and evaluating ABMs can be a demanding task. The revealed behaviours of simulations are usually not understandable at first glance (Srbljinovic & Skunca, 2003). Nonetheless, it is possible to evaluate an ABM or a simulation. The first criterion is an assessment of its reliability by allowing for different separate implementations and comparing the results. In other words, if time and resources allows it, it is good practice to implement the model on different machines on different platforms or even coding the model in different programming languages. This is by itself, however, not sufficient to evaluate an ABM, Taber and Timpone (1996) propose three more methods for validating a simulation model. They ask:

1. Do the results of a simulation correspond to those of the real world (if data are available)?
2. Is the process by which agents and the environment interact corresponding to the one that happens in the real world (if the processes in the real world are known)?

3. Is the model coded correctly so that it is possible to state that the outcomes are a result solely of the model assumptions?

Answering the first two questions allows for assessing the validity of the representation (model), thus gauging how well the real system we want to describe is captured and explained by its representation. Answering the third question guarantees that the model's behaviour is what the modeller really intended it to be (Galán et al., 2009). Evaluating an ABM requires data from the real world and the involvement of knowledgeable experts that might be able to give insights into the "real" processes and dynamics and hence help evaluate its ability to represent reality.

Moreover, it is worth highlighting the importance of the conceptual accuracy that is needed in order to build ABMs that are able to advance our theoretical understanding of a system. Every part of the code in a model should be grounded in the literature or be informed by "experts" (i.e. empirical researcher, practitioners etc.), and the final test of any ABM is its importance in advancing the understanding and the development of new formal theories. ABMs explain rather than predict, allowing for a qualitative understanding of the fundamental processes underlying the system modelled. Finally, as Henrickson and McKelvey (2002: 7295) state:

> Future, significant, social science contributions will emerge more quickly if science-based beliefs are based the joint results of both ABMs and subsequent empirical corroboration.

5.3 Assessing Resilience: Case Study Research

Case study research has been widely used in the past. More precisely, in the 1930's case study research was already employed in the University of Chicago amongst sociologists (Tellis, 1997b). The popularity of case study research led to a public debate between the Chicago school and researchers and professors at Columbia University, who thought that case study methods led to biased result and were not-scientific. The debate was won by researchers and professors of the Columbia University, thus leading to a decline of case study methodology (Tellis, 1997b). Nonetheless, case study methodology is still widely used especially in social sciences, though the discussion on its validity is still ongoing (Gerring, 2004). Moreover, case studies have not been widely used exclusively in social sciences. Charles Darwin drew his ideas on evolution after a single trip to the Galapagos in 1835; Alfred Wegener discovered the same fossil species along the South American and the African coast, leading him to form his continental drift theory in 1915.

Often, one or more carefully chosen cases have led to amend, assess and/or reject theoretical frameworks. Therefore, a "case study is an intensive study of a single unit for the purpose of understanding a larger class of (similar) units" (Gerring, 2004: 342). Irrespective of the area of research, it is important to have a clear theoretical framework and a clear purpose when deciding on a suitable case. Theory plays a central role, knowledge of prior research is crucial in order to build up knowledge from a case study, and it is not simply a matter of answering a single, isolated empirical question (Yin, 1994). Having a clearly defined theoretical framework, as the one proposed in Chapters 3 and 4 and section 5.1, allows for selecting the case/cases to be studied, since case studies can be of single or multiple design (Gerring, 2004). A clearly defined theoretical framework enables to specify what is going to be explored, hence allowing to stipulate rival theories and generalising the results. In other words, a theoretical framework permits the definition of a limited number of variables (issues) considered crucial for the understanding of the system studied (Tellis, 1997b).

Case studies can be defined according to their purpose (Tellis, 1997a, 1997b; Yin, 1994). Exploratory case studies help the identification of research questions and hypotheses. Explanatory case studies try to give a plausible explanation of causal relations. Descriptive cases are used to assess the validity or to help in the formation of a theoretical framework, thus requiring a theory to be developed before starting the study. Case studies validity is enhanced when inferences are descriptive, when propositional depth is preferred over breadth, when discovering causal mechanisms is more important than discovering cause-effect, when the strategy of the research is exploratory, thus helping in tuning a theoretical framework (model), rather than confirm it (Gerring, 2004).

Can case studies be generalized? This is a long debated issue. Critics claim that results of a case study can not be widely generalized (see for example: Lincoln & Guba, 1985), although others counter this idea by differentiating between two main different types of generalization: analytic and statistical generalization (Yin, 1994). Yin defines analytic generalization as a "template with which to compare the empirical results of the case study" (Yin, 1994: 31), and statistical generalization when "an inference is made about a population (or universe) on the basis of empirical data collected about a sample" (Yin, 1994: 30). Analytical generalization is what is possible to achieve using a case study, thus ignoring the sampling limitations. Furthermore, single-unit case studies can allow for testing of causal implications of a theory and can provide evidence in order to validate/amend certain theoretical arguments since they are likely to be comparable (Gerring, 2004). However, single-unit case studies might show problems of representativeness if universal/general conclusions are drawn from a single case study. Multiple-unit cases are best suited in order to confirm results coming from given theoretical models, although one need to be careful in making assumptions on the comparability across the chosen case studies.

For the scope of this research, I do think that a single-unit case study might not be representative in order to confirm a theoretical model. Moreover, given that the concept of resilience is intrinsically dynamic, I do think that a single case study will not be suitable for enhancing the theoretical knowledge of how networks metrics can help us understand the resilience of SESs. Since a single unit case study is centred upon a single space and time unit, for the purpose of this thesis it is worth to resort to other methods in order to better comprehend the relations between network metrics and the resilience of a SES. Such methods are described in Chapters 3 and 4, and sections 5.1 and 5.2. Nonetheless, I do hope, in the future, to be able to have the necessary resources in order to design a multiple case study in order to validate and amend the models presented in Chapters 6, 7, and 8. Ideally, the multiple case studies will involve different locations and repeated visits over a determined time-span. Unfortunately, the design of such research is, at present, impossible, given the time-frame and the resources of a PhD student.

5.4 Concluding Remarks

This chapter described a first possible integration of the Resilience framework outlined in Chapter 4 and network theoretical tools as outlined in Chapter 3. Differences in impact between failures (or random removal of nodes) and attacks (or targeted removal of nodes) have been explained as depending on the network topology. Unfortunately, the differences have been assessed only in static networks, that is, networks that do not evolve over time. The problem of temporal spatial scales is paramount in assessing the resilience of a SES, thus two possible ways of assessing resilience of a SES have been outlined: a case study and the use of agent based models. Agent based models have the limitations and the problems of validation described in sections 5.2.3 and 5.2.4. However, if carefully planned and implemented they allow exploring the dynamics (the time dimension) and spatial features of a SES.

Case studies have the advantage of giving in depth information and directly link to reality, nonetheless, in order to assess the resilience of a system using network theoretical tools a case study should be investigated repeatedly in time. Moreover, the case study should be multiple; different case studies should be carried out in different location for a determined time-span. This is due to the specific properties of SES, the need to look for some universality in the integration that has been proposed. Given the scope, the time-frame and the resources of a PhD student, this avenue is not feasible at the moment, but it will be highly important in the future, in order to falsify, enhance, or accept the models that are presented and analysed in Chapters 6, 7, and 8.

Before discussing the work that forms the substantial contribution of this thesis and is presented in the following chapters, it might be worth summarizing the theoretical framework used in this thesis. Chapters 3, 4, and 5 have presented a number of methods and theories that form the theoretical basis for the development of the models presented in the subsequent chapters (i.e. 6, 7, and 8). It is also worth repeating that the main aim of this thesis is to enhance the understanding of how structural properties influence (or not) the resilience of a SES. In order to answer the main research questions outlined in section 1.1, this thesis develops a systemic approach that uses network theoretical tools to analyze structural properties, agent based models to simulate the evolution of a system and the resilience framework to analyze, conceptualize and discuss the results given by the theoretical models presented in the next three chapters.

6 Assessing Resilience: Integrating Network Metrics and Agent Based Modelling

As briefly outlined in section 5.4, Chapters 6, 7, and 8 aim at a formal integration of network metrics, resilience thinking and agent based modelling. It is worth to highlight the fact that initial parameters in the model presented in Chapters 6, 7 and 8 do not determine a priori the findings presented. That is, model's parameters have a probability of influencing a change in the basin of attraction, however, given the stochasticity of ABM (as explained in section 5.2) may allow for the same parameters to lead to a change in basin of attraction or to a change of the state in the same basin of attraction. A change in the basin of attraction refers to change in species composition (as explained in Chapter 6 and 7), while a change in the state of a system simply refers to different population levels or if local extinctions occurs without leading to global changes in the species composition. On the other hand, if deterministic models are used, it is possible to affirm that the initial parameter configuration already determines the state of the system and if a change in the basin of attraction occurs.

The model developed in this chapter has been published in Landscape Ecology (Baggio et al., 2011) and is a first step in the integration of the different methods extensively explained in Chapters 3, 4 and 5. This chapter will present an ABM of predator-prey dynamics on a landscape represented by a network. The agents of the model (predators and prey) are able to move between different nodes of the landscape network. Population levels and the coexistence probability given node-centrality and network metrics are analyzed. Here different basins of attraction (see Chapter 4) of the simple ecological system under study are represented by coexistence or not-coexistence of species. Different states of the system in the same basin of attraction are represented by different population levels and different dynamics that unfold during the simulations of the model. The model presented in this chapter shows that both predator and prey species benefit from living in globally well-connected patches enhancing the resilience of the "coexistence" basin of attraction. However, the maximum number of prey species is reached, on average, at lower levels of connectivity than for predator species. Hence, prey species benefit from constraints imposed on species movement in fragmented landscapes since these constraints reduce the need for anti-predatory strategies and may allow safe heavens for prey.

6.1 A simple ecological system

The model presents a simple ecological system in which two species (predator and prey) exist. Predator-prey relations represent the simplest possible food web as explained in section 3.4.1. Species are distributed heterogeneously and, given the variety of habitats that exist in nature, habitat fragmentation per se does not necessarily threaten species. However, in recent years, fragmentation seems to have conspicuously accelerated given human population growth and urban sprawl, and the pace and scale of fragmentation is increasingly posing threats for species' survival. Understanding the ecological consequences of habitat fragmentation is now part of many research agendas that deal with conservation, biodiversity and adaptation to climatic change. More recently there has been an increased use of network approaches in conservation of both marine and terrestrial landscapes (Bodin & Norberg, 2007; Planesa et al., 2009; Urban et al., 2009). This network approach describes landscapes as networks of habitat patches (nodes) connected by edges representing links between different patches (Urban & Keitt, 2001), indicating the ability of an organism to directly disperse/diffuse from one patch to another (from node *i* to node *j*) (Pascual-Hortal & Saura, 2006). Movement of organisms to/from a specific patch is limited to connected habitat patches, or patches that are situated close enough to allow species migration (Bodin & Norberg, 2007). Therefore, a network perspective allows combining landscape patterns and predator-prey dynamics (Bodin & Norberg, 2007; Minor & Urban, 2007; Urban & Keitt, 2001) so as to better understand the influence of structural properties on a simple ecological system (landscape on predator-prey dynamics hence on population persistence). However, almost all of these studies have focused on single species and how they might be affected by various levels of habitat fragmentation. Here, the focus will be more broadly on how habitat fragmentation (thus landscape heterogeneity) may affect two interacting species (a predator and a prey species) with active movement decisions as opposed to the widely used random movement.

Issues of space and time-scale increase the complexity of predator-prey dynamics as their inclusion leads to substantially different outcomes even if all other variables that affect these dynamics are kept constant (Fahrig & Nuttle, 2005). Past literature has dealt in depth with land-fragmentation and its effect on movement (Bolker, 2003; Droz & Pekalski, 2001; Fahrig & Nuttle, 2005; Inchausti & Ballesteros, 2008; Nonaka & Holme, 2007; Pascual-Hortal & Saura, 2006; Rougharden, 1977, 1978). In order to understand the importance of spatial heterogeneity (or landscape heterogeneity), it is necessary to focus on how fragmentation affects the resilience of the system. Recalling the importance of defining resilience of what to what (see Chapter 4), resilience refers to how levels of fragmentation measured through network metrics (explained extensively in Chapter 3) increase or decrease the probability of a change in the basin of attraction. Thus, landscapes are represented by a network in order to uncover the significance of heterogeneous fragmentation. Network representation of a landscape allows looking at the relationship that exists between predator-prey dynamics and network metrics. In other words, this chapter seeks to understand how the structure of habitat fragmentation affects the resilience of a simplified ecological system.

As species diffuse and respond to landscape patterns and the surrounding environment, connectivity properties, spatial conditions, hence fragmentation, need to be taken into account (Rougharden, 1977, 1978). According to previous experimental papers, the landscape structure is able to alter predation pressure (With et al., 2002), thus modifying how prey behave over time, depending on the landscape structural changes (Kareiva, 1987). Landscape heterogeneity *per se* does not seem to have any significant effect on predator-prey dynamics; however, when combined with movement capabilities, it may lead to important alterations of predators and prey populations (Fahrig, 1998).

The interaction between predators and prey has been studied with differential equations (i.e. Lotka-Volterra), reaction-diffusion equations (Benson et al., 1993;

McLaughlin & Roughgarden, 1991), and individual based models (Cuddington & Yodzis, 2000; DeAngelis & Mooij, 2005; Droz & Pekalski, 2001; Hovel & Regan, 2008). In analytical models, population is treated as a whole (homogeneous mixing) in order to achieve tractable results (see also section 5.2). Agent (individual) based models (IBM or ABM) centre on individual differences (Breckling et al., 2006; DeAngelis & Mooij, 2005; Grimm & Railsback, 2005). As extensively explained in sections 5.2.1, and 5.2.2, ABMs allow population dynamics to emerge from individual predators and prey. This approach is essential in order to uncover the complexities arising in predator-prey systems on heterogeneous and fragmented landscapes (McCauley et al., 1993).

This chapter focuses on the consequences of movement between patches, rather than the spatial details of a single patch, as the focus lies in uncovering how fragmentations alters the resilience of the system presented. Individual predator and prey on heterogeneous landscapes, represented as networks of habitat patches, are modelled. The central research questions that will be answered in this chapter are the following:

- How does the underlying network of habitat patches influence population levels?
- Does network connectivity, more precisely patch (node) centrality, drives predator-prey dynamics and the probability of coexistence?

Referring to the definition of system resilience given at the beginning of this chapter, and at the terminology extensively described in Chapter 4, the two questions above can be rewritten as follows

- How does network connectivity affect population levels in the same basin of attraction?
- How network connectivity favours or hinder the probability of shifting basin of attraction?

6.2 Methods

In a given landscape, predator-prey interactions are modelled according to the ABM proposed by Wilson (1998) (see section 5.2.2 for information on the model). The study presented by Wilson (1998) is extended by including a networked landscape where nodes represent habitat patches. Habitat patches are considered land where prey can eat, predators can hunt, and both species can reproduce (Droz & Pekalski, 2001; Ives & Dobson, 1987). Edges represent movement possibilities between different patches. In the past, species models of networks with small and large patch numbers have been studied. Small number of patches have been studied to resemble ecosystems, while a larger number have been used to examine the coexistence of multiple species (Blasius et al., 1999; Cominsa & Hassell, 1996; Hastings, 2001; Jansen, 2001). More recently Holland and Hastings (2008) have developed a manageable ten-patch model that supplements the realism of models with small number of patches while displaying results similar to networks with a larger number of habitat patches.

Given the aim of this model, the focus is centred on movement capabilities of agents between different habitat patches. Recently, the movement of predators and prey has been widely researched in order to explicitly incorporate space into modelling species interaction, with an emphasis on predators' searching strategies and the anti-predatory behaviour of prey (Inchausti & Ballesteros, 2008; Linhares, 1999; McLaughlin & Roughgarden, 1991). Nonetheless, few studies take active behavior into account and I think that species do move according to the feedback they receive from the surrounding environment (e.g. intra-species competition, search strategies and anti-predatory behavior). Therefore, in the model presented, agents actively choose to move according to signals (inputs) given by their surrounding environment. The results of the model presented here, where a threshold rule is used to determine the movement decisions by prey and predators, can be compared to more simplistic models of migration based on diffusive and random movement. This comparison may shed further light on the importance of understanding the effects of landscape connectivity.

A detailed description of the ABM proposed is provided in the ODD (Overview, Design concepts, and Details) protocol available in Appendix II, section II.i. The ODD protocol is a standard protocol for describing individual and agent based models (Grimm et al., 2006), so as to allow for a deeper understanding of the model and to facilitate replication.The code used for the model presented in this chapter is reported in Appendix III, section III.i.

6.2.1 The network of habitat patches

To build on the work of Holland and Hastings (2008), a landscape with N=10 habitat patches and varying number of edges (E) that connect them is considered. Habitat patches (nodes) are placed randomly on a two-dimensional grid and are connected through edges according to their proximity to other patches (patches within small Euclidean distance from each other are connected first). Geographic proximity is an important aspect concerning the network topology of a landscape (Minor & Urban, 2007, 2008); the networked landscape presented is based on Euclidean distances in order to better simulate movement of species on real landscapes. The network used is considered simple: the use of loops and multiple edges is not allowed. All habitat patches are considered equal; as a result, the ability to sustain prey does not vary throughout the patches. The landscape is interpreted as an undirected, un-weighted network (see section 3.1) and a graphical representation of the network used is given in Figure 6-1. An undirected network contains edges that enable movement from one node to another and vice versa. An un-weighted network only considers edges as connectors and not pathways with explicit distance (note, Euclidean distance is only used in order to determine if a connection, an edge, should exist between two patches). Although more complex network representation may lead to different results, an undirected, un-weighted network is still able to provide adequate information that enables the assessment of patch importance on the species' movement abilities (Estrada & Bodin, 2008).

6.2.2 The species

There are two types of agent-sets, predator and prey, each of which is assigned randomly to a habitat patch. In the mathematical notation subscript 1 is used to represent prey and subscript 2 is used to represent predators. The initial number of predators and prey is proportional to the number of nodes in the network, as shown in Table 6-1. Each prey has the ability to reproduce with probability $P_{r,1}$ at each time-step and to die via predation with probability $P_{k,2}$, if both prey and predator are assigned to the same patch i. Predators may also reproduce at every time-step with probability $P_{r,2}$, given they have successfully attacked (thus killed) a prey and are currently in their handling period (T_h), a timeframe in which predators are consuming the prey and hence have the "energy" to reproduce. Predators die naturally according to a fixed death rate ($P_{m,2}$). Drawing from the literature, movement behaviour of agents between patches is simplified. Agents move between patches according to density thresholds characterising one or both species. The prey moves if its density in a given patch i (Dn_{1i}) is higher than a predetermined threshold ($D_{U,1}$), so as to mimic intra-species competition for food. The prey also moves if the predator density (Dn_{2i}) rises above a predetermined threshold ($D_{U,2}$) in order to mimic anti-predator behaviour (Creel et al., 2005; Fischhoff et al., 2007; Ives & Dobson, 1987; Lima, 2002; Luttberg & Schmitz, 2000; Nelson et al., 2004). If prey density falls below a predetermined threshold ($D_{L,1}$), predators move between patches looking for higher densities of prey, thus imitating predatory search strategies (Ioannou et al., 2008; Lima, 2002; Linhares, 1999). Table 6-1 summarizes variables and values used in the ABM presented.

Table 6-1 Summary of variables, symbols and values used in the ABM.

Simbol	**Variable Name**	**Values from distributions used in Monte Carlo simulations**
N	Number of nodes	10
E	Number of edges	Varies from 0 to 45
C	Size of a node	100
n_1	Initial number of prey	Poisson with mean 25 * N
$P_{r,1}$	Prey reproduction rate	Poisson with mean 0.25 (25%)
$D_{U,1}$	Prey density upper limit	Random uniform distribution [0.5, 0.9]
$D_{L,1}$	Prey density lower limit	Random uniform distribution [0.2, 0.4]
n_2	Initial number of predators	Poisson with mean 10 * N
$P_{r,2}$	Predator reproduction rate	Poisson with mean 0.2 (20%)
$P_{k,2}$	Predation probability	Poisson with mean 0.2 (20%)
$P_{m,2}$	Predator death rate	Poisson with mean 0.06 (6%)
$D_{U,2}$	Predator density upper limit	Random uniform distribution [0.3, 0.6]
T_h	Predator handling time	3

Note: Parameters are set at the beginning of each run as described. Internal species parameters are drawn from the distributions described. The number of edges, *E*, varies from 0 to 45 as shown in Figure 6-1.

Population levels for both predators and prey are measured for every patch throughout the different simulation runs. The mean values of the parameters presented in Table 6-1 are one of the configurations that enable fairly stable coexistence in the model presented by Wilson (1998). That is, using the mean parameters presented and a full network, the likelihood of coexistence is almost certain (being probability of coexsistenc 99.9%). The Monte Carlo method is used to explore a wider parameter space and test for the sensitivity of the outcomes. The importance of landscape fragmentation in the welfare of predator-prey systems is assessed by altering the number of existing connections between patches independently from species reproduction, death and predation rates.

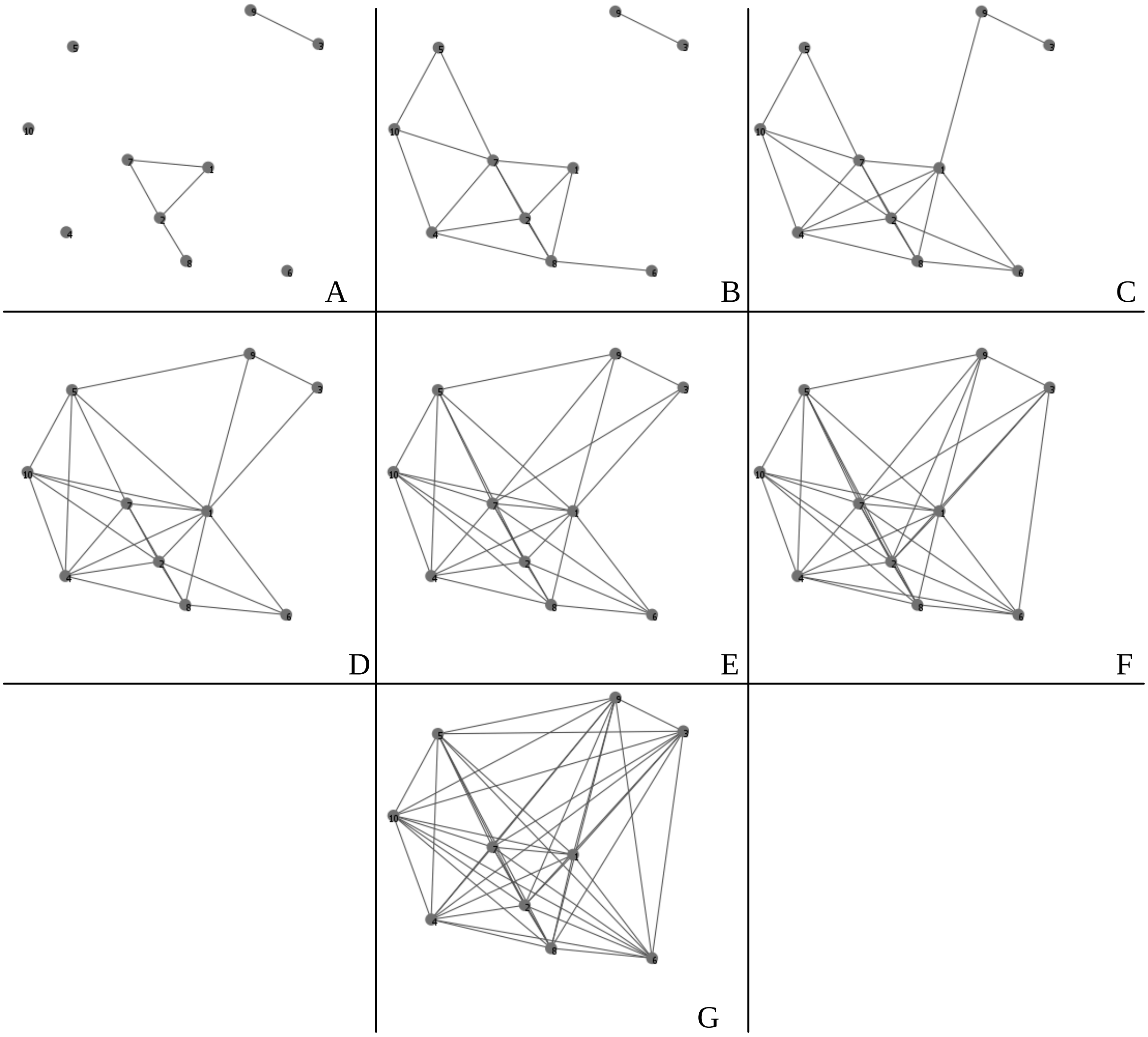


Figure 6-1 Geoproximity Network
Graphical representation of a geoproximity network for *E* = 5 (A), *E* = 15 (B), *E* = 20 (C) and *E* = 25 (D), *E* = 30 (E), *E* = 35 (F), and *E* = 45 (G) (Own Elaboration).

6.2.3 Network structures and predator-prey dynamics

The analysis is based on network metrics that statistically characterize landscape connectivity (extensively explained in sections 3.2 and 5.1). More precisely, the following node-centrality and network metrics are taken into account (numbers in parenthesis refer to sections in the thesis where in depth information on each of the metrics can be found).

- *closeness centrality (clos)* (section 3.2.1)
- *average closeness centrality (avgclos)* (section 3.2.1)
- *global efficiency (avgeg)* (section 3.2)

- *local efficiency (el)* (section 3.2)
- *average local efficiency (avgel)* (section 3.2)
- *degree centrality (deg)* (section 3.2)
- *average network degree (avgdeg)* (section 3.2)
- *cde:* (*clos* + *el* + *deg*) / 3
- *average cde (avgcde): avgcde* = (*avgclos* + *avgel* + *avgdeg*) / 3
- *density (dens)* (section 3.2 and 3.4.1)
- *giant connected component (gcc)* (section 5.1)
- *average cluster coefficient (avgcc)* (section 3.2).

The focus of the analysis is on node-centrality and other network metrics that are relevant for measuring the dispersal of species. Detailed results for each metric used are presented in Table 6-8 and Table 6.9.

Although results are presented for all outlined metrics the analysis is confined to selected metrics for the sake of simplicity. More precisely, the analysis is based on two node-centrality measures and three network metrics that are most important when assessing coexistence probabilities and shaping predator-prey population levels: i.e. closeness centrality (*clos*), an average of node-centrality measures (closeness centrality, node degree and local efficiency) denoted *cde*, network average local efficiency (*avgel*), global efficiency (*avgeg*), and the percentage of nodes belonging to the giant connected component (*gcc*). Closeness centrality measures the average geodesic distance (shortest path length) between one node and all other nodes in the network within its reach. In other words, a node is globally central if it is reachable from many other nodes. Local efficiency is the average efficiency of local sub-graphs (Latora & Marchiori, 2001). In essence, it is a measure of how effectively information spreads through a network on a local scale; in this case, the information is perceived as species diffusion between connected patches. Global efficiency is defined as the average of the inverse distance between two nodes; it is related to an agent's movement ability and it is measurable for unconnected graphs (Crucitti et al., 2004; Latora & Marchiori, 2001). The giant connected component can be defined as the largest part of the network whose nodes are connected to each other. All measures used are normalized to facilitate comparisons between the different networks created through the simulations.

6.3 Results

The Monte Carlo method is used to gain a broader understanding of the model dynamics. The number of edges varies from 0 to 45. For a given number of edges, 1000 simulations with different parameter configurations drawn from the distributions presented in Table 6-1 are performed. Each simulation lasts for 5000 time steps. Since the main focus is on long-term population dynamics and the probability of species coexistence, data on the average population levels of predators and prey from the last 1000 time-steps as well as data population levels for every time-step are collected.

The use of the Monte Carlo method enables to assess the importance of node centrality and other network metrics under a wide range of dynamics. Figure 6-2 displays the dynamics of 8 select runs from the original 10000. These runs were specifically chosen because they represent the distinct regimes and population patterns that arise from simulations. Figure 6-2A focuses on the population level of the whole network, while Figure 6-2B and Figure 6-2C focus on population at the node level, specifically nodes 1 and 5, respectively. Nodes 1 and 5 have been chosen as representative of local interaction. Note the differences between global and local dynamics. Species can abandon a certain node for some period of time due to intra- and/or interspecies competition (i.e. prey on node 1 at run 1) but may persist on other connected nodes, thus fostering global survival (i.e. total prey on the network during run 1). Moreover, if nodes are connected, temporary extinction on a node is also possible (i.e. local extinction), as shown in Figure 6-3D as the very same nodes may as well be repopulated by migration of species (due to its connectedness to other nodes where extinction has not occurred). The greater fluctuation of both species that occur on a local scale, compared with what happens to population trends at the network level, is due to migration, i.e. it is a local phenomenon (e.g. Figure 6-2A and Figure 6-2B or run 7 represented in Figure 6-3A and Figure 6-3B). Figure 6-3 displays selected runs from Figure 6-2 with shorter time intervals for magnified viewing of some of these dynamics.

Table 6-2 contains the internal species parameters used and the corresponding values for the metrics of the whole network, while Table 6-3 contains the centrality measures for nodes 1 and 5, for the 8 representative runs. Figure 6-2, Table 6-2, and Table 6-3, demonstrate the existence of a positive correlation between connectivity levels and long-term coexistence; as one progresses from run 1 to 8, the number of edges increase and so does the possibility for coexistence. However, between runs 4 and 6, where the network contains 30 to 35 edges, the predator population becomes variable. In run 4 (30 edges), the predators are able to coexist, while they fall victim to early extinction in runs 5 (30 edges) and 6 (35 edges). All three intermediate runs consist of similar network metrics (*avgeg* of 0.833, 0.826, and 0.889 respectively), and so, the reason for the variable dynamics stems from internal species parameters. The predation rate of predators in run 6 ($P_{k,2}$ = 0.12) is about half the value in other runs, and as a result, the predators reproduce slowly due to inefficient hunting and stay at relatively low levels until sudden extinction. The early dynamics of runs 4 and 5 are almost identical; increased predation rates ($P_{k,2}$ = 0.20 and 0.24, respectively) implies that the predators are more effective at capturing prey and hence boosting their population. It is this prey dependency that leads to heightened predator oscillations, as the efficient hunters begin to migrate from one node to another (if possible) in search of prey. The predator population in run 4 outlive that of run 5 due to the interplay between the movement thresholds of the prey. It is worth to take note of the reduced oscillations in run 4 versus run 5 on the network level in Figure 6-2A. Compared to run 5, the prey population in run 4 migrates to other connected nodes when its current node is less crowded with prey or more crowded with predators, which amounts to less variability in the 'boom-bust' cycles of the predator population.

The richness in dynamics that occur on each node, and the network as a whole, do depend on the internal species parameters. Nonetheless, various network metrics allow valuable conclusions to be drawn on the usefulness of a "corridor" or networked landscape approach. On average, well connected (or more central) patches enhance the probability of coexistence between predators and prey, independently from the different dynamics that arise across the broader parameter space analyzed.

Table 6-2 Parameters for selected runs graphically represented in Figure 6-2A, 6-3A and 6-3C

General		**Internal Species Parameters**									**Network Metrics (global-scale)**		
run	E	n_1	n_2	$P_{r,1}$	$P_{r,2}$	$P_{m,2}$	$P_{k,2}$	$D_{U,1}$	$D_{L,1}$	$D_{U,2}$	*avgel*	*avgeg*	*gcc*
1	0	27	15	0.28	0.25	0.09	0.21	0.626	0.238	0.359	0	0	0
2	5	28	16	0.3	0.21	0.1	0.19	0.793	0.252	0.4	0	0.133	0.3
3	10	45	14	0.24	0.21	0.04	0.2	0.578	0.258	0.598	0.397	0.375	0.8
4	30	33	18	0.28	0.25	0.06	0.2	0.701	0.346	0.3	0.892	0.833	1
5	30	42	16	0.31	0.2	0.03	0.24	0.856	0.217	0.392	0.898	0.826	1
6	35	46	18	0.28	0.31	0.09	0.12	0.545	0.349	0.346	0.934	0.889	1
7	40	39	13	0.23	0.12	0.01	0.27	0.664	0.33	0.484	0.959	0.944	1
8	45	40	13	0.34	0.16	0.08	0.24	0.58	0.248	0.475	1	1	1

Note: 8 runs representative of the different dynamic regimes of the parameter space. This table summarizes the values of the internal species parameters and metrics of the whole network for the 8 runs.

Table 6-3 Node-centrality metrics for runs represented in Figure 6-2B, 6-2C, 6-3B, 6-3D

General		Node Metrics (local-scale)	
Run	N_i	***clos***	***cde***
1	1	0	0
1	5	0	0
2	1	0.2	0.104
2	5	0	0
3	1	0	0
3	5	0.509	0.457
4	1	0.643	0.668
4	5	0.9	0.87
5	1	0.9	0.876
5	5	0.9	0.876
6	1	0.9	0.894
6	5	0.75	0.806
7	1	1	0.977
7	5	1	0.977
8	1	1	1
8	5	1	1

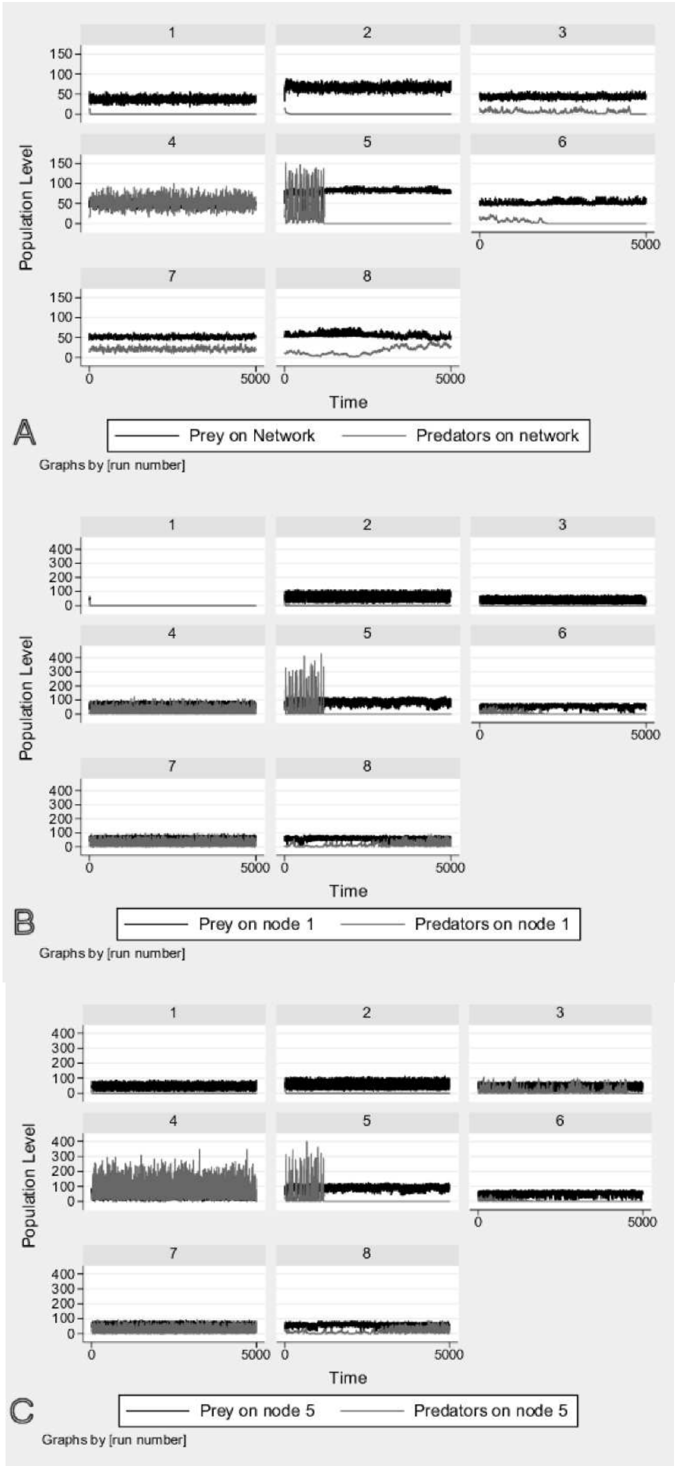


Figure 6-2 Dynamics of the model for 8 select runs.
These runs represent the total regime of dynamics under the parameter space explored. Global (network) dynamics (A) and local (node) dynamics (B and C) . Parameter values, network and node centralities are presented in Table 6-2. Network population levels are divided by 10. y axis represent population levels and x axis represent time-steps. Graphs are indexed by run (from 1 to 8 following Table 6-2 (A) and Table 6-3 (B and C) (Own elaboration).

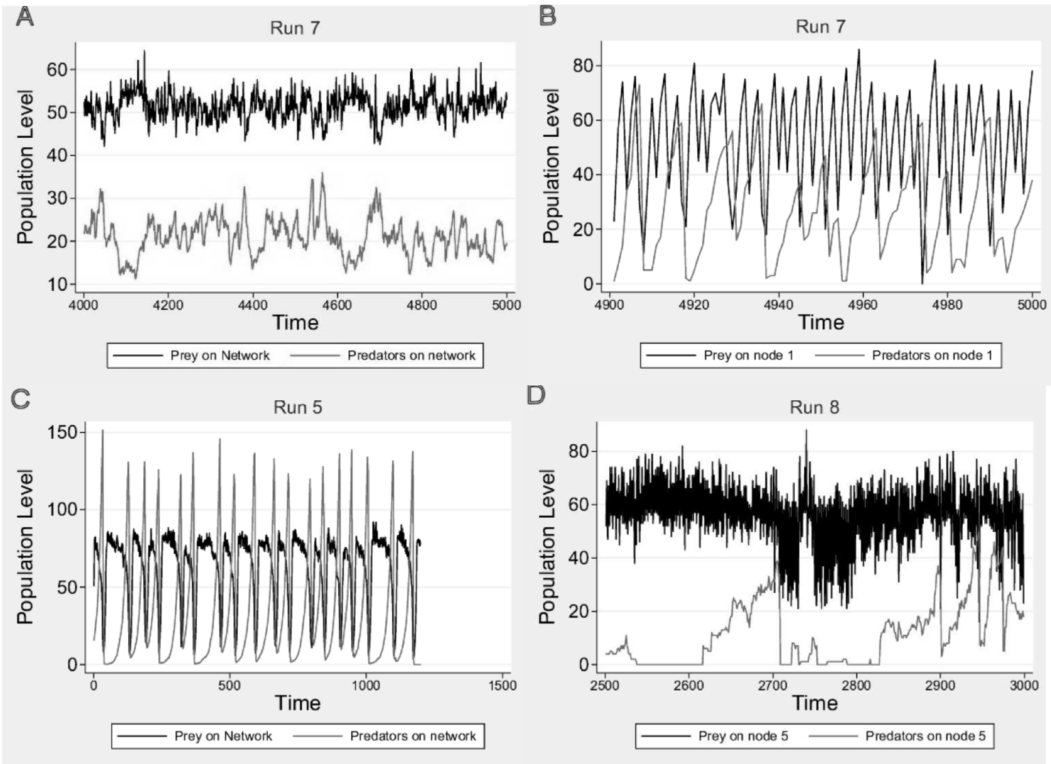


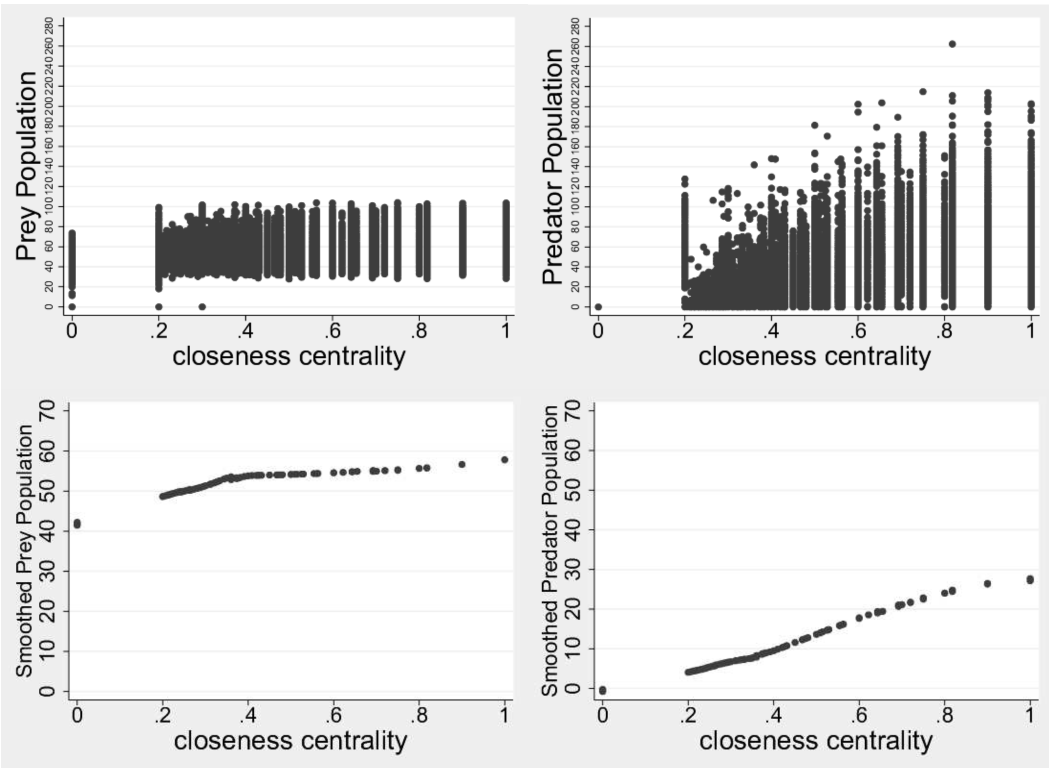
Figure 6-3 Magnified Dynamics
Dynamics of the model for selected runs, from Figure 6-2, on shorter time intervals (to magnify visuals). A and B represent run 7 at the global and at the local scale (network vs node 1), where local oscillations are more amplified. Differences in the time-scale used are necessary in order to clearly visualize the patterns. C represent a magnified visual of the high fluctuation that occur in run 5, while D is a magnified representation of predator-prey dynamics on node 5 of run 8, where temporary local predators extinction occur (Own elaboration).

Internal parameters regarding reproduction, predation, death rates and active movement behaviour are crucial in allowing coexistence in the long-term, and give rise to different dynamic regimes as depicted in Figure 6-2 and Figure 6-3. Independently from internal species parameters, alteration of the landscape by connecting different patches or enhancing the centrality of particular patches further increases the probability of coexistence between predator and prey. In short, increasing connectivity matters, as it is evident looking at run 3 in Figure 6-2B and Figure 6-2C. In this run only the connectivity properties of the nodes differ, leading to quick extinction of predators on node 1 (being *clos* = 0) , and leading to a longer persistence of predators on node 5 (being *clos* = 0.509).

The importance of node-centrality is visualized in Figure 6-4, where the behaviour of average population levels for the last 1000 time-steps is evaluated based on node-centrality measures. Given the stochastic nature of the model, data relative to predator and prey population levels are smoothed the using a locally weighted regression of predator and prey populations on the node-centrality measures used. The use of smoothed data allows for a better understanding of the relationship that exists between node-centrality and population levels of predators and prey. Additionally, regression results are truncated, so as to discard negative population levels. LOESS smoothing methods allows fitting low-degree polynomial regression to a subset of the observed data, giving lower (higher) weights to points further away from (closer to) where the dependent variable is being estimated (Cleveland, 1979; Cleveland & Devlin, 1988). The weights given to distance between points of the independent variable follow the tricube weighting function, which assigns weights as follows:

$$w(x) = \begin{cases} \left(1-|x|^3\right)^3 \; for|x| < 1 \\ 0 \; for|x| \geq 1 \end{cases}$$

[eq. 6-1]



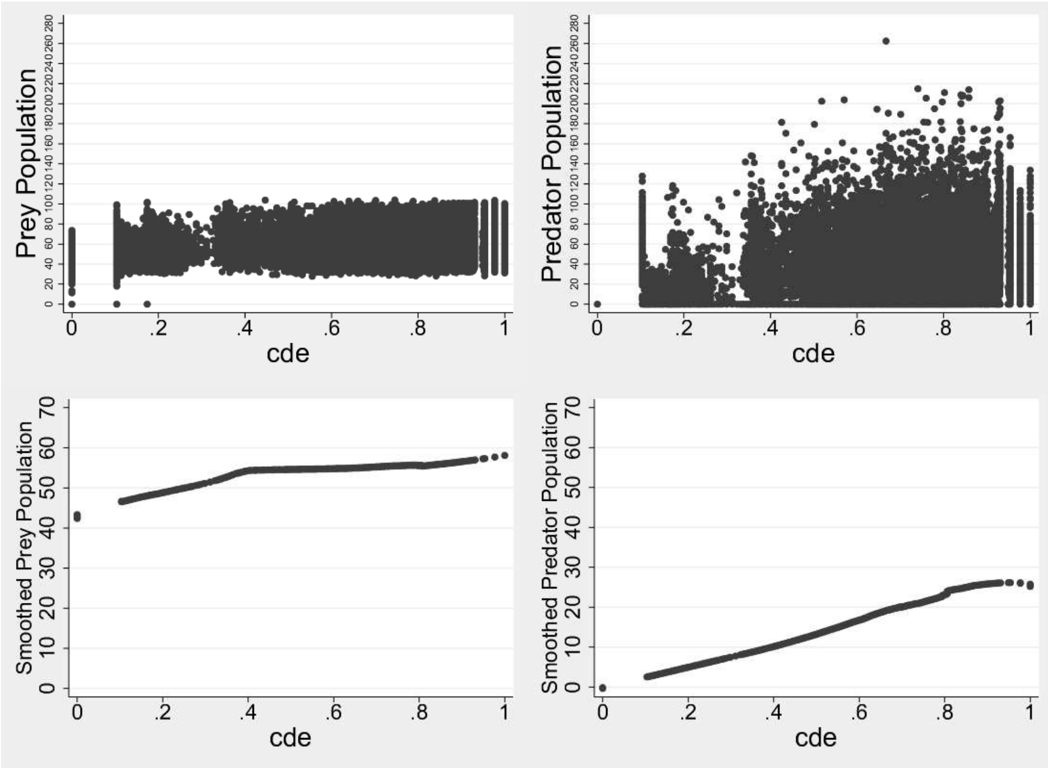


Figure 6-4 Node-Centrality vs Population Levels
Relation between node-centrality and population levels of predator and prey per node. Raw (the average population level of the last 1000 time-steps) and smoothed (resulted from the LOESS regressions) predator and prey population levels are reported on the y axis, while node-centrality measures are represented on the x axis. Graphs are drawn on two different scales: one for the raw data (from 0 to 280) one for the smoothed data (from 0 to 70) (Own elaboration).

Examining node-centrality measures allows for a better understanding of local connectivity properties of a node, and consequently, the importance of that node from an ecological point of view, as shown in Figure 6-4, where the direct effect of network connectivity measures on species population levels is visualized. Predators are the more dynamic species in this model as shown in Figure 6-2, Figure 6-3 and Figure 6-4. Moreover, data collected and analysed suggest that low node/network connectivity contributes directly to predator extinction both locally and globally. In other words, low node/network connectivity erodes the resilience of the system, facilitating a change of the basin of attraction. For example, as shown in Figure 6-4, an increase in local network connectivity, as measured by closeness centrality, promotes survival and coexistence of both species, and thus enhances the resilience of the system as previously defined. When closeness approaches 1 the population of both species begin to stabilize. A fully connected network represents a fully connected landscape. If a fully connected landscape, under the range of parameter values considered, promotes coexistence and convergence towards a viable population level (as shown in Figure 6-4), an interesting research question arises. Is closeness centrality (or, more generally, node-centrality) a significant measure for assessing the probability of coexistence between species in general, or better, how does closeness centrality influence the resilience of the basin of attraction?

In order to answer this question, data on predator population extinction for different measures of network connectivity have been collected. Extinction of predators is recorded at the node and network level, so as to assess how node-centrality and network metrics affect the probability of predator survival. The metrics used are real numbers that take values from the closed interval [0,1]. Our dependent variable is a dummy variable that assumes a value of 0 if predators go extinct on a specific node or on the network and 1 otherwise.

As preliminary analysis, Spearman correlations have been computed and are reported in the following tables. As Table 6-4 and Table 6-5 show, average population levels on the whole network and on the nodes cannot be directly associated with model parameters. The only internal parameter that seems to have a strong direct effect on population levels is the upper-prey density threshold ($D_{\boldsymbol{U},1}$) that influences average prey levels on nodes and on the network. Hence, from this preliminary analysis, it is possible to infer that general population levels are actually dependent on a combination of parameters. Moreover, if all parameters and centrality and connectivity measures are used in isolation, it is also possible to affirm that node centrality and network connectivity play a more important role than all but one internal species parameter ($D_{\boldsymbol{U},1}$) (confront Table 6-4, Table 6-5 Table 6-6 and Table 6-7). Connectivity seems to be more related to averaged population levels than most of the internal parameters (when taken singularly). Thus, connectivity matters and enhances the probability of coexistence independently from the internal parameters considered.

Table 6-4 Spearman correlations of prey and predators on nodes vs internal parameters.

	nodeprey	nodepred
n_1	0.0079*	-0.0051
$P_{r,1}$	0.1509*	0.2349*
n_2	-0.0013	0.0167*
$P_{r,2}$	-0.2011*	0.1925*
$P_{m,2}$	0.2392*	-0.2904*
$P_{k,2}$	-0.1269*	0.0969*
$D_{U,1}$	0.6010*	0.1900*
$D_{L,1}$	0.2077*	-0.1313*
$D_{U,2}$	-0.0071*	0.0261*

Note: * denote significance at 5% level

Table 6-5 Spearman correlations of prey and predators on network vs internal paramenters.

	netprey	netpred
n_1	0.0070*	-0.0055
$P_{r,1}$	0.1641*	0.2785*
n_2	-0.0037	0.0201*
$P_{r,2}$	-0.2163*	0.2063*
$P_{m,2}$	0.2591*	-0.3060*
$P_{k,2}$	-0.1393*	0.0851*
$D_{U,1}$	0.6394*	0.2267*
$D_{L,1}$	0.2249*	-0.1444*
$D_{U,2}$	-0.0050	0.0203*

Note: * denote significance at 5% level

Table 6-6 Spearman correlations of average prey and predators on nodes vs node centralities.

	nodeprey	nodepred
clos	0.3002*	0.4738*
cde	0.3004*	0.4622*

Note: * denote significance at 5% level

Table 6-7 Spearman correlations of average prey and predators on network vs network metrics.

	netprey	netpred
avgeg	0.2648*	0.4146*
avgel	0.2628*	0.4057*
gcc	0.2645*	0.4395*

Note: * denote significance at 5% level

The claim that connectivity matters and enhances or diminishes the probability of coexistence, thus the resilience of the system as defined in the beginning of this chapter, is reinforced by the results of the logit regressions reported in Table 6-8 and Table 6-9. Logit regressions have been calculated for different node-centrality and network metrics, all of which are relevant for locally regulating the dispersion of agents (i.e. all the metrics used have the same ecological meaning as they all relate to the ability of species to diffuse from one patch to another) (Estrada and Bodin, 2008). Results are similar given the high correlation that exists between the metrics used as reported in Table 6-10 and Table 6-11.

Table 6-8 Logit regression results of local survival probabilities for predator populations given node centrality measures

dep var	indep var	β par est	β par est	β par est	β par est
locpred	*clos*	3.505 (0.023)*			
	deg		2.787 (0.021)*		
	el			2.572 (0.195)*	
	cde				3.436 (0.023)*
	Pseudo R^2	0.179	0.142	0.151	0.178
	Class	67.90%	66.57%	66.73%	68.79%
	AIC	1.130	1.181	1.169	1.129

Note: Standard errors in parenthesis, * = significant at 1% level. 100000 observations, McFadden adjusted R^2 is reported as well as the probability of correctly classifying the dependent variable given the parameter estimates (Class). Akaike Information Criterion is reported (AIC).

Table 6-9 Logit regression results of global survival probabilities for predator populations given network metrics

Indep var	dep var	β par est	β par est	β par est	β par est	β par est	β par est	β par est	β par est
globpred	*avgclos*	3.162 (0.023)*							
	avgdeg		3.111 (0.003)*						
	avgel			3.204 (0.023)*					
	avgcde				3.163 (0.023)*				
	dens					2.799 (0.225)*			
	avgeg						3.140 (0.022)*		
	gcc							3.910 (0.029)*	
	avgcc								3.264 (0.233)*
	Pseudo R^2	0.142	0.122	0.157	0.146	0.122	0.152	0.167	0.150
	Class	66.69%	66.72%	67.08%	66.81%	66.72%	67.49%	67.51	66.77%
	AIC	1.187	1.213	1.166	1.182	1.213	1.172	1.149	1.176

Note: Standard errors in parenthesis, * = significant at 1% level. 100000 observations, McFadden adjusted R^2 is reported as well as the probability of correctly classifying the dependent variable given the parameter estimates (Class). Akaike Information Criterion is reported (AIC).

Table 6-10 Correlation between node-centrality used in the logit models presented in Table 6-8

	clos	***deg***	***el***	***cde***
clos	1			
deg	0.9764	1		
el	0.7938	0.7461	1	
cde	0.9708	0.9520	0.9100	1

Table 6-11 Correlation between network metrics used in the logit models presented in Table 6-9

	avgclos	***avgdeg***	***avgel***	***avgcde***	***dens***	***avgeg***	***gcc***	***avgcc***
avgclos	1							
avgdeg	0.9872	1						
avgel	0.9407	0.9071	1					
avgcde	0.9937	0.9816	0.9816	1				
dens	0.9872	1	0.9071	0.9816	1			
avgeg	0.9908	0.9638	0.9476	0.9854	0.9638	1		
gcc	0.8774	0.8012	0.8870	0.8725	0.8011	0.9198	1	
avgcc	0.9478	0.9253	0.9941	0.9753	0.9252	0.9455	0.8670	1

Centrality measures provide a mean to assess the probability of local survival of predators on a heterogeneous landscape. From the logit regressions reported in Table 6-8, closeness centrality has the strongest effect (magnitude of the coefficient) on survival probabilities. This preeminence is also shown in Figure 6-5, where predicted probabilities at specific closeness centrality values and at specific *cde* are reported. Predator survival probabilities gradually increase depending on the connectedness of the network, and no abrupt changes occur. These results seem to indicate that even without controlling internal species parameters, enhancing the connectivity between different patches increases the probability of coexistence between predators and prey. Moreover, if only a node is taken into account, a value of closeness centrality higher than 0.65 (or a value of *cde*>0.67) leads to a favorable probability (>0.5) of survival.

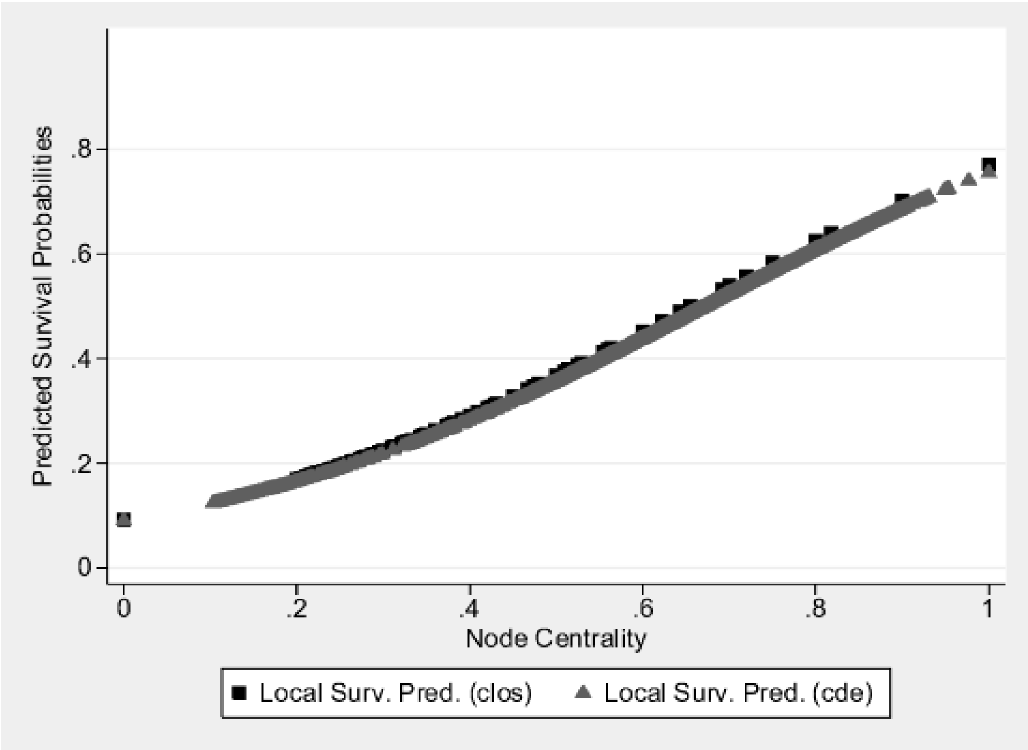


Figure 6-5 Predicted survival probabilities vs node centralities
Predicted predator survival probability (y axis) vs closeness centrality and cde (x axis) (Own Elaboration).

For nodes with closeness centrality equal to zero, the probability of predator survival is low as they are unable to disperse to any other nodes in search of new prey sources and, likewise, replenishment of their current prey source is also impossible from outside sources. It is important to stress that a favorable probability (>0.5) of survival for the predators does not guarantee species persistence. As the probability does not =1, at some point, the predators may still die out, though this time to extinction grows longer as increased connectedness of the patches and heightened feasibility of migratory movement for both predators and prey decreases the odds of predator extinction. It is also important to remember that even highly connected patches do not guarantee coexistence. Internal species parameters might be of fundamental importance in allowing persistence of a species, and this is well represented by the reported results, which demonstrate that even in fully connected landscape networks, where centrality measures reach their maximum value, 1, the probability predator survival is around 0.77 (hence much below 1).

Global survival probability is best predicted by *gcc* (i.e. the percentage of nodes belonging to the giant connected component), although other network metrics give similar estimates. Connectivity in a landscape network is crucial as it allows species more freedom of movement and enhances their ability to migrate in search of food and safety. Between the other metrics examined, *global efficiency* and the *average local efficiency* of the landscape networks also play an important role in assessing these probabilities. Both measures are related to the ability of the networked landscape to facilitate/hinder in species diffusion.

The importance of connectivity for increasing global survival probabilities is clear from the analysis performed. Both local and global survival probabilities gradually increase by increasing the level of connectivity at the node and at the network level. When the network is connected (i.e. when all its nodes belong to the giant component), global survival probabilities are enhanced, although, given the importance of internal species parameters, there is always a chance that even the most well connected network leads to some species extinction.

The robustness of the results of the model presented has been assessed by conducting similar analyses in different types of networks. First, the same ABM using a random network has been analyzed, varying the number of edges from 0 to 45. The results are qualitatively the same as those presented here. Next, an ABM using the same "geoproximity" network but with fixed parameters at the mean values used in this study, while varying the number of edges and reconfiguring the network structure, has been analyzed. Similar results are found, although in the latter case, network centrality measures play a major role in determining predator survival probability (logit regressions show a correct classification of over 90% compared to the 65% presented here). Moreover, at mean values, an increase in closeness centrality from 0 to 0.2 leads to an increase in predator survival probability from 0.09% to 5.79%, while an increase of closeness centrality from 0.2 to 0.4 leads to an increase in survival probability from 5.79% to 80.66%, thus suggesting the existence of “connectivity thresholds” for species with certain reproduction, death and predation rates, and with specific movement thresholds given by intra and inter species competition. Lastly, using mean values, favourable survival probabilities (i.e. above 0.5) arise at a much lower level of closeness centrality (0.333 instead of 0.65). Mean values of the model presented here are used in the model presented in Chapter 7 as to assess how management decisions affect the networked landscape and therefore the resilience of the system.

6.4 Discussion

Understanding the ecological consequences of habitat fragmentation is becoming increasingly important, given the mounting pressure of human population and the possible effects of climatic changes on ecosystems. Addressing possible effects of fragmentation on predator-prey dynamics becomes crucial for biodiversity conservation and in order to understand the resilience of a system. In this context, this study highlights three main findings.

First, at high levels of node-centrality for different patches, predators move so rapidly through the fully connected network that low prey numbers in any specific node do not hamper their population growth. In other words, predators become a successful population of migrants constantly moving in search of patches where it is easier to find, attack, and feed on prey. This first finding demonstrates that the connectivity of a landscape is of particular importance to predators’ survival, with the latter largely dependent on movement through different patches (ecological areas) due to range requirements, that is, the need to migrate long distances in search for food and mating (Coppolillo et al., 2004). Jaguars present a real world example of predators with large ranges that are highly dependent on movement between different patches, as landscape connectivity is essential for their survival (Michalski & Peres, 2005; Ortega-Huerta & Medley, 1999). Loss of prey is the driving force that leads predators to move between patches in the model presented here, and the possibility of migration is a key aspect of their survival.

Second, increasing connectivity benefits both predator and prey species however, the maximum population for both species occurs at different levels of connectivity. Predator and prey species benefit from living in globally central patches (i.e. with high closeness centrality) as shown in Figure 6-4. However, the maximum population of prey is reached, on average, at lower closeness centrality levels compared to predators. Prey benefits from the constraints imposed on predator movement, with the latter supporting prey populations, as the risk of predation and the use of anti-predatory strategies decreases. The reintroduction of grey wolves in North America and the respective decline in elk population densities provides a real world example of our model results. Increasing connectivity, as well as living on globally central and locally central patches, enhances the probability of coexistence between prey and predators, thus enhancing the resilience of the system. In this instance, the 'top-down' process of predation keeps prey populations in check, while allowing for coexistence, which is fundamental for the maintenance of biodiversity (Terborg et al., 1999).

Third, the results of the ABM presented match theoretical expectations from corridor ecology (Hilty et al., 2006). In corridor ecology, conservation centers upon connecting different patches rather than constructing isolated protected areas or islands of conservation. Moreover, it is important to notice how internal species parameters, such as reproduction rates, death rates, predation rates and active decision regarding migration, have a significant effect upon population levels. However, while human management of the connectivity between different patches is a possible conservation strategy, altering species internal parameters on a large scale is not (at least with present-day technology). As of today, biologically controlling for reproduction, death and predation rates of large animal populations have not succeeded (leaving ethical considerations and possible unintended consequences aside).

To conclude, the results of the effect of increased connectedness between patches on predator-prey dynamics can lead to different ways to manage a given landscape. Strategies of managing landscapes differ according to management objectives. Some possible management decisions depending on population levels are analyzed in the following chapter; nonetheless more connected environments increase the resilience of the system. The relation between connectivity and resilience is not so straight forward, as the model shows, the interplay of connectivity with population dynamics can be two-fold, leading to the need for thoughtful policies that take all the three main findings presented into account. Specifically, the model could be used to look at better ways to manage large mammal species, but also to manage possible pests that are able to move actively from one environment to another, following their prey. Finally, even if it is recognized that a simple network may hide important variables that drive predator-prey dynamics in reality, a simple network representation still allows for a coarse-grained assessment of which management strategies lead to set managerial goals.

7 Assessing Resilience: Introducing a simple social system

This chapter is an extension of the model presented in Chapter 6. The model presented in this chapter has also been presented in a paper at the NAACSOS conference in 2009 (Baggio et al., 2009). Both models deal with a landscape network on which predator and prey interact according to pre-determined rules. The main difference between the two models lies in the addition of an external manager that is able to alter the landscape network in the model presented in this chapter. Both models are ABMs (called also metapopulation models) and in both, the analysis centers upon the role of network metrics and how these metrics affect the probability of a regime shift. A regime shift, or change in the basin of attraction occurs when the species composition changes.

This chapter explores the consequences of management decisions in a networked landscape by adding management actions to the system. Management actions translate in the ability to increase or decrease species' cost of movement between habitat patches. The goal of this exercise is to understand the impacts of simple institutional arrangements within a complex system. More precisely, exploring how simple management rules may give rise to different landscape structures affecting predator-prey dynamics, hence affecting the resilience of a simple ecological system.

The interesting aspect of adding managers to the landscape arises because humans possess agency and have the ability to foresee and intentionally pursue different paths for managing landscapes (Holling, 2001; Holling & Gunderson, 2001 and section 4.1.2). Thus, managers can adapt to and adopt different mechanisms, which, based on their experience, they deem as most appropriate. They also have the ability to learn from their experience as well as experiment with new techniques in order to achieve desired outcomes. However, the ability to foresee and intentionally manipulate certain aspects of a landscape does not always lead to desired results (Holling & Gunderson, 2001 and section 4.1.2). This may happen for either of two reasons. Since our knowledge of complex adaptive ecological systems can never be complete, managers may not have sufficient information to make appropriate decisions. In addition, managers should be aware that due to system stochasticity, uncertain events and surprises will eventually occur (Holling, 1998).

In the system modelled in this chapter, predator-prey dynamics on a landscape are characterized by a degree of uncertainty and surprise (as in Chapter 6). Therefore, policies that are designed in the view of a manager's objectives, to optimise one possible foreseen future, could result in worsening the situation. As stressed during the whole thesis, it is not possible to exactly predict even the behaviour of a rather simple ecological system such as the one presented.

As in the previous chapter, the system changes basin of attraction according to species extinction. Three possible basins of attraction exist: in the first predators and prey coexist, the second is a landscape where only prey survives, and the third is a landscape where both predators and prey become extinct. The model allows to evaluate how management actions aimed at maintaining coexistence of species can have unintended consequences, hence leading to a loss of resilience. Thus, the model presented assesses the resilience of the predator-prey system in face of management actions that intentionally disturb the landscape network, so as to affect migration of species from one patch to another.

Managers interact with their environment in a variety of ways. Today's world is characterized by a high level of technology. Technology refers to the tools, both physical and institutional, that allow humans to alter their environment more effectively, and/or on a larger scale. Technology amplifies the actions undertaken and permits a wide range of possibilities as explained throughout section 4.1.2. More precisely, in this chapter technology refers to the ability to build bridges, tunnels, fences and other means able to modify ecological corridors so as to increase/decrease species' perceived distance (or cost of movement) between one patch and another within the landscape. In the language of network analysis, technology enables a manager to increase/decrease the weights of edges linking different nodes (patches). Technology may also be a drawback (again, as extensively explained in section 4.1.2), as it might add uncertainty, have unintended side effects, or allow people to over-harvest or improperly manage a landscape or resources and assets. As brief examples of the drawbacks of technology, one can think of the new fishing technology and the results on the cods in the North Sea. Further it is possible to look at how the building of huge dams changed the ecology of whole regions, hence adding new uncertainties such as the increased likelihood of events that never happened before. Finally, it is possible to look at unintended consequences of management actions suche as the constructions of the barriers that were supposed to protect New Orleans from flooding and how these technological solutions have performed during Hurricane Katrina.

Conservationists and protected area managers work with issues pertinent to the management of local and global species populations and patch dynamics on a daily basis. Many of their options focus on increasing or decreasing the cost of movement between patches through habitat restoration, the creation of barriers and bridges to habitat movement, and the translocation of species (Gordon, 1994; Griffith et al., 1989) given budgetary constraints. Translocation of species relates to the forced movement of species or of individuals pertaining to a species towards or to a certain area. Due to increasing habitat fragmentation (Franklin et al., 2002), the difficulty in bringing more land under strict protected area status (Brockington et al., 2008), encroachment on existing protected areas by human communities (Child, 2004), and threats to species from global and regional climate change (Hannah et al., 2002), many conservationists now view protected areas as only part of a broader set of conservation options. Instead of parks that protect key landscape patches in corridors of conservation, managers work to protect animal movement between patches within a protected area and between patches along a larger corridor that may include protected areas (Beier & Noss, 1998; van Aarde & Jackson, 2007). In this particular context, it is possible to use the model presented here to look at habitat patches as nodes and the corridors that connect different patches as edges.

As seen in Chapter 6, node characteristics on local and global population dynamics is a very important feature for the resilience of a system as the one modelled here. More precisely, centrality measures or measures of how tightly the nodes of a network are interlinked, affect predator-prey dynamics. Although species have always dealt with habitat fragmentation, fragmentation is rapidly increasing mainly due to human interventions. Populations are endangered not only by natural means such as climatic change, but also due to rapid human population expansion (Meyer & Turner II, 1992), increased urbanization, and the ever-increasing impact of humans on the landscape through technology that allows for heavy landscape alterations. As elucidated in Chapter 6, spatial heterogeneity plays a crucial role in the coexistence of species, given the importance of the structure of a landscape due to its effect on movement ability of a species. Therefore, species need patches across a landscape to be connected in order to maintain local and global populations (Weins, 1997).

Consequently, this chapter centers upon the ability of a manager to alter the landscape in order to allow coexistence while not depleting resources that are fundamental for prey survival. As previously explained (see section 5.2), the main objective of using ABM is not to prove theorems, but to allow a better understanding and representation of reality, hence, hopefully, fostering improved landscape management based on given objectives.

7.1 Methods

As mentioned above, the aim of this chapter is to uncover possible management strategies that lead to coexistence of species, in our case predators and prey, while maintaining vegetation, i.e. the resources needed for the prey to be able to feed themselves and reproduce. The ABM designed is an extension of the model developed in Chapter 6[13].

7.1.1 The landscape

Habitat patches are represented by nodes and the whole landscape is fixed (that is, nodes do not vary throughout simulations) with 10 nodes (N = 10). Every node has an ability to sustain prey (C), which affects prey density. The ability of a node to sustain prey decreases if the number of prey is higher than a determined threshold; nonetheless, the same node is able to recover to the original ability to sustain prey

[13] Please refer to the ODD presented in Appendix II , section II.ii II.ii for in depth information on the ABM proposed, and to Appendix III, section III.ii, for the code of the ABM presented in this chapter.

when prey density is below a determined threshold. This assumption is based on a recent study by Asner (2009) who shows significant differences in the structural diversity of canopy in African savannas between protected and accessible to herbivores areas. However, research to uncover the relation between herbivores and vegetation, hence ecological restoration, is still underway, and results might differ (Suding et al., 2004) as they are space and time-dependent (e.g. topographic location, and geologic substrate) (Asner et al., 2009). The time of recovery will be different depending on the density of prey present on a specific node. More precisely, *ti* (time of recovery) varies according to $D_{i,1}$ (density of prey on a specific node *i*) as follows:

```
if  0.15 < D_{i,1} ≤ 0.3
set  ti_t = ti_{t-1} − 0.5;
if   0 < D_{i,1} ≤ 0.15
set  ti_t = ti_{t-1} − 0.75;
if  D_{i,1} = 0
set  ti_t = ti_{t-1} − 1.
```

The number of edges (E) is fixed in order to represent a fully connected network ($E = N(N-1)/2 = 45$), and the presence of an edge captures the possibility for a predator (or prey) to diffuse from one patch to another. Multiple edges and loops are not considered. Edges will have an initial weight computed as the Euclidean distance between the nodes they connect (we_{ij}). The weights mimic the difficulty/ease with which predators and prey are able to move from one patch to another, in other words, weights of edges correspond to the cost of movement from one node to another for predators and prey.

7.1.2 The Species

The number of prey and predators will be proportional to the number of nodes ($n_1 * N$ and $n_2 * N$). At every time-step, both type of agents (predators and prey) have the ability to reproduce according to a predetermined probability ($P_{r,1}$ and $P_{r,2}$). Predators and prey also have the ability to die from natural causes with probability

$P_{m,1}$ and $P_{m,2}$ respectively. The prey has a probability $P_{k,2}$ of dying via predation, if a predator and the designed prey find themselves on the same node. Both, predators and prey have the ability to move according to a Poisson distribution with mean S_1 and S_2. Movement behaviour between patches is simplified adopting a recent framework proposed by Nathan et al. (2008) that enables the study of species' movement by looking at four different dimensions and their interaction. In this context, in order to mimic the external conditions of the framework used, movement between different nodes is possible only if an edge exists and if the weight of that edge is lower than the predator or prey movement capability. Prey and predators move only to nodes where $we_{ij} < S_1$ (or S_2). If no edge exists or all edges have an exceedingly high cost of movement being $we_{ij} > S_1$ for all we_{ij}, the agent (predator or prey) dies. In order to simplify the work by Nathan et al. (2008), agents are thought to be "semi-intelligent", thus predators and prey have limited navigation capacity, as they are only able to locate reachable nodes (where $we_{ij} < S_1$ or S_2) (Nathan et al., 2008). If more than one reachable node exists, the agent chooses randomly one of its possible destinations. Both agent types (predators and prey) face no limitation on in-patch movement, however, between-patch movement is limited by the motion capacity of each predator (or prey), based on S_1 and S_2 respectively (Nathan et al., 2008). Agents move driven by "internal motivations" (internal state of the framework proposed by Nathan et al. (2008)) associated with intra-species competition, anti-predatory behaviour and predator's search strategies.

Thus, agents move between different nodes based on the density of that particular species and its competitors on the same node. Densities are computed based on the node size as follows: $D_{i,1} = \frac{\sum n_{1i}}{C_i}$ and $D_{i,2} = \frac{\sum n_{2i}}{C_i}$. Such densities are compared to density thresholds. Prey move according to a prey upper limit threshold ($D_{U,1}$) in order to mimic intra-species competition (for food and space), thus referring to the internal state or motivation for movement (Bartumeus & Levin, 2008). Furthermore, prey move between nodes if predator density rises above a certain threshold ($D_{U,2}$), mimicking anti-predatory behaviour (Creel et al., 2005; Fischhoff et al., 2007; Ives & Dobson, 1987; Lima, 2002; Luttberg & Schmitz, 2000; Nelson et al., 2004). Finally, predators move between patches if prey density falls below a pre-determined threshold ($D_{L,1}$) to mimic predatory search strategies (Bartumeus & Levin, 2008; Ioannou et al., 2008; Lima, 2002; Linhares, 1999).

7.1.3 Management of a landscape

Since the aim of this chapter is to look at possible landscape management strategies and subsequent effects on predator-prey dynamics, coexistence and ability to sustain prey preservation, a manager agent is added to the model. The manager has the ability to act on every edge of the network. During each time-step, a manager is given a budget (*B*). The budget will vary across the different runs, but not during a single run (that is, the budget allocated at each time-step is determined a-priori).

Humans, as previously mentioned, have the ability to foresee and alter landscape thanks to the modern technology (Holling & Gunderson, 2001) (see section 4.1.2 for more information on the unique abilities of humans in a resilience context). Thus, a manager will act upon those patches that s/he considers endangered, in order to maintain either coexistence, or prey on a single node (patch); i.e. in order to maintain a desired basin of attraction. A manager will act according to his/her own thresholds that mimic alarms or warning signals (Mt_U and Mt_L). Both thresholds refer to prey, since a large number of prey (Mt_U) endangers the ability to sustain prey of a node, due to vegetation depletion; while a critically low density of prey (Mt_L) endangers the existence of predators (at least locally) as food resources become scarce. Moreover, there is a possibility that a manager miscalculates the density of predators and prey. This error, if present, will be normally distributed with mean 0 and standard deviation of 5. The error term follows a normal distribution with mean 0 as it can be assumed that the over and under estimation of population size are likely to be balanced. Standard deviation is chosen arbitrarily in order to induce mistakes that might affect the action of the manager on the overall system, but are not too high in magnitude, given the recent advances in technology (e.g. use of aerial surveys, GPS, satellites etc.). In other words, a manager takes action according to the following rules:

```
if
```
$n_{1i} + err_i > C_i * D_{U,1_i} * Mt_U$

`and/or`

`if` $n_{1i} + err_i < C_i * D_{L,1i} * Mt_L$

`set node` *i* `“endangered”.`

The manager also assesses the need to take action based on the ability to sustain prey on a node and a corresponding threshold (*Mct*) is set. *Mct* represents another type of warning signal. It relates to the preservation and/or the will to recover the ability to sustain prey of a single patch (node). In other words, if the ability to sustain prey *C* of node *i* is lower than the threshold *Mct* the manager will act trying to reduce the number of prey on that very same node. However, a manager might hold his/her own views or estimates of the ability to sustain prey of the node (*C*), hence a variable *V* that represent a manager's own view of is introduced. The view of a manager has effects on the ability to sustain prey (*C*), and thus a manager will always over or underestimate the ability to sustain prey of a specific node *i*. More precisely, considering $-20 \le V \le +20$, a manager will take action based on *Mct* according to the following rule:

`if` $C_i + V < Mct$

`set node` *i* `“endangered”.`

The manager selectively takes action to protect the most endangered nodes. Endangered nodes are those node `set “endangered”` by the rules described in this section. A manager takes action by manipulating the cost of movement (weights) of the edges. Increasing and decreasing we_{ij} bears a fixed cost (Mc_I, Mc_D respectively) and a maintenance cost. Maintenance costs refer, for example, at the necessary costs to maintain a tunnel, a bridge or an electrified fence. The maintenance cost is calculated as the natural logarithm of the absolute value of the original Euclidean distance used to compute the weight of edges at time 0 (we_{ijo}) and the actual weight at time-step *t* we_{ijt}; thus, the maintenance cost is $\ln\left|we_{ij0} - we_{ijt}\right|$. The use of natural logarithm is given by the negative returns of scale of maintenance cost. Increasing we_{ij} imitates the building of fences and other activities aimed at preserving predetermined areas from predators and prey (at this stage other human activities other than the manager are not taken into account), while decreasing we_{ij} mimics the building of tunnels, bridges, corridors, and other means that facilitate the diffusion of species from one patch to another.

However, the manager is able to act upon the landscape only if the budget (*B*) s/he is allocated covers for both the maintenance as well as fixed costs. Every time a manager takes action, he/she has to check whether the budget is sufficient. For instance, if a manager needs to act upon different nodes and thus edges that are connected to these nodes, and wants to increase the cost of movement towards one node, or decrease the cost of movement towards another node, s/he will assess actions and for every action s/he will have to perform the following check, thus actually solving a maximisation under constraints.

if $\left(B - \ln\left|we_{ij0} - we_{ijt}\right|\right) > Mc_I$ (if increasing cost of movement)

increase we_{ij} by S_I

if $\left(B - \ln\left|we_{ij0} - we_{ijt}\right|\right) > Mc_D$ (if decreasing cost of movement)

decrease we_{ij} by S_D

As the aim of the paper is centred upon the ability of a manager to alter a landscape and look at the landscape itself from a network perspective, parameters regarding predators and prey are kept constant at the mean levels used in Chapter 6. Variables concerning the manager such as the budget size (*B*), prey population thresholds (Mt_U and Mt_L), the increased and decreased cost of movement for every action (S_I and S_D), the fixed costs sustained (Mc_I and Mc_D), the view of the manager (*V*), and the possibility to miscalculate the predator and prey numbers (*err*) are varied throughout the simulations as depicted in Table 7-1.

Table 7-1 Managing Landscapes: ABM input parameters

Simbol	Variable Name	Value
N	Number of nodes	10
E	Number of edges	45
we	Cost of movement (weight)	Varies according to manager actions (MAX *we* = 92 without manager action)

Simbol	Variable Name	Value
ti	Time-lag of recovery	5
C	Capacity of a node	100, varies according to simulation events
n_1	Initial number of prey	25 * 10
$P_{r,1}$	Prey reproduction rate	0.25 (25%)
$P_{m,1}$	Prey natural death rate	0.10 (10%)
S_1	Prey movement ability	Poisson distributed with mean 30 calculated at every time-step
$D_{U,1}$	Prey density upper limit	0.9
$D_{L,1}$	Prey density lower limit	0.15
n_2	Initial number of predators	10 * 10
$P_{r,2}$	Predator reproduction rate	0.2 (20%)
$P_{k,2}$	Predation probability	0.2 (20%)
$P_{m,2}$	Predator natural death rate	0.06 (6%)
S_2	Predator movement ability	Poisson distributed with mean 60 calculated at every time-step
$D_{U,2}$	Predator density upper limit	0.6
T_h	Predator handling time	3
B	Manager budget (does not accumulate)	100, 250, 500
V	Manager view of capacity	-15, 0, 15
err	Errors in counting species	Yes/No variable if Yes, error varies at every time-step
Mt_U	Manager Upper threshold	0.6, 0.8
Mt_L	Manager lower threshold	1.2, 1.4
Mct	Manager capacity threshold	50, 70, 90
Mc_D	Cost of decreasing *we*	50
Mc_I	Cost of increasing	100
S_I	Amount of *we* increase in case of action that increases *we*	100
S_D	Amount of *we* decrease in case of action that decreases *we*	10

7.1.4 Running the model

As explained in section 7.1.1, the landscape is here represented by a fully connected network and internal species parameters are kept constant during the simulations, while parameters regarding management decisions are varied as reported in Table 7-1. Managers are able to act upon we_{ij}, since the purpose of this chapter is to shed light on the impacts of simple management decisions on the landscape structure (as well as explore how corresponding landscape structures affect predator-prey levels). Structural properties are here measured via average closeness centrality, global efficiency, average local efficiency and average strength (see section 3.2 for in depth information on the metrics used). Average strength is used instead of average degree given that weights on edges exist.

The model runs for 10000 time-steps and is repeated 30 times per parameter combination. From Table 7-1 is easy to infer that 216 parameter combinations based on management decisions are explored. The landscape network is recorded at every time-step as management decisions may alter we_{ij} according to the rules outlined in section 7.1.3. Moreover, prey and predators levels are recorded at every time-step at the network level. Differently from the model presented in Chapter 6, here only network levels are analyzed, but population levels and network metrics are collected at every time-step (as they may change at every time-step). Figure 7-1 is a snapshot of the model interface used in NetLogo 4.1.

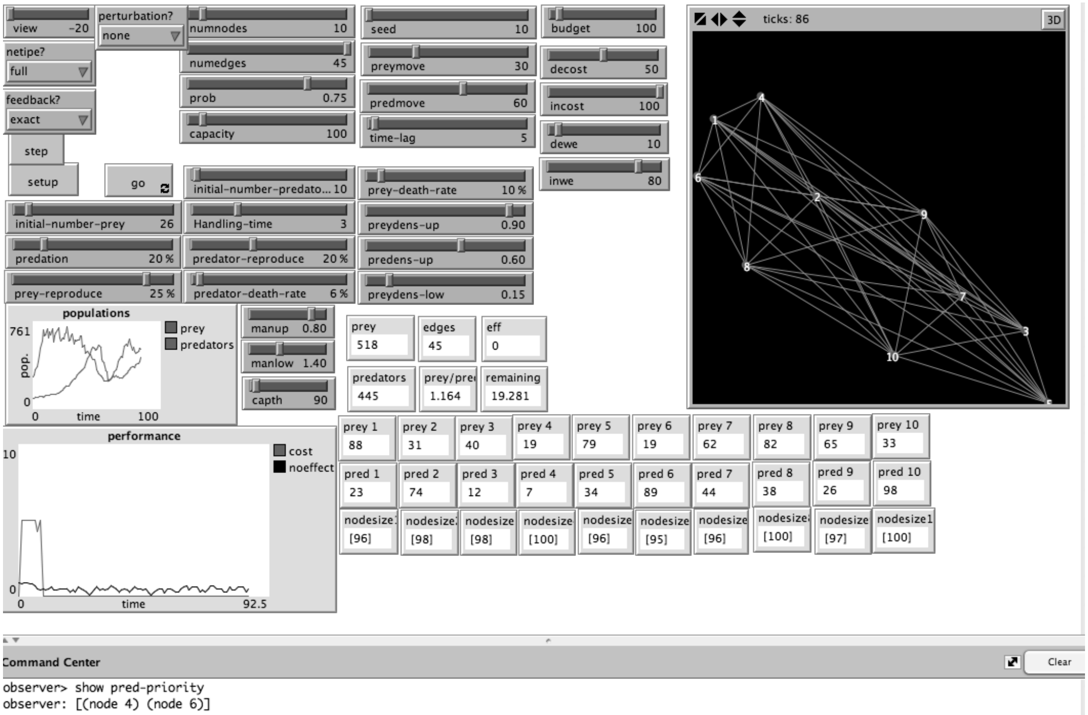


Figure 7-1 Snapshot of the Netlogo interface (Own elaboration).

7.2 Results

The analysis of the model centres upon the structural properties resulting from management decisions. The key variables of interest are the following (numbers in parenthesis refer to sections in the thesis where in depth information on each of the metrics can be found):

- *average closeness centrality* (section 3.2.1)
- *average local efficiency* (section 3.2)
- *average strength* (or average weighted degree) (section 3.1 and 3.2)
- *global efficiency* (section 3.2)

All measures used to assess the structural properties of the networked landscape have the same ecological meaning, as in Chapter 6. They all relate to the ability to facilitate or impede diffusion/movement from one patch to another. Amongst the metrics proposed, global efficiency is the measure that better captures the overall ability of the network of diffusing species (predators and prey). All the metrics used depend on management decision (the alteration of we_{ij}). The evolution of network measures over time is analyzed. Thus time series of network metrics are considered as the best method of analyzing the results. However, no standard statistical time series analysis is used given the limitation of these techniques explained in section 5.2. In other words, in order to look at how different structural properties influence the probability of coexistence, the evolution of network metrics over time has been used (as shown in Figure 7-2).

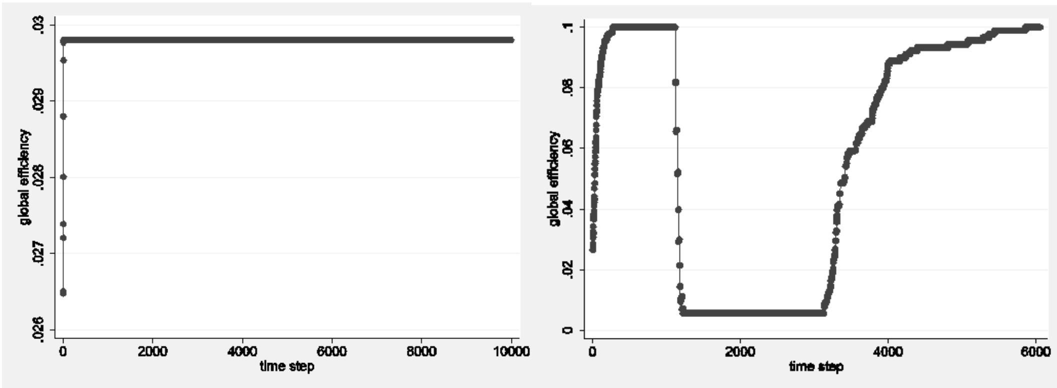


Figure 7-2 Global efficiency vs time
Left Figure represents a landscape on which coexistence is highly possible, while right Figure represent a landscape on which total or predator extinction is very likely. y and x axes are on different scales as what is important is the qualitative difference in the global efficiency evolution, independently of the actual values. (Own elaboration).

Looking at Figure 7-2 two different patterns emerge. The pattern on the left displays convergence and stability, and it indicates higher probabilities of coexistence, while the pattern on the right displays two critical transitions and corresponds to systems that are more likely to shift basin of attraction. Here, as in the previous chapter, a change in basin of attraction occurs if species composition changes; three basins of attraction exist, one in which species coexist, one in which predators go extinct but prey survive, and one in which both, predators and prey go extinct. Thus, it is possible to assess the resilience of the system, as defined at the beginning of this chapter, by looking at the two distinct patterns visualized in Figure 7-2. Figure 7-2 clearly shows a difference in the evolution of global efficiency. Figure 7-2 is an example of two main different patterns observed over 6480 similar figures (216 parameter combinations times 30 repetitions). Thus, different patterns as reported in Figure 7-2 influence the resilience of the system as defined at the beginning of this chapter. As the analysis can not be based only on visual intuition, global efficiency variance and has been calculated (that is the second statistical moment). Variance, and higher statistical moments relate to the distribution of the time series thus highlighting characteristics on the amplitude and possible transitions of such series. Moreover, they are the simplest tools to assess differences in patterns such as the one visualized in Figure 7-2.

Other methods can be used to assess critical transitions in time series or to highlight how chaotic is a time series. These techniques, such as the use of Lyapunov and Hurst exponents, are prone to different interpretations and different methods are actually used for their calculations. For this reason, this thesis prefers to use the simplest possible tool that is able to deliver meaningful (insightful) results given the models presented, and the intuition given by the visual results of the model. This approach follows the modeller's paradigm that it is unnecessary to increase difficulties and complexities when other, simpler and easier to use instruments are available. Table 7-2 presents the two classifications rationales used in order to divide the evolution of networks into two main groups. Finally, the author is aware that parameters configuration has an effect on the probability of coexistence and thus on the resilience of a system. However, the aim of this chapter is to analyze how the evolution of structural properties influences the resilience of the system portrayed. Thus the analysis will concentrate on the evolution of global efficiency over time starting by the visual results and intuition as explained above.

Table 7-2 Rationale of time series classification

Groups of time series / Classification type	Group 0	Group 1
Ist: Variance	*var* close to 0	*var* > 0
IInd: Higher moments: sd of skewness (*sdskew*) sd of kurtosis (*sdkurt*)	*sdskew* < or close to 0.025 AND *sdkurt* < or close to 0.05	*sdskew* > 0.025 AND *sdkurt* > 0.05

Note: variance and higher moments refer to variance and higher moments of the evolution of the global efficiency metric

Variance of global efficiency can be used as a tool to assess the probabilities of changing basin of attraction as also shown in Figure 7-3.

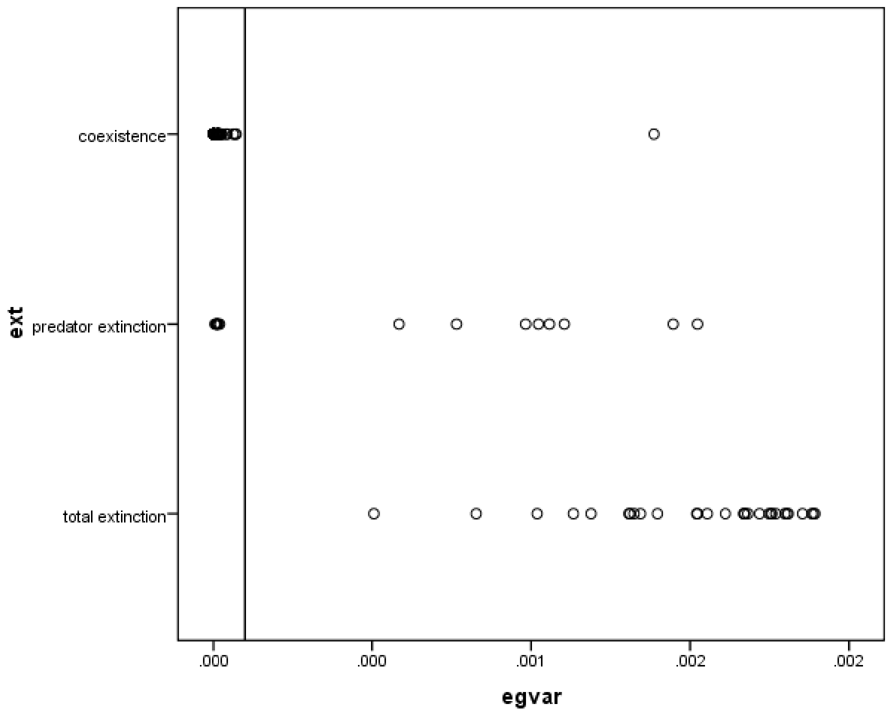


Figure 7-3 Time series Ist classification
(i.e. classification of the basin of attraction based on variance of global efficiency (egvar) (Own elaboration).

More precisely, Figure 7-4 divides the predator-prey outcomes into two groups based on the structural properties of the evolving network. In fact, it looks at the evolution of global efficiency. The first group of time series (noted as group 0), has variance of global efficiency close to zero (or in the neighbourhood of 0), and resembles the pattern visualized on the left of Figure 7-2. The first group (or group 0) allows for high probabilities of coexistence (0.95 or in the 95.48% of cases). However, even if the evolution of the networked landscape resembles the pattern followed by the second group, there is still a probability that only prey survives, i.e. there is still a probability of a change in the basin of attraction, with the probability of predator extinction close to 0.05 (or in the 4.51% of cases).

The second group of time series (noted as group 1), has variance of global efficiency $>\approx 0$ (where ≈ 0 denotes in the neighbourhood of 0), and corresponds to the pattern visualized on the right of Figure 7-2. If the networked landscape evolves over time resembling this pattern, total extinction has a high probability of occurrence (0.77 or in the 76.92% of cases); predator extinction has a moderate probability of occurrence (0.21 or in the 20.51% of cases), while coexistence is very unlikely (probability of coexistence being 0.03 or in the 2.56% of cases).

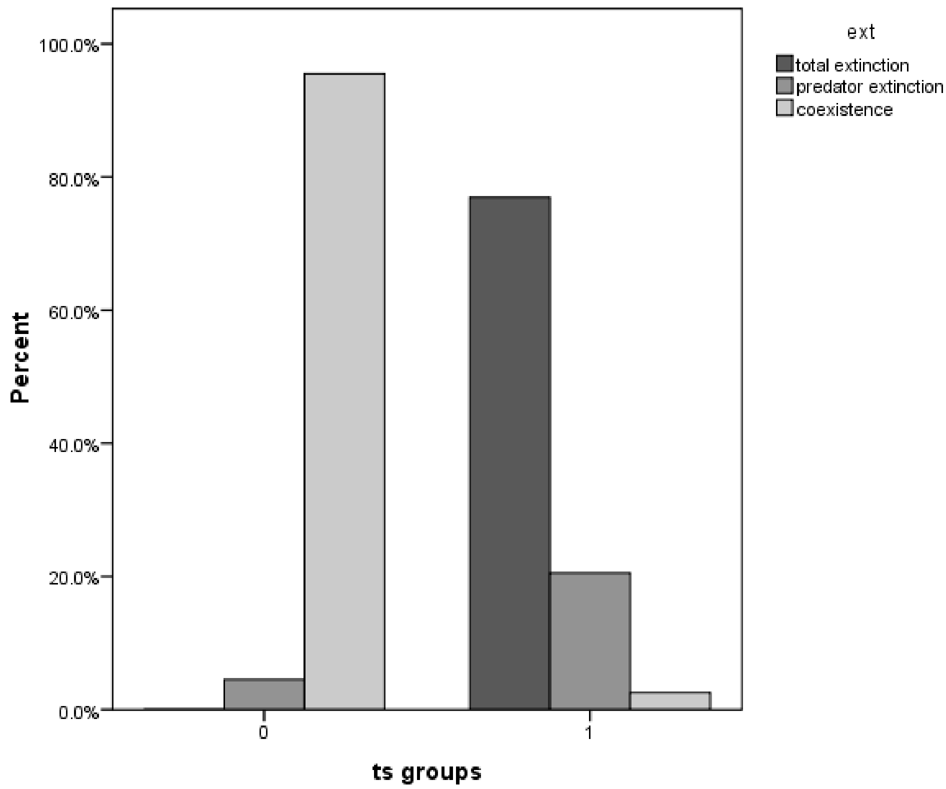


Figure 7-4 Probabilities of shifting basin given Ist classification
i.e. probabilities of coexistence, total extinction and predator extinction given variance of global efficiency. Groups are characterized as in Table 7-2, where group 0 characterizes runs in which variance of global efficiency is close to 0 and group 1 has variance of global efficiency > 0 (Own elaboration).

Moreover, it is possible to classify the two different clusters of global-efficiency evolution over time by analyzing higher moments of global efficiency. Here, the author of this thesis recognizes the arbitrariness of the approach. However, increasingly higher moments of the global efficiency time-series have been tried so as to look for the “lowest higher moments” that lead to a perfect classification of at least one basin of attraction (i.e. total extinction in this case). As a matter of fact, looking at higher moments of global efficiency (i.e. skewness’ standard deviation and kurtosis’ standard deviation), it is possible to have a more precise division, as visualized in Figure 7-5. The classification based on higher moments clearly divides total extinction from the other two possible outcomes (coexistence, predators’ extinction) as it is shown in the following figure.

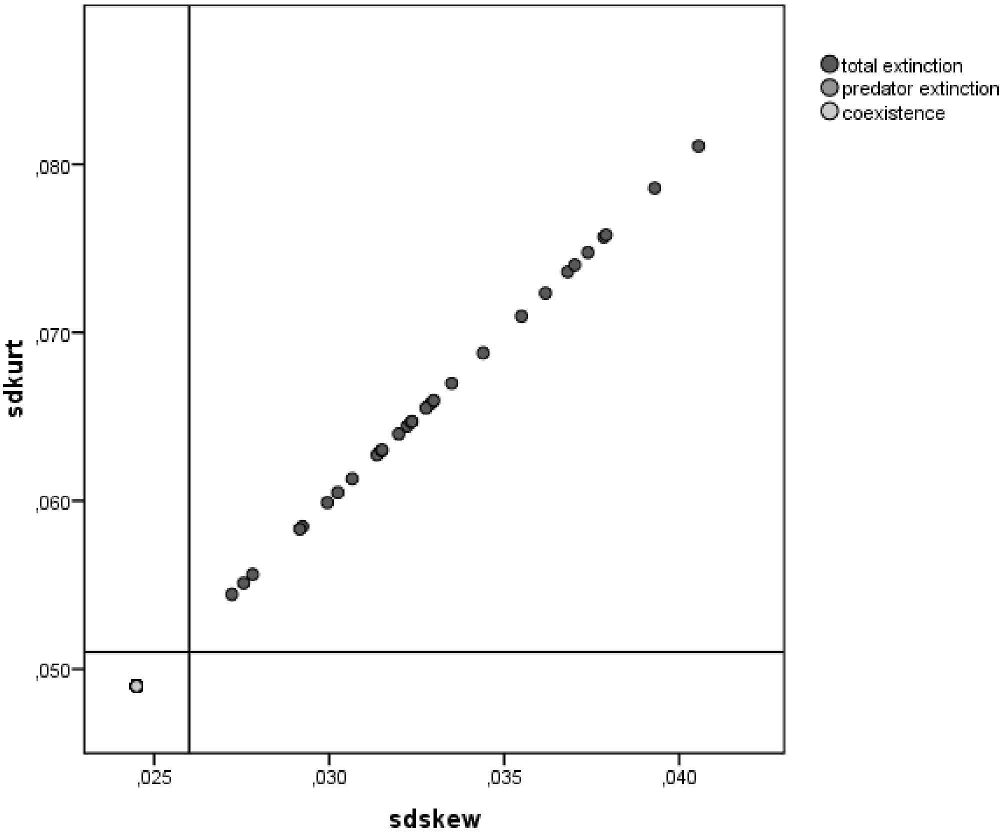


Figure 7-5 Time series IInd classification
i.e. classification of the basin of attraction based on standard deviation of skewness (sdskew) and standard deviation of kurtosis (sdkurt) (Own elaboration).

Recalling that 216 parameter configurations exist, it is indeed valuable to be able to classifying different simulations runs independently from their configuration. Being able to classify all the different simulation runs looking at the evolution of structural properties, more precisely, at the evolution of just one dimension (one variable, one structural property in our case), allows to assess the important impact that network metrics have on population dynamics. Based on Figure 7-5 and on higher statistical moments, it is possible to divide the evolution of global efficiency into two main groups (as before). The first group (noted group 0) is characterized by low values of higher moments of the evolution of global efficiency over time, being standard deviation of kurtosis lower than the neighbourhood of 0.05 and standard deviation of skewness is lower than the neighbourhood of 0.025. If the evolution of global efficiency over time has characteristics belonging to this first group (noted as group 0) in Figure 7-6, it will be highly unlikely that total extinction will occur, although it may be possible that a change in the basin of attraction will happen, as probability of coexistence is close to 0.91 (or 91.40% of cases) while probability of predator extinction = 0.09 (or 8.60% of cases).

The second group (noted as group 1) is characterized by higher values of higher statistical moments of the global efficiency time series; more precisely, standard deviation of kurtosis is higher than 0.05 and standard deviation of skweness is higher than 0.025. If global efficiency follows the pattern characterized by this second group, as Figure 7-6 clearly shows, total extinction will most likely occur, being probability of total extinction = 1.

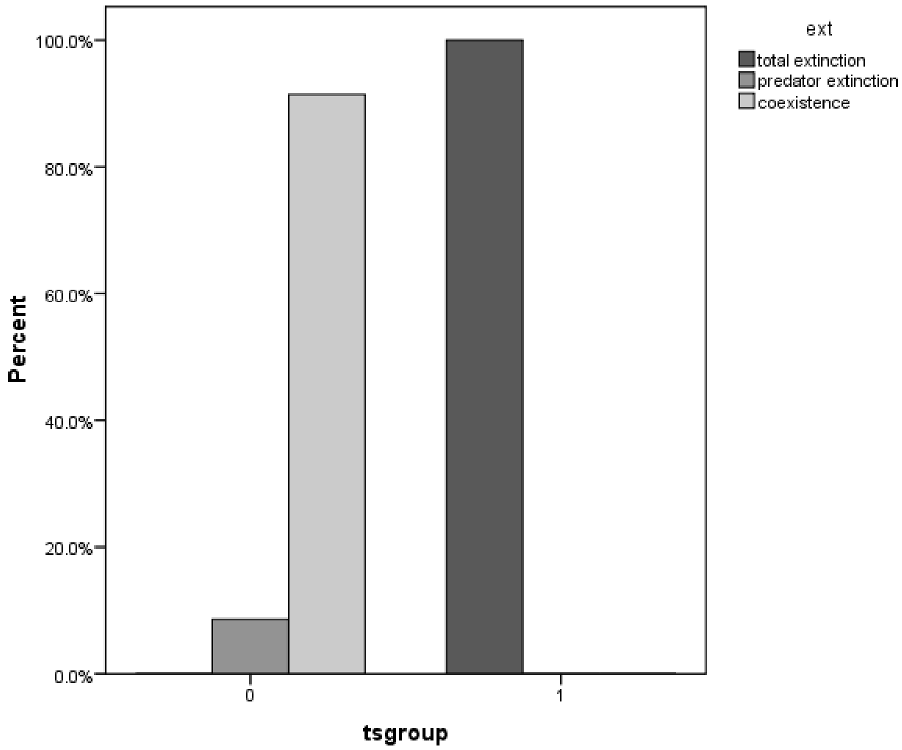


Figure 7-6 Probabilities of shifting basin given IInd classification
i.e. probabilities of coexistence, total extinction and predator extinction given the groups defined in Table 7-2. where group 0 characterizes runs in which the standard deviation of kurtosis (sdkurt) of global efficiency is < 0.05 and the standard deviation of skewness (sdskew) of global efficiency is < 0.025. Group 1 represent runs in which the sdkurt of global efficiency is > 0.05 and the sdskew of global efficiency is > 0.025. (Own elaboration)

7.3 Discussion

The model presented in this chapter is an extension of the model analyzed in chapter 6. However, the model presented in Chapter 6 did not explicitly look at possible management interventions on a landscape. Although recognizing consequences of habitat fragmentation on the resilience of simple ecological system is important, understanding consequences of simple management strategies is crucial in order to assess possible outcomes that may enhance or reduce the resilience of a simple ecological system. Moreover, looking at possible management strategies also enables to start to understand how management can actually add uncertainty to the whole system. Further, looking at the implementation of management strategies may facilitate the recognition of which actions may foster or lower the resilience of a SES. .

The model presented here assumes that management actively pursues the maintenance of the system in a specific basin of attraction (i.e. coexistence) and is able to alter the landscape thanks to technological solutions in order to favor the achievement of such objectives. Nonetheless, the will to achieve coexistence and the technology available to reach such purposes may have unintended consequences. Unintended consequences (here the transition to a new basin of attraction where either of the two or both types of agents go extinct) may arise, in case of managers possessing poor or wrong information (the latter two being represented by the parameters *err* and *V*), but it may also arises due to the complexities and the non-linear dynamics inbuilt in the ecological system.

As the complexities inbuilt in SES are difficult to understand, surprise is always possible. As an example, of possible surprises generated by management paths chosen, Liu et al (2007: 1514) report the following:

> Smelt (Osmerus mordax) was initially introduced to Wisconsin as a prey species for game fish such as walleyes (Stizostedion vitreum), but smelt ate juvenile walleyes leading to loss of walleye populations. In Puget Sound, growth management policy has caused urban density to intensify inside the urban growth boundary while

unintentionally facilitating sprawl outside the urban growth boundary

Moreover, given the complexities described above, when planning possible protected areas, not only predator-prey relations need to be taken into account, but also the presence of humans. Establishing protected areas, if not carefully planned, can have unintended consequences. High-quality panda habitat, for example, has degraded faster when a protected area was established, than before the creation of the reserve (Liu et al., 2001).

Further, management paths that are thought to be the cause of the ecological system degradation could result to be quite the opposite. The Kristianstads Vattenrike has been established as a protected area under the Ramsar Convention (is an intergovernmental treaty on maintaining the ecological character of their wetlands of international importance). In protected areas such the Kristianstads Vattenrike human activities such as grazing were not allowed as they were thought to be one of the causes of wetland's degradation. However, as Olsson et al. (2004) have demonstrated, without grazing, the wetland was overgrown. This consequence led to rethink management strategies and allowed human activities, such as grazing, in the Vatternike. Grazing is now perceived as an important aspect for conserving the wetland system. (Olsson et al., 2004).

The model presented in this chapter is a step towards the understanding of the interplay between humans and nature. Given the strategies and the behavior of the manager, according to the rules expressed in section 7.1.3, the landscape is altered. Looking at the evolution of the landscape's structural properties, it is possible to assess the probability of maintaining a determined basin of attraction; that is, simple rules give rise to different landscape structures and these structures allow us to assess possible effects on predator-prey dynamics.

Moreover, while in Chapter 6 the landscape is described as an un-weighted, undirected network, here the landscape is viewed as a weighted although undirected network. Global efficiency has been proposed as "synthesis" measure of the structural properties. Global efficiency has the same ecological meaning as the other metrics presented (i.e. average closeness centrality, average local centrality, average strength), but is more suitable to be applied in the case of weighted and not fully connected networks as explained in section 3.2. Measuring global efficiency through time, it is possible to reach the following main conclusions. First, structural properties are a promising indicator when assessing the resilience of an ecological system. Second, if no critical transition occurs in the evolution of network metrics, the system is more likely to remain stable, thus staying in the same basin of attraction. On the other hand, if critical transitions have occurred in the past, the system is more likely to approach a threshold and hence change its basin of attraction.

The main conclusions above could have important policy applications. As of now, few studies have concentrated on how the underlying evolving network alters dynamics over time. The model presented is a first attempt in this direction. Policies could then look at problems of structural properties and how they impact upon population dynamics, leading to better plan reserve networks based on the corridor ecology approach, or foster new understanding and experimenting new ways of managing natural resources and maintaining biodiversity. For example, it is possible to devise interventions that aim to exclude species from a certain area (e.g. through fencing) in order to maintain or to allow vegetation to grow back again. Excluding species from a certain area is likely to give rise to a critical transition in the network metrics over time such as the one presented in Figure 7-2. Therefore, it may be best to search for possible alternatives such as the creation of protected areas that find themselves geographically near the one that needs to be fenced, so as not to allow a critical transition in the structural properties of the network of protected areas.

Extensions of the model are possible, but may come at the expense of methodological problems; i.e. the risk that the ABM becomes too complicated (see section 5.2.4) and provide few meaningful insights; in addition, complicating the model further may also give rise to errors and artifacts (see section 5.2.3) that may be difficult to discover. Nonetheless, the model could be extended by adding possible perturbations on the capacity of the nodes (C) and/or on the weight of the edges

(we_{ij}) and/or on the recovery of the node's capacity (ti) or by endogenising the management thresholds and views (Mt_U, Mt_L, and Mct). Extending the model considering different type of perturbations (or disturbances) could deliver insights on which simple management strategies are more effective in reducing the probability of shifting basins of attraction. Extending the model by endogenising management thresholds (on which rules for altering the landscape are based) may allow for the introduction of learning, although as in the previous case, the model may loose its value as it can easily become too complicated to provide meaningful insights.

To conclude, by altering the connectedness between patches (nodes), simple management decisions have important consequences on predator-prey dynamics. Strategies of managing landscapes differ according to management objectives, and ability to learn from or imitate successful (or not) strategies implemented by other managers, with whom information is shared. The next chapter looks at how diverse strategies evolve depending on authority of a manager's network. The existence of multiple managers in a network, that are individually able to alter only a fraction of the landscape, is the next step towards a more comprehensive integration of Social and Ecological Network Resilience. Chapter 8 will present a model of strategy diffusion looking at how different atuhority distributions give rise to more homogeneous or more heterogeneous strategies.

8 The Social System: Strategy Diffusion between Managers

Chapters 6 and 7 introduce models that mainly centre upon the ecological side of a SES. Chapter 6 looks at network effects on a simple ecological system, while Chapter 7 introduces feedback mechanisms between the ecological and the social system; however, in Chapter 7 only one single manager takes action. This chapter expands on the previous ones and deals with the existence of multiple managers and management communities and the interaction amongst them. In other words, this chapter deals with the diffusion of possible different management strategies (management paths) between *N* management units. This chapter can be thought as an extension of the manager unit of Chapter 7, although no explicit reference to the ecological system is made. Moreover, Chapter 8 does not explicitly analyze the resilience of a system. However, resilience is an indirect consequence of the number of options existing in a system. More precisely, if more room for pursuing novel strategies exists, a system will be more resilient (more options), while if strategies are homogenous and there is no room for experimentation and for developing new management paths, a system is likely to be less resilient (less options). As of now, it is best to keep separated the ecological and the social part of a SES due to the complications that arise when the systems are analyzed in conjunction. In other words, there is a need to first understand how structural properties influence the ecological part of the system, analyze possible feedback mechanisms and effect between the social and the ecological systems, and finally, looking at an expanded social system.

Humans have distinctive abilities, as extensively explained in section 4.1.2. As already seen in the introduction to Chapter 7, humans are able to forecast, within the limits of prediction regarding complex systems, and to pursue different management paths. Moreover, managers communicate with one other ideas and experiences. Communication is a fundamental feature for developing flexible strategies to adaptively manage a SES. Finally, thanks to technology, humans are able to implement a devised set of alternative strategies (e.g. see section 7.1.3) having sensible effects on the ecological system (as seen in the model presented in Chapter 7). Therefore, human (inter)actions play a crucial role in influencing the resilience of a SES. More precisely, the ability to foresee and pursue different management paths and the technology used to implement different strategies[14] depend on the ability to learn, interact and communicate. Humans that are able to alter or to have a say in devising strategies for managing an ecological system can be defined as managers. Therefore, in managing natural resources, it is reasonable to assume that if no interaction occurs, each manager adopts a personal strategy, given the inputs received from the environment, but independently from the behaviour/choices of other managers in the network (Castellano et al., 2009). On the other hand, if managers are able to communicate effectively, opinions, ideas, and strategies may be exchanged and diffuse. These distinctive abilities allow humans to adaptively manage a SES. In order to adaptively manage a SES one needs to define *adaptive capacity*.

Following Nelson et al. (2007: 397) adaptive capacity can be defined as the "preconditions necessary to enable adaptation, including social and physical elements, and the ability to mobilize these elements". Adaptive capacity is a crucial attribute of a resilient SES, being the capacity to manage a SES so that the SES can maintain itself in the same basin of attraction, despite internal and external shocks that may affect the ecological, the social or both components of the system. Moreover, adaptive capacity also allows managers to try to shift the SES towards a more desired (according to who manages it) basin of attraction. Adaptive capacity, as the definition hints, is time and space specific, that is, adaptive capacity is local, being dependent on elements that are specific to a given community or environment at a given time. Nonetheless, it is possible to define preconditions necessary for adaptive capacity that are common to all communities and environments at all times. These preconditions, from here on named generic adaptive capacity, depend on ideas, opinions, and hence management strategies that exist in the SES. Thus, it is important to assess the diversification of ideas, opinions and strategies as they represent very important determinants of adaptive capacity.

[14] In this chapter strategies and management paths are used as synonyms.

In order to clarify the concept of generic adaptive capacity, it is possible to look at real world example and plan a scenario with highly homogeneous societies. A determined management path is thought to be causing degradation in the whole SES. A new management strategy is devised by a highly homogeneous society. The new management path involves declaring the Kristianstads Vatternike protected area. No human activity is allowed inside the protected area. The manager(s) that devise this strategy are those with the highest power to influence behaviours or opinions through reputation and legal means. In a highly homogeneous society no one is able to challenge this strategy. Although the technology and possible solutions are at hand, as demonstrated by Olsson et al. (2004), new management paths will not be implemented, thus in our hypothetical scenario, the wetland will overgrow thus nullifying the purpose of the implemented strategy.

Generic adaptive capacity not only results from how different managers perceive the world and the range of their managerial objectives, but also, and foremost, on the ability of these managers to exchange, learn, adapt, imitate their strategies from and with each other. Communication as well as the existence of different management paths is crucial for adaptive capacity and thus for adaptive management of a SES. The existence of different strategies is important for adaptively manage a SES, consequently it is important to understand under which conditions homogenization of management paths is more likely to occur. More precisely, if authority is defined as the power to influence behaviours or opinions through reputation and legal means:

- Are there different authority structures that favour the homogenization (or synchronization) of management strategies, thus reducing the adaptive capacity to manage a SES?
- What is the importance and what are the consequences of having an “external force” that pushes management towards a unified opinion, idea and consequently, towards the existence of one management path?

In order to answer the questions posed above, it is necessary to understand what variables are fundamental in order to enable managers to synchronize their strategies.

Management strategies depend to some extent on personal opinions and the way an individual perceives the world given his entrenched personal, social and cultural values (*worldview* from here on). The chosen strategies often depend on the network of contacts and the authority of this of these contacts (Henrich, 2004). In this context, the role of worldview often explains the difficulty in diffusing novel ideas that may counter the entrenched worldviews that exist in a particular community, even though such new strategies potentially allows for improvements in the management of natural resources (Deffuant et al., 2005). Deffuant et al. (2000) proposed a model of opinion diffusion, were people interact only if their worldview is similar enough, while they do not interact if the magnitude of difference in worldview exceeds a predetermined threshold (please refer to section 5.2.2 for in depth information on the Deffuant model). The original model has been studied in different settings and with several minor modifications (Castellano et al., 2009; Deffuant et al., 2005; Stauffer et al., 2004), but none deals specifically with issues of authority and allows not only to assess the presence of strategies, but also their potential synchronisation. Moreover, it is reasonable to assume that strategies may change over time due to internal (change of opinion, or idea, or learning etc.) and external (change in management objective, new constraints etc.) factors.

Societies where strategies are highly synchronized represent more homogeneous societies, where less room for experimenting with new ideas is allowed. If no or less room for novel strategies is permitted, imitation of strategies implemented by managers with higher authority may lead, in the long-run, to a reduced generic adaptive capacity, or in other words, a reduced ability to adapt to slow and fast changes surrounding environment (Levinthal & March, 1993). As an example, it is possible to imagine a particular community/society that has the technology and the resources to deal with shocks that affect the environment in which they live, such as climatic changes, lakes' eutrophication, and coral bleaching. The community is highly homogeneous, thus only traditional strategies are explored. If the traditional strategies fail, and there is no room for experimenting novel strategies, the society is bound to not to be able to adapt and risks to collapse.

As exemplified above, in highly synchronized, hence homogeneous societies, where strategies are similar, and no room for novel experimentation is given, managers may be unable to understand the appropriate way to deal with a highly unpredictable environment, where extreme events have a non-zero probability to occur. Not being able to express new ideas that lead to new strategies lowers the generic adaptive capacity of the society itself, impacting on the adaptive capacity and ultimately on the resilience of the whole SES.

8.1 The Model

Let's assume that strategies used in order to deal with our surrounding environment (ecological system in our case) vary with time. Let's also assume that these strategies are not fixed but they can change ("oscillate" with a given frequency or time interval) over time and a mechanism that synchronizes individual strategies exists. Under these conditions, the homogenization problem becomes a problem of synchronization. The pioneering work of Kuramoto (1975) and subsequent modifications (Arenas & Pérez Vicente, 1994; Pluchino et al., 2006) become highly relevant in this type of analysis. The model presented by Kuramoto (1975) is very generic, but is still able to highlight the fundamental drivers of spontaneous synchronization. The model refers to an ensemble of oscillators that have an intrinsic frequency (i.e. oscillators move with different "speed"); all oscillators influence one another, so that the frequency at time t is given by the intrinsic frequency plus the influence that oscillators have on one another. The influence or coupling, can be thought of as a "force" that draws the oscillators towards a common centre. Numerous applications and modification of the Kuramoto model exist in biological sciences, engineering, and computer science (refer to Arenas et al (2008) for an in depth review of the Kuramoto model). Applications of the Kuramoto model can be also found in social sciences. More precisely, applications in social sciences mainly refer to opinion formation (Pluchino et al., 2006) and economics and finance, where synchronization is normally assessed looking at correlations (Forbes & Rigobon, 2002; Onnela et al., 2003). The Kuramoto model has been widely studied on different network topologies (Arenas et al., 2008).

Humans communicate and exchange ideas and opinions through networks of contacts (Boccaletti et al., 2006; Bodin et al., 2006; Caldarelli, 2007; Dorogovtsev & Mendes, 2002; Galstyan & Cohen, 2007). These networks influence the possibility of synchronization. Although in a different context Bodin and Norberg (2005) have presented a very interesting result relating the connectedness of the underlying social network and the ability of the social system to be flexible. The more a community behaves as a single entity, the more there is a risk that the resilience of the overall SES is reduced, as no room for novelty and experimentation is allowed. Nonetheless, a degree of connectedness is necessary so as to foster novel ideas and flexibility in management.

In this chapter, the synchronization of strategies depends on how different people that have the authority to manage a given system (managers) are connected to each other, and on how different levels of authority influence the synchronization of strategies. Managers share information, ideas, opinions, and hence strategies based on a network of contacts. Since different management communities exist, the network on which managers act can be thought of as a highly modular network (i.e. a network whose density of edges within a module/community is fairly higher than the density of edges between modules/communities, as seen in section 3.3.5). When acting on a modular network, every module represents a "management community". Managers are able to share strategies along their connections within their community based on their own world view and the authority they have within the community. Managers are also able to share strategies with managers from different communities; in the latter case, the synchronization of strategies will depend on their own world view and the authority of the whole community to which a manager belongs.

8.1.1 Constructing the Model

As mentioned in the previous section, managers act on a modular network[15]. Every node of such a network represents a single manager. The modular network is created

[15] Please refer to Appendix III, section III.iii for the code of the model presented in this chapter.

by joining different random networks that represent different management communities. More precisely, the modular networks, visualized in Figure 8-1, are created as follows:

1. 10 different random networks are generated with 20 nodes each, so as to represent a network of management communities made by 200 people (10 management communities, each having 20 managers).
2. Each of the nodes has a probability p_c to be connected to another node belonging to the same initial random network.
3. Every node of the ten different networks has a probability p_{oc} to be connected to a node of a different initial random network.
4. $p_c > p_{oc}$, where p_c is drawn from a random uniform distribution between 0.9 and 1, while p_{oc} varies from 0 to 0.2 with a 0.025 increment, hence creating 9 different networks, so as to mimic a modular network whose modules (or communities) are very densely connected compared to the connections between modules (communities).

Once the network is created, attributes are assigned to every manager as follows:

1. The community to which a manager belongs, calculated with the algorithm proposed by Newman and Girvan (2004) and reported in section 3.3.5: ci
2. Initial strategy of manager i, represented by a number drawn from a random uniform distribution between -1 and 1: x_i
3. Authority that a manager has within the community: Pw_i that assumes values in the interval [0,1]
4. Authority that a management community has when deals with managers belonging to other communities: Pb_i that assumes values in the interval [0,1]
5. Its own world view, represented by a number drawn from a random uniform distribution between 0 and 1: w_i

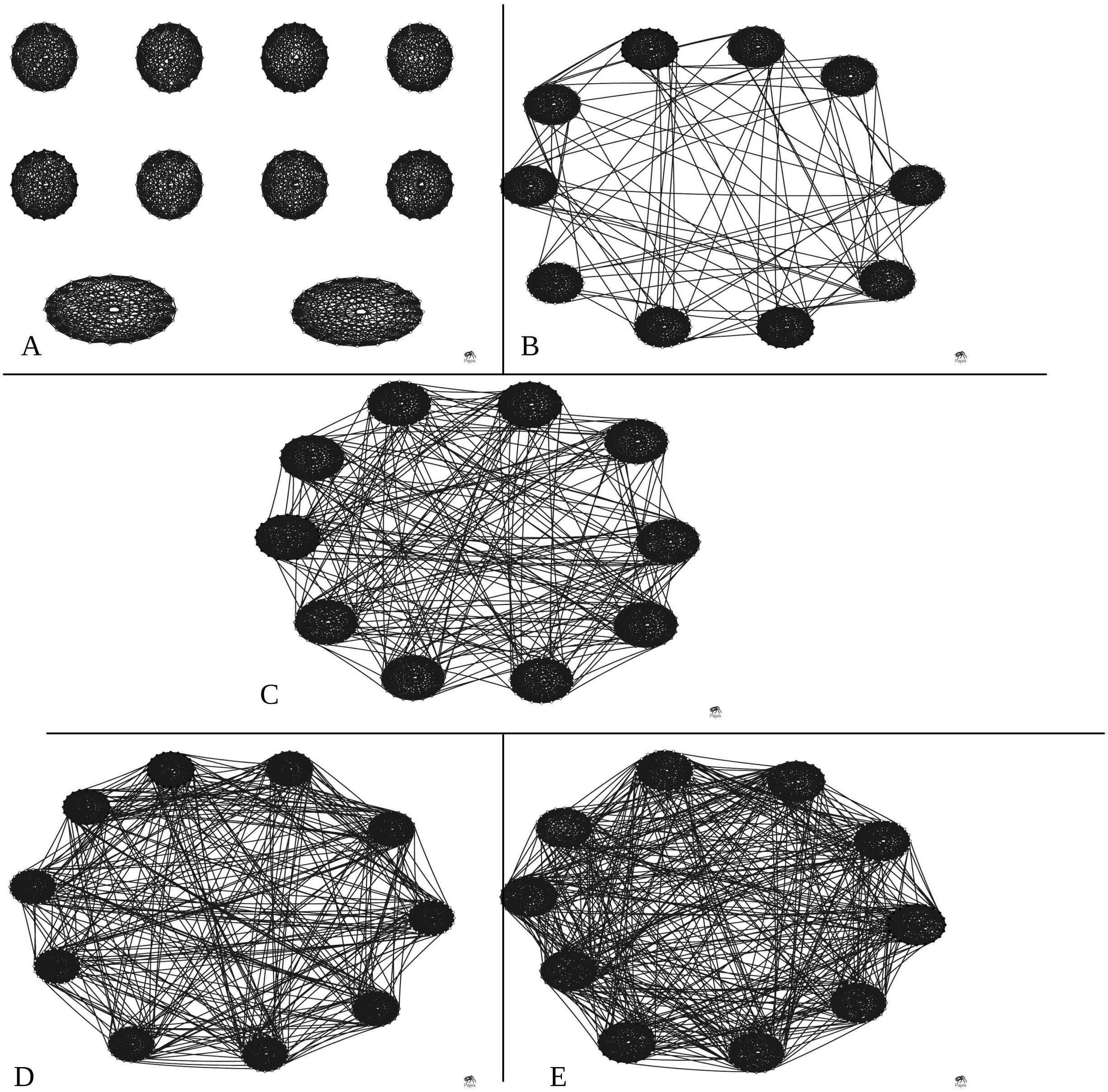


Figure 8-1 Networks visualization for different values of p_{oc} where p_{oc} = 0 (A), 0.05 (B), 0.1(C), 0.15(D), and 0.2(E) (Own Elaboration).

A general parameter representing the “strength” of an external force is proposed: α. When $\alpha = 0$ no external force acts upon the system, while when $\alpha = 1$ a powerful external force pushes the whole system towards synchronization. This external force can be a homogenising factor that exists in a given region of management communities such as strong cultural values or religious beliefs or the external influence of an organization such as the UN.

The dynamics on the network unfold as follows:

$$\dot{x}_i = x_i + \sum_{j \in K} \sigma_{ij}^{w_{ij}} * \sin(x_j - x_i) - \alpha * \sin(x_i) \qquad \textbf{[eq. 8-1]}$$

when world views throughout the managers differ,

and as according to:

$$\dot{x}_i = x_i + \sum_{j \in K} \sigma_{ij} * \sin(x_j - x_i) - \alpha * \sin(x_i) \qquad \textbf{[eq. 8-2]}$$

when no different world view exist.

Where:

$K =$ first neighbours of node i

$\sigma_{ij} = Pw_j - Pw_i$ if $i, j \in ci$ AND if $\sigma_{ij} = Pw_j - Pw_i \geq 0$

$\sigma_{ij} = Pb_j - Pb_i$ if $i, j \notin ci$ AND if $\sigma_{ij} = Pb_j - Pb_i \geq 0$

$\sigma_{ij} = 0$ if $Pw_j - Pw_i < 0$ OR $Pb_j - Pb_i < 0$

If $\sigma_{ij} = 0$ than $\sigma_{ij}^{w_{ij}} = 0$

$w_{ij} = |w_i - w_j|$

Constraints on σ_{ij} are imposed, as it is reasonable to assume that a manager will synchronize his/her strategies only with those managers that have a higher degree of authority.

8.1.2 Simulating the Model

Different modular networks with increasing p_{oc} are constructed. Manager's parameters are initialized 50 times for each network, and the dynamics represented by eq.8-1 and eq.8-2 are run for 1000 time-steps (t-s).

The model is run for different α values (i.e. 0, 0.25, 0.5, 0.75, and 1) and for different authority distributions. Authority within communities is distributed as follows:

1. Pw is normally distributed with mean 0.5 and standard deviation 0.125. If values are above 1 or below 0, they are reported to be equal to 1 and 0 respectively, so that: $0 \leq Pw \leq 1$.
2. Pw is exponentially distributed with one agent having authority = 1. If values above 1 or below 0 exist, they are reported to be equal to 1 and 0 respectively, so that: $0 \leq Pw \leq 1$.

Authority between communities is distributed as follows:

1. Pb is equally distributed (every community has the same authority) with value 0.5
2. Pb represents a more "democratic" distribution of authority between communities, and thus is represented by a normal distribution with mean 0.5, and standard deviation 0.125. If values above 1 or below 0 exist, they are reported to be equal to 1 and 0 respectively, so that: $0 \leq Pb \leq 1$.
3. Pb represents a highly hierarchical system in which one community has $Pb = 1$ and the other communities have Pb exponentially distributed between 0 and 1. If values above 1 or below 0 exist, they are reported to be equal to 1 and 0 respectively, so that: $0 \leq Pb \leq 1$.

Table 8-1 reports a summary of the different combinations explored and the symbols used to represent different authority distributions.

Table 8-1 Symbols used and corresponding authority distributions

Symbol	Distribution of authority within community	Distribution of authority between communities
dexp	exponential	normal
dnorm	normal	normal
eqexp	exponential	equal
eqnorm	normal	equal
exexp	exponential	exponential
exnorm	normal	exponential

Simulations for eq.8-1 and eq.8-2 are performed for different values of α (being α = 0, 0.25, 0.5, 0.75 and 1), for different values of p_{oc} (being p_{oc} = 0, 0.025, 0.05, 0.075, 0.1, 0.125, 0.150, 0.175, 0.2) and for the authority distributions described in Table 8-1. Furthermore, it is important to note that all values that represent different authority and different worldviews are not to be interpreted in absolute terms but only relatively to other values of the same attribute.

8.2 Results

In order to assess if different authority distributions lead to different synchronization states at the end of the simulation (1000 time-steps), average "strategy values" of the 50 initializations are collected for every period *t*. To assess the synchronization degree at the end of every run, a synchronization parameter is calculated following Pluchino et al. (2006).

$$r(t) = 1 - \sqrt{1/N \sum \left(x_i(t) - \overline{X_i(t)}\right)^2} \qquad \textbf{[eq. 8-3]}$$

The system is fully synchronized when $r(t) = 1$. Once the synchronization parameter given by eq.8-3 is calculated, the different distribution combinations shown in Table 8-1 are ranked from the most synchronized to the least synchronized one (ranking values from 1 to 6, with 1 being the authority distribution combination that leads to the most synchronized state and 6 the least synchronized one). Ranks are used as the focus is on how different authority distributions lead to different synchronization states, hence, the focal point is on which authority distribution leads to the most synchronized state relatively to the other authority distributions, rather than in absolute terms. It is important to look at the relative synchronization in order to highlight how differences in authority distributions across and within management communities lead to relatively different synchronized states. Uncovering the relation between synchronization and authority distributions allows understanding how different structures of authority lead to different degrees of homogenisation.

Figure 8-2 reports rank distribution and the type of authority distribution used. Figure 8-3 reports the mean rank (*r(t)*) for different authority distributions, Figure 8-4 reports median rank (*r(t)*) for different authority distributions and Figure 8-5 reports the mode rank (*r(t)*) for different authority distribution. All figures indicate which of the different authority distribution combinations is the most likely to lead to a more synchronized (homogeneous) state.

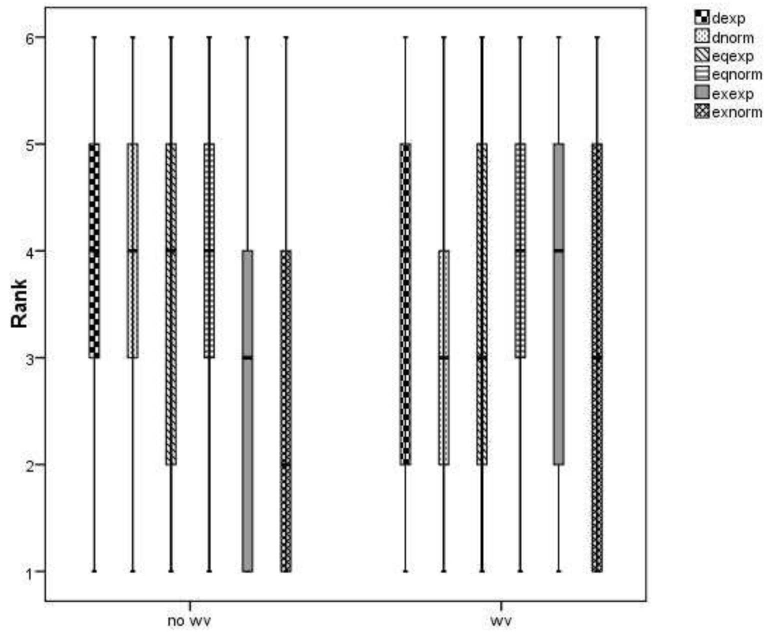


Figure 8-2 Distribution of rank versus authority distribution
Rank is displayed on the y axis, while different authority distributions are displayed on the x axis for eq. 8-2 (no wv) and for eq. 8-1 (wv). Highest homogenization is reached at rank 1, lowest at rank 6 (Own Elaboration).

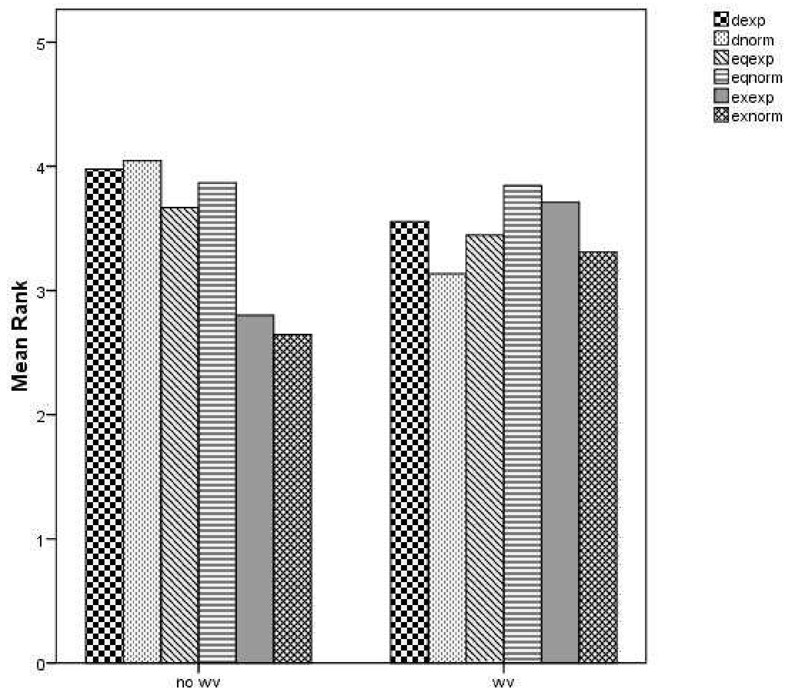


Figure 8-3 Mean rank versus authority distribution
Mean rank for the different simulation performed is displayed on the y axis, while different authority distributions are displayed on the x axis for eq. 8-2 (no wv) and for eq. 8-1 (wv). Highest homogenization is reached at rank 1, lowest at rank 6 (Own Elaboration).

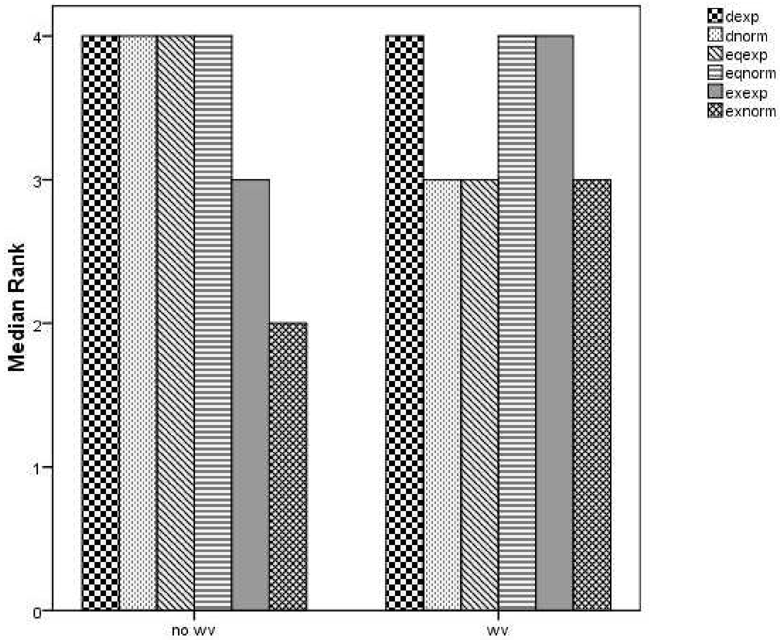


Figure 8-4 Median rank versus authority distribution
Median rank for the different simulation performed is displayed on the y axis, while different authority distributions are displayed on the x axis for eq. 8-2 (no wv) and for eq. 8-1 (wv). Highest homogenization is reached at rank 1, lowest at rank 6 (Own Elaboration).

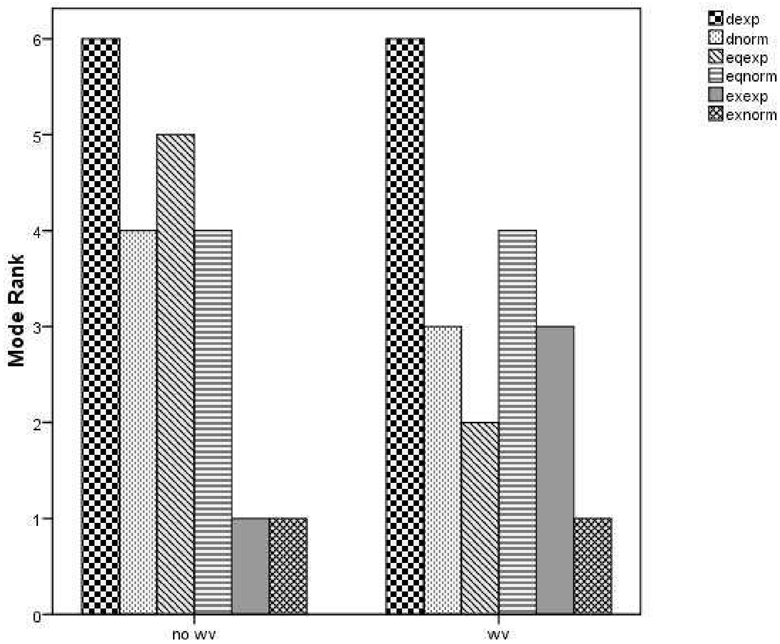


Figure 8-5 Mode rank versus authority distribution
Mode rank for the different simulation performed is displayed on the x axis, while different authority distributions are displayed on the x axis for eq. 8-2 (no wv) and for eq. 8-1 (wv). Highest homogenization is reached at rank 1, lowest at rank 6 (Own Elaboration).

As it is evident, the authority distributions have an important effect when a worldview is absent (i.e. following eq.8-2). The differences in our worldview, could in theory mitigate the effect of differences in authority, but, when worldviews are very similar (or alternatively when cultural, social and personal beliefs are not crucial in devising strategies) different distributions of authority give rise to different degrees of homogeneity. More precisely, exponential distributions are more prone to lead to the most homogeneous states as shown in Figure 8-2, Figure 8-3, Figure 8-4 and Figure 8-5.

Moreover, most of authority distributions result in higher synchronization when α is not present (= 0). Thus, it is possible, even if this result may seem counterintuitive, that an external force that pushes individuals towards synchronization, does actually generate more heterogeneity. In short, α does not seem to significantly alter the synchronization characteristics, as shown in Figure 8-6.

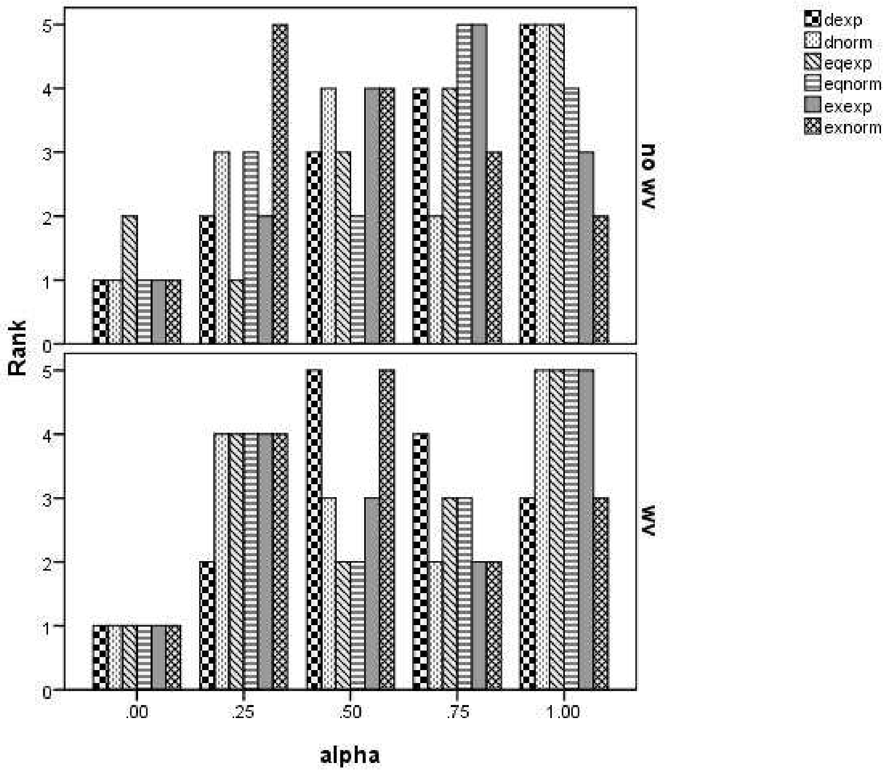


Figure 8-6 Rank for different values of alpha
Rank (y axis) from 1 (highest ranking) to 5 (lowest ranking) for the six authority distributions given different alpha (x axis) for eq. 8-2 (no wv) and eq. 8-1 (wv). Authority distributions are ranked according to alpha (i.e. which alpha value leads to the most homogeneous state in a particular authority distribution) (Own Elaboration).

The fact that the external force gives results that are not aligned with our intuition is common in socio-physics (Castellano et al., 2009). A similar model (i.e. with respect to the role of external influence) that helps explaining the counterintuitive results of the α parameter has been proposed and studied in relation to opinion formation by Tessone et al. (Tessone et al., 2006; Tessone & Toral, 2009). The model differs from the one presented here as its coupling is not given by dissimilarities between individuals and the dynamics are qualitatively different since it does not take different phases (thus oscillating strategies) into account. However, the external force (social pressure, advertisement etc.) is modelled as periodic forcing (e.g. in the form $C * \sin(x)$) similarly to the model presented in this chapter. The external force in the model presented in eq.8-1 and eq.8-2 ($-\alpha * \sin(x_i)$) represents a common institution whose strength is given by the parameter α. The institution acts upon the whole system and, has different effects according the homogeneity or heterogeneity of strategies, as in Tessone et al.(2006) and Tessone & Toral (2009). Despite the differences in the synchronization of the various authority distributions, the proportion of non-synchronized individuals is very low (see Table 8-2 where minimum and maximum degrees of synchronization for every authority distribution for eq.8-1 and eq.8-2 are reported), thus, given the relative high homogeneity that results from the model, the external common driver is not able to act and force individuals towards a specific phase. Moreover, Figure as 8-6 shows, α seems to significantly affect the results only when it is absent (i.e. $\alpha = 0$ thus $-\alpha * \sin(x_i) = 0$), leading almost in all cases and for both eq.8-1 and eq.8-2 to the most synchronized state.

Table 8-2 Min and max values of synchronization as resulted by the simulations performed

authority	**eq. 8-1**		**eq.8-2**	
distribution	**min**	**max**	**min**	**max**
dexp	0.7982	0.8916	0.8048	0.9260
dnorm	0.7897	0.8994	0.8103	0.9226
eqexp	0.7859	0.8800	0.8042	0.9049
eqnorm	0.7914	0.8747	0.8108	0.9153
exexp	0.8016	0.8933	0.7942	0.9282
exnorm	0.7953	0.8968	0.8178	0.9188

This counterintuitive result could be a consequence of the model inbuild characteristics, since given the dynamics of described in eq.8-1 and eq.8-2, α, acts upon the reinforcement of the original "strategy phase", hence, in presence of a highly synchronized society, it counter-balances the coupling parameter $\sigma_{ij}^{w_{ij}}$ or σ_{ij}, limiting the synchronization factor. This result, as previously mentioned, is not new in the socio-physics domain. External forces have a strong "homogenization" effect only if an intermediate degree of heterogeneity exists in the system (Tessone et al., 2006; Tessone & Toral, 2009). Figure 8-7 gives a visual representation of the explanation given regarding α so as to facilitate the understanding of the relationship between the external force effect and homogenization. As Figure 8-7 shows, the external force has a substantial positive effect only at intermediate levels of heterogeneity, while it has a negative effect (thus lowering synchronization) at high level of heterogeneity or very low level of heterogeneity. In other words, at intermediate levels of heterogeneity, the external force will drive the system towards homogenization, while at low and high levels of heterogeneity, the external force will act as a positive feedback, thus enhancing heterogeneity.

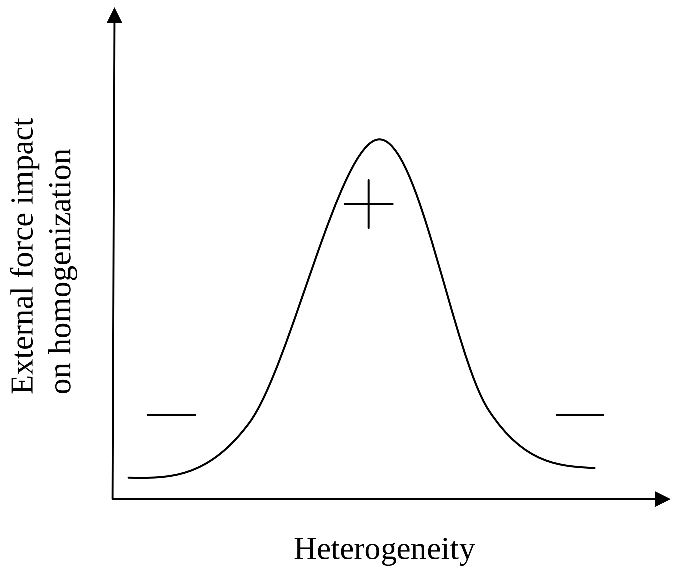


Figure 8-7 Relation between external force and heterogeneity: negative and positife effects Positive and negative effects on homogenization are portrayed by the signs (Own Elaboration).

The relationship between heterogeneity and the effect of an external force can also be applied in an archaeological context, such as the one described by Nelson et al.

(2006). In their paper Nelson et al. (2006), describe how Mimbres villages went from a more centralized (thus more homogeneous society) to a decentralized (or more heterogeneous society). Mimbres villages refers to villages in the Mimbres region in the modern US Southwest around the 12th century AD, as during that time the Mimbres region underwent a transition from what is called the classic Mimbres period to the post-classic reorganization phase (Nelson et al., 2006). More precisely, regarding the aspects that more are affected by different management paths, Nelson et al. (2006: 425) affirm the following:

> House size and configuration and the organization of storage and food preparation were not more homogeneous or standardized immediately preceding reorganization; on the contrary, they became increasingly homogeneous after the abandonment of Mimbres villages and reorganization in to dispersed hamlets.

This can be explained by the model presented in this chapter as the external force (e.g. common overarching state organization, strong cultural beliefs common to all the Mimbres villages) acting upon all members of the village becomes 0 (i.e. $\alpha = 0$), thus allowing for authority distributions to affect the homogenization of strategies between different households (in this case one may think of households of the Mimbres villages as managers in the model presented in this chapter).

8.3 Discussion

Three main conclusions can be drawn from the results described in the previous section. First, as shown in Figure 8-3 there is a significant difference amongst the different authority distributions in case of equal world views. More precisely, if the authorities of the different communities follow an exponential distribution, resembling highly hierarchical governance structures, the whole system becomes more homogeneous. It is possible to argue that highly synchronized systems are beneficial in the *K* phase of the adaptive cycle as homogeneous management improves efficiency; however, a small degree of homogeneity is actually beneficial and necessary in any phase of the adaptive cycle as it allows preserving strategies to manage resources and relations (Nelson et al., 2006). In this context, the small degree of homogeneity can be thought of as a necessary condition for the social system to preserve valuable knowledge ("remember") (see section 4.1.1 on the adaptive cycle).

The second conclusion drawn from the model presented confirms that authority distributions between different management communities influence far more significantly the possibility of synchronization and thus homogenization of strategies than differences of authority distribution within the same management community. As Figure 8-2 and Figure 8-3 show, differences between distributions of authority inside the very same community do not lead to significant differences (e.g. *dexp* vs *dnorm, eqexp* vs *eqnorm* and *exexp* vs *exnorm*), while distributions of authority between community seem to have a highly significant effect. Therefore, more effort should be put into examining cross-community relations, as these may as well be the drivers of strategic decisions. The third main conclusion drawn suggests that for high synchronization values, an external force causes more heterogeneity (asynchronization) rather than homogeneity (synchronization) at least in relative terms. This result should lead to a reconsideration of the role of informal and formal institution in presence of different levels of heterogeneity and synchronization in the system. The so called external force can be envisioned as an overarching institution (formal or informal) that is common to all managers and hence management communities who exist in the system.

Given the results of the model presented, a high degree of synchronization is generally observed (as shown in Table 8-2). High homogenization is responsible for narrowing the windows of opportunity for experimentation. Thus, high homogenization reduces what has been previously defined as generic adaptive capacity and lead to an "efficiency trap", where no novel strategies are explored and managers concentrate on a single way of dealing with the environment. Managers that are able to devise only one type/set of strategies will refine the very strategies they are familiar with, at the expenses of other possible ones (Levinthal & March, 1993; Scheffer & Westley, 2007). In other words, thanks to the available technology, managers will become increasingly competent in changing the environment rather than adapting to it. In the long-run, different strategies are lost thus lowering the generic adaptive capacity. The reduction in generic adaptive capacity leads to a system that lacks the precondition necessary for adaptive capacity especially in case of novel disturbances. In other words, such system loses the ability to adapt to shocks that have not been previously experienced or that are not known or expected by the managers of a SES.

In order to be adaptive, the management of the SES should exhibit some degree of heterogeneity, if the management's objective is to find the best possible strategy while maintaining flexibility and the possibility for novel ideas to emerge (Levinthal, 1997). Given the results above, highly hierarchical governance structure are less able to respond to fundamental shifts in the slow variables that causes the system to change its basin of attraction. This final statement is also confirmed by a study on the resilience of three different archaeological cases in the U.S Southwest by Hegmon et al. (2008).

More specifically, regarding the hierarchy thus the distribution of authority, the authors find a relation between highly hierarchical societies (in our model represented by the *exexp* distribution) and the magnitude of the societal collapse. Moreover, it is possible to assume that the people living in the three societies studied (Mimbres, Mesa Verde and Hohokam) had very similar if not the same worldview within their own community. In this context, eq.8-2 can fairly represent the diversification of strategies or management paths present in the three different settlements. As it has been explained in this paragraph, homogeneity reduces the window of opportunity, thus lowering the generic adaptive capacity that will reduce localized adaptive capacity that will reduce the resilience of a SES. Hegmon et al. (2008: 319) affirm that in "Mimbres there are only tentative indications of social differentiations" hence authority could have been equally or normally distributed throughout the population (being here the population also able to manage the environment, thus effectively being represented by the "managers" of our model). Mesa Verde, present more social differentiation but mostly in the latest years, thus again, Mesa Verde can be represented by a normal or exponential distribution within and between communities belonging to it. Finally, as noted by Hegmon et al. (2008: 319) "in the Hohokam case, there is strong evidence of differential access to social power as well as wealth and status, although there was intraregional variation".

Analyzing the three cases supports the conclusion presented here and allows for an understanding of the role of authority in the adaptive capacity and at last on the resilience of a SES. The three cases can be represented by different authority distributions of the model presented, and as such, they can be seen at different levels of homogenization. These levels of homogeneity have had an important effect on the outcome of the societal collapse, as the authors affirm, “the Mimbres transformation was clearly the least severe” while “Mesa Verde and Hohokam, evidenced much harsher conditions prior to their more severe transformations” (Hegmon et al., 2008: 321), due to the rigidity imposed by a homogeneous society and the lack of new possible management paths that could have facilitated the adaptation or transformation of these societies.

The importance of the management or social system for the resilience of an SES is clear. Different ways to manage our landscape, our ecological system may lead to resilient paths or may lead to painful collapses and changes in the basin of attraction. Throughout history there have been different societies that are thought to have collapsed due to purely ecological reasons (Diamond, 2005). Thesis such as the one proposed by Diamond can be and have been disputed, as the social component of the SES is often what actually triggers transformation, adaptation and in cases, a painful shift in the basin of attraction. As Tainter points out (2006) a pure ecological collapse (i.e. a change of the basin of attraction only due to ecological reasons) has not been proven as it “denies the human capacity for flexible adjustments, including intensifying production” (Tainter, 2006: 72).

To conclude, this chapter has shown how different management systems may actually facilitate or hinder the fostering of new management paths. Possible strategies that managers could implement are explored in Chapter 7. This chapter starts posing question of relating authority within and between communities and the ecological system that is been managed. Answering and developing questions on issues of authority in the management of ecological systems may help the understanding of how SES resilience is eroded or if the SES finds itself in an efficiency trap. The following and last chapter of this thesis will first summarize the conclusions drawn from Chapters 6, 7, and 8. Further it will build a common framework in order to unify the models presented in this thesis so as to integrate social and ecological networks that, as it has been demonstrated, play a crucial role in shaping the resilience of a Social-Ecological System.

9 Conclusions

Linking social and ecological systems in an evolving and complex world poses great challenges. Linear thinking, deterministic and based on a reductionist approach, has proved to be inadequate to explain complexities and behaviours of such systems. New approaches are deemed necessary in order to study a SES with its strengths and weaknesses. More precisely, this work integrates network theoretical tools and agent based modelling in the resilience framework so as to approach SESs from a structural perspective.

As recalled throughout this thesis, the concept of resilience developed by Holling and co-workers (Brand & Jax., 2007; Holling, 1973, 1998; Holling & Gunderson, 2001; Walker et al., 2004) is an appropriate lens through which analyse and understand spatial and temporal evolution of a SES. The concept of resilience is based on non-equilibrium or multi-equilibrium; it takes uncertainties and surprises into account, and looks at feedbacks and cross-scale interactions within and between the social and the ecological components of the system.

However, resilience concepts do not automatically identify a set of straightforward metrics and techniques able to assess the state and the resilience of a SES. Given the complexities of such coupled systems, an approach drawing from and integrating different disciplines, methods and tools in a coherent and rigorous framework is needed. In this research, tools and methods provided by network science (Albert & Barabási, 2002; Barabási & Albert, 1999; Boccaletti et al., 2006; Börner et al., 2007; Caldarelli, 2007; da Fontoura Costa et al., 2007; Dorogovtsev & Mendes, 2002; Newman, 2003; Watts, 2004; Watts & Strogatz, 1998) are used to analyze SES from a structural perspective. Representing a SES as an ensemble of networks is a first step towards a network of networks representation. A structural perspective helps to understand structural weaknesses and strength of a system, so that it is possible to plan and adapt accordingly, as the relationship occurring between structural properties and functions of a complex system has been recognized in different fields , both theoretically and empirically (Baggio et al., 2010; Boccaletti et al., 2006; Bodin

& Norberg, 2005; Pastor-Satorras & Vespignani, 2001; Planesa et al., 2009; Stauffer et al., 2004; Vazquez, 2006). A resilience assessment from a structural perspective may allow a clearer understanding of the fundamental features of SES, enhancing knowledge of adaptation and transformation occurring in an interdependent and interconnected world.

9.1 Advancing SES science: new methods and tools for understanding SES resilience

In order to gain the insights presented in sections 6.4, 7.3, 8.3, and summarized in sections 9.2 and 9.3, a mix of methods and tools have been used throughout this thesis. More precisely, as explained in Chapter 2, the thesis makes extensive use of analogy, adapting tools and methods drawn from different disciplines. It combines network theoretical methods with the resilience framework and makes extensive use of ABMs, since they are judged to be the most appropriate modelling technique when dealing with CAS (as explained in Chapter 5). The aim of this thesis is to uncover the relation between structural properties and resilience of a SES. The structural properties of a system are the focus of the analysis in all the models presented; nonetheless, networks are considered as static and supportive of the evolution of dynamic processes in the models presented in Chapters 6 and 8. In Chapter 7, the network supports dynamic processes and also evolves over time according to predetermined rules.

It is well known that dynamic processes unfolding on networks relates to the topology and the characteristics of the network on which they evolve (i.e. metrics or structural properties) (Boccaletti et al., 2006). However, the way in which the underlying network influences dynamics of SES is still an open question. Different tools and methods are needed in order to understand SES resilience from a network perspective. The analysis of CAS such as SES should be based on the continuous interactions between the abstraction of fundamental variables (model), pilot studies and experiments in order to validate or falsify the model constructed, and actual case studies and fieldwork. This thesis represents the first step of this cycle. Agent based models are used in order to mimic dynamics on an underlying network, approximating reality in order to understand the influence of networks on the resilience of SES.

Significant contributions in social sciences and, I would say, in the understanding of SES will, in the words of Henrickson and McKelvey (2002: 7295) “emerge more quickly if science-based beliefs are based on the joint results of both agent-modelling and subsequent empirical corroboration.” This thesis is thus a step towards building science beliefs based on ABM, accompanying their use with network theoretical tools, both set in the resilience framework.

9.2 Understanding resilience from a network perspective

As stated in the introduction, two research questions are central to this thesis, the first being:

- Is it possible and to integrate resilience principles and network theory, and if yes, how?

To set the background in which this work has been conducted, aspects of both, resilience thinking and network science are introduced in Chapters 3 and 4. A first working definition of resilience from a network perspective is given in Chapter 5: network resilience is the amount of disturbances a network can undergo without being totally disrupted, that is, without breaking down its giant component.

Chapter 5 reports literature results regarding the well known existing relationship between the topology and the resilience of a network (Albert et al., 2000; Crucitti et al., 2004; Latora & Marchiori, 2001). Failures influence the most important network metrics such as the size of the giant component, the efficiency (global and local) and the average shortest path length. However, the results described refer to a semi-static analysis, where networks do not evolve and no dynamical process except the collapse of nodes is present. To mimic the evolution of SES from a network perspective, it is possible to think at how networks evolve when nodes are added or disappear, edges are added, disappear or are rewired. It is also possible to envisage networks remaining fairly stable (e.g. infrastructure and landscape networks), and working as a support for dynamical processes, such as predator prey interactions, epidemics, or rumour and information spreading (Boccaletti et al., 2006). SESs are evolving systems, they may move between different states in the same basin of attraction, or shift basin of attraction. These concepts and findings lead to a second research question of this thesis:

- How do the dynamics of a system unfold and how are they influenced by the structural properties of the system?

To answer this question, it is necessary to assess the resilience of a system from a structural perspective, analyzing dynamic processes that unfold on fairly stable networks. Given the presence of feedbacks, cross-scale dynamics (temporal and spatial), emergence and self-organisation that characterise SESs, networks are used as a support for the models developed in Chapters 6, 7 and 8. In these chapters, networks are the “infrastructure” on which certain dynamic processes evolve. More precisely, in order to assess how structural properties may influence the resilience of a system, following Carpenter et al. (2001), “resilience of what to what” is defined in the first section of every chapter. It is here worth highlighting that resilience is a neutral term, and that there are different types of resilience. Further, there is often a trade-off between resilience to different type of disturbances and between resilience at different spatial and temporal scales. In other words, it is possible to enhance resilience at a particular spatial and temporal scale, while decreasing resilience at a different temporal and spatial scale as well as it is possible to enhance resilience of a system to a specific type of perturbation while decreasing resilience to another specific perturbation. Therefore, when analyzing the resilience of a SES, it is necessary to identify as precisely as possible the resilience of what to what (Carpenter et al., 2001).

Chapter 6 presents a first theoretical model where a simple landscape, represented as a network, is built. The landscape is first represented as a disconnected network, and connections are added until the landscape is represented by a fully connected network. The effects of the underlying landscape network are assessed on predator-prey interactions. In Chapter 6 and Chapter 7 a shift in the basin of attraction occurs when there is a change in the species composition of the system. Hence, in theory, three basin of attraction exist: one in which predators and prey coexist, one in which only prey survive, one in which there are no predators and no prey. More precisely, Chapter 6 centres upon understanding one main aspect of the relationship between structural properties and system resilience as defined, namely:

- Does network connectivity facilitate or hinders the shift onto a new basin of attraction?

As seen in sections 6.3 and 6.4, the connectivity of the network and the probability of shifting basin of attraction are related. Node centrality influences probability of coexistence on a local scale (e.g. on one node) while centrality at the network level influences the probability of coexistence on a global scale (e.g. on the whole network). The relationship discovered supports existing theories such as corridor ecology and the creation of reserve networks in order to foster long-term biodiversity (Cabeza & Moilanen, 2001; Hilty et al., 2006): connecting different patches of protected areas seems to enhance the resilience of the system modelled with respect to the coexistence of species. Thus, network connectivity has a tangible effect on the resilience of the ecological system as demonstrated in Chapters 6 and 7.

In order to investigate further the relationship that exists between structural properties of a SES and the resilience of a SES, another model is presented in Chapter 7. This model builds on the results obtained in Chapter 6, adding management (human) interaction with the ecological system. A manager is able to voluntarily alter the landscape that in return, will affect predator prey interactions (as demonstrated in Chapter 6). While Chapter 6 centres on the relation between basin of attraction and network metrics, Chapter 7 explicitly addresses the temporal dynamics of structural properties, introducing the simplest possible social system, formed by one social agent (manager in this case) able to alter the landscape network. More precisely, the manager is able to act upon the edges' weights, representing an animal perceived cost of movement, and connecting different landscape patches represented as nodes. Further, the model presented in Chapter 7 looks at possible feedbacks existing between social actors (such as managers) and the ecological system. Most importantly, the model described in Chapter 7 allows to relate the evolution over time of structural properties and the resilience of the system; in other words, it answers the following question:

- How does the evolution of structural properties facilitate or hinders the shift to another basin of attraction?

From the outcomes presented (see sections 7.2 and 7.3), the evolution of structural properties seems to play an important role in the resilience of a system. Using network metrics that are suitable for weighted networks, a relation between the temporal dynamics of these metrics and the resilience of a system is found. More precisely, using simple statistical measures such as variance, kurtosis and skewness (i.e. statistical moments) of the evolution over time of selected structural properties, it is possible to have a coarse-grain assessment of the probabilities that the system will shift basin of attraction. If no critical transition occurs in the time evolution of network metrics, the system is more likely to remain in the same basin of attraction. If critical transitions occur in the evolution of network metrics, the system is more likely to approach a threshold and hence change its basin of attraction. As in Chapter 6, structural properties are confirmed to be a promising indicator when assessing the resilience of an ecological system. Chapter 6 presents a model mainly centred on a simple ecological system; Chapter 7 builds on the model presented in Chapter 6 and introduces a simple social system and feedbacks between the social and the ecological system. Chapter 7 may represent a first attempt to model a SES through ABM using network theoretical tools in order to analyze the effects of structural properties on the resilience of the SES. However, both chapters are more centred on the ecological system rather than the social one.

The model presented in Chapter 8, on the other hand, does not take explicitly into account the ecological system and focuses on the social system. The model portrayed, analyzes the relationship between authority distributions and homogenization of strategies. Being homogenization the act of becoming more and more synchronized. In contrast to the previous chapters, Chapter 8 does not assess the resilience of a SES per se. However, Chapter 8 highlights the existing relationship between strategy homogenization and what is defined as generic adaptive capacity (i.e. the preconditions necessary to be adaptive and that relate to learning, experience and knowledge). Thus, the focus is on social characteristics assumed to be necessary for adaptive management of a SES. The model mainly aims to uncover the relation between authority structures and homogeneity of management paths; thus, by extension, the relation between authority structures and generic adaptive capacity. The model presented in Chapter 8 is built mainly to answer the following question related to the resilience of a SES:

- Are there different authority structures that favour the homogenization (or synchronization) of management strategies, thus reducing the adaptive capacity to manage a SES?

Authority distributions in management communities influence the homogenization of strategies as seen in section 8.2 and 8.3. High homogenization of management paths is responsible for narrowing the possibility of experimentation and pursuing novel management paths. In other words, high homogenization reduces generic adaptive capacity. Systems in which strategies are highly homogeneous are assumed to lose the ability to adapt to shocks that have not been previously experienced or that are unknown or unexpected by the management of a SES. Moreover, the model confirms previous findings as, for example, those from archaeological studies in the U.S Southwest by Hegmon et al. (2008): highly hierarchical governance structure are less able to respond to fundamental shifts in the slow variables, to novel shocks and unexpected outcomes, hence lowering the adaptive capacity of a SES.

Previous findings have shown the importance of the social system for the resilience of a SES (see for example: Adger, 2000; Anderies et al., 2004; Anderies et al., 2006; Bodin et al., 2006; Bodin & Norberg, 2005; Carpenter et al., 2001; Elmqvist et al., 2003; Folke, 2006; Holling, 2004; Liu et al., 2007; Olsson et al., 2004; Walker et al., 2002). Different ways to manage the ecological system may lead to resilient paths or to painful collapses and changes in the basin of attraction. In this context, adaptive capacity is a fundamental feature of the resilience of a SES. Lowering adaptive capacity decreases the possibility to experiment with novel management paths, and ultimately, lowers the ability of the social system to proactively build resilience.

9.2.1 Relevance for policymakers

As seen in section 9.2, and throughout the thesis, structural properties influence the resilience of SES. These findings are also supported by previous research that links networks and resilience of SES (Bodin et al., 2006; Bodin & Norberg, 2005; Janssen et al., 2006; Newman & Dale, 2005). Remembering that the models presented in Chapters 6, 7 and 8, following Carpenter et al. (2001), define typologies of resilience, it is possible to affirm that in the cases presented, connectivity plays a central role in increasing or decreasing the resilience of a SES. Moreover, as seen in Chapters 6 and 7, there is a number of well-known network metrics that play an important role in assessing resilience from a structural perspective. These metrics are the ones that indicate the easiness or the difficulty of dispersal and diffusion of processes from one node to another (i.e. closeness centrality, global efficiency, local efficiency, giant connected component, degree, strength or weighted degree, density, betweenness etc.). Variation in the structure of a system (viewed from a network perspective) influences the ability of a SES to maintain its original functions and controls despite disturbances and other parameters. Moreover, as described in Chapter 8, authority distributions influence the homogenization of management paths. Thus network properties and authority distribution have an important effect on the ability of a SES to self-organize, learn and adapt.

Structural properties of the landscape or the social-network are thus important for SES resilience. This importance can be also assessed by real-life examples. As described in section 6.4, jaguars' behaviour provides a first real world example of the conclusions drawn in section 9.2 and Chapter 6. They are highly dependent on movement for searching prey and for mating. Connectivity is thus essential for their survival, hence for the resilience of the system studied (Michalski & Peres, 2005; Ortega-Huerta & Medley, 1999).

These findings have implications for policies that aim at biodiversity conservation. Such policies, based on the conclusions drawn from Chapters 6 and 7 should avoid establishing isolated protected areas, and consider the opportunity to establish a network of protected areas. Increasing connectivity, as well as occupying globally and locally central patches, enhances the probability of coexistence between prey and predators, hence maintaining biodiversity. Impeding movement, on the other hand, by fencing and other means, may actually produce unintended effects, as seen in the model presented in Chapter 7. Excluding species from a certain area in order to maintain vegetation or other specific endangered species may give rise to a critical transition in the evolution of the structural properties of the landscape. As seen in section 7.2 and 7.3, these transitions negatively affect the probability of coexistence, hence biodiversity and ultimately the resilience of the system under study. Both Chapters 6 and 7 lead therefore to the conclusion that policies that aim at biodiversity conservation should foster the creation of a network of protected areas. Moreover, following the results presented in sections 6.4 and 7.3, it is important to create potential protected areas geographically near to other areas of the reserve network that may need to be enclosed. The enclosure of protected areas may be decided for vegetation depletion or increased human pressure. Whatever the reason, it is important to pinpoint alternative areas in spatial proximity so as to avoid a critical transition in the evolution of the reserve network's structural properties, which will erode the resilience of the specific SES under study, with respect to biodiversity.

Further, human activities (i.e. management paths) need to be taken into account along with possible unexpected consequences and surprises that specific strategies may raise. Examples of unexpected consequences of SES management can be drawn from Olsson et al. (2004) and Liu et al. (2007; 2001). In both cases protected areas were designed without taking into account the social system and the actual effect of some existing management strategies. In both cases this has produced unintended results. Thanks to what can be referred to as authority (as defined in Chapter 8), at least in the case of the Kristianstadt Vetternike, the consequences were addressed by changing management path (Olsson et al., 2004) (see section 7.3 for a more complete description of the examples reported here).

Management paths decided by the social component of a SES are fundamental for the resilience of the whole system. As mentioned throughout the thesis (i.e. section 4.1.2, and Chapters 7 and 8), the social system has some peculiar features, such as the ability to foresee, communicate, and the technology to heavily affect the ecological system. These features allow the social system to play a crucial role in a SES, devising different management strategies in order to maintain the SES in the desired basin of attraction. In this context, homogenization of strategies and its consequences have been analyzed. Some conclusion for policymakers can be drawn also from the analysis and the findings of Chapter 8. Policymakers should concentrate not only at the creation of networks of protected areas while taking human (inter)actions always into account, but they also need to consider the authority structure of the social system that is part of the SES they are trying to address.

Homogeneity as defined in Chapter 8, reduces the possibility of pursuing different strategies, thus lowering the generic adaptive capacity that will reduce the resilience of a SES. However, it is possible to speculate that homogeneous societies are economically more efficienct and thus work better in case of fairly stable systems. Unfortunately, SESs are generally, at present, becoming more and more unstable given globalization and the continuous changes experienced throughout the world (i.e. changes in the geopolitical arena, information technology, technology, climate changes etc.). Policy makers should then devise strategies that press on highly hierarchical governance structures to allow the implementation novel strategies and experimentation. Therefore they need to look at the heterogeneity that already exists in a social system and relate the existing heterogeneity/homogeneity to the possibility of acting as an external force in order to increase it, based on the conditions of a SES and the desired goals. The statement that homogeneity of strategies lowers adaptive capacity is supported by various studies on ancient civilizations and populations, such as the one reported by Nelson et al. (2006) and Hegmon et al. (2008) in the U.S. Southwest and some of the examples proposed by Tainter (2006).

To conclude, structural properties influence the resilience of a system and should be taken into account when devising policies that aim to increase or decrease the resilience of a specific system to a specific disturbance. More so, if the disturbances that need to be addressed relate to diffusion and dispersal. It is also important to mention, that connectivity may not be always positive, but can generate traps and lock-in situations (Bodin & Norberg, 2005, 2007; Newman & Dale, 2005). As explained in section 9.4, none of the models presented has tried to address the drawbacks of connectivity, such as the spreading of pests and viruses.

9.3 Future directions

The main aim of this work is to assess the importance of structural properties and how structural properties affect the resilience of SES. As it is possible to recall from section 5.2, CAS, such as SES, differ from stable, linear systems, where once it is possible to know the starting conditions and the laws that govern the system, it is also possible to exactly predict its evolution. Given the complexities of SES, the role of a model should be to understand, rather than predict, the fundamental processes that govern it and the effect of these processes. In this highly uncertain context, simulations may prove to be the most appropriate tool to analyse and understand the complexities of a SES from a structural perspective.

The models presented in Chapters 6, 7 and 8 represent fundamental processes that interplay in a simple SES. It is also known that a model is only as good as its assumptions, and for this reason, all assumptions on the behaviour of agents (predators, prey, and managers) in the models presented have been accurately checked so as to ground every behavioural rule and every relation between variables in the available literature. The work presented is built on key papers in the literature concerning the tools and methods used, at the best of my knowledge; been the fields of study (networks, resilience and ABM) expanding fast it is possible that not all the available literature has been taken into account. There are two main limitations of the work presented here, limitations that are also avenues for future research. Future work will concentrate on the empirical validation of the models presented and the diffusion/dispersal of concurrent processes such as propagation of shocks viruses, invasive species and pests so as to assess how structural properties influence enhancement and, at the same time, the decrease of a SES resilience.

9.3.1 Empirical validation of the models presented

As explained in section 5.2.4, validating, verifying and evaluating ABMs can be a demanding task. It is worth recall here, that the first criterion to assess an ABM is its reliability by allowing for different separate implementations and comparing the results. The ABM presented are written in NetLogo (Chapters 6 and 7) and Matlab (Chapter 8), and have been implemented on different platforms (namely Windows, Unix/Linux and MacOs). However, the same models have not been recoded in different languages; that is, the models have not been coded in C++ or Java and compared to the ones written in Netlogo and Matlab. As described in Chapter 5, in order to evaluate ABM Taber and Timpone (1996) ask the following questions:

1. Do the results of a simulation correspond to those of the real world (if data are available)?
2. Is the process by which agents and the environment interact corresponding to the one that happens in the real world (if the processes in the real world are known)?
3. Is the model coded correctly so that it is possible to state that the outcomes are a result solely of the model assumptions?

It is possible to state that the results reported in sections 6.3, 7.2 and 8.2 are the result of model assumptions, as the code has been checked different times by different scholars and no errors or artefacts exist, at the best of my knowledge. On the other hand, the first two evaluation questions can be assessed only through in depth, multiple case studies over a period of time. In order to validate empirically the models presented, a large amount of data needs to be collected. Data that are not easily available: reproduction, death and predation rates for predators are very difficult to obtain (it is very easy to “miss” an event, even using new technologies such as GPS collars); authority distributions within and between communities and their effect over time (as synchronization happens over time) can also be hard to acquire. The processes presented, the rules, and the funadamental variables are grounded in the available literature. However, more empirical work is needed to confirm the validity of the rules, processes, variables and parameter values proposed in the models. Moreover, in order to validate the ABM presented, data on predator prey are not the only ones needed. The evolution of structural properties over time is a critical component of every resilience assessment, as resilicence of a SES is an intrinsically dynamic, spanning over different temporal and spatial scales (as reported in Chapter 4). Unfortunately, empirical data that span over different temporal and spatial scales are difficult to obtain.

To conclude, a complete empirical evaluation of the work presented in this thesis requires data from the real world and the involvement of knowledgeable experts, possibly through focus groups. Thus, in order to gauge the validity of the models presented it will be necessary to perform a multi-unit case study over time. In other words, in order to validate, modify or falsify the models presented, multiple case studies in different locations need to be designed. Further, these case studies should be analyzed on at least a 5 year time span, as resilience is an intrinsically dynamic concept. Cross temporal and spatial scales interactions are fundamental in order to understand the resilience of a SES.

9.3.2 Network effects on diffusion of concurrent processes

The second main avenue for future research focuses on analyzing network effects on the diffusion of concurrent processes. More precisely, the models presented in Chapters 6 and 7 refer to diffusion and dispersal as "positive" or beneficial. In other words, diffusion and dispersal are viewed as factors that help the system to remain in the same, desired, basin of attraction. The effect of the interplay between beneficial and detrimental dynamics on a network has not been fully investigated. More precisely, future work will need to address the two following questions:

1. Which network structures facilitate or impede the unfolding of positive and negative dynamics on the social and on the ecological network related by feedbacks mechanisms?
2. How is it possible to influence the network structure of a system in order to minimize the diffusion of negative dynamics and enhance the diffusion of positive dynamics?

These two questions are directly related. Only once it is possible to understand the influence of the network on the diffusion of positive and negative dynamics, it is possible to look at how to intervene on the edges and nodes of a network to uncover which structures minimize negative dynamics (such as viruses and pests and shocks that may alter the system) and enhance positive dynamics (such as predator dispersal or information diffusion).

9.3.3 A network of networks to represent SESs

Network analysis as demonstrated throughout this thesis, is a promising tool to understand weaknesses and strengths of a SES so as to assess its resilience. The language of networks, carefully defined, is common for social and ecological systems. Despite the fact that nodes and edges may perform functionally different tasks, the overall structural properties (i.e. network metrics) and the representation of social and ecological systems remains the same.

A first possible avenue to unify social and ecological networks such as the ones presented here is to represent a SES network as a network where humans are nodes of a wider food-web. In this context “human nodes” are classified according to their main occupations (e.g. fishermen, farmers, hunters, extraction of natural resources such as logging, minerals, etc...). The edges of this network are weighted and weights represent energy exchanges between species. The main problem of this approach is in the difficulty of reaching meaningful results and an understanding of the dynamics of the system. A network such as the one described, risks to be very densely connected, not allowing a clear comprehension of the implications and the effects of different structures on resilience.

However, it is possible to envision a network of networks (Buldyrev et al., 2010; Gao et al., 2010; Parshani et al., 2010; Shao et al., 2010), comprised of a network representing a landscape, such as the one presented in Chapters 6 and 7, a network representing management communities, such as the one presented in Chapter 8, and a food-web, whose predator-prey interactions in Chapters 6 and 7 are a simplification. Two types of edges need to be taken into account in designing a network of networks such as the one described: one type representing information flows between nodes, and the other representing support (dependency) relationships. The first type of edges mainly exists within the management network, while support/dependency edges exist within and between the three networks. The basic structure of a possible network is depicted in Figure 9-1.

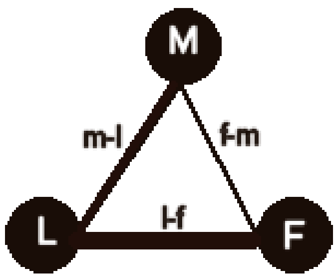


Figure 9-1 Network of Networks
Where M = management community network, L = landscape/resource network, F = food web. Edges between the networks are bidirectional, while their weights represent the density of support/dependency edges that exist between two networks of the network of networks (Own elaboration).

The analysis of such network of networks may enable the analysis of SES as one whole network, looking at different connectivity levels and how the interplay of connectivity within and between the networks affects the resilience of SES from a structural perspective. The robustness of a network of networks has only been recently investigated. More precisely, only a few specific cases have been analyzed, one example being the analysis of the power disruption occurred in Italy in 2003 (28th of September) where the network of networks comprehend the power grid network and the Internet (Buldyrev et al., 2010; Gao et al., 2010; Parshani et al., 2010; Shao et al., 2010). These studies seem to uncover an inbuilt fragility of networks of network increasing with the number of networks that are interrelated. However, research in this field is just at the beginning and more is needed. Nonetheless, I do think that a network of networks can be a very promising avenue in order to unify social and ecological networks in one network of networks representing a SES. Further, the design of a unified network of networks representing a SES could and should be coupled with dynamic processes unfolding on them, such as harvest, predation, reproduction, erosion of resources, diffusion/dispersal of species, viruses, pests, shocks, and management paths. The study of dynamic processes that unfold on this network of networks involves the use of ABM, for the reasons explained in Chapter 5 and as demonstrated throughout this thesis, so as to further enhance our understanding of SES and better assess their strength, weaknesses and resilience.

This thesis is a step towards representing a SES from a structural perspective. Network theoretical tools and ABM have been embedded within the resilience framework. Structural properties influence the resilience of SES. Numerous challenges lie ahead in order to reach a comprehensive representation of a SES network that is able to take into account dynamic processes and cross scale interactions (Cumming et al., 2010). This section of the thesis suggests interesting developments in SES network representation. Starting from the fundamental processes used in this work, it is possible to link different networks and the dynamics unfolding on them. Hopefully, in the future, it will be possible to to represent a SES from a network perspective, and thus, it will be feasible to assess strength, weaknesses, traps and resilience of a SES by analyzing its structural properties.

9.4 Stating the innovations presented in this work

Besides the answer to the research questions posed at the beginning of this work, and summarized in section 9.2, this thesis has made a number of significant contributions to the study of resilience of SES and the study of CAS.

The first, and most important one, is of methodological nature. The combination of models and techniques drawn from different disciplines has been synthesised in order to develop a uniform set of tools which has proved effective for the structural analysis of SES. As it has been noticed several times in the discussion contained in this Chapter and throughout this thesis, both quantitative and qualitative instruments are necessary to fully exploit the potential of the methods presented here. This work, therefore, strongly supports the idea, already expressed by many scholars, that triangulation of research methods can give the necessary clues to lead to a 'truer analysis' of SES.

As it has been discussed, network representation allows a wide range of simulations. Even simplified models, such as the one presented in Chapters 6, 7 and 8 are able to provide insightful results that have relevant suggestions for policymakers (as discussed in section 9.2.1). This is an important outcome. Social-Ecological systems are, indeed, complex, adaptive phenomena and this complexity is the essential unit of analysis for the understanding of the resilience of a SES. Its behaviour can be well considered to be in that ideal phase space region between a completely ordered conduct and a completely disordered one which has been also called the edge of chaos. This idea has been intuitively with us for a long time. However, only in the last years a group of scholars has considered that a linear deterministic description is largely insufficient to explain the behaviour of a system whose components interact in so different ways as extensively explained throughout this thesis. The relationships among the different component of a SES can be highly nonlinear and the whole ensemble can exhibit features which cannot be (or can be with enormous difficulty) derived by meaningful compositions of those of the single components.

Probably the most important result of this vision is the claimed impossibility to predict fully the dynamic evolution of the system and to recognise that a successful management of a CAS need to be adaptive itself. Numerical simulations seem to be the only real possibilities to overcome, at least partially, these difficulties and provide a range of solutions which will (Bankes, 2002: 7266) “allow users to iterate with the computer to gradually evolve policy schemas that have particular policy instances with desirable properties”.

The dynamic progress of the ecological system has been related to the modifications of the network topology and proved models have been invoked to explain this evolution. Again, even with the limitations discussed, the results presented can prove extremely useful, as a first assessment of the resilience of a SES and thus for assisting policymakers in taking more appropriate decisions. In other words, this work is another step towards assisting policymakers to make decisions based on a combination of computer assisted reasoning, needed to help understanding (theoretically) the complex evolutionary mechanisms that govern a SES, and empirical data.

As a final point, it is a firm conviction of the author that a more rigorous establishment of methodological tools such as those used in this work, can be a powerful way to help a transition towards a less undisciplined set of theories and models for SES and that this can be greatly beneficial for the understanding of the structure and the behaviour of these systems and its components.

10 References

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I. Appendix: Glossary

Glossary Term	*Definition*
Adaptive cycle	Is an abstract construction composed by for stages. These stages are defined as growth, accumulation, restructuring, and renewal. A system jump from one stage to another forward or backward.
Adjacency matrix	Is a square matrix that defines a network in which rows and columns represent different nodes and the values are n if there exist a connection between a pair of nodes, and 0 otherwise, where n is 1 if the network is unweighted. If the matrix represents an undirected network, it will be symmetrical. If the matrix represents a weighted graph, the strength of the edges is represented (i.e. the strength of the connection between the pair of nodes is represented by n).
Assortativity	Measures the correlation between the nodes of a network. It indicates if a network's nodes will preferentially attach to similar nodes (assortative mixing) or to nodes that are different (disassortative mixing)
Attacks	Failures of a network's nodes and/or edges (e.g. highest degree, betweenness etc.)
Average mass of a graph	It consists in computing how many nodes are possible to find within a specified geodesic distance.
Average shortest path length	Is the average of all shortest path length that exists in the network. The shortest path length is the shortest geodesic distance that exists between a pair of nodes.
Betweenness centrality	Is a measure used to describe the importance of a node in a network. This importance is given by the uniqueness of a node (or edge). Betweenness centrality can be calculated for nodes or edges.
Closeness centrality	Is a measure used to calculate the geodesic distance between different nodes. A node is globally central if it is neighbour of many other nodes. The shorter the path between a particular node and other nodes, the more that particular node will be central.
Clustering coefficient	Is the probability that two neighbours of a node are also neighbours to each other.
Connectance	Is the number of edges that are present with respect to the maximum number of possible edges. (see also edge density).
Degree	The number of edges connected to a node. If the edges are directed it is possible to distinguish in-degree from out-degree of a node (being the first the number of incoming edges, and the latter the number of outgoing edges.
Degree distribution	Is the probability that a particular node will have a determined degree.
Directed edge	An edge that connect a pair of node in a given direction. They are normally represented by an arrow indicating the direction of the relation.
Disassortativity	(see assortativity)
Edge	A connection between two network elements (between a pair of nodes)
Edge density	Is a measure used to calculate the "density" of the edges. Namely it is the ratio between the existent number of edges and the maximum number of possible edges of a network.
Errors	Random failures of a network's nodes and/or edges
Geodesic distance	Is the distance between a pair of nodes connected through an edge. It is always unitary.
Giant component	Can be defined as the largest part of the network whose nodes are connected to each other. The giant component contains most of the networks’ nodes.

Global efficiency	Is the average efficiency of a network where efficiency in communication between a pair of nodes can be defined as being inversely proportional with respect to the shortest path.
Graph	(see Network)
Local efficiency	Is the average efficiency of sub-graphs.
Modularity	It refers to a network whose nodes are densely connected within a specific group and loosely connected to nodes belonging to other groups.
Network	A set of elements connected to each other. It can be considered a tool to analyse and abstractly represent complex systems.
Node	A network element
Panarchy	Can be defined as the whole of the hierarchical levels each of whom is constituted by an adaptive cycle. The concept of Panarchy combines the hierarchical structure of systems going from small to and fast to large and slow.
Percolation threshold	Can be defined as the number of edges that exist in the network when the giant component emerges.
Random graph	Random graph are networks in which nodes are connected randomly to each other. In random graphs the average shortest path length increases as the natural logarithm of the number of nodes and the degree distribution follows a Poisson (i.e. nodes that deviate significantly from the average degree are extremely rare).
Regular network	Regular networks display the smallest average path length and the highest clustering coefficient. The regular lattice is an example of a regular network in which all nodes have the same degree.
Resilience of an SES	Is the ability of a Social-Ecological System (SES) to absorb disturbance and re-organize while undergoing change so as to still retain essentially the same function, structure, identity and feedbacks.
Scale-free	Networks that are scale-free are mainly characterized by their degree distribution that follows power law. It seems that most real networks follow this power law distribution.
Small world	Small worlds are network whose characteristic lies in between random graphs and regular networks. This class of networks is characterized by small average shortest path length (thus similar to that of a random graph) and a high clustering coefficient (feature of regular networks).
Sub-graph	A Graph whose nodes and edges are also nodes and edges of the Network. The simplest sub-graphs are called trees, cycles and complete sub-graphs.
Undirected edge	An edge that connect a pair of nodes in a transitive fashion. They are normally represented by a straight line.

II. Appendix: ODD for the models presented

II.i. Landscape connectivity and predator-prey dynamics

Purpose:

An agent (individual) based model has been developed to assess how connectivity of patches on a landscape influences predator-prey dynamics and to assess the dependence of population levels on nodes and/or network connectivity measured in node degree and network density.

State Variables and Scales:

The model contains predator, prey and habitat patches (the latter is also referred to as nodes). Variables differ for the three main groups as follows.

Individual predator-prey variables

- Prey:
    - Location (which node they feed on)
    - Density (of prey) on a node
    - Reproduction rate

- Predators:
    - Location (which node they search for prey)
    - Density (of predators) on a node
    - Reproduction rate
    - Predation (probability of attacking and killing a prey that is located on the same node)
    - Handling (time in which the predator does not attack but can reproduce)

Landscape variables:

- Nodes (or habitat-patches):
    - Number of nodes
    - Size of nodes (based on maximum number of prey it can support)
    - Connectivity of the network (number of edges in the network and the configuration)

Process Overview and Scheduling:

The initial network of patches will not vary, as we are mainly interested in how the landscape (viewed as a network) affects the dynamics and the population sizes of predators and prey.

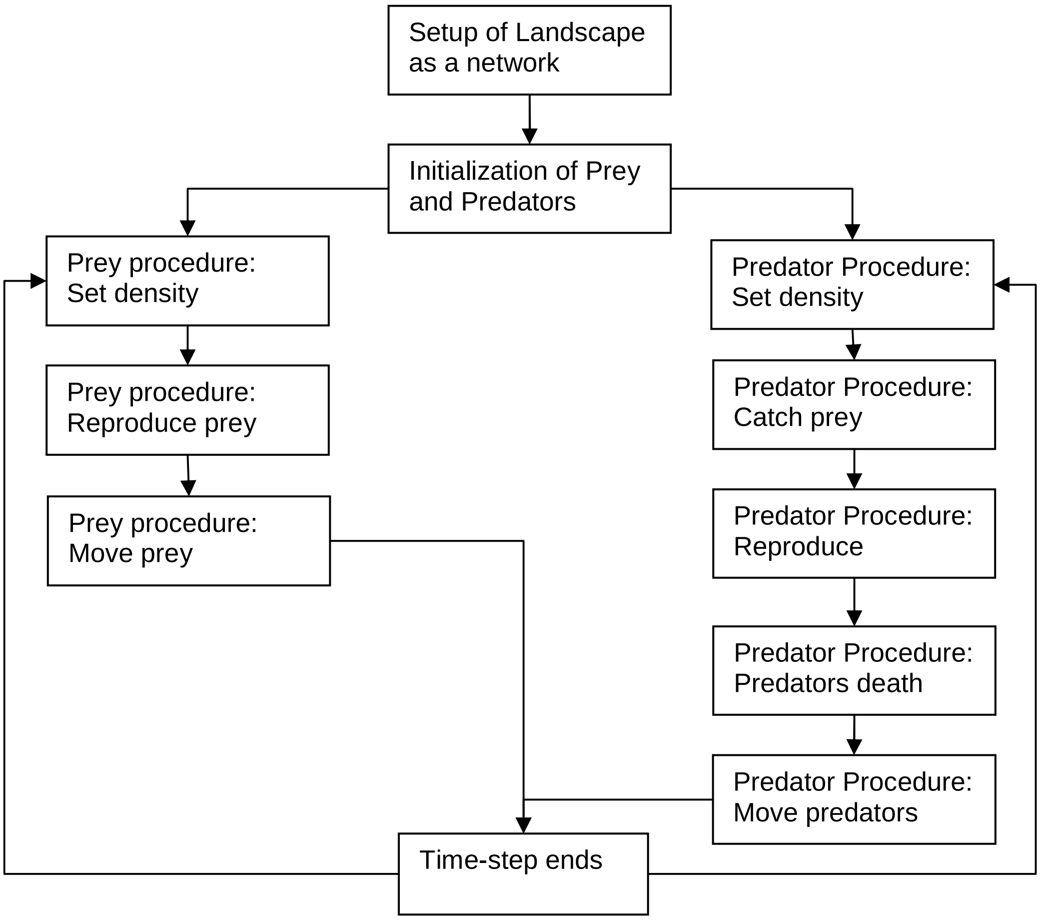
The landscape is initialized first, the number of nodes is fixed, and distances between nodes are not taken into account (thus the existence (or absence) of an edge connecting two nodes is the only point of relevance). Moreover, the size of the nodes is assumed constant and equal for every node. The number of edges present in the network varies but not during the simulation (only in the initial settings). Nodes are randomly set on a two-dimensional grid; edges are added based on the proximity of the nodes, starting with the nodes that are closest to each other.

Prey and Predators are assigned randomly to each node; though, their initial population is fixed.

The following is a precise outline of model procedures during one time step. The procedures are sequential (i.e. one prey performs the whole procedure, followed by another prey etc.). However, the order in which agent are selected is random (prey1 may perform the procedure before prey2 in a given time-step, but prey2 may perform the procedures described before prey1 in a later time-step). Each agent (predator or prey) will complete the first procedure before moving on to the next:

1) Each prey sets node density (Dn_{1i}), so they know how many predators and prey reside on their current patch.
2) Each predator also sets node density (Dn_{2i})
3) Each prey has the ability to reproduce with probability $P_{r,1}$.
4) Each prey then has the ability to move to another node based on current density thresholds. That is, if the current node is connected and possesses high predator or prey density, each prey moves to a randomly chosen connected node and recalculates current node density, else the prey dies. More precisely, prey move if $Dn_{1i} = \frac{n_{1i}}{C} > D_{U,1}$ or $Dn_{2i} = \frac{n_{2i}}{C} > D_{U,2}$. If the chosen node for migration already has a high prey density, the migratory prey dies instantly. This is the final prey procedure in one time step
5) In the same time step, each predator can successfully catch and kill a single prey with probability $P_{k,2}$; given both prey and predator reside on the same patch.
6) Successful capture of prey means the predator is now in the handling period, where it may give birth to a single offspring with probability $P_{r,2}$. Note, predators may be in the handling period for several time steps, during this time, they cannot hunt prey.
7) Then, with probability $P_{m,2}$, each predator may die 'naturally'.
8) Lastly, predators may move between nodes according to a prey density threshold. If the current node is connected and possesses low prey density, predators move to a randomly chosen connected node and recalculate current node density, else the predator immediately dies. If the prey density of the chosen node is low, the migratory predator dies immediately. More precisely, predators move if $Dn_{1i} = \frac{n_{1i}}{C} < D_{L,1}$ and die if $Dn_{1i} < D_{L,1}$ on the chosen node. This is the final predator procedure in one time step, and the final procedure of any agent.

The following diagram gives a graphical representation of what has been explained in this chapter:



Design Concepts:

Emergence

- Population cycles and size depending on the landscape (network) configuration

Interaction

- Prey and predator interact through predation and density-dependent migration.

Stochasticity

- The model assumes probabilistic events (predation, reproduction, death, movement to other nodes, connection between nodes, initial placement of predators and prey).

Observation

- The focus is on the size of predators and prey for every node and node degree.

Initialization:

The total number of nodes are fixed and each of them are placed randomly on a two dimensional grid. Edges are formed based on Euclidean distances between nodes, connecting the nearest nodes first. Predators and prey are randomly assigned to a node. Their numbers are proportional to the number of nodes. Reproduction rates are fixed within a given species (thus every prey/predator has the same probability of reproducing). Rates of mortality and predation are also fixed for all predators.

Upper and Lower density thresholds are assigned to prey, while just an upper density threshold is assigned to predators. Density thresholds do not vary across nodes.

Variables are initialized as shown in the table below. In order to correct for the high stochasticity of the model, repeated runs are performed. Moreover, during the simulations the number of edges will vary from 0 to 45 with a 5 edge increment, while internal species parameters such as reproduction, death, predation rates and movement decision are initialized according to the table below and fixed. The biological parameters are not varied during the simulation because the purpose of the model is to assess the effect of network connectivity on predator-prey population dynamics.

Input:

Symbol	Variable Name	Values drawn from distribution used for Monte Carlo simulations
N	Number of nodes	10
E	Number of edges	Varies from 0 to 45
C	Size of a node	100
n_1	Initial number of prey	Poisson with mean 25 * 10
$P_{r,1}$	Prey reproduction rate	Poisson with mean 0.25 (25%)
$D_{U,1}$	Prey density upper limit	Random uniform distribution [0.5, 0.9]
$D_{L,1}$	Prey density lower limit	Random uniform distribution [0.2, 0.4]
n_2	Initial number of predators	Poisson with mean 10 * 10
$P_{r,2}$	Predator reproduction rate	Poisson with mean 0.2 (20%)
$P_{k,2}$	Predation probability	Poisson with mean 0.2 (20%)
$Pm,2$	Predator death rate	Poisson with mean 0.06 (6%)
$D_{U,2}$	Predator density upper limit	Random uniform distribution [0.3, 0.6]
T_h	Predator handling time	3

Submodels:

Model Setup:

- Network
  - Landscape is represented by an undirected network
  - Multiple edges and loops are not allowed
  - Edges are placed between nodes based on Euclidean distances
  - N number of nodes are generated
  - The network will contain E edges where: $0 \le E \le N(N-1)/2$
  - Size C is assigned to every node

- Prey and Predators
  - Initial number of prey, n_1, calculated from a poisson distribution with mean 25 (before every run, a value is chosen according to a poisson distribution with mean 25).

- Initial number of predators, n_2, calculated from a poisson distribution with mean 10 (before every run, a value is chosen according to a poisson distribution with mean 10.)
- Random assignment of predators and prey to a node i
- The density of prey on node i, $Dn_{1i} = \frac{n_{1i}}{C}$
- The density of predators on node i, $Dn_{2i} = \frac{n_{2i}}{C}$

<u>Model Development:</u>

- Prey
    - Prey reproduce with probability $P_{r,1}$ derived from a poisson distribution with mean 0.25 (for every run, a value is chosen according to a poisson distribution with mean 0.25. The value is fixed for the whole simulation run).
    - Intraspecific competition for space/food
        - If the current node is isolated (its degree = 0), then the migratory prey dies.
        - If $Dn_{1i} > D_{U,1}$ then prey move to a randomly chosen connected node j and recalculate current node density
        - If $Dn_{1i} > D_{U,1}$ then the prey dies.
    - Anti-predator behaviour
        - If the node is isolated (its degree = 0), then a migratory prey dies.
        - If $Dn_{2i} > D_{U,2}$ then prey move to a randomly chosen connected node j and recalculate current node density
        - If $Dn_{2i} > D_{U,2}$ then the prey dies.
- Predators
    - Predators search and attack prey. If predators and prey are on the same node i, and handling time, T_h, equals zero, Predators kill prey with probability $P_{k,2}$ derived from a poisson distribution with mean 0.2 (for every run, a value is chosen according to a poisson distribution with mean 0.2. The value is fixed for the whole simulation run)

    - If predator is successful then it sets T_h to *3*
        - T_h decreases by 1 at every timestep
- If predator is successful then it reproduces with probability $P_{r,2}$ derived from a poisson distribution with mean 0.2 (for every run a value is chosen according to a poisson distribution with mean 0.2. The value is fixed for the whole simulation run)
- Predator search behaviour
    - If the current node is isolated (its degree = 0), the migratory predator dies.
    - If $Dn_{1i} < D_{L,1}$ then predators move to a randomly chosen connected node *j* in order to look for prey.
    - Recalculate density of the prey on the new node *j*
    - If $Dn_{1i} < D_{L,1}$ then the predator dies.
- Predators die of natural death with probability $P_{m,2}$ derived from a poisson distribution with mean 0.06 (for every run, a value is chosen according to a poisson distribution with mean 0.06. The value is fixed for the whole simulation run).

Implementation

The model is implemented in NetLogo 4.1

II.ii. Managing Landscapes' Resilience

Purpose

An agent (individual) based model has been developed in order to assess how a single manager is able to alter the connectivity of a landscape thus influencing predator-prey dynamics. Do population levels of predators and prey depend on actions a manager undertakes via changes in the network connectivity, hence can manager enhance resilience of a system or preventing resilience erosion?

State Variables and Scales

The model presents one manager agent, populations of predators and prey, and habitat patches (nodes). Variables differ for the four main groups as follows.

Individual predator-prey variables

- Manager
  - Budget (yearly and does not accumulate)
  - Cost of infrastructure (one time cost for every time the manager acts)
  - Cost of maintenance (defined as the natural logarithm of the absolute value of the original weights divided by the current weight of the edges on which he has acted upon)
  - View of the world
  - Possibility of errors in counting species
  - Priority list based on densities of predators and prey
  - Possibility of decreasing/increasing the cost of movement (weight) of an edge

- Prey:
  - Location (which node they feed on)
  - Density on a node

- Reproduction rate
- Natural death rate
- Movement capability

- Predators:
  - Location (which node they search for prey)
  - Density on a node
  - Reproduction rate
  - Natural death rate
  - Predation (probability of attacking and killing a prey that is located on the same node)
  - Handling (time in which the predator does not attack but can reproduce)
  - Movement capability

Landscape variables:

- Nodes (or habitat-patches):
  - Number of nodes
  - Size of nodes (maximum capacity)
  - Time till recovery of maximum capacity
- Edges
  - Number of edges in the network
  - Weight of edges represent the cost of movement for both species

Process Overview and Scheduling

The landscape is initialized first, the number of nodes is fixed, and edges are placed randomly between nodes with a given weight (cost of movement) that is, originally, the Euclidean distance between two given nodes. The capacity of the nodes is equal for every node, but it can decrease if too many prey feed upon a given node (patch). Moreover, the capacity of the node is recovered if there are no preys present or if prey density on that node is particularly low for a given number of time-steps. The number of edges present in the network varies but not during the simulation (only in the initial settings), but their weight will vary according to the actions taken by the manager.

Prey and predators are assigned randomly to each node: their initial number is fixed and proportional to the number of nodes.

Prey have the ability to reproduce or die via predation at every time-step (with some probability). Moreover, prey die according to a fixed death rate (natural death). Note that the predation event will only occur if predators and preys are located on the same node.

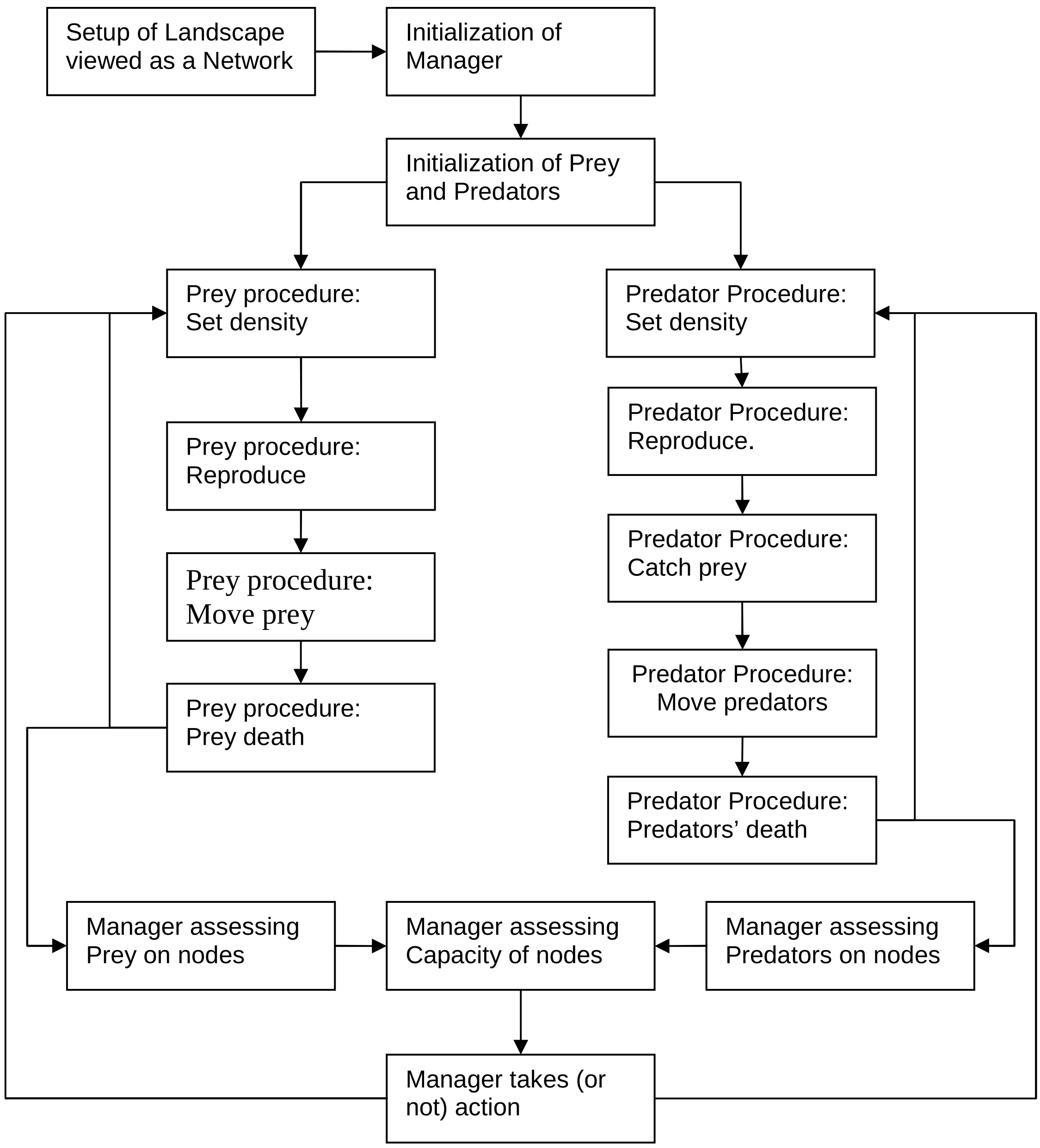
Predators also have the probability to reproduce at every time-step, given they have successfully attacked a prey and find themselves in handling time. Predators die naturally according to a fixed death rate.

Prey move between nodes according to densities thresholds, that is, if the density of prey is too high and/or the predator density is too high in their current node, prey will move towards a randomly chosen connected node within reach. Prey die if their current node has no connections, the weights of the edges attached to their current node are all higher than their ability to move (thus the other nodes are not reachable), or the chosen node has a prey density considered too high.

Predators move between nodes according to a density threshold, more precisely, if the prey density of the current node is too low, predators move to a randomly chosen connected node within reach Predators die if the current node is isolated, the weights of the edges attached to their current node are all higher than the predator’s ability to move (thus not reachable), or the prey density of the chosen node is too low.

Managers have a given budget, and they have the possibility of reducing/increasing the weights of the edges (cost of movement for prey and predators). The manager decides to decrease the cost of movement based on his own species density thresholds (which differ from predator and prey density threshold) on a given node. The manager decides to increase the cost of movement if the capacity of the node falls below a certain threshold. Moreover, managers can have a “view of the world” that causes them to over/under estimate the capacity of a node; moreover, managers can be inaccurate when counting the prey and the predators (thus adding an error term to the count of predators and preys on a given node).

The following diagram gives a graphical representation of the process above:



Design Concepts

Emergence

- Population cycles and size dependent on landscape (network) configuration and the actions of the manager

Interaction

- Prey and predator interact through predation and densities that depend on the capacity of the node on which they are located. The manager interacts with the landscape based on predator and prey densities, which depend on the capacity of the node on which the species are located.

Stochasticity

- The model assumes probabilistic events (predation, reproduction, death, movement to other nodes, connection between nodes, initial placement of predators and prey).

Observation

- The focus is on the size of predators and prey for every node and on the overall network, and on the ability of the manager to alter the landscape by altering the cost of movement (weights of edges).

Initialization

Nodes are fixed and placed randomly. The network is fully connected and edges have a weight attribute initially based on Euclidean distances between the nodes (between 0.1 and 92 given the size of the "environment"). Initial node's capacity is equal for every node. Predators and prey are randomly assigned to a node. Their numbers are proportional to the number of nodes. Reproduction and death rates are fixed for predators and prey (thus every prey /predator has the same probability of reproducing and to dying from natural causes). Predation, the probability that a predator will kill a prey at every given time-step, is also fixed.

Upper and Lower density limits are assigned for prey, while an upper density threshold is assigned for predators. Density thresholds do not vary across nodes.

A budget is assigned to a manager who will act based on fixed density thresholds that refer to predators and prey. The manager agent can be inaccurate in counting these densities or not. Moreover, the manager has his own personal view of the world that influences the capacity threshold and thus the action taken in reference to the node capacity.

Variables are initialized as shown in the table below. In order to correct for the high stochasticity of the model, repeated runs with the same set of parameters are performed. Budget levels, fixed costs, and threshold levels for the manager will also vary since the objective of the model is to look at possible strategies and their consequences on population dynamics.

Input

The following table summarizes symbols, actual variable names and values used in the simulations.

Simbol	**Variable Name**	**Value**
N	Number of nodes	10
E	Number of edges	45
we	Cost of movement (weight)	Varies according to manager actions (MAX *we* = 92 without manager action)
ti	Time-lag of recovery	5
C	Capacity of a node	100, varies according to simulation events
n_1	Initial number of prey	25 * 10
$P_{r,1}$	Prey reproduction rate	0.25 (25%)
$P_{m,1}$	Prey natural death rate	0.10 (10%)
S_1	Prey movement ability	Poisson distributed with mean 30 calculated at every time-step
$D_{U,1}$	Prey density upper limit	0.9
$D_{L,1}$	Prey density lower limit	0.15

Simbol	Variable Name	Value
n_2	Initial number of predators	10 * 10
$P_{r,2}$	Predator reproduction rate	0.2 (20%)
$P_{k,2}$	Predation probability	0.2 (20%)
$P_{m,2}$	Predator natural death rate	0.06 (6%)
S_2	Predator movement ability	Poisson distributed with mean 60 calculated at every time-step
$D_{U,2}$	Predator density upper limit	0.6
T_h	Predator handling time	3
B	Manager Yearly budget (does not accumulate)	100, 250, 500
V	Manager view of capacity	-15, 0, 15
err	Normally distributed errors in counting species	Yes/No variable if Yes, error varies at every time-step
Mt_U	Manager Upper threshold	0.6, 0.8
Mt_L	Manager lower threshold	1.2, 1.4
Mct	Manager capacity threshold	50, 70, 90
Mc_D	Cost of decreasing *we* by a fixed amount	50
Mc_I	Cost of increasing *we* by a fixed amount	100
S_I	Amount of *we* increase in case of action that increases *we*	100
S_D	Amount of *we* decrease in case of action that decreases *we*	10

Submodels

<u>Model Setup:</u>

- Network
  - Landscape is represented by an undirected network
  - Multiple edges and loops are not allowed
  - N number of nodes is chosen
  - Edges are placed randomly between nodes
  - Edges will have an initial weight (cost of movement) computed as Euclidean distance between the nodes they connect (we).

- The network will contain $E = 45$ edges (fully connected network)
- Capacity C is assigned to every node: $C = 120 \forall N$
- Capacity is recovered at speed ti (that is, ti is initially set, and when it reaches 0, o1 unit of capacity is recovered). ti varies according to the density of prey present on a specific node. ($ti_t = ti_{t-1} - 0.5$ if $0.15 < D_{i,1} \leq 0.3$; $ti_t = ti_{t-1} - 0.75$ if $0 < D_{i,1} \leq 0.15$; and $ti_t = ti_{t-1} - 1$ if $D_{i,1}$).

- Prey and Predators
  - Initial number of $n_1 = 25 * N$
  - Initial number of predators $n_2 = 10 * N$
  - Random assignment of predators and prey to a node i
  - Let $n_{i,1}$ be a prey assigned to node i, then the density of prey on node i $D_{i,1} = \frac{\sum n_{i,1}}{C}$
  - Let $n_{i,2}$ be a predator assigned to node i, then the density of predators on node I $D_{i,2} = \frac{\sum n_{i,2}}{C}$
- Manager
  - Budget is assigned at each time-step and does not accumulate (B will vary)
  - Manager has the probability of making mistakes in counting prey and predators for its own thresholds (*err Yes/No*). Thresholds (Mt_U and Mt_L) are used in order to decide when to act in reducing *we* between nodes. Decreasing *we* has a fixed cost Mc_D and *we* is reduced by a variable amount S_D.
  - Manager has its own view of the capacity of the nodes (V) and, based on a threshold (Mct), he decides whether to increase the cost of movement to a specific node or not. Increasing cost of movement *we* has a fixed cost Mc_I and *we* by a variable amount S_I.
  - Manager maintenance costs defined as: $\ln\left|we_{ij0} - we_{ijt}\right|$.

Model Development:

- Prey
  - Prey reproduce with probability $P_{r,1} = 0.25$
  - Intraspecific competition for space/food
    - If the node is not connected (its degree = 0), or $we_{ij} > S_1$ for every connected node, the prey dies.
    - If $D_{i,1} > D_{U,1}$ then prey move to a randomly chosen connected node j if $we_{ij} < S_1$
    - Recalculate density of the prey on the new node j
    - If $D_{i,1} > D_{U,1}$ then the prey dies.
  - Anti-predator behaviour
    - If the node is not connected (its degree = 0), or $we_{ij} > S_1$for every connected node, the prey dies.
    - If $D_{i,1} > D_{U,2}$ then prey move to a randomly chosen connected node j if $we_{ij} < S_1$
    - Recalculate density of the prey on the new node j
    - If $D_{i,1} > D_{U,1}$ then the prey dies.
  - Prey die of natural causes with probability $P_{m,1} = 0.08$
- Predators
  - If handling time $T_h > 0$ predators reproduce with probability $P_{r,2} = 0.20$
  - Predators search and attack preys. If predators and prey are on the same node i, and handling time $T_h = 0$, Predators kill preys with probability $P_{k,2} = 0.2$
    - If predator is successful then it sets $T_h = 3$
      - T_h decreases by 1 at every timestep
  - Predator search behaviour
    - If the node is not connected (its degree = 0), or $we_{ij} > S_2$ for every connected node, the predator dies.
    - If $D_{i,1} < D_{L,1}$ then predators move to a randomly chosen connected node j if $we_{ij} < S_2$ in order to look for prey.
    - Recalculate density of the prey on the new node j

- If $D_{i,1} < D_{L,1}$ then the predator dies.
  - Predators die of natural causes with probability $P_{m,2} = 0.06$
- Manager
  - Renew B
  - Assess the need to take action to preserve the capacity of a single node (if $C + V < Mct$).
    - Calculate maintenance cost, if $\left(B - \ln\left|we_{ij0} - we_{ijt}\right|\right) > Mc_I$ then the manager acts and increases the cost of movement we_{ij} by S_I to prevent prey from entering a particular node i from its neighbouring nodes.
  - Determine the need to take action in order to avoid local extinction of prey and predators acting upon the number of prey on node i (if $n_1 + err > C{*}D_{U,1}{*}Mt_U$ and/or $n_1 + err < C{*}D_{L,1}{*}Mt_L$)
    - Calculate maintenance cost, if $\left(B - \ln\left|we_{ij0} - we_{ijt}\right|\right) > Mc_D$ then the manager acts and decreases the cost of movement by S_D according to priority lists from the highest $| n_1 + err - C{*} D_{U,1}{*}Mt_U |$ to be connected to the lowest $| n_1 + err - C{*} D_{L,1}{*}Mt_L |$ and so on.

Implementation

The model is implemented in NetLogo 4.1

III.Appendix: Models' codes

Code belonging to models presented in chapter 6 and 7 and explained thanks to the ODD protocol in Appendix II, section II.i and II.ii respectively are implemented in NetLogo 4.1. The model presented in chapter 8 is implemented in Matlab R2008a. Some of the modules used in order to build the model presented in chapter 8 have been adapted from matlab files build by other authors. References to the author are made in the comments to the code. More precisely, the code of the following functions has been adapted from Gergana Bounova: *random-graph* and *writepaj*, the code of the module *substr* has been adapted from Peter J. Acklam and *randint* from Christoph Teuscher.

III.i. Landscape connectivity and predator-prey dynamics

This model is implemented in Netlogo 4.1.

```
breed                  [prey a-prey]
breed                  [predators predator]
breed                  [nodes node]
breed                  [donothing]
undirected-link-breed [edges edge]
globals                [time
                        pred-extinction-time
                        prey-extinction-time
                        geo
                        name
                        filename
                        netime
                        initial-number-prey
                        initial-number-predators
                        prey-reproduce
                        predation
                        predator-reproduce
                        predator-death-rate
                        preydens-up
                        preydens-low
                        predens-up
 prey1
 prey2
 prey3
 prey4
 prey5
 prey6
 prey7
 prey8
```

```
 prey9
 prey10
 pred1
 pred2
 pred3
 pred4
 pred5
 pred6
 pred7
 pred8
 pred9
 pred10
 degree1
 degree2
 degree3
 degree4
 degree5
 degree6
 degree7
 degree8
 degree9
 degree10
                       ]
predators-own         [handling]
patches-own           [countdown]
turtles-own           [preydens
                       predens
                       nodenum
                       nodesize
                       my-node
                       node-degree
                      ]
edges-own             [geodist]


;;;;;;;;;;;;;;Setting Landscape Network Configuration;;;;;;;;;;;;;;;;

to setup-one
  clear-all

  set-default-shape donothing "triangle"
  create-donothing 1
  [ set color black]
  ask turtles with [color = black] [die]   ;; the who = 0 dies out
before the first report
end
to setup
 ; random-seed seed

  set-default-shape nodes "circle"
  create-nodes numnodes [
    set color blue
    set size 0.1
    set nodesize capacity
    if nodesize = 0 [
    set nodesize 1]
    set nodenum [who] of self
    set label nodenum
    setxy random-xcor random-ycor
```

```
  ]


if (netipe? = "full") [          ;;creates a fully connected network
  ask nodes [
    create-edges-with other turtles
    set node-degree count edge-neighbors
  ]
]

if (netipe? = "geoprox")[
 ;; creates a network based on geographical proximity with N nodes and
edges in the interval [0, N(N-1)/2]

  ask nodes [
    create-edges-with other turtles
  ]
    set geo (list)
  ask edges [
    set geodist precision link-length 8
    set geo fput geodist geo
  ]
  while [count links > numedges] [
    ask edges with [geodist = max geo] [
      die
    ]
    set geo remove max geo geo
  ]
]

if (netipe? = "random")[                                     ;;
creates a simple random network with N nodes and N(N-1)/2 edges
  while [count links < numedges] [
      ;;Note that if the link already exists, nothing happens
      ask one-of nodes [create-edge-with one-of other turtles]
  ]
  ask nodes[
  set node-degree count edge-neighbors
  ]
]
if (netipe? = "e-r")[                                        ;;
creates an Erdos and Reiny graph
  ask nodes [
     ;;we use "self > myself" here so that each pair of turtles
     ;;is only considered once
    create-edges-with turtles with [self > myself and
                                    random-float 1.0 < prob]
    set node-degree count edge-neighbors
  ]
]


  set-default-shape prey "square"
  set initial-number-prey random-poisson 25
  create-prey initial-number-prey * numnodes ;; create the sheep, then
initialize their variables
  [
    set color white
    set label-color blue - 2
```

```
    set nodenum random numnodes
;;number of the node i belong to
    if nodenum = 0 [
      set nodenum numnodes]
    set my-node one-of nodes with [nodenum = [nodenum] of myself]   ;;
same as nodenum, but useful for some coding procedures
  ;  setxy random-xcor random-ycor
    hide-turtle
  ]

  set-default-shape predators "square"
  set initial-number-predators random-poisson 10
  create-predators initial-number-predators * numnodes ;; create the
predators, then initialize their variables
  [
    set color red
    set handling 0
    set nodenum random numnodes
;;number of the node i belong to
    if nodenum = 0 [
      set nodenum numnodes]
    set my-node one-of nodes with [nodenum = [nodenum] of myself]  ;;
same as nodenum, but useful for some coding procedures
  ;  setxy random-xcor random-ycor
    hide-turtle
  ]

  ask prey[                                   ;;set intial densities
   set-dens
  ]
  ask predators[
   set-dens
  ]
  export-network

   set  degree1 [node-degree] of nodes with [nodenum = 1]
   set  degree2 [node-degree] of nodes with [nodenum = 2]
   set  degree3 [node-degree] of nodes with [nodenum = 3]
   set  degree4 [node-degree] of nodes with [nodenum = 4]
   set  degree5 [node-degree] of nodes with [nodenum = 5]
   set  degree6 [node-degree] of nodes with [nodenum = 6]
   set  degree7 [node-degree] of nodes with [nodenum = 7]
   set  degree8 [node-degree] of nodes with [nodenum = 8]
   set  degree9 [node-degree] of nodes with [nodenum = 9]
   set  degree10 [node-degree] of nodes with [nodenum = 10]

  set  prey1 0
  set  prey2 0
  set  prey3 0
  set  prey4 0
  set  prey5 0
  set  prey6 0
  set  prey7 0
  set  prey8 0
  set  prey9 0
  set  prey10 0
  set  pred1 0
  set  pred2 0
  set  pred3 0
```

```
  set  pred4 0
  set  pred5 0
  set  pred6 0
  set  pred7 0
  set  pred8 0
  set  pred9 0
  set  pred10 0

  set time 0

  ;; Setting parameters using Monte Carlo method:
  set initial-number-prey random-poisson 25
  set initial-number-pred random-poisson 10
  set prey-reproduce random-poisson 25
  set predation random-poisson 20
  set predator-reproduce random-poisson 20
  set predator-death-rate random-poisson 6


  set preydens-up random-float 0.4 + 0.5
  set preydens-low random-float 0.1 + 0.3
  set predens-up random-float 0.3 + 0.3

end

to go
  if not any? prey and not any? predators [ stop ]

  ask prey[
   set-dens
  ]
  ask predators[
   set-dens
  ]

  ask prey [

    reproduce-prey
    if preydens > preydens-up
      [move-prey]
    if predens > predens-up
      [move-prey]
  ]

  ask predators [
    if handling > 0 [set handling handling - 1]
    catch-prey
    if handling > 0 [reproduce-predators]
    mortpred
    if preydens < preydens-low
     [move-predators]
  ]

 if pred-extinction-time = 0 [
   if not any? predators[
    set pred-extinction-time time
   ]
 ]
 if prey-extinction-time = 0[
```

```
    if not any? prey [
     set prey-extinction-time time
    ]
  ]

  if time > 4000[
    set prey1 (prey1 + count prey with [nodenum = 1] * 0.001)
    set prey2 (prey2 + count prey with [nodenum = 2] * 0.001)
    set prey3 (prey3 + count prey with [nodenum = 3] * 0.001)
    set prey4 (prey4 + count prey with [nodenum = 4] * 0.001)
    set prey5 (prey5 + count prey with [nodenum = 5] * 0.001)
    set prey6 (prey6 + count prey with [nodenum = 6] * 0.001)
    set prey7 (prey7 + count prey with [nodenum = 7] * 0.001)
    set prey8 (prey8 + count prey with [nodenum = 8] * 0.001)
    set prey9 (prey9 + count prey with [nodenum = 9] * 0.001)
    set prey10 (prey10 + count prey with [nodenum = 10] * 0.001)
    set pred1 (pred1 + count predators with [nodenum = 1] * 0.001)
    set pred2 (pred2 + count predators with [nodenum = 2] * 0.001)
    set pred3 (pred3 + count predators with [nodenum = 3] * 0.001)
    set pred4 (pred4 + count predators with [nodenum = 4] * 0.001)
    set pred5 (pred5 + count predators with [nodenum = 5] * 0.001)
    set pred6 (pred6 + count predators with [nodenum = 6] * 0.001)
    set pred7 (pred7 + count predators with [nodenum = 7] * 0.001)
    set pred8 (pred8 + count predators with [nodenum = 8] * 0.001)
    set pred9 (pred9 + count predators with [nodenum = 9] * 0.001)
    set pred10 (pred10 + count predators with [nodenum = 10] * 0.001)
  ]

   tick
   set time time + 1
   update-plot
end

to set-dens    ;; to set densities
   set nodesize [nodesize] of my-node
   set preydens ((count prey with [nodenum = [nodenum]  of myself]) /
nodesize)
   set predens ((count predators with [nodenum = [nodenum] of myself])
/ nodesize)
end


to move-prey  ;; prey procedure, prey move along edges depending on
the denisities

     ifelse any? [edge-neighbors] of my-node
      [set nodenum [nodenum] of one-of [edge-neighbors] of my-node
       set my-node one-of nodes with [nodenum = [nodenum] of myself]
       set nodesize [nodesize] of my-node
        set preydens ((count prey with [nodenum = [nodenum]  of
myself]) / nodesize)
          if preydens > preydens-up [
          die]
       ]
       [die]
end

to move-predators  ;; predator procedure, predaot move along edges
depending on the densities
```

```
    ifelse any? [edge-neighbors] of my-node
      [set nodenum [nodenum] of one-of [edge-neighbors] of my-node
       set my-node one-of nodes with [nodenum = [nodenum] of myself]
       set nodesize [nodesize] of my-node
       set preydens ((count prey with [nodenum = [nodenum]  of
myself])/ nodesize)
         if preydens < preydens-low [
         die]
      ]
      [die]
end

to reproduce-prey  ;; prey procedure
  if random-float 100 < prey-reproduce [  ;; throw "dice" to see if
you will reproduce
    hatch 1 [
              set nodenum [nodenum] of myself
    ]
  ]
end

to reproduce-predators  ;; predators procedure
  if random-float 100 < predator-reproduce [  ;; throw "dice" to see
if you will reproduce
    hatch 1 [  ;set handling 0
     set nodenum [nodenum] of myself

    ]  ;; hatch an offspring and move it forward 1 step
  ]
end

to catch-prey  ;; predator procedure
  if handling = 0 [
    if any? prey with [nodenum = [nodenum] of myself] [
      let victim one-of prey with [nodenum = [nodenum] of myself]
;; grab a random prey
      if random-float 100 < predation
;; did we get one?  if so,
        [ ask victim [ die ]
;; kill it
          set handling handling + handling-time
;; get energy from eating
        ]
    ]
  ]
end

to mortpred  ;; turtle procedure
  if random-float 100 < predator-death-rate [ die ]
end

to update-plot
  set-current-plot "populations"
  set-current-plot-pen "prey"
  plot count prey
  set-current-plot-pen "predators"
  plot count predators
end
```

```
;;;;;;;;;;;;;REPORTING THE NETWORK;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to-report pad [ number digits ]
  let expanded ( word "000000000000000" number )
  let len length expanded
  report substring expanded ( len - digits ) len
end

to-report next-log-filename [ prefix digits suffix]
;; report the first filename that does not exist
 let next-id# 0
 let next-id$ ""
 let keep-looking? true
 while [ keep-looking? ]
   [ set next-id# next-id# + 1
     set next-id$ ( word prefix ( pad next-id# digits ) suffix )
     set keep-looking? file-exists? next-id$
   ]
report next-id$
end

to export-network
   set name new-seed
    random-seed name
    let z random 10000
    set netime date-and-time
    set netime remove ":" netime
    set netime remove "." netime
    set netime substring netime 0 10
    set netime word z netime
    set filename next-log-filename netime 5 ".txt"
    file-open filename
      let blank "   "
      let namenodes [who] of nodes
      let nnodes max [who] of nodes
      file-type "*Vertices"
      file-type blank
      file-print nnodes
      file-print "*Arcs"
      ask nodes   [
        let neigh link-neighbors
        if (count neigh) > 0 [
          foreach [who] of neigh [
            file-type who
            file-type blank
            file-type  ?
            file-type blank
            file-print 1
          ]
        ]
      ]

  file-close
end
```

III.ii. Managing Landscapes' Resilience

This model is implemented in Netlogo 4.1.

```
breed                  [prey a-prey]
breed                  [predators predator]
breed                  [manager]
breed                  [nodes node]
breed                  [donothing]
undirected-link-breed  [edges edge]
globals                [time

                        pred-extinction-time
                        prey-extinction-time
                        error-nodelist
                        prey-priority
                        pred-priority
                        neutral-priority
                        ce
                        eff
                        cost
                        cost-previous
                        no
                        pri
                        remaining
                        maincost
                        maincost_list
                        filename
                        netime
                        name



 prey1
 prey2
 prey3
 prey4
 prey5
 prey6
 prey7
 prey8
 prey9
 prey10
 pred1
 pred2
 pred3
 pred4
 pred5
 pred6
 pred7
 pred8
 pred9
 pred10
nodesize1
nodesize2
```

```
nodesize3
nodesize4
nodesize5
nodesize6
nodesize7
nodesize8
nodesize9
nodesize10

                       ]
predators-own          [handling]
patches-own            [countdown]
turtles-own            [
                        preydens
                        predens
                        count_prey
                        count_pred
                        nodenum
                        nodesize
                        my-node
                        node-degree
                        dist-prey
                        dist-pred
                        my-desired-node
                       ]
 edges-own             [origdist
                        dist
                        dist-previous
                       ]
 manager-own           [mmm]
 nodes-own             [time2
                        fence
                        time-recovery
                        real_lag
                        reco]


;;;;;;;;;;;;;;;;;Setting Landscape Network Configuration;;;;;;;;
to setup-one
  clear-all

  set-default-shape donothing "triangle"
  create-donothing 1
  [ set color black]
  ask turtles with [color = black] [die]   ;; the who = 0 dies out
before the first report

;; procedure for avoiding same output filename in multiple core
;; behaviour space!
    set name new-seed
    random-seed name
    let z random 10000
    set netime date-and-time
    set netime remove ":" netime
    set netime remove "." netime
    set netime substring netime 0 10
    set netime word z netime
```

```
  set filename next-log-filename netime 5 ".txt"
  file-open filename

end

to setup

  random-seed seed

  set-default-shape nodes "circle"
  create-nodes numnodes [
    set color blue
    set size 2
    set nodesize capacity
    if nodesize = 0 [
    set nodesize 1]
    set nodenum [who] of self
    set label nodenum
    set time2 time-lag
    set real_lag time-lag
    set fence 0
    setxy random-xcor random-ycor
    loop [
    ifelse count nodes-here > 1 [
    setxy random-xcor random-ycor]
    [stop]
    ]
  ]


if (netipe? = "full") [           ;;creates a fully connected network
  ask nodes [
    create-edges-with other turtles
    set node-degree count edge-neighbors
  ]
  ask edges [
    set dist link-length
    set dist-previous dist
    set origdist link-length
  ]
]

if (netipe? = "random")[
;; creates a simple random network with N nodes and N(N-1)/2 edges
  while [count links < numedges] [
      ;;Note that if the link already exists, nothing happens
      ask one-of nodes [create-edge-with one-of other turtles]
  ]
  ask nodes[
  set node-degree count edge-neighbors
  ]
  ask edges [
    set dist link-length
    set dist-previous dist
    set origdist link-length
  ]
]
if (netipe? = "e-r")[
;; creates an Erdos and Reiny graph
```

```
  ask nodes [
     ;;we use "self > myself" here so that each pair of turtles
     ;;is only considered once
    create-edges-with turtles with [self > myself and
                                    random-float 1.0 < prob]
  ]
  ask edges [
    set dist link-length
    set dist-previous dist
    set origdist link-length
  ]
]

  set-default-shape manager "triangle"
  create-manager 1
  [hide-turtle]

  set-default-shape prey "square"
  create-prey initial-number-prey * numnodes  [
    set color white
    set label-color blue - 2
    set nodenum random numnodes
;;number of the node i belong to
    if nodenum = 0 [
      set nodenum numnodes]
    set my-node one-of nodes with [nodenum = [nodenum] of myself]
;; same as nodenum, but useful for some coding procedures
    setxy random-xcor random-ycor
    hide-turtle
  ]
  set-default-shape predators "square"
  create-predators initial-number-predators * numnodes
;; create the predators, then initialize their variables
  [
    set color red
    set handling 0
    set nodenum random numnodes
;;number of the node i belong to
    if nodenum = 0 [
      set nodenum numnodes]
    set my-node one-of nodes with [nodenum = [nodenum] of myself]  ;;
same as nodenum, but useful for some coding procedures
    setxy random-xcor random-ycor
    hide-turtle
  ]

   set prey1 count prey with [nodenum = 1]
   set prey2 count prey with [nodenum = 2]
   set prey3 count prey with [nodenum = 3]
   set prey4 count prey with [nodenum = 4]
   set prey5 count prey with [nodenum = 5]
   set prey6 count prey with [nodenum = 6]
   set prey7 count prey with [nodenum = 7]
   set prey8 count prey with [nodenum = 8]
   set prey9 count prey with [nodenum = 9]
   set prey10 count prey with [nodenum = 10]
   set pred1 count predators with [nodenum = 1]
   set pred2 count predators with [nodenum = 2]
   set pred3 count predators with [nodenum = 3]
```

```
   set pred4 count predators with [nodenum = 4]
   set pred5 count predators with [nodenum = 5]
   set pred6 count predators with [nodenum = 6]
   set pred7 count predators with [nodenum = 7]
   set pred8 count predators with [nodenum = 8]
   set pred9 count predators with [nodenum = 9]
   set pred10 count predators with [nodenum = 10]
  set nodesize1 capacity
  set nodesize2 capacity
  set nodesize3 capacity
  set nodesize4 capacity
  set nodesize5 capacity
  set nodesize6 capacity
  set nodesize7 capacity
  set nodesize8 capacity
  set nodesize9 capacity
  set nodesize10 capacity

  set time 0

  export-network

  ask prey [                                   ;;set intial densities
             set-dens
             set-dist-prey
           ]
  ask predators [
                  set-dens
                  set-dist-pred
                ]
  ask nodes[
            set my-node self            ;so nodes can also run the
'set-dens' code with no errors
            set-dens
           ]
  set remaining budget
  set maincost_list []
end

;;;;;;;;;;;;;;;;;;;;;RUNNING PROCEDURE;;;;;;;;;;;;;;;;;;;;;;;;;;;

to go
  if not any? prey and not any? predators [stop]


  ask nodes[
;; ADDING NODESIZE (CAPACITY) EROSION need to do better for the time
lag when preydens=0
            set reco 0
            set-dens
            recovery
  ]


  ask prey [
  set-dens]
  ask predators [
  set-dens]
```

```
 ask prey [
   reproduce-prey
   if preydens > preydens-up
     [move-prey]
   if predens > predens-up
     [move-prey]
   mortprey
   ]

 ask predators [
   if handling > 0 [reproduce-predators]
   if handling > 0 [set handling handling - 1]
   catch-prey
   if preydens < preydens-low
   [move-predators]
   mortpred
 ]

if pred-extinction-time = 0 [
  if not any? predators[
   set pred-extinction-time time
  ]
]
if prey-extinction-time = 0[
  if not any? prey [
   set prey-extinction-time time
  ]
]

;if time > 4000[
  set prey1 count prey with [nodenum = 1]
  set prey2 count prey with [nodenum = 2]
  set prey3 count prey with [nodenum = 3]
  set prey4 count prey with [nodenum = 4]
  set prey5 count prey with [nodenum = 5]
  set prey6 count prey with [nodenum = 6]
  set prey7 count prey with [nodenum = 7]
  set prey8 count prey with [nodenum = 8]
  set prey9 count prey with [nodenum = 9]
  set prey10 count prey with [nodenum = 10]
  set pred1 count predators with [nodenum = 1]
  set pred2 count predators with [nodenum = 2]
  set pred3 count predators with [nodenum = 3]
  set pred4 count predators with [nodenum = 4]
  set pred5 count predators with [nodenum = 5]
  set pred6 count predators with [nodenum = 6]
  set pred7 count predators with [nodenum = 7]
  set pred8 count predators with [nodenum = 8]
  set pred9 count predators with [nodenum = 9]
  set pred10 count predators with [nodenum = 10]
;]
 set nodesize1 ([nodesize] of nodes with [nodenum = 1])
 set nodesize2 ([nodesize] of nodes with [nodenum = 2])
 set nodesize3 ([nodesize] of nodes with [nodenum = 3])
 set nodesize4 ([nodesize] of nodes with [nodenum = 4])
 set nodesize5 ([nodesize] of nodes with [nodenum = 5])
 set nodesize6 ([nodesize] of nodes with [nodenum = 6])
 set nodesize7 ([nodesize] of nodes with [nodenum = 7])
 set nodesize8 ([nodesize] of nodes with [nodenum = 8])
```

```
  set nodesize9 ([nodesize] of nodes with [nodenum = 9])
  set nodesize10 ([nodesize] of nodes with [nodenum = 10])


    if (feedback? = "error")[
      set prey-priority []
      set pred-priority []
      set remaining  budget
      ask-concurrent nodes [set-error]
      ask manager [manager-strategy]
    ]

    if (feedback? = "exact")[
      set prey-priority []
      set pred-priority []
      set remaining budget
      ask-concurrent nodes [set-count]
      ask manager [manager-strategy]
    ]

  ask edges [
  if dist <= 10 [
  set dist 10]
  ]
  export-network
  tick
  set time time + 1
  update-plot
  update-plot2
end


to set-dens    ;; to set densities
   set nodesize [nodesize] of my-node
   if nodesize = 0 [
   set nodesize 1]
   set preydens ((count prey with [nodenum = [nodenum]  of myself]) /
nodesize)
   set predens ((count predators with [nodenum = [nodenum] of myself])
/ nodesize)
end


to set-dist-prey
 set dist-prey  random-poisson preymove
end

to set-dist-pred
 set dist-pred random-poisson predmove
end

to move-prey  ;; prey procedure, prey move along edges depending on
the denisities
    ifelse any? ([edge-neighbors] of my-node) with [[dist] of edge
[who] of self [who] of [my-node] of myself < [dist-prey] of myself]
      [
       set my-desired-node one-of ([edge-neighbors] of my-node) with
[[dist] of edge [who] of self [who] of [my-node] of myself < [dist-
prey] of myself]
```

```
       set nodenum [nodenum] of my-desired-node
       set my-node one-of nodes with [nodenum = [nodenum] of myself]
       set nodesize [nodesize] of my-node
       set preydens ((count prey with [nodenum = [nodenum]  of
myself]) / nodesize)
         if preydens > preydens-up [
         die ]
      ]
      [die]
 end


to move-predators  ;; predator procedure, predators move along edges
depending on the densities

  ifelse any? ([edge-neighbors] of my-node) with [[dist] of edge [who]
of self [who] of [my-node] of myself < [dist-pred] of myself]
    [
      set my-desired-node one-of ([edge-neighbors] of my-node) with
[[dist] of edge [who] of self [who] of [my-node] of myself < [dist-
pred] of myself]
      set nodenum [nodenum] of my-desired-node
      set my-node one-of nodes with [nodenum = [nodenum] of myself]
      set nodesize [nodesize] of my-node
      set preydens ((count prey with [nodenum = [nodenum]  of myself])
/ nodesize)
      if preydens < preydens-low [
        die]
     ]
     [die]
end

to reproduce-prey  ;; prey procedure
  if random-float 100 < prey-reproduce [  ;; throw "dice" to see if
you will reproduce
    hatch 1 [
              set nodenum [nodenum] of myself
    ]
  ]
end

to reproduce-predators  ;; predators procedure
  if random-float 100 < predator-reproduce [  ;; throw "dice" to see
if you will reproduce
    hatch 1 [  ;set handling 0
     set nodenum [nodenum] of myself

    ]  ;; hatch an offspring and move it forward 1 step
  ]
end

to catch-prey  ;; predator procedure
  if handling = 0 [
    if any? prey with [nodenum = [nodenum] of myself] [
      let victim one-of prey with [nodenum = [nodenum] of myself]
;; grab a random prey
      if random-float 100 < predation
;; did we get one?  if so,
```

```
        [ ask victim [ die ]
;; kill it
          set handling handling + handling-time
;; get energy from eating
        ]
    ]
  ]
end

to mortprey
   if random-float 100 < prey-death-rate [ die ]
end

to mortpred  ;; turtle procedure
  if random-float 100 < predator-death-rate [ die ]
end

to update-plot
  set-current-plot "populations"
  set-current-plot-pen "prey"
  plot count prey
  set-current-plot-pen "predators"
  plot count predators
end

to update-plot2
  set-current-plot "performance"
  set-current-plot-pen "cost"
  plot cost-previous
  set-current-plot-pen "noeffect"
  plot no
end

;;;;;;;;;;;;;;;;;;;;;;;ADAPTIVE STRATEGIES;;;;;;;;;;;;

;strategies to be implemented:
; ERROR in MEASURMENT
; error = follows a normal distribution with mean 0 and sd to be
decided (error_pred and error_prey)
; correctestimation = no error in feedback, that is count prey/pred is
exactly known by the manager (count_prey and count_pred)

to set-error
      set count_prey count prey with [nodenum = [nodenum] of myself]
+ ( random-normal 0 5)
          if count_prey < 0 [set count_prey 0]
      set count_pred count predators with [nodenum = [nodenum] of
myself] + (random-normal 0 5 )
            set prey-priority []
            set pred-priority []
                   if (count_prey > nodesize * preydens-up * manup)  [
                        set prey-priority fput my-node prey-priority
                     ]
                     if (count_prey < nodesize * preydens-low *
manlow) [
                        set pred-priority fput my-node pred-priority
                     ]
      set prey-priority sort-by [[count_prey] of ?1 > [count_prey] of
?2] prey-priority
```

```
      set pred-priority sort-by [ [count_prey] of ?1 > [count_prey] of
?2] pred-priority
      set pri (length prey-priority) + (length pred-priority)
end

to set-count
      set count_prey count prey with [nodenum = [nodenum] of myself]
      set count_pred count predators with [nodenum = [nodenum] of
myself]
         set prey-priority []
         set pred-priority []
                     if (count_prey > nodesize * preydens-up * manup)
[
                        set prey-priority fput my-node prey-priority
                     ]
                     if (count_prey < nodesize * preydens-low *
manlow) [
                        set pred-priority fput my-node pred-priority
                     ]
set prey-priority sort-by [[count_prey] of ?1 > [count_prey] of ?2]
prey-priority
set pred-priority sort-by [ [count_prey] of ?1 > [count_prey] of ?2]
pred-priority
set pri (length prey-priority) + (length pred-priority)
end

; TYPE OF PARAMETER CONFIGURATION
; 3 types: need to be found in the literature (possibly empirical
data,
;          so as to relate it to possible different ecosystems)
;

;  AIM OF THE MANAGER
;  carrying capacity threshold before size
;  coexistence
;  combination of carr capacity and coex

;
; HOW MANAGER CAN INTERVENE
; increasing/lowering cost of movement (thus the variable cost ) one
time (and then it returns to its previous value)
; increasing/lowering cost of moevement permanently
; limited intervention to x unit of increase/reduction

to manager-strategy

;;to calculate maintenance cost, we use the original distance (link-
lenght) - the actual distance (dist) in absolute value and sum it
;;subtracting it from remaining

 ask edges [
      set maincost_list fput (((abs (origdist - dist)) / 2) )
maincost_list
 ]
 set maincost sum maincost_list
 if maincost != 0[
 set remaining remaining - 10 * ln maincost
 ]
 if remaining < 0 [
```

```
 set remaining 0 ]

 ask edges [set dist-previous dist]

if remaining > 0 [

 ;; How the manager intervenes to preserve patch (node) capacity by
fencing and excluding animals on a determined patch

   ask nodes [

      if nodesize + view < capth [
        if fence = 0 [
         if remaining > incost [
          ask edges with [end1 = myself or end2 = myself] [
            set dist dist + inwe
          ]


        set fence 1
        set remaining remaining - incost
         ]
        ]
       ]
        if fence = 1 and (nodesize + view = capacity + view) [
          if remaining > 10 [
            ask edges with [end1 = myself or end2 = myself] [
              set dist dist - inwe
            ]
            set fence 0
            set remaining remaining - incost
          ]
        ]
   ]

  ask nodes [
  if fence = 0 [

    while [(empty? prey-priority = false) and (empty? pred-priority =
false)]
     [
       let target_node  one-of prey-priority
       let endangered_node one-of pred-priority
       ifelse remaining > decost[
         ifelse any? edges with [end1 = target_node and end2 =
endangered_node] or any? edges with [end1 = endangered_node and end2 =
target_node][
           ask edge [who] of target_node [who] of endangered_node [
             set dist dist - dewe
             set prey-priority remove target_node prey-priority
             set pred-priority remove endangered_node pred-priority
           ]
         set remaining remaining - decost
         ]
         [stop]
       ]
       [stop]
      ]
```

```
   while [(empty? prey-priority = false) and (empty? pred-priority =
true)]
      [
        let target2_node one-of prey-priority
        let neutral one-of nodes with [member? self prey-priority =
false]
        ifelse neutral != nobody [
          ifelse remaining > decost [
            ifelse any? edges with [end1 = target2_node and end2 =
neutral] or any? edges with [end1 = neutral and end2 = target2_node][
              ask edge [who] of target2_node [who] of neutral [
                set dist dist - dewe
                set prey-priority remove target2_node prey-priority
              ]
            set remaining remaining - decost
            ]
            [stop]
          ]
          [stop]
        ]

        [stop]
      ]

   while [(empty? prey-priority = true) and (empty? pred-priority =
false)]
      [
        let endangered_node2 one-of pred-priority
        let neutral2 one-of nodes with [member? self pred-priority =
false]
        ifelse neutral2 != nobody [
          ifelse remaining > decost[
            ifelse any? edges with [end1 = endangered_node2 and end2 =
neutral2] or any? edges with [end1 = neutral2 and end2 =
endangered_node2][
              ask edge [who] of endangered_node2 [who] of neutral2[
                set dist dist - dewe
                set pred-priority remove endangered_node2 pred-
priority
              ]
            set remaining remaining - decost
            ]
            [stop]
          ]
          [stop]
        ]
        [stop]
      ]
  ]

  ]

]

end

;;;;;;;;;;;;;;;;;;;;;;;;;RECOVERY:;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to recovery
```

```
     if count prey with [nodenum = [nodenum] of myself] >= (nodesize *
preydens-up +  nodesize * preydens-up / 100 * 10)[
        set nodesize nodesize - 1
        set reco 1
        set time-recovery time-lag
        if nodesize = 0 [
          set nodesize 1
        ]
        set time2 time-lag
        set real_lag time-lag
     ]
     if reco = 0 [
       let rec (count prey with [nodenum = [nodenum] of myself] /
nodesize)
       if rec > 0.15 and rec <= 0.3 [
          set time-recovery real_lag - 0.5
          set real_lag time2
          set time2 time2 - 0.5
           if time-recovery <= 0 [
            set nodesize nodesize + 1
            set time2 time-lag
            set real_lag time-lag
           ]
       ]
       if rec > 0 and rec <= 0.15 [
          set time-recovery real_lag - 0.75
          set real_lag time2
          set time2 time2 - 0.75
           if time-recovery <= 0 [
            set nodesize nodesize + 1
            set time2 time-lag
            set real_lag time-lag
           ]
        ]
       if count prey with [nodenum = [nodenum] of myself] = 0 [
          set time-recovery real_lag - 1
          set real_lag time2
          set time2 time2 - 1
           if time-recovery <= 0 [
            set nodesize nodesize + 1
            set time2 time-lag
            set real_lag time-lag
           ]
       ]
       if nodesize >= capacity [
              set nodesize capacity
       ]
     ]
 end

;;;;;;;;;;;;;;;;;;REPORTING THE NETWORK;;;;;;;;;;;;;;;;;;;;;;;;

to-report pad [ number digits ]
  let expanded ( word "000000000000000" number )
  let len length expanded
  report substring expanded ( len - digits ) len
end

to-report next-log-filename [  prefix digits suffix]
```

```
;; report the first filename that does not exist
 let next-id# 0
 let next-id$ ""
 let keep-looking? true
 while [ keep-looking? ]
   [ set next-id# next-id# + 1
     set next-id$ ( word prefix ( pad next-id# digits ) suffix )
     set keep-looking? file-exists? next-id$
   ]
report next-id$
end

to export-network
  if any? nodes [
   let blank "   "
   let namenodes [who] of nodes
   let nnodes max [who] of nodes
   file-print "*start*"
   file-type "prey on node"
      file-type blank
   file-type prey1
      file-type blank
   file-type prey2
      file-type blank
   file-type prey3
      file-type blank
   file-type prey4
      file-type blank
   file-type prey5
      file-type blank
   file-type prey6
      file-type blank
   file-type prey7
      file-type blank
   file-type prey8
      file-type blank
   file-type prey9
      file-type blank
   file-print prey10
   file-type "predators on node"
      file-type blank
   file-type pred1
      file-type blank
   file-type pred2
      file-type blank
   file-type pred3
      file-type blank
   file-type pred4
      file-type blank
   file-type pred5
      file-type blank
   file-type pred6
      file-type blank
   file-type pred7
      file-type blank
   file-type pred8
      file-type blank
   file-type pred9
      file-type blank
```

```
   file-print pred10
   file-type "node-capacity"
      file-type blank
   file-type nodesize1
      file-type blank
   file-type nodesize2
      file-type blank
   file-type nodesize3
      file-type blank
   file-type nodesize4
      file-type blank
   file-type nodesize5
      file-type blank
   file-type nodesize6
      file-type blank
   file-type nodesize7
      file-type blank
   file-type nodesize8
      file-type blank
   file-type nodesize9
      file-type blank
   file-print nodesize10
   file-type "predator extinction"
      file-type blank
   file-type pred-extinction-time
      file-type blank
   file-type "prey extinction"
      file-type blank
   file-type prey-extinction-time
      file-type blank
   file-type "remaining budget"
      file-type blank
   file-type remaining
      file-type blank
   file-type "id"
      file-type blank
   file-print netime

   file-type "*Vertices"
   file-type blank
   file-print nnodes
   file-print "*Arcs"
      ask nodes   [
      let neigh link-neighbors
        if (count neigh) > 0 [
           foreach [who] of neigh [
           file-type who
           file-type blank
           file-type  ?
           file-type blank
           let i  who
           let j  ?
           file-print [dist] of edge i j
           ]
        ]
     ]
  ]
end
```

III.iii. Management strategy synchronization

This model is implemented in Matlab2008a.

```
%This script runs all the model with different power structures
between and within communities. More precisely the first term is the
power btw, the second the power structure within.

clear
clc
if exist('D:\A_STUDI\Analysing\Matlab\strategy_dyn_model\data')~=7
    mkdir('data');
end

diary ('data\modelrun.txt')

%number of networks is 10,with increasing connectivity btw communities
R = 10;               %number of runs per network
T = 1000;             %time-steps per run
c = 10;               %components of the network
n = 20;               %nodes for every component

for p_bet = 0:0.025:0.2           %probability of having edges outside
a community
    hh = ['netnum: ' num2str(p_bet)];
    disp(hh);

    a = 0.8;  b = 1;
    p_att = a + (b-a)* rand;
%prob of attach within communities [0.8,1]

    [ci net] = modnet (n,c,p_att,p_bet);
    N = length(net);
    %this is to write the network in pajek format
    nome_rete = strcat('net_',num2str(p_bet),'.net');
    writepaj (net,nome_rete);



    for state=0:0.25:1

        disp('eq_norm'); datestr(now)
        eq_norm_strategy_dyn (R,T,c,n,state,net,ci,p_bet);

        disp('eq_mono'); datestr(now)
        eq_mono_strategy_dyn (R,T,c,n,state,net,ci,p_bet);

        disp('dem_norm'); datestr(now)
        dem_norm_strategy_dyn (R,T,c,n,state,net,ci,p_bet);

        disp('dem_mono'); datestr(now)
        dem_mono_strategy_dyn (R,T,c,n,state,net,ci,p_bet);

        disp('mono_norm'); datestr(now)
        mono_norm_strategy_dyn (R,T,c,n,state,net,ci,p_bet);

        disp('mono_mono'); datestr(now)
```

```
        mono_mono_strategy_dyn (R,T,c,n,state,net,ci,p_bet);

    end
end
    disp('Finish all');datestr(now)
    diary off
```

BUILDING THE MODULAR NETWORK

```
function [ci net] = modnet (n, c, p_att, p_bet)

%creates a modular network,
 N = n*c;            %number of nodes (agents) of the whole network

%following loop needed to generate c number of random networks where c
is the number of communities.

for i = 1:c ;
    z = genvarname (strcat ('gi', num2str (i)));
    eval ([ z '=rnd (n, p_att);']);
end

%following procedure is needed in order to chain the different c
networks in one single matrix (or network)
a = [];
for i = 1:c;
    a = [a strcat(',gi',num2str(i))];
end
aa = substr(a,1);
z = genvarname ('net');
eval ([z '= blkdiag(' aa ');']);

%following procedure needed to connect different communities with
%probabilty p_bet

ci = components (net);
for i = 1:c;
    a = find (ci==i);
    b = find (ci~=i);
    for i = 1:N;
        aa = randselect (a,1);
        bb = randselect (b,1);
        if rand < p_bet ;
            net(aa,bb)=1; net(bb,aa)=1;
        end
    end
end

function graph = rnd (n, p_att)
%this function creates random-graphs and connects them into one single
%modular network.

    graph = random_graph (n, p_att);
    graph = connect_graph (graph);
end

% Random graph construction routine with various models
```

```
% INPUTS:  N - number of nodes
%          p - probability, 0<=p<=1
%          E - fixed number of edges
%          distribution - probability distribution: use the
"connecting-stubs model" generation model
%          fun - customized pdf function, used only if distribution =
'custom' - used as:
%                random_graph(n,p,E,distribution,@myfun,degrees),
where myfun is the function name,
%                of a fn saved in myfun.m
%          degrees - particular degree sequence, used only if
distribution = 'sequence'
% OUTPUTS: adj - adjacency matrix of generated graph (symmetric)
% Note 1: Default is Erdos-Renyi graph G(n,0.5)
% Note 2: Can generate a disconnected, multi-edge graph with self-
loops - check using isconnected.m/issimple.m
% Source: Various random graph models from the literature
%
% Gergana Bounova, October 31, 2005

function adj = random_graph(n,p,E,distribution,fun,degrees)

adj=zeros(n); % initialize adjacency matrix

switch nargin
    case 1  % just the number of nodes, n
        p = 0.5; % default probability of attachment
        for i=1:n
            for j=i+1:n
                if rand<=p
                    adj(i,j)=1; adj(j,i)=1;
                end
            end
        end

    case 2
% the number of nodes and the probability of attachment, n, p
        for i=1:n
            for j=i+1:n
                if rand<=p
                    adj(i,j)=1; adj(j,i)=1;
                end
            end
        end

    case 3 % fixed number of nodes and edges, n, E
        while numedges(adj) < E
            i=ceil(rand*n); j=ceil(rand*n);
            if not(i==j) % do not allow self-loops
                adj(i,j)=adj(i,j)+1; adj(j,i)=adj(i,j);
            end
        end

    otherwise % pick from a distribution; generate *n* random numbers
from a distribution
        Nseq=1;  % ensure the while loops start
        switch distribution
            case 'uniform'
                while mod(sum(Nseq),2)==1 % make sure # stubs is even
```

```
                Nseq = ceil((n-1)*rand(1,n));
            end
        case 'normal'
            while mod(sum(Nseq),2)==1 % make sure # stubs is even
                Nseq = ceil((n-1)/10*randn(1,n)+(n-1)/2);
            end
        case 'binomial'
            p=0.5;  % default parameter for binomial distribution
            while mod(sum(Nseq),2)==1 % make sure # stubs is even
                Nseq = ceil(binornd(n-1,p,1,n));
            end
        case 'exponential'
            while mod(sum(Nseq),2)==1 % make sure # stubs is even
                Nseq = ceil(exprnd(n-1,1,n));
            end
        case 'geometric'
            while mod(sum(Nseq),2)==1 % make sure # stubs is even
                Nseq = ceil(geornd(p,1,n));
            end
        case 'custom'
            % pick a number from a custom pdf function
            % generate a random number x between 1 and N-1
            % accept it with probability fun(x)
            while mod(sum(Nseq),2)==1 % make sure # stubs is even
                Nseq = [];
                while length(Nseq)<n
                    x = ceil(rand*(n-1));
                    if rand <= fun(x)
                        Nseq = [Nseq x];
                    end
                end
            end
        case 'sequence'
            Nseq = degrees;
    end

    % connect stubs at random
    nodes_left = [1:n];
    for i=1:n
        node{i} = [1:Nseq(i)];
    end

    while numel(nodes_left)>0   % edges < sum(Nseq)/2

        randi = ceil(rand*length(nodes_left));
        nodei = nodes_left(randi);               % pick a random
node
        randj = ceil(rand*length(node{nodei}));
        stubj = node{nodei}(randj);              % pick a random
stub

        randii = ceil(rand*length(nodes_left));
        nodeii = nodes_left(randii);             % pick another
random node
        randjj = ceil(rand*length(node{nodeii}));
        stubjj = node{nodeii}(randjj);           % pick a random
stub

        % connect two nodes, as longs as stubs different
```

```
            if not(nodei==nodeii & stubj==stubjj)
                % add new links
                adj(nodei,nodeii) = adj(nodei,nodeii)+1;
                adj(nodeii,nodei) = adj(nodei,nodeii);
                % remove connected stubs
                node{nodei} = setdiff(node{nodei},stubj);
                node{nodeii} = setdiff(node{nodeii},stubjj);
            end

            % remove empty nodes
            nodes_left1 = nodes_left;
            for i=1:length(nodes_left)
                if length(node{nodes_left(i)})==0
                    nodes_left1 = setdiff(nodes_left1,nodes_left(i));
                end
            end
            nodes_left = nodes_left1;

        end

end  % end nargin options

% Gergana Bounova, December 18, 2005


function A = connect_graph(B)
%the following code connects different random-graphs so as to build a
modular network

A = B;
N = length(A);
[ci cmp] = components(A);
if length(cmp)>1
    nn = find(ci>1);
    k = length(nn);
    if k>0
        r = randint(k,1,[1,N]);
        A(nn,r)=1; A(r,nn)=1;
        for i=1:N
            A(i,i)=0;
        end
    end
    [ci cmp]=components(A);
    if length(cmp)>1
        A = connect_graph(A);
    end
end

function [ci sizes] = components(A)
% Compute connected components
% [ci sizes] = components(A) returns the component index vector (ci)
and the size of each of the connected components (sizes).  The number
of connected components is max(components(A)).  The algorithm used
computes the strongly connected components of A, which are the
connected components of A if A is undirected (i.e. symmetric).
%
% This method works on directed graphs.

A = double(A);
```

```
if ~issparse(A)
    A = sparse(A);
end

[ci sizes] = comps(A); %refers to a dll library.

function writepaj(adj,fnm,x,y,z)

% Write adjacency matrix to a Pajek .net format
%
% CAUTION: Before loading the .net file into Pajek, open, save and
% close it in WordPad. That fixes some strange UNIX-Win
incompatibility
% Gergana Bounova, March 14, 2006

% EXAMPLE
% *Vertices    4
%        1 "v1"                                       0.1000    0.5000
0.5000
%        2 "v2"                                       0.1000    0.4975
0.5000
%        3 "v3"                                       0.1000    0.4950
0.5000
%        4 "v4"                                       0.1001    0.4925
0.5000
% *Edges
%       14       31 1
%       46       51 1
%       51       60 1

dirname = 'U:\AA_JACO\strategy_dynamics\strategy_dyn_model\data\';
% dir for net file
filename =  strcat (dirname, fnm);

N = length(adj); % number of nodes
fid = fopen(filename,'w');

fprintf(fid,'*Vertices  %6i\r',N);
if nargin < 3
  for i=1:N
    fprintf(fid,'     %3i %s                     %1.4f    %1.4f
%1.4f\r',i,strcat('"v',num2str(i),'"'),rand,rand,0.5);
  end
elseif nargin >2 && nargin < 5
  for i=1:N
    fprintf(fid,'     %3i %s                     %1.4f    %1.4f
%1.4f\r',i,strcat('"v',num2str(i),'"'),x(i),y(i),0.5);
  end
else % 3D coords
  for i=1:N
    fprintf(fid,'     %3i %s                     %1.4f    %1.4f
%1.4f\r',i,strcat('"v',num2str(i),'"'),x(i),y(i),z(i));
  end
end

fprintf(fid,'*Edges\r');
for i=1:N
  for j=1:N
    if adj(i,j)>0
```

```
      fprintf(fid,'    %4i   %4i   %2i\r',i,j,adj(i,j));
    end
  end
end

fclose(fid)
```

SETTING ATTRIBUTES FOR THE DYNAMICS OF THE MODEL

Equal authority/reputation distribution between communities, normal distribution within

```
function eq_norm_strat_dyn (R,T,c,n,state,net,ci,p_bet)


    strategy = [];
    op_mod = [];
    norm_dyn = zeros(T, c*n);


    for p = 1:R

        %attributes assigned to every node
        attrib = eq_norm_gen_attr(ci,c,n);

%Run the dynamics of the kuramoto model and retreive opinion evolution
and last opinion(dyn and end_strat). Opinions are normalized (a-
min)/(max-min)

        dyn = dynamics (net,attrib,c,n,T,state,p_bet);
        [r cc]=size(dyn);
        end_strat = dyn(r,:);
        strategy = [strategy ;end_strat];
        norm_dyn = norm_dyn + dyn;
    end

% save dynamics matrix (averaged node dynamics per network)
    norm_dyn = norm_dyn./R;
    matname =
['data\eq_norm_dyn_','state_',num2str(state),'_net_',num2str(p_bet),'.
txt'];
    save (matname, 'norm_dyn','-ascii', '-tabs')


function attrib = eq_norm_gen_attr(ci,c,n)

N = length(ci);
attrib = ci;                 %= component to which a node belongs
attrib = [attrib rand(N,1)] ;        %= World view [0,1]
aj=-1;
bj=1;
attrib = [attrib (aj+(bj-aj)*rand(N,1))];  %= strategy [-1,1]

w = 0.5                      ;        %= mean of normal
sd = 0.125                   ;        %= sd of normal

%generating normal distribution for power within communities
```

```
pw = zeros(N,1);
for zz = 1:c
    normpw = normrnd(w,sd,n,1);
    pw(ci==zz) = normpw;
end
attrib = [attrib pw];               %= power within communities
p_bet2 = repmat(0.5,1,c);
p_bet3 = repmat(p_bet2,n,1);
attrib = [attrib p_bet3(:)];        %= power between communities
```

Equal authority/reputation distribution between communities, exponential distribution within

```
function eq_mono_strat_dyn (R,T,c,n,state,net,ci,p_bet)

    strategy = [];
    op_mod = [];
    norm_dyn = zeros(T, c*n);

    for p = 1:R

        %attributes assigned to every node
        attrib = eq_mono_gen_attr(ci,c,n);

%Run the dynamics of the kuramoto model and retreive opinion evolution
and last opinion(dyn and end_strat). Opinions are normalized (a-
min)/(max-min)
        dyn = dynamics (net,attrib,c,n,T,state,p_bet);
        [r cc]=size(dyn);
        end_strat = dyn(r,:);
        strategy = [strategy ;end_strat];
        norm_dyn = norm_dyn + dyn;
    end

    % save dynamics matrix (averaged node dynamics per network)
    norm_dyn = norm_dyn./R;
    matname =
['data\eq_mono_dyn_','state_',num2str(state),'_net_',num2str(p_bet),'.
txt'];
    save (matname, 'norm_dyn','-ascii', '-tabs')


function attrib = eq_mono_gen_attr(ci,c,n)

N = length(ci);
attrib = ci;                    %= component to which a node belongs
attrib = [attrib rand(N,1)] ;    %= World view [0,1]
aj=-1;
bj=1;
attrib = [attrib (aj+(bj-aj)*rand(N,1))];   %= strategy [-1,1]

%procedure for calculating power within:
pw = zeros(N,1);
for zz = 1:c
    pwr = round (1+rand*19);        %= select random agent that will
be the most powerful
    monopw = exprnd(0.125,n,1);     %= generate vector of low power
```

```
    monopw(pwr,1) = 1;              %= insert powerful agents in
vector
    pw(ci==zz) = monopw;
end
attrib = [attrib pw];               %= power within communities
p_bet2 = repmat(0.5,1,c);
p_bet3 = repmat(p_bet2,n,1);
attrib = [attrib p_bet3(:)];        %= power between communities
```

Normal authority/reputation distribution between communities, normal distribution within

```
function dem_norm_strat_dyn (R,T,c,n,state,net,ci,p_bet)

    strategy = [];
    op_mod = [];
    norm_dyn = zeros(T, c*n);


    for p = 1:R

        %attributes assigned to every node
        attrib = dem_norm_gen_attr(ci,c,n);

%Run the dynamics of the kuramoto model and retreive opinion evolution
and last opinion(dyn and end_strat). Opinions are normalized (a-
min)/(max-min)

        dyn = dynamics (net,attrib,c,n,T,state,p_bet);
        [r cc]=size(dyn);
        end_strat = dyn(r,:);
        strategy = [strategy ;end_strat];
        norm_dyn = norm_dyn + dyn;
    end

% save dynamics matrix (averaged node dynamics per network)
    norm_dyn = norm_dyn./R;
    matname =
['data\dem_norm_dyn_','state_',num2str(state),'_net_',num2str(p_bet),'
.txt'];
    save (matname, 'norm_dyn','-ascii', '-tabs')

function attrib = dem_norm_gen_attr(ci,c,n)

N = length(ci);
attrib = ci;                   %= component to which a node belongs
attrib = [attrib rand(N,1)] ;              %= World view [0,1]
aj=-1;
bj=1;
attrib = [attrib (aj+(bj-aj)*rand(N,1))];   %= strategy [-1,1]

w = 0.5;
sd = 0.125;
%procedure for calculating power within:
pw = zeros(N,1);
for zz = 1:c
    normpw = normrnd(w,sd,n,1);
    pw(ci==zz) = normpw;
```

```
end
attrib = [attrib pw];                %= power within communities

%procedure for power between:
p_bet2 = normrnd(0.5,0.125,1,c);
p_bet3 = repmat(p_bet2,n,1);
monopb = p_bet3(:);
attrib = [attrib monopb];          %= power between communities
```

Normal authority/reputation distribution between communities, exponential distribution within

```
function dem_mono_strat_dyn (R,T,c,n,state,net,ci,p_bet)


    strategy = [];
    op_mod = [];
    norm_dyn = zeros(T, c*n);


    for p = 1:R

        %attributes assigned to every node
        attrib = dem_mono_gen_attr(ci,c,n);

%Run the dynamics of the kuramoto model and retreive opinion evolution
and last opinion(dyn and end_strat). Opinions are normalized (a-
min)/(max-min)

        dyn = dynamics (net,attrib,c,n,T,state,p_bet);
        [r cc]=size(dyn);
        end_strat = dyn(r,:);
        strategy = [strategy ;end_strat];
        norm_dyn = norm_dyn + dyn;
    end

% save dynamics matrix (averaged node dynamics per network)
    norm_dyn = norm_dyn./R;
    matname =
['data\dem_mono_dyn_','state_',num2str(state),'_net_',num2str(p_bet),'
.txt'];
    save (matname, 'norm_dyn','-ascii', '-tabs')


function attrib = dem_mono_gen_attr(ci,c,n)

N = length(ci);
attrib = ci;                        %= component to which a node belongs
attrib = [attrib rand(N,1)] ;                 %= World view [0,1]
aj=-1;
bj=1;
attrib = [attrib (aj+(bj-aj)*rand(N,1))];   %= strategy [-1,1]

%procedure for calculating power within:
pw = zeros(N,1);
for zz = 1:c
    pwr = round(1+rand*19);        %= select random agent that will be
the most powerful
```

```
    monopw = exprnd(0.125,n,1);    %= generate vector of low power
    monopw(pwr,1) = 1;             %= insert powerful agents in vector
    pw(ci==zz) = monopw;
end
attrib = [attrib pw];          %= power within communities

%procedure for power between:
p_bet2 = normrnd(0.5,0.125,1,c);
p_bet3 = repmat(p_bet2,n,1);
monopb = p_bet3(:);
attrib = [attrib monopb];          %= power between communities
```

Exponential authority/reputation distribution between communities, normal distribution within

```
function mono_norm_strat_dyn (R,T,c,n,state,net,ci,p_bet)

    strategy = [];
    op_mod = [];
    norm_dyn = zeros(T, c*n);

    for p = 1:R

        %attributes assigned to every node
        attrib = mono_norm_gen_attr(ci,c,n);

%Run the dynamics of the kuramoto model and retreive opinion evolution
and last opinion(dyn and end_strat). Opinions are normalized (a-
min)/(max-min)
        dyn = dynamics (net,attrib,c,n,T,state,p_bet);
        [r cc]=size(dyn);
        end_strat = dyn(r,:);
        strategy = [strategy ;end_strat];
        norm_dyn = norm_dyn + dyn;
    end

% save dynamics matrix (averaged node dynamics per network)
    norm_dyn = norm_dyn./R;
    matname =
['data\mono_norm_dyn_','state_',num2str(state),'_net_',num2str(p_bet),
'.txt'];
    save (matname, 'norm_dyn','-ascii', '-tabs')

function attrib = mono_norm_gen_attr(ci,c,n)

N = length(ci);
attrib = ci;                      %= component to which a node belongs
attrib = [attrib rand(N,1)] ;              %= World view [0,1]
aj=-1;
bj=1;
attrib = [attrib (aj+(bj-aj)*rand(N,1))];   %= strategy [-1,1]

w = 0.5;
sd = 0.125;
%generating normal distribution for power within communities
pw = zeros(N,1);
for zz = 1:c
    normpw = normrnd(w,sd,n,1);
```

```
    pw(ci==zz) = normpw;
end
attrib = [attrib pw];               %= power within communities

%procedure to calculate power between
p_bet2 = exprnd(0.125,1,c);
p_bet3 = repmat(p_bet2,n,1);
monopb = p_bet3(:);
pbr = round (1+rand*9);            %= select powerful community
maxpbc = ones(n,1);                %= max power of community
monopb(ci==pbr) = maxpbc;          %= one community has max power
attrib = [attrib monopb];          %= power between communities
```

Exponential authority/reputation distribution between communities, exponential distribution within

```
function mono_mono_strat_dyn (R,T,c,n,state,net,ci,p_bet)

    strategy = [];
    op_mod = [];
    norm_dyn = zeros(T, c*n);

    for p = 1:R

        %attributes assigned to every node
        attrib = mono_mono_gen_attr(ci,c,n);

%Run the dynamics of the kuramoto model and retreive opinion evolution
and last opinion(dyn and end_strat). Opinions are normalized (a-
min)/(max-min)
        dyn = dynamics (net,attrib,c,n,T,state,p_bet);
        [r cc]=size(dyn);
        end_strat = dyn(r,:);
        strategy = [strategy ;end_strat];
        norm_dyn = norm_dyn + dyn;
    end

% save dynamics matrix (averaged node dynamics per network)
    norm_dyn = norm_dyn./R;
    matname =
['data\mono_mono_dyn_','state_',num2str(state),'_net_',num2str(p_bet),
'.txt'];
    save (matname, 'norm_dyn','-ascii', '-tabs')

function attrib = mono_mono_gen_attr(ci,c,n)

N = length(ci);
attrib = ci;                      %= component to which a node belongs
attrib = [attrib rand(N,1)] ;              %= World view [0,1]
aj=-1;
bj=1;
attrib = [attrib (aj+(bj-aj)*rand(N,1))];   %= strategy [-1,1]

%procedure for calculating power within:
pw = zeros(N,1);
for zz = 1:c
    pwr = round (1+rand*19);        %= select random agent that will
be the most powerful
```

```
    monopw = exprnd(0.125,n,1);     %= generate vector of low power
    monopw(pwr,1) = 1;              %= insert powerful agents in
vector
    pw(ci==zz) = monopw;
end
attrib = [attrib pw];
%procedure to calculate power between
p_bet2 = exprnd(0.125,1,c);
p_bet3 = repmat(p_bet2,n,1);
monopb = p_bet3(:);
pbr = round (1+rand*9);            %= select powerful community
maxpbc = ones(n,1);                %= max power of community
monopb(ci==pbr) = maxpbc;          %= one community has max power
attrib = [attrib monopb];          %= power between communities
```

Dynamics of the model

```
function  dyn = dynamics(net,attrib,c,n,T,state,p_bet)

%dynamics of the model: Syncrhonization = homogeneization of
strategies. in case of equation 8.2 wv=1 as 1 is the "neutral" (thus
is like saying that wv has no effect on the authority/reputation
differences.

N = length(net);
alfa = 3;
fac = 10;

for t = 1:T

    for i = 1:N
        neighb = find(net(i,:)==1);
        oscilw_v = [];
        oscilb_v = [];
        sum_oscilw = 0;
        sum_oscilb = 0;
        sum_w = [];
        sum_b = [];
        cpw=[];
        cpb=[];
        for k = 1:length(neighb)
            if attrib(i,1)==attrib(neighb(k),1)
                coup_w = (attrib(neighb(k),4) - attrib(i,4));
                wv = (abs(attrib(i,2) - attrib(neighb(k),2)));
                if coup_w <= 0
                    coup_w = 0;
                else
                    coup_w = (coup_w^wv)*fac;
                end
                strat1= attrib(i,3);
                strat2= attrib(neighb(k),3);
                oscilw= (sin(strat2-strat1)-state*sin(strat1));
                oscilw_v(1,k) = oscilw;
                sum_oscilw = coup_w*(oscilw);
                sum_w(:,k) = sum_oscilw;
            else
                coup_b = (attrib(neighb(k),5)- attrib(i,5));
                wv = (abs(attrib(i,2) - attrib(neighb(k),2)));
```

```
                if coup_b <= 0
                    coup_b = 0;
                else
                    coup_b = (coup_b^wv)*fac;
                end
                strat1= attrib(i,3);
                strat2= attrib(neighb(k),3);
                oscilb= (sin(strat2-strat1)-state*sin(strat1));
                oscilb_v(1,k) = oscilb;
                sum_oscilb = coup_b*(oscilw);
                sum_b(:,k) = sum_oscilb;
            end
        end

        strat1 = strat1+ sum(sum_w)+sum(sum_b);
        attrib(i,3)=strat1;
        dyn(t,i)=strat1;
    end
end
```

Functions used as "utilities" in the building of model

```
function outstr = substr(str, offset, len, repl)
%SUBSTR Extract a substring out of a string.
%
%   SUBSTR(STRING, OFFSET, LENGTH) extracts a substring out of STRING
with
%   given LENGTH starting at the given OFFSET.  First character is at
offset 0.
%   If OFFSET is negative, starts that far from the end of the string.
If
%   LENGTH is omitted, returns everything to the end of the string.
If LENGTH
%   is negative, removes that many characters from the end of the
string.
%
%   SUBSTR(STRING, OFFSET, LENGTH, REPLACEMENT) will not return the
substring
%   as specified by STRING, OFFSET, and LENGTH (see above) but rather
replace
%   it by REPLACEMENT and return the result.
%
%   Examples:
%
%      Get first character:              substr(string,  0, 1)
%      Get last character:               substr(string, -1, 1)
%      Remove first character:           substr(string,  1)
%      Remove last character:            substr(string,  0, -1)
%      Remove first and last character:  substr(string,  1, -1)
%
%   SUBSTR is a MATLAB version of the Perl operator with the same
name.
%   However, unlike Perl's SUBSTR, no warning is produced if the
substring is
%   totally outside the string.

%   Author:      Peter J. Acklam
%   Time-stamp:  2004-02-21 22:49:14 +0100
```

```
%   E-mail:      pjacklam@online.no
%   URL:         http://home.online.no/~pjacklam

   % Check number of input arguments.
   error(nargchk(2, 4, nargin));

   n = length(str);

   % Get lower index.
   lb = offset + 1;              % offset from beginning of string
   if offset < 0
      lb = lb + n;               % offset from end of string
   end
   lb = max(lb, 1);

   % Get upper index.
   if nargin == 2                % SUBSTR(STR, OFFSET)
      ub = n;
   elseif nargin > 2             % SUBSTR(STR, OFFSET, LEN)
      if len >= 0
         ub = lb + len - 1;
      else
         ub = n + len;
      end
      ub = min(ub, n);
   end

   % Extract or replace substring.
   if nargin < 4
      outstr = str(lb : ub);                        % extract
substring
   else
      outstr = [str(1:lb-1) repl str(ub+1:end)];    % replace
substring
   end
```

```
function r = randint(i,j,interval)
% Random integers

% r = randint(i,j,[from,to]) Returns a ixj matrix with random
% integers from the interval [from,to].
%
% Note that randint is also function of the Matlab communication
% toolbox!
%
% Inputs:
%   i            : Matrix i dimension
%   j            : Matrix j dimension
%   interval     : Integer interval [from to]
%
% Outputs:
%   r            : ixj random integer matrix
%
% Examples:
%   r = randint(1,1,[1,10])
%   r = randint(1,1,[1,10])
%   r = randint(3,4,[1,10])
```

```
%-----------------------------------------------------------------
% (c) 2006 Christof Teuscher
% christof@teuscher.ch | http://www.teuscher.ch/christof
%-----------------------------------------------------------------


from     = interval(1);
to       = interval(2);

r = from + round(rand(i,j) * (to - from));

function A = randselect(x,n)
% Select n random elements from a list

if size(x,1)==1
    x=x';
end
c = length(x);
y = rand(c,1);
C = sortrows([x y],2);
A = C(1:n,1);

function [ A ] = intrnd(n, min, max, rep)
% Generates n random integers in (min, max), no repetitions
% rep = 0 -> no repetitions
% rep = 1 -> repetitions

if nargin<4
    rep = 0;
end
if rep>1
    rep=1;
end
if max<=n
    error('Interval must be > No. of items');
end

if rep==1
    A = round(min + (max-min).*rand(n,1));
else
    A = [];
    A(1) = round(min + (max-min)*rand);
    i=2;
    while i<n+1
        k = round(min + (max-min)*rand);
        if ~ismember(k, A)
            A(i) = k;
            i = i+1;
        end
    end
end
A = A';

function norm = normalize(mat,type)
norm = [];
[row col]=size(mat);

if nargin<2
    type=0;
```

```
end

if type~=1;
    ms=max(mat);
    ms=max(ms);
    mn=min(mat);
    mn=min(mn);
    norm=(mat-mn)./(ms-mn);
end

if type==1
    ms=max(mat);
    mn=min(mat);

    for ii=1:col
        norm=[norm (mat(:,ii) - mn(:,ii))/(ms(:,ii) - mn(:,ii))];
    end
end

end
```

Results analysis (or degree of synchronization/homogenisation)

```
function order = rparam(mat)
%to calculate the synchronization parameter of our model, based on
pluchino et al.; in order to measure the synchronization of the
system, we adopted an order parameter related to the standard
deviation of the end-strategies.

[row,col] = size(mat);
m = mean(mat);
diff=[];

for co=1:col;
    diff =[diff (mat(:,co)-m(:,co)).^2];
end

sdiff = sum(diff);
order = 1-sqrt(sdiff.*(1/(r
ow)));
```