This is a pre-print of: Parrott, L. and Lange, H. 2013. An Introduction to Complexity Science. In: Managing Forests as Complex Adaptive Systems: Building Resilience to the Challenge of Global Change. Edited by Christian Messier, Klaus J. Puettmann, K. David Coates. Routledge, 368 pages.

Chapter 2: An introduction to complexity science

Parrott, L.^{*} & Lange, H.

Introduction

Over the past 40 years, a new multidisciplinary field of study has emerged which is characterised by at least two major changes in the way some scientists treat systems. First, it is increasingly accepted that we cannot fully understand the laws that govern a system simply by studying its parts, nor can we fully understand the behaviour of the parts without placing them in the context of the larger system in which they are embedded. This realization, which has arisen as we face the limits of reductionist science, has given rise to the development of new models and methods that facilitate the study of systems across multiple scales of organization. Second, the notions of equilibrium and predictability in natural systems, developed in the 19th Century and continuously pursued until far into the 20th Century, are being rejected in favour of models that embrace variability, diversity, continual change, adaptation and some level of unpredictability as the status quo. Traditional analytical models that assume a stable equilibrium are being replaced by new approaches that facilitate the exploration of a system's natural range of variation and its possible emergent responses to changing external conditions. The implications of this new field, now known as *complexity science*, are manifest across disciplines, fundamentally changing the way we study, analyze and perceive natural systems (Waldrop, 1992; Lewin, 1999; Cho, 2009; Mitchell, 2009).

Complexity science provides an integrative, multidisciplinary framework to studying the structure and dynamics of forest ecosystems. It provides a new conceptual model of the forest as a dynamic, non-linear system. By studying forests as complex systems we may gain new insight into their structure and functioning, leading to better recommendations for their management. In particular, complexity science teaches us that we cannot treat a forest as a simple, predictable system that can be managed from the top-down; we need to develop new methods of forest management that take into consideration the complex properties of the system, its transient dynamics and the resulting uncertainty about its future behaviour (Puettmann et al., 2009). Doing so may be increasingly important in the context of climate change and society's growing demands for forest ecosystems that meet multiple ecological, societal and economic objectives.

In this first chapter, we introduce complexity science and provide some key definitions. We hope that this introduction will incite the reader to delve deeper

^{*} Corresponding author. Current address: lael.parrott@ubc.ca

into complexity and explore how this new field may affect the way forests are studied, modelled and managed.

What is a complex system?

Most natural and social and also some technological systems are complex systems. The origins of the term can be traced back to work of researchers in diverse fields across the natural and social sciences (Waldrop, 1992; Lewin, Working in their respective fields, many scientists arose to similar 1999). conclusions: the systems that they study have emergent properties, selfreinforcing feedback loops, historical contingency (or "frozen accidents") leading to the "lock-in" of sometimes sub-optimal states, a hierarchical, "systems within systems" type of structure, and an unpredictable dynamics that cannot be adequately described using existing methods of analysis. In the early 1990's, increased communication amongst researchers from the different disciplines led to a convergence of ideas and the discovery of the many commonalities in the questions and lines of inquiry that were being pursued in varied systems. The term "complex system" began to be formally recognized, and multidisciplinary institutes dedicated to the study of complex systems were created to foster exchange between the disciplines.

A complex system is first and foremost a *system*. Thus, to arrive at a working definition of a complex system, we first have to be concerned about the delineation of the system. This involves defining the system boundary, identifying relevant components within the boundary, and determining the granularity of description of the individual components. The choices made are in part subjective and in part determined by processes acting on specific temporal and spatial scales – some choices are more natural than others. A fundamental distinction can be made between closed and open systems. The latter involve fluxes of matter, energy or information across their boundaries. Yet another distinction is between systems in equilibrium (a configuration corresponding to the lowest attainable energy state in which system-wide macroscopic variables do not change with time) or out of equilibrium.

Keeping this terminology in mind, a *complex system* can be most simply defined as an open non-equilibrium system composed of multiple interacting components whose aggregate behaviour cannot be predicted by studying the components in isolation. This definition encompasses most biophysical and social systems, ranging from human societies and natural ecosystems, to genetic networks and unicellular organisms. All of these systems have a diverse array of components in interaction (e.g., organisms or molecules) whose combined activity gives rise to emergent patterns and processes at higher levels of organization. The notion of levels of organization across multiple scales is key to the study and analysis of any complex system and much of the research in complexity science focuses on developing methods to deal with cross-scale linkages and interactions.

A complex system can thus be represented as being composed of multiple components in interaction, whose collective dynamics gives rise to emergent

entities at a higher level, whose existence in turn affects the comportment of the lower-level components (via feedback) (Figure 1). These higher-level emergent entities are also in interaction, and their interactions give rise again to structure at even higher levels of organization, etc. For example, individual humans in interaction create social networks; social networks give rise to cultural institutions which give rise to governance structures. In return, belonging to a given social network influences the behaviour of individual humans who in turn influence the dynamics of their social network, etc. In the simplified schema shown in Figure 1, there are only four levels of organization, and only biological (as opposed to social) entities are represented. In reality, the number of levels of organization may be much greater, structures at each level may occupy bigger or smaller footprints (in terms of utilization of space or another resource), the different levels might thus overlap in the plane displayed in the Figure, and their local dynamics may operate at different temporal scales. The interactions between these structures thus link scales of space, time and organization.

Figure 1: Conceptual diagram of a complex system, showing interactions and feedbacks between entities within and across scales. This could represent an ecosystem at large-spatial scales, such as a watershed.



In characterizing complex systems as containing different levels of organization and acting on a range of scales, we are tacitly assuming that these levels and scales are identifiable. This is possible for some systems when there are clearly preferred scales on which the processes considered act, or when there are barriers (e.g. membranes) separating system elements. However, the separation into different units, levels and scales in a discrete manner (atoms, molecules, macromolecules, cells, etc.) is a vestige of a reductionist framework since scale is a continuous quantity. For ecosystems, this division into identifiable scales of organization (e.g., cells, organisms, populations, communities...) will probably remain pertinent. Thus, defining (or more commonly verbally describing) levels of organization and hierarchy is an important aspect of system delineation; both the highest as well as the lowest level considered define the boundaries of the system at an abstract level.

In many complex systems, however, there are no natural preferred scales (West and Shlesinger, 1990; Brown et al., 2002; Bettencourt et al., 2007). A characteristic indicator of the lack of identifiable scales of organization is when the size distribution of events in the system decays only as a power law, as opposed to exponentially (Schroeder, 1991). This has been observed for avalanches, earthquakes, forest fires, floods, and other natural phenomena (West and Brown, 2004). Also the structure of metabolic networks or food webs can be well described using scale-free networks (Enquist et al., 2003).

Complex systems typically have a diversity of component types, and this diversity gives rise to heterogeneous responses to the same stimulus, variation in system level properties and redundancy in the form of alternate pathways for material, information or energetic flow. Contrary to the simple input-output systems considered in older ("general") system theory (Bertalanffy, 1968) or cybernetics (Wiener, 1948), complex systems do not exhibit reproducible behaviour, since they do not necessarily ever return to the same "initial" state. On the contrary, these systems are "always running" and have a history. For example, in most complex systems, diversity is an inevitable outcome of competition for finite energetic and material resources. Ecological niche theory is a classic example of how diversity emerges within a system as species evolve to exploit unoccupied niches.

Diversity is, however, not a sufficient condition for complex dynamics to arise. A house built of a million blocks of different shapes, sizes, and colours may have a high diversity but is usually not considered as complex in complexity science (and is not a typical unit of study in this field as well). Likewise, a spatial configuration of unconnected, chaotically oscillating populations will give rise to a non-complex, random distribution of population densities across space and time. In contrast, a spatial configuration of the same oscillators coupled together via dispersal or some other regulating process may generate surprisingly complex spatial dynamics at the system level (Solé and Bascompte, 1998; Strogatz, 2003). In natural ecosystems, interactions occur across multiple scales of space, time and organization and across the physical and biological parts of the systems. Clearly interactions are central to making a system complex. Without interactions, there is no emergence, no feedback and no cross-scale linkages.

Principal properties of complex systems

All complex systems share a number of key structural and dynamical properties. Structural properties include, but are not limited to: openness, heterogeneity and diversity, hierarchy, and memory. Dynamical properties include, but are not limited to: self-organization, emergence, uncertainty, and adaptation.

Openness: As discussed above, a complex system is an open system, through which material, energy or information may be exchanged with its external environment.

Heterogeneity and diversity within a complex system can be manifested in multiple ways. First, the system may be composed of many different kinds of components (and this is what is typically used to define the diversity of a system). Second, these components, even if initially identical, are likely to respond to stimulus in a heterogeneous fashion as a result of their different histories and positions relative to other components within the system, rapidly giving rise to divergent behaviours. For example, two genetically identical trees planted in a managed forest will grow at different rates and develop different crown structures depending on the availability of light and nutrients, as well as disease and herbivory at the specific locations where they are planted. In addition to being composed of heterogeneous components, the spatial and organizational structure of a complex system may also be heterogeneous. The spatial distribution of water and nutrients in a soil, for example, is rarely homogeneous and this heterogeneity contributes to structural heterogeneity in the vegetation types and associations that grow at a site.

Hierarchy is a key element of any complex system. Most conceptual models of a complex system are based on a vision of a system of interacting entities present at one level of organization or spatiotemporal resolution whose collective behaviour gives rise to other emergent entities at a higher level (Figure 1). Complex systems can thus be seen as aggregated systems of systems.

Many complex systems have *memory* in the sense that past events can influence the future trajectory of the system through a persistent change in the system's structure or composition. In many cases, these may be seemingly random or minor events, such as a tree falling to create a new gap in the forest, which are reinforced through feedback mechanisms in the system (e.g., the gap may remain due to increased settlement of cold air which creates frost pockets and stunts vegetation or, in warmer climates, due to increased evaporation that restricts colonization at the site). In ecology, system memory is present in the form of historical legacies of past events in a landscape or ecosystem that have a lasting influence on the structure and composition of ecological communities. An example might be a long-past disturbance such as human construction that compacted the soil, or a forest fire that changed the soil's nutrient composition and affected the seed bank, both of which may affect which species are present in the system hundreds of years later.

Self-organization is the dynamical process by which a system forms persistent structures in space or time, often in response to a flow of energy, matter or

information within and across the system boundary. It is thus the ability of an open system to create order from disorder autonomously (without external stimulus). Self-organization is a normal and regularly occurring property of complex systems. Examples include vortexes in physical systems or networks of influence in social systems. The process of ecological succession may be characterized as an example of self-organization in ecosystems, in which persistent community assemblages develop in response to fluxes of solar energy, water and nutrients. These assemblages are then maintained by self-reinforcing cycles (e.g., vegetation in a semi-arid woodland maintains a local micro-climate that favours the presence of vegetation).

Self-organization is often the cause behind *emergence*: the unexpected occurrence of structures, processes or functions at one scale within a complex system that are the aggregate result of interactions between components at a finer scale. These emergent structures, processes and functions feed back upon the components at lower levels, thus modifying their behaviour. For example, the individual trees growing in a forest give rise to a specific stand structure, which is a property of the stand and not of any individual tree. The stand structure, however, affects the availability of light, which in turn influences the growth patterns of individual trees.

Uncertainty is a key notion associated with the dynamics of complex systems, which have non-linear dynamics that may be statistically predictable (e.g., climate) but is not predictable in practice (e.g., weather). The size and frequency of forest fires, for example, can be well described by power law distributions. From this distribution, one can calculate the probability that a fire of a certain size may occur in a given region in a given year, but it is not possible to predict the precise locations and timing of fires. Uncertainty in a complex system can arise from stochastic processes or from deterministic chaos (i.e., strong dependence of future behaviour on the details of the initial configuration of a system). In the former, the source of uncertainty is random variation. In the latter, the uncertainty arises from a fundamental inability to precisely predict the future trajectory of the system, even when the equations of motion are known, since it is impossible to measure the current state of the system with perfect precision (Crutchfield et al., 1986). For a chaotic system, infinitesimal errors in measurement of a system's state give rise to exponentially increasing errors in prediction of its future state. The two different sources of uncertainty may be extremely difficult to tell apart on the basis of observations (measurements) from a natural system. An attempt to distinguish noise from chaos using complexity measures is provided by Rosso et al. (2007). These authors develop a parameter-free procedure to conclude on the presence of noise in any series, with the non-surprising result that noise is ubiquitous in observations of natural systems (Rosso et al., 2012).

A third source, less genuine to the system but nevertheless of utmost importance in many situations, is incomplete or inaccurate knowledge about the system, e.g., crucial but non-measured variables. In practice, these sources of uncertainty reduce our ability to predict the future state of the system and generate variability that may (or may not) be amplified by positive feedback loops, leading to the emergence of novel structures within the system (Shinbrot and Muzzio, 2001). This type of uncertainty is extremely common in human systems. Since we cannot know or measure all variables related to human behaviour and decisionmaking, human systems will often respond to a new law or change in their environment in novel and unforeseen ways. The result can be emergent systems of governance or emergent behavioural patterns to counteract a new law, for example. This type of emergence can often be explained in retrospect, but is rarely predictable beforehand due to inaccurate or incomplete models of the system.

The dynamical property of *adaptation* in complexity science is used in the loose sense of the word to refer to the process of a system adjusting its structure or configuration in response to external forces. Similar to self-organization, adaptation can contribute to the maintenance of system function or to the creation of new functions. Adaptation, however, is driven by external stimuli, such as a change in the magnitude of flows of energy or matter across the system boundary which might be caused by a disturbance or changing external environmental conditions. Heterogeneity of system components, redundancy (in terms of function and pathways of material and energetic flow), as well as a flexible organizational structure are key structural properties that contribute to a system's adaptive capacity. Adaptation is connected to "rule discovery": interacting entities (also termed "agents" in this context) learn from each other and from environmental stimuli and thereby replace behaviours which are no longer effective with new behaviours better adapted to their experiences (Heinimann, 2010). Not all complex systems can adapt; the term complex adaptive system, originally coined by Holland (Holland, 1992; 1995) is often used to refer to the special class of complex systems having this ability.

Following Holland (1992; 1995), a system is a complex adaptive system (CAS) if the properties of hierarchy (or aggregation), diversity, openness, and nonlinearity (which causes emergence, self-organisation, memory effects and uncertainty) as well as the following three mechanisms can be found: 1) "tagging", implying that agents (entities) in the system come with tags allowing them to identify and categorize each other (in the animal kingdom, this is akin to physical or other features that allow individuals to recognise members of their species and to differentiate members of their species from other species); 2) "internal models", implying that agents in a CAS use internal models to anticipate their environment (these models may serve to explore the outcome of alternative actions or to plan future actions in the context of present and forecast environmental conditions); 3) "building blocks", or the idea that the system has simple reusable components from which it can construct higher-level aggregates (this mechanism is fundamental to the property of aggregation, and allows different types of hierarchical organizations to be generated in the system in response to internal and external stimuli). Holland proposed that these three mechanisms are necessary and sufficient to permit a system to adapt and devised a simple model to demonstrate this proposition (Holland, 1995). Following this definition, forests, and most living systems, or systems of living systems, can be considered as complex adaptive systems.

Two other properties used frequently in the context of adaptation are *resilience* and robustness. Formally, robustness has been defined in the engineering literature as "the degree to which a system operates correctly in the presence of invalid (exceptional) inputs or stressful environmental conditions" [IEEE Std 610.12.1990]. Resilience, in the engineering literature, refers to the time it takes for a system to return to its original state after a perturbation. Both concepts have recently been appropriated in the ecology literature and although they are difficult to quantify for ecosystems, they have proved to be popular metaphors. Holling, for example, defined ecological resilience as the magnitude of disturbance that can be absorbed before the system changes its structure to such an extent that system function or behaviour is affected (Holling, 1996; Gunderson and Holling, 2002). Both robustness and ecological resilience focus on the maintenance of system function. Much of the literature on ecological resilience stresses the importance of maintaining the adaptive capacity of a system. However, there is no obvious connection between resilience and adaptive capacity. For example, adaptation may enable a system to move away from a previous state that was maladapted to current environmental conditions and may also result in a change in system function. In the case of a poorly functioning or maladapted system, resilience is not necessarily a desirable property. Many social institutions are highly resilient (sensy Holling) but may not necessarily be desirable from a point of view of human rights or sustainable development (Tainter, 2006). Likewise, many degraded ecosystems, particularly in arid regions, are perhaps poorly functional but highly resilient (and hence difficult to restore to a more desirable previous state).

Dynamics of complex systems

Heterogeneity, diversity, interactions and feedbacks across scales, and adaptation in complex systems all give rise to intriguing dynamics that can generate unexpected, emergent system behaviours. A typical implication is that the response of a complex system to external stimuli is not directly proportional to the magnitude of the stimuli; the system behaves in a non-linear way. This has important repercussions for forest ecosystems: the response of a forest to a disturbance is not necessarily proportional to the magnitude of the disturbance. For example, many studies have shown that most species can be maintained in a forested landscape that is subject to harvesting (Reich et al., 2001), but that biodiversity drops dramatically if a critical degree of harvest is exceeded, thus exhibiting a non-linear relationship between total species richness and area harvested, in this case in the form of a *threshold* nonlinearity (Fahrig, 2003).

If a system exhibits a linear response to external stimuli, it is usually not considered complex. A deterministic linear system would represent the prototype of a simple system. In this sense, complexity science is a branch of the theory of nonlinear systems and dynamics. Here we briefly describe some of the types of

dynamics that can occur within a non-linear system and which may be important for understanding and managing forest ecosystems.

Like the forest in which biodiversity loss is dramatic after a critical degree of harvest, many non-linear systems have thresholds, beyond which the system state is significantly different from a previous state. Such thresholds have also been called "tipping points" or "critical transitions" (Gladwell, 2000; Scheffer, et al., 2001) and are relatively common in natural systems. As one or more environmental variables change, the system may show no (or little) apparent response and then suddenly flip to an alternative stable state. Classic examples include: the switch from a coral dominated reef to an algae dominated one as a result of overfishing that removes herbivorous fish that would normally control the algae, or the switch from clear to turbid water in lakes (eutrophication) due to high phosphorus inputs (Scheffer et al., 2001; Hughes et al., 2005). Current research suggests that the global biosphere may also be close to a tipping point and certainly a nonlinear response of the Earth system to human activity can be expected (Barnosky et al., 2012; Turner, 2012).

Forests, like all dynamic systems, are in a state of continual change due to species turnover, disturbances, environmental variability, and internal factors such as interspecies interactions. While some forests may appear, on the short term, to be in states of dynamic equilibrium (e.g., a mature forest in a relatively unchanging climax state), at the system level, a forest is in constant evolution. At short time scales, decomposition, species turnover and changes in the properties of individuals cause internal fluctuations that may lead to the emergence of larger scale patterns. Over the long-term, often at scales longer than human life spans and certainly longer than the duration of most monitoring efforts, a forest's species composition may be shifting, or a forest understory may be becoming denser or sparser, sometimes due to changing environmental conditions or disturbance regimes (e.g., an increase or decrease in the frequency of fire). In addition, changing environmental (boundary) conditions also change the range of possible states that a forest may attain. The lesson to be retained here is that a forest, like most complex systems, is in a state of constant flux at both short and long time scales and management programs should explicitly acknowledge this change.

Challenges in dealing with complex systems

Working at multiple scales

One of the main challenges faced when working with complex systems is finding new multi-scale methods of studying and analyzing the system. As mentioned above, the collective dynamics of the interacting elements within a complex system gives rise to a structure and dynamics that are difficult to analyze or describe using only one scale or resolution. The behaviour of a human, for example, cannot be fully interpreted without considering several organizational and temporal scales: at the organizational level, one must minimally study the individual, the family unit and socio-cultural context within which the individual lives, as well as certain lower levels (e.g., the level of organs, cells and perhaps even genes) in order to understand why an individual acts in a certain way. One must also study the individual within a historical context, considering the effects of present, past and potential future events on the individual's behaviour.

Similarly, in ecology, where understanding population and community dynamics are key issues, a multi-scale and multi-level approach from the individual organisms to the landscape scale is often required. For example, in the Canadian Boreal forest, the woodland caribou (*Rangifer tarandus*) population is controlled from the top-down by its primary predator, the wolf (*Canis lupis*). Understanding caribou population dynamics thus requires an understanding not only of intrinsic caribou recruitment and mortality rates but also of its interactions with its predators. Numerous studies have shown that these interactions are mediated by landscape structure, which modifies the movement patterns of individuals of these species (James and Stuart-Smith, 2000; Wittmer et al., 2007). Changes in the landscape structure as the result of human activities such as logging and oil extraction can thus increase caribou mortality by increasing its encounters with predators. This is one of many examples where predicting a species' population dynamics requires an understanding of landscape structure, population-level attributes and individual behaviour.

Working at multiple scales requires the development of new conceptual models that go beyond traditional reductionist approaches that treat only one scale at a time. New methods in bottom-up modelling (e.g., individual-based models, agent-based models, cellular automata) provide one way of exploring cross-scale interactions within complex systems such as ecosystems (Parrott et al., in press). Such models represent a system at a lower level in the organizational hierarchy (for example, at the scale of the interacting components in Figure 1) and, as in the real world, let higher-level structures emerge (Judson, 1994; Levin, 1999; Grimm and Railsback, 2005; Parrott, 2011). New methods in the analysis of complex networks may also permit the representation of interactions across multiple scales and subsystems (see Boccalettia et al. (2006) for a review of complex networks).

Forecasting and prediction

The non-linear nature of complex systems, and their tendency to self-organize and adapt, makes their behaviour impossible to predict precisely. Two pertinent examples mentioned above are the weather and forest fires. It is thus more realistic to use models to explore the range of probable future states of a complex system rather than attempting precise predictions. Recent research promotes the use of *scenario building* to explore an envelope of possible futures for a given system that becomes wider as we look farther into the future (Lempert, 2002; Parrott and Meyer, in press) (this approach is often called ensemble prediction and is already common practice in daily weather forecasting as well as long-term climate simulations).

What is complexity?

Complexity is a system attribute and much research in the science of complexity has been devoted to developing measures of complexity. In the field of ecology, such measures show promise as ecological indicators that can be used as holistic descriptions of the state of an ecosystem and may be used to detect change (Parrott, 2010).

Although there will never be a "complexometer" for natural systems, complexity should be seen as a variable to which we can assign a number (or set of numbers). A system may thus be ranked on a scale of complexity that ranges between the hypothetical limits of zero and a maximal value. In taking this approach, one is able to describe the relative degree of complexity of a given system, and may then proceed with comparing the system to other systems where possible. Many researchers have proposed a positive correlation between biodiversity and habitat complexity, or between complexity and ecological integrity. Developing suitable measures of complexity for ecosystems can serve to test such hypotheses, and has been done in a number of studies for terrestrial and marine ecosystems (Heck Jr and Wetstone, 1977; August, 1983; Roberts and Ormond, 1987; Hauhs and Lange, 2004; Lassau et al., 2005; Hauhs and Lange, 2008; Proulx and Parrott, 2009; Mellin et al., 2012).

While there is no universally accepted measure of complexity, most scientists would agree that complexity is related to the length of a description of a system (Gell-Mann and Lloyd, 1996). In a very simple case, this may correspond to the number of pictographs, signs or other symbols needed to describe the system.

A vast amount of literature exists on the topic of measuring complexity (Grassberger, 1986; Crutchfield, 1994; Kurths and Witt, 1994; Wackerbauer et al., 1994; Gell-Mann and Lloyd, 1996; Martin et al., 2006). Many measures attempt to capture one or more aspects of the system's dynamics, the system's structure and configuration, and the diversity of its components. A highly complex system will display high complexity in its spatial and temporal dynamics, high component diversity, and a network structure that is neither random nor perfectly ordered.

In this sense, a system displaying perfectly periodic dynamics in space and time is thus a relatively simple system, since its dynamics can be easily described using a sinusoidal function. Likewise, a system displaying truly random (i.e., uniformly distributed white noise) spatiotemporal dynamics is also a simple system since this behaviour can be modelled using a probability distribution, usually involving only a few parameters. It is important to note that the interest is not in the details of one actual realization of a system's dynamics (a specific sequence of perfectly random numbers in this case) but in the stochastic properties of the process generating it. White noise is very easy to describe in this sense. The truly complex systems are those for which no single function exists to describe or model their dynamics. These are the systems that have spatiotemporal signals displaying patterns at all scales and thus for which a description at a given spatial or temporal resolution does not suffice. The same can be said for the system structure. The most complex systems have signals that natural scientists know well: signals containing some apparent organization or repeatable patterns at certain resolutions or characteristic scales, overlain by considerable "noise" or variability. One of the challenges in the study of complex systems is, therefore, to find ways of describing or quantifying this type of pattern.

In general, the application of complexity measures requires fixing a set of parameters and also a coarse-graining of the data or system description. This refers in the simplest case to the spatiotemporal resolution of the data. Some of the measures work on discrete symbol sequences (Wackerbauer et al., 1994), others on the order patterns - the rank of the values from smallest to largest (Rosso et al., 2007). It is crucial that in comparison of data from different systems, all these settings have to be identical; complexity measures are dependent on the level of detail resolved with the data investigated. Parrott (2010) gives an overview of some approaches that have been applied to ecological data to measure and compare the degree of complexity of different ecosystems.

Managing for complexity

Advances in complexity science make it clear *that most natural systems, including forest ecosystems, are complex systems.* But what are the broader implications of complexity science for forest management? Many of the chapters in this book attempt to respond to this question through case studies and by providing examples of complex properties in different types of forest ecosystems.

As discussed above, the manifestation and quantification of complexity in forests depends on the scale at which one works (i.e., plot, stand, landscape) and whether spatial or temporal aspects of the system are considered, and its implications for management are highly dependent on management objectives. For example, at the plot or stand scale, if the objective is maximising commercial wood production, then a simple structure (e.g., low species diversity) and a predictable temporal signal (e.g., growth) are desirable properties of the system and in this case one may seek to reduce the complexity of the forest through management actions. As is typically the case for plantation forestry, an intensive management system with frequent interventions is used to maintain the forest in a relatively simple state of complexity. The manager thus seeks to reduce uncertainty, limit diversity, inhibit self-organization and emergence, etc. In other cases, if management objectives are multiple, combining conservation, ecotourism and forest harvesting for example, then a more complex forest may better respond to these different requirements. The same is probably true for management at the landscape scale. At this scale, heterogeneity and diversity as well as a more complex stand structure are probably desirable attributes, to reduce risk by buffering against disturbances and long-term environmental change. The forester is thus wise to maintain the complexity of the forest at the landscape level as high as possible to sustain the adaptive capacity of the landscape to respond to a broad range of possible future events.

Most management interventions in the forest probably reduce its complexity by simplifying its structure and dynamics. Many natural disturbances may also reduce forest complexity at certain spatial scales and for some components of the system by creating even-aged populations of trees, for example. We hypothesize that if left alone (unmanaged), a forest will on average increase its complexity; however, given a chosen quantitative complexity indicator, it will turn out that there are limits to the complexity obtainable depending on the environmental conditions in which the forest evolves (Parrott, 2010). We hypothesize further that a more complex forest is more robust, more adaptive, and better able to provide multiple ecosystem services in the long-term (sustainability) than a less complex forest. With increasing demands to manage the forest to meet multiple ecological, societal and economic objectives and with increasing uncertainty associated with global change, maintaining high system complexity may thus become a management objective.

Given the inherent uncertainty of forest systems, models should be developed to explore possible forest futures, given different human interventions or environmental change scenarios. Such models could be used to explore how the shape and size of the envelope of possible behaviour can be modified by our actions and to inform decision-making rather than provide definitive answers about the future of the forest. The envelope itself is as well plagued with uncertainties and should be conceptualized as a blurred area rather than a sharp boundary. Nevertheless, there are techniques from risk analysis and control theory to tackle and quantify this uncertainty (Heinimann, 2010). Managers should use models as decision support tools with which they may explore the impact of alternative management scenarios on the desired management objectives (Seely et al., 2004).

Conclusions

It is increasingly becoming accepted that forests are complex adaptive systems. Like all complex systems, they are in a state of continual change, renewal and self-organization. This is added to an increasing demand in many parts of the world to manage the forest for multiple objectives. Managers thus find themselves dealing with complex systems and complicated, multi-faceted management objectives. While it does not suggest solutions, complexity science provides a theoretical framework and numerous quantitative methods that may be useful to today's foresters and managers to navigate through these uncertain times. We hope that the work presented in this volume as well as ongoing research emphasizing interactions and connectivity across scales in forested landscapes, coupled with increased monitoring efforts, may all contribute to bringing complexity science to the forefront in forestry. By all means, ecosystem management will remain a moving target, an arena where persistent learning, rule discovery and discussions between practitioners and scholars should take place. In a time when forests are subject to rapid environmental change and increasing levels of disturbance, management that maintains system complexity may be the best way to ensure the perpetuation of the world's forests.

Acknowledgments

The authors thank Dr. Élise Filotas and the three editors of the book for providing excellent comments and feedback on previous versions of this manuscript.

Bibliography

- August, P. V. (1983) 'The role of habitat complexity and heterogeneity in structuring tropical mammal communities', *Ecology*, vol 64, no 6, pp1495-1507
- Barnosky, A. D., Hadly, E. A., Bascompte, J., Berlow, E. L., Brown, J. H., Fortelius, M., Getz, W. M., Harte, J., Hastings, A., Marquet, P. A., Martinez, N. D., Mooers, A., Roopnarine, P., Vermeij, G., Williams, J. W., Gillespie, R., Kitzes, J., Marshall, C., Matzke, N., Mindell, D. P., Revilla, E. and Smith, A. B. (2012) 'Approaching a state shift in Earth's biosphere', *Nature*, vol 486, no 7401, pp52-58.
- Bertalanffy, L. V. (1968) *General System theory: Foundations, Development, Applications*, Braziller, New York.
- Bettencourt, L. M. A., Lobo, J., Helbing, D., Kühnert, C. and West, G. B. (2007) 'Growth, innovation, scaling, and the pace of life in cities', *Proceedings of the National Academy of Sciences*, vol 104, pp7301-7306.
- Boccalettia, S., Latorab, V., Morenod, Y., Chavez, M., and Hwanga, D.-U. (2006) 'Complex networks: Structure and dynamics', *Physics Reports*, vol 424, pp175-308.
- Brown, J. H., Gupta, V. K., Li, B.-L., Milne, B. T., Restrepo, C. and West, G. B. (2002) 'The fractal nature of nature: power laws, ecological complexity and biodiversity', *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences,* vol 357, pp619-626.
- Cho, A. (2009) 'Ourselves and our interactions: The ultimate physics problem?', *Science,* vol 325, pp406-408.
- Crutchfield, J. P. (1994) 'Observing Complexity and the Complexity of Observation', in H. A. Atmanspacher and G. J. Dalenoort (eds) *Inside versus Outside*, Springer, Berlin.
- Crutchfield, J. P., Farmer, J. D., Packard, N. H. and Shaw, R. S. (1986) 'Chaos', *Scientific American*, vol 255, pp46-57.
- Enquist, B. J., Economo, E. P., Huxman, T. E., Allen, A. P., Ignace, D. D. and Gillooly, J. F. (2003) 'Scaling metabolism from organisms to ecosystems', *Nature* vol 423, no 6940, pp639-642.
- Fahrig, L. (2003) 'Effects of habitat fragmentation on biodiversity', *Annual Review* of Ecology, Evolution, and Systematics, vol 34, pp487-515.
- Gell-Mann, M. and Lloyd, S. (1996) 'Information measures, effective complexity and total information', *Complexity*, vol 2, pp44-52.

- Gladwell, M. (2000) The Tipping Point How Little Things Can Make A Big Difference, Little, Brown and Company, Boston.
- Grassberger, P. (1986) 'Toward a Quantitative Theory of Self-Generated Complexity', *International Journal of Theoretical Physics* vol 25, pp907-938.
- Grimm, V. and Railsback, S. (2005) *Individual-based modeling and ecology*, Princeton University Press, New York.
- Gunderson, L. H. and Holling, C. (2002) *Panarchy: understanding transformations in human and natural systems*, Island Press, Washington, DC.
- Hauhs, M. and Lange, H. (2004) 'Modeling the complexity of environmental and biological systems - Lessons of ecological modeling', in P. Klonowski (ed) *Nonlinear Dynamics in Environmental and Biological Sciences*, PABST Science Publisher, Lengerich.
- Hauhs, M. and Lange, H. (2008) 'Classification of Runoff in Headwater Catchments: A Physical Problem?', *Geography Compass* vol 2, pp235-254.
- Heck Jr, K. L. and Wetstone, G. S. (1977) 'Habitat complexity and invertebrate species richness and abundance in tropical seagrass meadows', *Journal of Biogeography*, vol 4, no 2, pp135-142.
- Heinimann, H. R. (2010) 'A concept in adaptive ecosystem management-An engineering perspective', *Forest Ecology and Management*, vol 259, pp848-856.
- Holland, J. (1992) Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications in Biology, MIT Press, Cambridge, Massachusetts.
- Holland, J. (1995) *Hidden Order: How Adaptation Builds Complexity*, Helix Books, Reading Massachusetts.
- Holling, C. S. (1996). 'Engineering resilience versus ecological resilience', in P. Schulze (ed) *Engineering within ecological constraints*, National Academy, Washington.
- Hughes, T. P., Bellwood, D. R., Folke, C., Steneck, R. S. and Wilson, J. (2005) 'New paradigms for supporting the resilience of marine ecosystems', *Trends in Ecology & Evolution,* vol 20, pp380-386.
- James, A. R. C. and Stuart-Smith, A. K. (2000) 'Distribution of caribou and wolves in relation to linear corridors', *The Journal of Wildlife Management*, vol 64, pp154-159.

- Judson, O. (1994) 'The rise of the individual-based model in ecology', *Trends in Ecology and Evolution*, vol 9, pp9-14.
- Kurths, J. and Witt, A. (1994) 'On Complexity Measures', *World Futures*, vol 42, pp177 192.
- Lassau, S. A., Hochuli, D. F., Cassis, G. and Reid, C. A. M. (2005) 'Effects of habitat complexity on forest beetle diversity: do functional groups respond consistently?', *Diversity and Distributions*, vol 11, pp73-82.
- Lempert, R. (2002) 'A new decision sciences for complex systems', *Proceedings* of the National Academy of Sciences, vol 99, pp7309-7313.
- Levin, S. (1999) Fragile Dominion, Perseus Publishing, Cambridge.
- Lewin, R. (1999) *Complexity: Life at the edge of chaos*, University of Chicago Press, Chicago.
- Martin, M. T., Plastino, A. and Rosso, O. A. (2006) 'Generalized statistical complexity measures: Geometrical and analytical properties', *Physica A: Statistical Mechanics and its Applications* vol 369, pp439-462.
- Mellin, C., Parrott, L., Andréfouët, S., Bradshaw, C., MacNeil, M. A. and Caley, M. J. (2012) 'Multi-scale marine biodiversity patterns inferred efficiently from habitat image processing', *Ecological Applications*, vol 22, no 3, pp792-803.
- Mitchell, M. (2009) Complexity: A guided tour, Oxford University Press, USA.
- Parrott, L. (2010) 'Measuring Ecological Complexity', *Ecological Indicators,* vol 10, no 6, pp1069-1076.
- Parrott, L. (2011) 'Hybrid modelling of complex ecological systems for decision support: Recent successes and future perspectives', *Ecological Informatics*, vol 6, no 1, pp44-49.
- Parrott, L. and Meyer, W. 'Future landscapes: Managing within complexity', *Frontiers in Ecology and the Environment*, in press.
- Parrott, L., Chion, C., Gonzales, R. and Latombe, G. 'Agents, Individuals and Networks: Modeling Methods to Inform Natural Resource Management in Regional Landscapes', *Ecology & Society*, in press.
- Puettmann, K. J., Coates, K. D. and Messier, C. (2009) *A Critique of Silviculture: Managing for complexity*, Island Press, Washington, DC.
- Proulx, R. and Parrott, L. (2009) 'Structural complexity in digital images as an ecological indicator for monitoring forest dynamics across scale, space and time', *Ecological Indicators*, vol 9, no 6, pp1248-1256.

- Reich, P. B., Bakken, P., Carlson, D., Frelich, L. E., Friedman, S. K. and Grigal, D. F., (2001) 'Influence of logging, fire, and forest type on biodiversity and productivity in southern Boreal forests', *Ecology*, vol 82 no 10, pp2731-2748.
- Roberts, C. and Ormond, R. (1987) 'Habitat complexity and coral reef fish diversity and abundance on Red Sea fringing reefs', *Marine Ecology Progress Series, Oldendorf*, vol 41, no 1, pp1-8.
- Rosso, O. A., Larrondo, H. A., Martin, M. T., Plastino, A. and Fuentes, M. A. (2007) 'Distinguishing noise from chaos', Physical Review Letters vol 99, no 15, pp154102-154105.
- Rosso, O. A., Carpi, L. C., Saco, P. M., Gómez Ravetti, M., Plastino, A. and Larrondo, H. A. (2012) 'Causality and the entropy-complexity plane: Robustness and missing ordinal patterns', *Physica A: Statistical Mechanics and its Applications*, vol 391, no 1-2, pp42-55.
- Schroeder, M. R. (1991) *Fractals, Chaos, Power Laws Minutes from an Infinite Paradise*, W.H. Freeman, New York.
- Scheffer, M., Carpenter, S., Foley, J. A., Folke, C. and Walker, B. (2001) 'Catastrophic shifts in ecosystems', Nature, vol 413, pp591-596.
- Seely, B., Nelson, J., Wells, R., Peter, B., Meitner, M., Anderson, A., Harshaw, H., Sheppard, S., Bunnell, F. and Kimmins, H. (2004) 'The application of a hierarchical, decision-support system to evaluate multi-objective forest management strategies: a case study in northeastern British Columbia, Canada', *Forest Ecology and Management*, vol 199, pp283-305.
- Shinbrot, T. and Muzzio, F. J. (2001) 'Noise to order', *Nature*, vol 410, pp251-258.
- Solé, R. and Bascompte, J. (1998) 'Emergent phenomena in spatially extended model systems', in J. Bascompte and R. Solé (eds) *Modeling spatiotemporal dynamics in ecology*, Springer-Verlag, New York.
- Strogatz, S. H. (2003) *Sync: The emerging science of spontaneous order*, Hyperion, New York.
- Tainter, J. A. (2006) 'Social complexity and sustainability', *Ecological Complexity*, vol 3, pp91-103.
- Turner, G. (2012) 'On the Cusp of Global Collapse? Updated Comparison of The Limits to Growth with Historical Data', *GAIA*, vol 21, no 2, pp116-124.
- Wackerbauer, R., Witt, A., Atmanspacher, H., Kurths, J. and Scheingraber, H. (1994) 'A Comparative Classification of Complexity Measures', *Chaos, Solitons & Fractals*, vol 4, no 1, pp133-173.

Waldrop, M. M. (1992) Complexity, Touchstone, New York.

- West, B. J. and Shlesinger, M. (1990) 'The noise in natural phenomena', *American Scientist*, vol 78, no 1, pp40-45.
- West, G. B. and Brown, H. J. (2004) 'Life's Universal Scaling Laws', Physics Today, vol 57, no 9, pp36-42.
- Wiener, N. (1948) *Cybernetics or Control and Communication in the Animal and the Machine*, John Wiley & Sons, New York.
- Wittmer, H. U., McLellan, B. N., Serrouya, R. and Apps, C. D. (2007) 'Changes in landscape composition influence the decline of a threatened woodland caribou population', *Journal of Animal Ecology*, vol 76, no 3, pp568-579.