# Network theory in the assessment of the sustainability of social-ecological systems

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## 1. Introduction

Due to increasing pressure on the Earth's ecosystems by human activities, the sustainable management of natural resources is an important focus of concern for scientists and local populations in most parts of the world today. Sustainable resource management has been an important research subject for a long time (i.e. indices like "maximum sustainable yield" in fisheries have been studied actively since the 1930s). However, most studies have been specific to particular aspects of the system, missing important connections within these complex systems (Levin 2008). In order to tackle sustainability questions in a more comprehensive way, other conceptual frameworks, acknowledging the interconnectedness of humans and their environment, have been developed more recently. Social-Ecological Systems (SESs) (Becker n.d.; Ostrom 2009) or Coupled Human and Natural Systems (CHAN) (Liu et al. 2007; Stevenson 2010) serve as a starting point for these frameworks (Ostrom 2009). They effectively step back from strictly reductionist approaches and embrace holistic, complex approaches to better describe the dynamics of human communities interacting with their environment (Waltner-Toews 2008).

Many approaches, either qualitative or quantitative, have been used to assess SESs sustainability (Bell & Morse 2008). Recently, a structural approach based on describing the interactions of human and natural elements has been proposed (Janssen et al. 2006; Cumming et al. 2010); as SESs usually include discrete, heterogeneous elements involved in local interactions, they can be effectively represented as networks. In these networks, human and biogeophysical elements of interest are connected to each other through a selection of links to form a structure whose properties can then be analysed quantitatively. An increasing number of scientists from many fields are now focusing their efforts toward assessing SESs' sustainability in this manner, using the broad set of metrics from network theory.

In this paper, we review general methods used to study SESs from a network perspective. We start by defining concepts such as SES, social-ecological networks (SENs), and resilience within the context of social-ecological sustainability. We then present some of the most popular methods used in studying the resilience of social-ecological systems within a network analysis framework. Finally, we underline some of the important limitations and challenges of this approach.

## 2. Resilience in the context of SEN

### 2.1. Definitions

#### What is a SES?

A SES is a system composed of human elements and natural elements interacting with each other in different ways through temporal, spatial and organizational scales. A SES often describes a setting where a human community is in interaction with its natural environment through the exploitation of one or several natural resources. It can therefore focus on a variety of settings, such as traditional or industrial fisheries, wood extraction and forest management, mining, agriculture and water management, parks and tourism, etc. In any case, it is the interactions among and between the human and ecological elements that make it a system. These interactions may be relative to money or information exchange between human actors, to energy transfer between species belonging to the same food web, to resource extraction from the natural world to human subsystems, etc. Real-world SESs are typically complex adaptive systems (CAS): they are dynamic (in that the amounts of matter, information or energy flowing through social and ecological subsystems varies in time), self-organizing and adaptive to the system's environment. As a consequence, their dynamics are non-linear and difficult to predict.

**What is a network?**

Focusing on local interactions, networks are simplified representations of relationships among discrete elements. They are composed of two simple elements: nodes (or vertices) representing discrete entities, and edges (or ties, links) representing the interactions between the nodes. These nodes can have a set of characteristics distinguishing one from another; they can have a weight in the network to reflect their relative importance. Edges can also be weighted to indicate the relative strength of the relationship they represent, and be directional if the relationships are not equal in both directions. Networks can be composed of a single, or multiple, kinds of nodes. They can also display only one kind of relationship or on the contrary be multiplexed and allow for the representation of different linkages.

Network analysis is based on more than a hundred years of research and is rich with many powerful and versatile tools, each crafted to describe and quantify a particular aspect of a network (Scott 2000). Networks were first studied in the social sciences, where researchers were trying, among other things, to understand the structure of communities emerging from local relationships between individuals (Borgatti et al. 2009) or to study asocial structures related to resource management (Crona 2006; Ernstson et al. 2010). The same tools have, however, also been used for decades in the natural sciences to explore, to cite only two examples, food webs (Tylianakis et al. 2007; Berlow et al. 2009) and habitat fragmentation (Bodin et al. 2006; Baranyi et al. 2011) (for an overview of the last ten years in network research, please refer to (Barabasi 2009)). Within the natural and social sciences, applications in geography are also numerous (Barthélémy 2011; Cumming 2011). However, if network analysis has been widely used for both social and ecological systems, it has only recently been applied to social-ecological systems (Cumming et al. 2010).

## 2.2. SESs modelled as SENs

It is now commonly accepted that network theory may contribute a wide range of tools and concepts to the study of sustainability in SESs (Bodin 2006; Janssen et al. 2006; Cumming et al. 2010). Local interactions are central to the emergence of global patterns and properties of robust complex and adaptive systems (Levin 1998). Therefore, network analysis, which focuses explicitly on the structure of interactions between the system's components, can provide a valuable angle to understand and better assess the performance of the system (Janssen et al. 2006; Webb & Bodin 2008), help identify structures favouring sustainable natural resource management (Bodin 2006) and provide a framework to compare SESs' structures despite the large differences between systems (Janssen et al. 2006).

To represent a SES as a network, human or ecological components of the system (such as resource users, regulating institutions, fragmented land patches, animal species, etc.) might become nodes, and edges may explicitly show selected linkage between these nodes (energy transfer between species, information and knowledge sharing between human components, etc.). This approach raises a lot of questions, conceptual concerns and challenges, as discussed below.

**Network simplification and boundary setting**

A social-ecological network (SEN) is a representation of a chosen SES laid out in such a manner that it can be useful to explore a set of questions regarding a system. It is a model that uses concepts from mathematical graph theory to effectively map the interactions between a selected set of a SES's most important elements. As for any model, a SEN is a simplification of reality. It is nonetheless a simplification that must be meaningful to the researchers' questions of interest.

The choices regarding the boundaries of the network (i.e., how far to go in spreading the network in its periphery? (Reed et al. 2009)), the inclusion or exclusion of potential nodes and edges, the level of aggregation of the elements, the temporal and spatial scales to consider, etc. must therefore be clearly defined. As it is practically impossible to include all elements directly or indirectly connected to each other in a SES, nodes need to be carefully selected among a potentially large number of candidates. The selection can be partially, and for the human sub-network only, motivated by a stakeholder analysis. This kind of analysis can help clarify the list of human actors involved in a SES, evaluate their power and level of interest (Prell et al. 2009), as well as help decide if actors should be implemented as individuals or aggregated as groups of common interests and power. The characteristics of the nodes also need to be simplified as to only include the elements that are the most relevant to explain the dynamic of the system. Similarly, links between nodes must be selected carefully: choosing to implement a currency of flux over another would lead to the study of a system from radically different angles. These steps are of the utmost importance as a SEN must be complete enough to be useful in helping to explore relevant scientific questions, and not too complicated as to prevent a clear explanation of results.

## 3. Network theory metrics to help assess the resilience of SENs

### 3.1. What is a resilient SEN?

SESs collapses around the world are often seen as the result of social-ecological unsustainability, or as a lack of resilience of these systems. The concept of sustainability holds many definitions, but is most often seen as "(...) the challenge of servicing current system demands without eroding the potential to meet future needs" (Walker & Salt 2006, pp.1-2). In its simplest terms, however, a part of what sustainability represents is the capacity of a system to persist in time (Costanza & Patten 1995). This last definition is very close to the one of resilience: according to Holling (1973) who, at that time, focused primarily on ecosystems alone, resilience refers to how a function persists within a system (please refer to Folke (2006) for a short review on the roots of the resilience concept). Specifically, it measures the amount of disturbance that would shift an ecological system out of its domain of stability and affect one of its functions in a significant way. In a more recent understanding of the concept, resilience is also related to a system's capacity to learn and re-organize in a changing socio-economical or environmental setting (Carpenter et al. 2001; Gunderson & Holling 2002; Carpenter 2008).

As such, the concept of resilience can be difficult to apply in empirical studies. There are, in a single SES, many possible applications of resilience depending on which of the system's functions is at stake, the potential threats to this important function, and the time scale of interest (Ludwig et al. 1997, Carpenter et al. 2001). Additionally, this concept is often difficult to translate into clear, measurable, system variables. Given these challenges, in cases where an SES can be effectively represented as a network, network analysis may provide tools to measure certain structural characteristics relevant to the system's resilience.

#### Finding a network-compatible proxy to assess SESs' resilience

If resilience is a useful concept in the study of SESs' dynamics, it cannot easily be directly measured in SENs. However, the definition of resilience proposed above highlights a series of characteristics that the network-compatible concept of "robustness" could come close to.

Robustness takes into account the "organizational architecture of the system of interest, [the] interplay between organization and dynamics, [the] relation to evolvability in the past and future, [...] [its] ability [...] to switch among multiple functionalities [...]" (Jen 2003 p.3), which relates to the capacity of a resilient system to adapt to new situations. Also, robustness is "a measure of feature persistence in systems where the perturbations to be considered are not fluctuations in external inputs or internal system parameters, but instead represent changes in system composition, system topology, or in the fundamental assumptions regarding the environment in which the system operates" (ibid p.3), which relates to the capacity of a resilient system to maintain its identity despite perturbations.

In the field of network analysis, the robustness of a network is related to its persistence in terms of maintaining its defining functions and its ability to withstand fragmentation as a number of its components are removed (Brandes & Erlebach 2005, Webb & Bodin 2008). This is close to both the definition of resilience and of system robustness.

## 3.2. Linking robustness to network theory metrics

While there is not a unique formula for measuring robustness in a SES, some important particularities of a robust system have been identified in the literature (Carpenter et al. 2001; Perrings 2006). Most particularly, Webb & Bodin (2008) provide a detailed review of some of the methods used to assess robustness in social and ecological systems through network analysis. We will, in this section, focus on a few of them, namely: diversity, redundancy, connectivity, centrality, modular structure and control of flow.

### 3.2.1. Diversity and redundancy

It is commonly admitted that a high diversity of components within a system helps build robustness (Ehrlich 1998; Norberg & Cumming 2008; Webb & Bodin 2008). Generally, the more components filling similar functions in the system, the higher are the chances that these components will have different responses to disturbance. Indeed, the probability for the system to keep functioning despite the elimination of some of its components is higher when diversity of components meets redundancy in function. This has been noted for both the ecological and social parts of SESs (Walker 1995; Carpenter et al. 2001; Scheffer et al. 2001; Folke et al. 2002a; Folke et al. 2002b; Janssen et al. 2006).

The combination of: 1) diversity of a system's components (in terms of their potential vulnerability), and 2) their redundancy (in terms of their function in the system), is closely related to the network's robustness. Diversity and redundancy can mean different things though, and to illustrate what they mean in our context, let's consider an imaginary SES where four human groups are closely related to the management of a fishery (Figure 1). Nodes 1, 2 and 4 are three different institutions interacting with each other and with node 3, which represents the fishing industry. Nodes *a, b, c, d*, and *f* represent an ecosystem in which *a* and *b* are two species of fish that are harvested by node 3. Let's assume that all these nodes (1, 2, 3, 4, *a, b, c, d, e*) are different in terms of vulnerability to the perturbation that interests us, but have different functions in the system (functions are noted $\alpha$, $\beta$, $\gamma$, $\delta$, $\varepsilon$, $\zeta$, and $\theta$). We can say that the human subsystem and the ecological subsystem are equally diverse (each node is different from the other in terms of vulnerability). Although they are not equal in terms of redundancy of functions: indeed, if the human subsystem has a rather high redundancy (nodes 1, 2, and 4 fulfil a similar function), the ecological subsystem has a very low redundancy with each species fulfilling a different function. Robustness would therefore be higher in the social subsystem than in the ecological subsystem it interacts with. Let's now assume that nodes *a* and *c* are over-harvested due to a misevaluation of (or a lack of regulation related to) the maximum sustainable yield of the fish populations, the functions $\alpha$ and $\gamma$ fulfilled by *a* and *c* cannot be replaced and the system is likely to endure severe structural damage.

These two characteristics (diverse while redundant) seem difficult to measure at the same time. The problem can be avoided by focusing alternatively on each of the two characteristics (**diversity of vulnerabilities** and **redundancy of functions**).

There are many metrics of diversity available, and each method has its advantages and disadvantages. Magurran (1988) provides an extensive review of each of these measures. In ecology, two indices are commonly employed: the Simpson index (Simpson 1949) and the Shannon index (Magurran 1988). These methods are not specifically network metrics, they are statistics mostly used to quantify diversity of species in ecosystems (i.e. biodiversity), but are applicable for any situation where the total number of components is known and where each class of components can be enumerated. This is the case for SENs built on enough empirical data, and, although more research needs to be done in order to formally understand the limitations of using such metrics in a network context, the methods may be sufficient for describing the diversity and redundancy of components in a network. Here we show how they could be used to measure the diversity of vulnerability or of functionality in a SEN.

**Simpson's diversity index**

Simpson's diversity index can be calculated with the following equation:

$$D = 1 - \sum_{i=1}^{S} p_i^2$$

Where D is Simpson's index of diversity, S is the total number of categories of components in the system, and $p_i$ is the proportion of components belonging to the $i^{th}$ category.
This index calculates the probability for two randomly picked nodes to belong to different categories. To measure the diversity of vulnerability or the functional diversity in an SEN, categories could correspond to nodes that would respond to perturbations in different ways or nodes that perform different functions in the system. A perfectly homogenous population would have a score of zero, while a perfectly heterogeneous population would have a score of one.

**Shannon's diversity index**

Shannon's index can be calculated with this equation:

$$H = -\sum_{i=1}^{S} p_i \ln p_i$$

Where H is Shannon's diversity index, S is the total number of categories (or species richness) in the system, and $p_i$ is the proportion of components that belong to the $i^{th}$ category.
This index increases in value when either the number of categories or the category evenness increases. Therefore, a lower H value means less diversity, while a higher value means more diversity (the equation as presented here is not normalized, but could easily be constrained between 0 and 1). Again, categories could be selected to group nodes according to their vulnerability to perturbation or according to their functional roles.

**Redundancy**

Redundancy can be seen as the inverse function of diversity. Measuring it would involve repeating the diversity metrics, but taking into account the **functional diversity** of the system's nodes as opposed to their **vulnerability diversity**. Functional redundancy can then be defined as the inverse of the functions described above.

### 3.2.2. Evaluating connectivity and centrality

Connectivity can be defined as the extent to which nodes are more or less connected to each other. Centrality measures how a node is, by being more connected to other nodes than average, more "central" at the local or global scale (Scott 2000). As Webb & Levin (2005) point out, a higher system complexity (which is a consequence of self-organization within a system) leads to robustness at higher levels of organization. Janssen et al. (2006) further note that scale-free networks, a structure seen in many natural and social self-organized networks, is characterized by high centrality. They also suggest that a higher connectivity increases the capacity for a flux to travel efficiently through the network.

**Connectivity**

Connectivity can have very different effects in an SEN. It is a positive characteristic as an efficient network must be able to carry its flow through many different nodes to be robust. Indeed, in a highly connected network, a perturbation that would remove edges between nodes could be quickly attenuated by the use of alternative routes (for example, in an ecological network focusing on habitat connectivity, a highly connected landscape can often improve chances for a species to survive landscape fragmentation (Baranyi et al. 2011)). On the other hand, in social networks related to resource management, an excess of connectivity can lead to a more homogenized knowledge and refrain the emergence of new ideas, hence limiting the capacity of the system to solve natural management issues (Bodin & Norberg 2005).
There are different ways to calculate connectivity. The most straightforward and intuitive one is the **density** metric, which can be seen as the degree of

"completeness" of the network, and can be calculated as the proportion of links within all the possible links of the network:

$$D = \frac{n}{N}$$

Where D is the density of the network, n is the actual number of links in the network, and N is the total number of possible links. A network where no node is connected to any other node would score zero, while a clique (a network or sub-network where every node is connected to every other node) would score one.

Another way to measure connectivity is through the **reachability** concept, which is "the extent to which all nodes in the network are accessible to each other" (Janssen et al. 2006). It can be measured through its **network diameter**, which is the number of links needed to reach the two most separated nodes of the network, and **minimum tree span**, which is the smallest tree connecting all the nodes of the network (Scott 2000).

Janssen et al. (2006) warn about an essential point related to network connectivity. If, on the one hand, a highly connected network provides a robust structure by making available a set of potential alternative routes for the flow to keep transiting despite the disturbance, it also, on the other hand, provides a structure highly adapted for a quick dispersion of pollutants, or diseases.

**Centrality**

Centrality measures the degree of connectedness of any given node of the network. It is often viewed as a position of power, or influence, within a social network when focusing on knowledge or information sharing linkage (as it can be a position of control of information, for instance) (Ernstson et al. 2008, McAllister et al. 2008, Bodin & Crona 2009; Prell et al. 2009; Reed et al. 2009; Crona 2010; Marín & Berkes 2010; Newig et al. 2010). In ecosystems, a highly central species or vegetation patch may be important in terms of robustness as well, as the removal of such a node could fragment the network (Estrada & Bodin 2008; Zetterberg 2009; Cinner et al. 2010; Baranyi et al. 2011). Centrality can be either local and calculated through metrics of **betweenness** and **degree**, which count all the adjacent connections of any node, or global and can be measured via the **closeness** measure, which computes the distance of a node to any other node. A node with a high degree of closeness will therefore be located close to many other nodes (Scott 2000).

### 3.2.3. Evaluating the modularity of the structure and the control of the flow

Webb & Levin (2005) identify a set of mechanisms characterizing robust CASs when considered more particularly through the lens of network analysis: control of flow and modular structure. These two characteristics are central to robustness in CASs because a controlled flow of matter, energy or information within the system by a limited number of nodes acting as "brokers," when combined with the structural modularity of the system (the extent to which the system is composed of more or less separated sub-networks), helps reduce the spread of a disturbance in a system while making sure that the flow is efficient.

As opposed to diversity and redundancy, which measure two characteristics related to the components of a network (without taking into account their relations to each other), the modular structure of, and the control of flow in, the network focuses on the system's structure and its capacity to absorb perturbations. According to Webb & Bodin (2008), these two criteria are essential for reducing the impact of disturbance within the system. On one hand, a highly modular network composed of completely separated modules, or clusters of nodes (Figure 2.a) would make for a more robust system: a perturbation would not spread beyond the cluster in which it happened. On the other hand, the robustness of the system also depends on its capacity to efficiently carry the flow of information, energy, or matter through the entire network. These two characteristics are opposite and, according to Webb & Bodin (2008), a balance, within the structure of the network, between a high modularity and an effective sub-group connectivity should be a characteristic of robust systems. This is, in other words, a state of intermediate modularity, where effective bridges connect groups of strongly interconnected nodes (Figures 2.b and 2.d are examples of systems with this kind of trade off).

**Modular structure**

The modular character of the structure can be measured with different network modularity metrics. Once again, there is no universal measure upon which all scientists agree, and much research is still on-going to develop fast and general algorithms. Most methods fall into two main categories called "agglomerative" and "divisive" (Scott 2000), and involve measures of **clustering** (often done through a **hierarchical clustering** procedure, or dendrogram. See (Scott 2000 p. 129), **clique**, and **blockmodeling**. For a detailed review of these methods, see (Scott 2000 p. 126-145). The goal of these metrics is to measure the degree of network partitioning. That is, to quantify to what extent a network is built up from smaller, separated subsystems.

Figure 2.a is an example of a modular structure, where two separated modules exist by themselves. It is easy to understand that if a perturbation were to happen in module A (let's assume A is the social sub-system of the SES), it would only affect this module, and leave module B intact. However, for the SES to work properly, the different subsystems must "communicate" efficiently. In robust systems, this exchange is carried through intermediary nodes that control the flow through the SES.

**Control of flow**

The control of flow helps explain how a perturbation spreads within a network, as well as how information, matter or energy transits efficiently through a network. This control of flow can be quantified by the measure of betweenness centrality, which quantifies the extent to which a given node links other nodes that would otherwise not be linked (Scott 2000). Nodes with a high level of betweenness centrality act as intermediaries within the system, and therefore hold a very important role in the network (ibid). As such, they often manifest themselves as "bridges" (node 2 in Figure 2.b) or as nodes belonging to two or more overlapping groups at the same time (nodes 1 and 2 in Figure 2.d). Betweenness centrality is particularly complicated to quantify; (Scott 2000 p. 86-89) provides a description of the methodology. Furthermore, the control of the flow must be measured according to the direction of the flow. An actor functioning as a bridge who transmits information from a group A to a group B only (while (s)he does not transmit any information back) will not act as the same kind of flow controller as an actor transmitting both ways.

While weak ties (like bridges linking modules, cliques and clusters) are, as we saw, important to the topology of a robust network, such a structure has downsides worth mentioning. According to Janssen et al. (2006), although centrality is important to control the network flow, it also builds networks where only a limited number of nodes are in charge of distributing the flux, and therefore distribute similar content to a large number of other nodes, which limits creativity. It also makes the network vulnerable to directed, selective attacks: if a few of these nodes (like node 2, or even nodes 1 and 3 in Figure 2.b) are removed, the whole structure would be separated into different modules and its function would likely be destroyed.

## 4. Discussion

**Coupling social and ecological networks**

As SENs are typically built from edges and nodes that are potentially heterogeneous, coupling the social and ecological parts of a SEN is challenged by issues related to the incompatibility of elements. We saw that according to the kind of system one wants to study, nodes can represent many different sorts of individuals, institutions, pieces of land, or animal species at the same time, while edges can represent, in the same network, a variety of exchanges of linkage. With such heterogeneity, can the concept of robustness be considered consistent from one subsystem to another? In other words, can we quantitatively study the robustness of a whole SES without falling into the trap of subsystems non-comparability, or should we couple social and ecological networks in a less integrative way? Webb & Bodin (2008) also point out that while a lot of research is being done towards understanding robustness of individually considered social and ecological networks, the robustness of SENs is still not well understood. More recently, Cumming et al. (2010) identified several kinds of couplings, including 1) analysing each sub-network independently and 2) integrating the two sub-networks as one SEN. The first approach avoids most compatibility issues by letting researchers synthesise each subnetwork's features to make conclusions about the whole system's qualities. The latter directly examines SENs structural qualities and usually avoids compatibility issues by using a common currency transiting from one node to another, no matter its social or environmental nature (ibid).

### SENs change over time

Another important characteristic of robust SESs is their capacity to change and adapt over time. This is one of the fundamental characteristics of the adaptive cycle in system resilience (Gunderson & Holling 2002). Although all the metrics presented here are static, and can provide valuable snapshot assessments of the robustness of a system at a given time, they also leave aside its important dynamic features. For instance, Janssen et al. (2006) note that an essential common feature of robust systems is to be able to activate "sleeping" nodes or edges in dire situations, which are hard to identify with static measures. They also suggest that within the adaptive cycle (Gunderson & Holling 2002), each phase (exploitation, conservation, release and reorganization) should display a different set of structural characteristics, the resilience of the system should therefore be assessed in light of the history of the structure. Research is active in this domain with valuable contributions in both theoretical and applied network analysis (Leskovec et al. 2005; Palla et al. 2007; McCulloh & Carley 2008; Bohannon 2009; Mucha et al. 2010; Szell et al. 2010).

## 5. Conclusion

In this paper, we have explored how some characteristics of social-ecological systems' sustainability could be quantitatively assessed in SESs through network analysis metrics. This has been done by first focusing on the concept of resilience, which, as Folke (2006) puts it, is an essential component "for the sustainability discourse". A proxy to resilience that would be general enough to encompass the main characteristics of SESs, while being well enough defined to be quantitatively measured was then sought. A review of the most recent literature on the subject led to the choice of robustness. From there, a series of some the most cited characteristics of "robust" SESs were defined, and some of these characteristics were linked to quantitative network analysis metrics.

Despite its advantages, a network approach to analysing the sustainability of SESs faces many challenges, including properly modelling the SES (during this process, coupling or embedding natural and social sub-networks is a particularly sensitive task) and gathering quality datasets from empirical studies, which is especially difficult for the social system (Marsden 1990).

The use of network theory as a framework to study SESs is still in the early stages of development. Despite certain limitations, which requires more theoretical work (e.g. dynamic integrated SENs), and more empirical case studies (e.g. to validate models with more certainty), research seems to be progressing rapidly on this promising path and we are optimistic that such tools may eventually provide practical insights into the management and creation of sustainable social-ecological systems.

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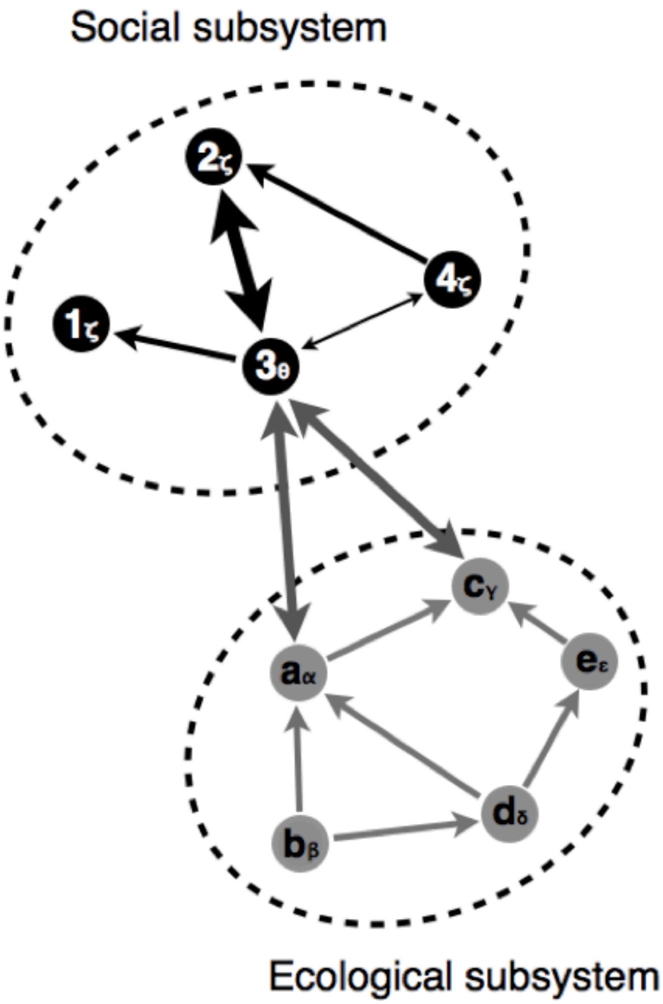


**Figure 1.** This figure shows an imaginary fishery-oriented integrated SEN where a human subsystem is in interaction with an ecological sub-system. Nodes 1, 2, 3 and 4 represent 4 human groups (3 institutions and one industry represented by node 3). Nodes a, b, c, d, and f represent an ecosystem in which a and b are two species of fish that are harvested by node 3. In this example, we assume each node has a different response to external or internal perturbations. The Greek letters represent their functions in the system, which are or are not different from one node to another.

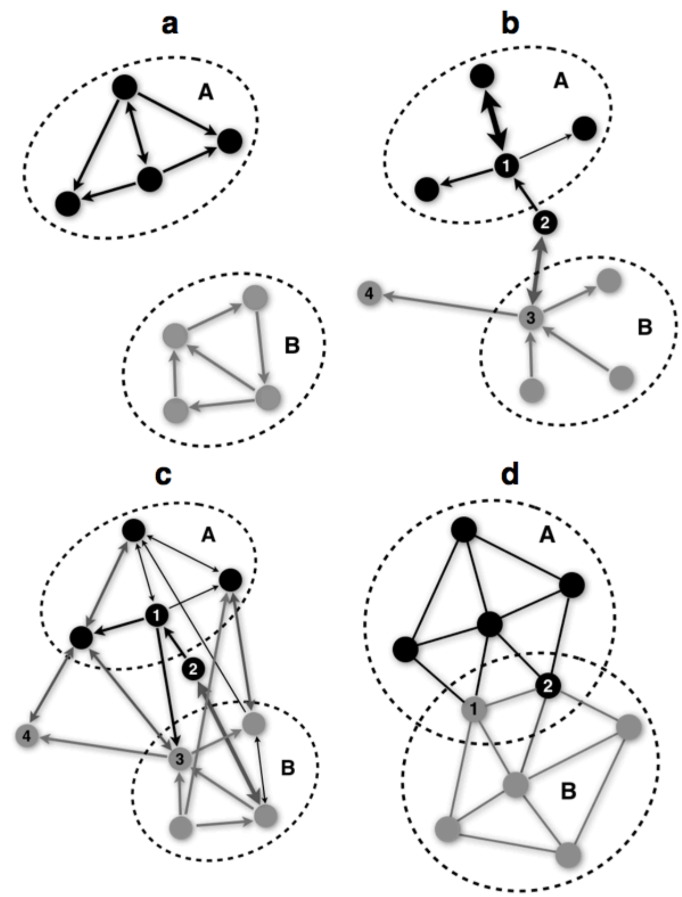


**Figure 2**. Three examples of networks. Figure 2.a, shows a modular structure consisting of distinct modules or clusters. In Figure 2.b, the two clusters are connected to each other. We can describe four different noticeable nodes in Figure 2.b: nodes 1 and 3 could be considered as "peaks" of the system (they are connected to more nodes than other nodes are), and node 2 is a "bridge" as it connects two peaks (or two clusters, like in this example). This figure also shows how edges can be represented as being uni or bi-directional and weighted according to the strength of the flux. Figure 2.c shows an example of low modularity. Finally, Figure 2.d shows an example of overlapping groups.