Université de Montréal

COGESTION DES RESSOURCES NATURELLES : UNE APPROCHE STRUCTURALE POUR QUANTIFIER LA CONTRIBUTION DES RÉSEAUX D'ACTEURS À LA RÉSILIENCE DES SYSTÈMES SOCIO-ÉCOLOGIQUES

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Thèse présentée à la Faculté des études supérieures
en vue de l'obtention du grade de *Philosophiæ Doctor* (Ph.D)
en géographie

Décembre 2015

Université de Montréal

Faculté des arts et des sciences

Cette thèse intitulée :

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RÉSUMÉ

Alors que les activités anthropiques font basculer de nombreux écosystèmes vers des régimes fonctionnels différents, la résilience des systèmes socio-écologiques devient un problème pressant. Des acteurs locaux, impliqués dans une grande diversité de groupes — allant d'initiatives locales et indépendantes à de grandes institutions formelles — peuvent agir sur ces questions en collaborant au développement, à la promotion ou à l'implantation de pratiques plus en accord avec ce que l'environnement peut supporter sur le temps long. De ces collaborations répétées émergent des réseaux complexes, et il a été montré que la topologie de ces réseaux peut améliorer la résilience des systèmes socio-écologiques (SSÉ) auxquels ils participent.

La topologie des réseaux d'acteurs favorisant la résilience de leur SSÉ est caractérisée par une combinaison de plusieurs facteurs : la structure doit être modulaire afin d'aider les différents groupes à développer et proposer des solutions à la fois plus innovantes (en réduisant l'homogénéisation du réseau), et plus proches de leurs intérêts propres ; elle doit être bien connectée et facilement synchronisable afin de faciliter les consensus, d'augmenter le capital social, ainsi que la capacité d'apprentissage ; enfin, elle doit être robuste, afin d'éviter que les deux premières caractéristiques ne souffrent du retrait volontaire ou de la mise à l'écart de certains acteurs.

Ces caractéristiques, qui sont relativement intuitives à la fois conceptuellement et dans leur application mathématique, sont souvent employées séparément pour analyser les qualités structurales de réseaux d'acteurs empiriques. Cependant, certaines sont, par nature, incompatibles entre elles. Par exemple, le degré de modularité d'un réseau ne peut pas augmenter au même rythme que la connectivité de ce réseau, et cette dernière ne peut pas être améliorée tout en améliorant sa robustesse. Cet obstacle rend difficile la création d'une mesure globale, car le niveau auquel le réseau des acteurs contribue à améliorer la résilience du SSÉ ne peut pas être la simple addition des caractéristiques citées, mais plutôt le résultat d'un compromis subtil entre celles-ci. Le travail présenté ici a pour objectifs

(1), d'explorer les compromis entre ces caractéristiques ; (2) de proposer une mesure du degré auquel un réseau empirique d'acteurs contribue à la résilience de son SSÉ ; et (3) d'analyser un réseau empirique à la lumière, entre autres, de ces qualités structurales.

Cette thèse s'articule autour d'une introduction et de quatre chapitres numérotés de 2 à 5. Le chapitre 2 est une revue de la littérature sur la résilience des SSÉ. Il identifie une série de caractéristiques structurales (ainsi que les mesures de réseaux qui leur correspondent) liées à l'amélioration de la résilience dans les SSÉ. Le chapitre 3 est une étude de cas sur la péninsule d'Eyre, une région rurale d'Australie-Méridionale où l'occupation du sol, ainsi que les changements climatiques, contribuent à l'érosion de la biodiversité. Pour cette étude de cas, des travaux de terrain ont été effectués en 2010 et 2011 durant lesquels une série d'entrevues a permis de créer une liste des acteurs de la cogestion de la biodiversité sur la péninsule. Les données collectées ont été utilisées pour le développement d'un questionnaire en ligne permettant de documenter les interactions entre ces acteurs. Ces deux étapes ont permis la reconstitution d'un réseau pondéré et dirigé de 129 acteurs individuels et 1180 relations. Le chapitre 4 décrit une méthodologie pour mesurer le degré auquel un réseau d'acteurs participe à la résilience du SSÉ dans lequel il est inclus. La méthode s'articule en deux étapes : premièrement, un algorithme d'optimisation (recuit simulé) est utilisé pour fabriquer un archétype semi-aléatoire correspondant à un compromis entre des niveaux élevés de modularité, de connectivité et de robustesse. Deuxièmement, un réseau empirique (comme celui de la péninsule d'Eyre) est comparé au réseau archétypique par le biais d'une mesure de distance structurelle. Plus la distance est courte, et plus le réseau empirique est proche de sa configuration optimale. La cinquième et dernier chapitre est une amélioration de l'algorithme de recuit simulé utilisé dans le chapitre 4. Comme il est d'usage pour ce genre d'algorithmes, le recuit simulé utilisé projetait les dimensions du problème multiobjectifs dans une seule dimension (sous la forme d'une moyenne pondérée). Si cette technique donne de très bons résultats ponctuellement, elle n'autorise la production que d'une seule solution parmi la multitude de compromis possibles entre les différents objectifs. Afin de mieux explorer ces compromis, nous proposons un algorithme de recuit simulé multiobjectifs qui, plutôt que d'optimiser une seule solution, optimise une surface multidimensionnelle de solutions.

Cette étude, qui se concentre sur la partie sociale des systèmes socio-écologiques, améliore notre compréhension des structures actorielles qui contribuent à la résilience des SSÉ. Elle montre que si certaines caractéristiques profitables à la résilience sont incompatibles (modularité et connectivité, ou — dans une moindre mesure — connectivité et robustesse), d'autres sont plus facilement conciliables (connectivité et synchronisabilité, ou — dans une moindre mesure — modularité et robustesse). Elle fournit également une méthode intuitive pour mesurer quantitativement des réseaux d'acteurs empiriques, et ouvre ainsi la voie vers, par exemple, des comparaisons d'études de cas, ou des suivis — dans le temps — de réseaux d'acteurs. De plus, cette thèse inclut une étude de cas qui fait la lumière sur l'importance de certains groupes institutionnels pour la coordination des collaborations et des échanges de connaissances entre des acteurs aux intérêts potentiellement divergents.

Mots clés:

Systèmes socio-écologiques, marginalisation de groupes d'acteurs, capacité de liaisons entre groups d'acteurs, cogestion de ressources naturelles, Eyre Peninsula, Réseaux sociaux, Réseaux d'acteurs, Résilience, Optimisation, recuit simulé multiobjectif.

ABSTRACT

As anthropic activities are slowly pushing many ecosystems towards their functional tipping points, social-ecological resilience has become a pressing concern. Local stakeholders, acting within a diversity of groups — from grassroots organizations to higher-scale institutional structures — may act on these issues and collaborate to develop, promote, and implement more sustainable practices. From these repeated collaborations emerge complex networks, the topologies of which have been shown to either enhance or hinder social-ecological systems' (SES) resilience.

The main topological characteristics of a stakeholder network enhancing SES's resilience include a combination of: a highly modular community structure, which helps groups of stakeholders develop and propose solutions both more innovative (by reducing knowledge homogeneity in the network), and close to their interest and values; high connectivity and synchronizability, in order to improve consensus building, social capital and learning capacity; and high robustness so as to prevent the first two characteristics from sharply decreasing if some stakeholders were to leave the network.

These characteristics are straight-forward both in concept and in their mathematical implementation, and have often been used separately to discuss the structural qualities of stakeholder networks in case studies. However, some of these topological features inherently contradict each other. For example, modularity is in direct conflict with connectivity, which is in conflict with a network's robustness. This issue makes the creation of a more global measure difficult, as the level to which stakeholders contribute to enhancing SES's resilience cannot simply be a summation of these features, but instead needs to be the outcome of a delicate trade-off between them. The present study aims to: (1) explore the trade-offs at work between these structural features; (2) produce a measure of how well-suited empirical stakeholder networks are to enhancing the resilience of their SES; and (3) thoroughly analyze an empirical stakeholder network in the context, among other things, of its resilience-enhancing qualities.

This dissertation is organized in four parts. The first part (Chapter 2) is a review of the literature on SES resilience. It identifies a series of structural features (as well as their corresponding network metrics) associated with resilience-enhancement in SES. The second part (Chapter 3) is a case study on the Eyre Peninsula (EP), a rural region of South Australia where land-use, as well as climate change, contribute to biodiversity erosion. For this case study, field work was conducted in 2010 and 2011, during which time a series of face-to-face interviews was conducted to populate a list of individuals — and groups of individuals — holding a stake in biodiversity conservation on the EP. The data was thereafter used to develop an online questionnaire documenting interactions between these stakeholders. The two steps led to produce a weighted, directed network of 129 stakeholders interacting through 1180 collaboration links. The third part (Chapter 4) describes a methodology to measure the level to which stakeholder networks contribute to resilience-building in SES. The method is articulated in two steps: (i) an optimization algorithm (simulated annealing — SA —) is used to craft a semi-random archetypal network which scores high in one compromise of modularity, connectivity, synchronizability, and robustness, and (ii) an empirical stakeholder networks (such as our EP network) is compared to the archetypal network through a measure of structural distance. The shorter the distance, the closer the empirical network is to its ideal configuration. The fourth and last part of the dissertation research (Chapter 5) is an improvement on the simulated annealing used in Chapter 4. As is frequently done for this kind of optimization technique, the SA used in Chapter 4 projected the four dimensions of the multi-objective problem into one (as a weighted average). While performing well, this only resolves one of the possible trade-offs between the objectives. To better explore the trade-offs at work in this optimization problem, a true multi-objective simulated annealing (MOSA) is proposed where, instead of optimizing one solution, the algorithm optimizes a multidimensional surface of solutions scoring better than the others in a least one of the objectives.

This study, which focuses on the social part of SESs, improves our understanding of the stakeholder collaboration structures which, theoretically, best contribute to resilient SESs. It shows that while some resilience-enhancing topological characteristics are in conflict (modularity vs. connectivity, and connectivity vs. robustness to a lesser extent) others can

be easily reconciled (connectivity vs. synchronizability, and, less-so, modularity vs. robustness). It also provides an intuitive method to quantitatively assess empirical stakeholder networks, which opens the way to comparisons between case studies, or monitoring of stakeholder network evolution through time. Additionally, this thesis provides a case study which highlights the importance of a key institutional group in coordinating collaborations and information exchanges among other stakeholders of potentially diverging interests and values.

Keywords:

Social-ecological systems, Stakeholder group marginalization, Bridging capacity, Natural resources co-management, Eyre Peninsula, Social networks, Stakeholder network, Resilience, Optimization, Multi-objective simulated annealing.

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APL	Average Path Length
CAS	Complex Adaptive Systems
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DENR	Department for Environment and Natural Resources
EP	Eyre Peninsula
EP NRM	Eyre Peninsula Natural Resource Management
GMI	Group Marginalization Index
LEADA	Lower Eyre Agriculture Development Association
MOSA	Multi-Objective Simulated Annealing
NDS	Non-dominated Solutions
NRM	Natural Resource Management
PIRSA	Primary Industry and Regions South Australia
RES Network	Resilience-Enhancing Stakeholder Network
RSÉ	Réseau Socio-Écologique
SA	Simulated Annealing
SARDI	South Australia Research & Development Institute
SEN	Social-Ecological Network
SES	Social-Ecological System
SND	Solutions Non Dominées
SSÉ	Système Socio-Écologiques

LISTE DES SYMBOLES

d	Distance minimum moyenne dans un réseau
d_M	Diamètre d'un réseau
$\tilde{d}$	Médiane de tous les degrés pondérés mesurés dans un réseau
f	Fréquence d'interactions en jours
λ_2	Synchronisabilité d'un réseau (connectivité algébrique)
m	Modularité d'un réseau calculée par la méthode de Louvain
N^o	Indicateur ordinal
p_i	Proportion des composants appartenant à la catégorie i
Q_n	$N^{ième}$ quartile d'un jeu de données ordonné
r	Robustesse d'un réseau
s	Scores utilisés pour les recuits simulés
σ_{st}	Nombre total de plus courts chemins entre deux nœuds notés s et t
$\sigma_{st}(v)$	Nombre de plus courts chemins sur lesquels figurent un nœud noté v
t	Seuil de modularité pour les calculs de scores composites lors de l'optimisation de réseaux par recuit simulé
T	Pour les recuits simulés, température courante de la simulation
T_M	Pour les recuits simulés, température initiale de la simulation
T_m	Pour les recuits simulés, température finale de la simulation
V, N	Ensemble des nœuds d'un réseau
w	Poids des arrêtes (dans les réseaux), ou facteur de pondération (dans les équations)

REMERCIEMENTS

On dit d'une thèse de doctorat que c'est un exercice long, difficile et solitaire. Si la longueur et la difficulté sont avérées, l'effort est moins solitaire qu'on ne le pense. Je tiens ici à exprimer mes remerciements sincères à celles et à ceux qui m'ont accompagné et soutenu durant cette thèse. À ma directrice de thèse Lael Parrott bien sûr, pour son temps, son dévouement, son aide intellectuelle et matérielle, et son enthousiasme. Sans flagornerie, j'insiste sur le fait que cette thèse n'aurait pas abouti sans elle. À mon codirecteur de thèse Wayne Meyer pour son accueil et son aide lors de mes passages dans son laboratoire à Adélaïde. À mes parents Roger et Annie Gonzalès pour leur soutien. À ma copine Catherine Mercier pour le sien. À mes amis et camarades en France et au Québec. Aux membres du laboratoire de systèmes complexes : Clément, Guillaume, Cristiane, Samuel, Caroline, Philippe et Patrick (membre *honoris causa* en quelque sorte), et aux professeurs et professeures du département de géographie pour leur disponibilité et leur amicale assistance. Aux habitants de la péninsule d'Eyre qui ont pris de leur temps pour partager avec moi leurs préoccupations. Aux membres du comité de sélection du Fond Québécois de Recherche Nature et Technologie (FQRNT) pour la bourse de doctorat qu'ils et elles ont jugé bon de m'octroyer. Je tiens également à remercier le personnel non-enseignant du département de géographie, à commencer par Claude Lefebvre. Leur travail, qui passe parfois inaperçu, est très apprécié.

Alors que je remets cette thèse aujourd'hui, j'ai également une pensée fraternelle pour ceux et celles qui, ici ou ailleurs, prennent acte de l'ampleur des catastrophes sociales et environnementales de notre époque. À ceux et à celles qui analysent les injustices en termes de systèmes, qui s'organisent solidairement et qui luttent malgré les lois iniques et la terreur politique de nos démocraties de façade. Aux actes de courage, en somme, dans le vacarme paralysant du capitalisme qui détruit tout.

Dans la nature, c'est le mutualisme qui gagne et la compétition qui perd —

André J. Fortin

1. INTRODUCTION[1]

1.1. CONTEXTE ET MOTIVATIONS DE LA THÈSE

Les paysages que nous habitons sont le résultat d'une longue coévolution socio-écologique. Les activités humaines liées à l'agriculture, au déboisement, à l'extraction de matières premières, à l'aménagement d'habitations, de chemins, de routes et de canaux, ont lentement modelé l'environnement naturel tel que nous le connaissons aujourd'hui. Toutefois, depuis le XIXe siècle et le début de la révolution industrielle, la planète serait entrée dans une époque nouvelle, l'anthropocène (Crutzen 2002), où l'Humain est désormais le principal moteur des changements environnementaux. De par cet impact continu et profond sur l'environnement, la durabilité des relations socio-écologiques est mise à mal.

Aux échelles locales ou régionales, les conséquences sont souvent sévères lorsque, cédant sous la pression, les écosystèmes changent de régime et ne fournissent plus les services matériels et culturels sur lesquels les populations locales dépendent pour leur bien-être. Afin d'anticiper et d'éviter ces effondrements écosystémiques, des efforts sont entrepris pour imaginer, négocier et développer des règles et des pratiques permettant des relations socio-écologiques plus durables. Pour de nombreux chercheurs, l'étude de la durabilité des systèmes socio-écologiques (SSÉ) doit passer par une vision complexe des relations entre humains et écosystèmes (Ostrom 2007). D'autre part, il est généralement accepté qu'une gestion durable des ressources est plus facilement applicable aux échelles locales qu'à des échelles nationales ou supranationales, car si ces dernières fournissent un cadre et imposent des contraintes législatives ou financières, c'est principalement à l'échelle du paysage que peuvent émerger — par la motivation, l'intérêt, et les connaissances spécifiques des acteurs — des règles et des pratiques d'utilisation plus durables des ressources (Ostrom, Walker et al. 1992, Bowler 2001, Bryant 2001, Olsson and Folke 2001, Doyon 2009).

[1] Ce chapitre sera bref car une revue complète de la littérature est disponible dans le chapitre 2.

Un nombre conséquent d'études de cas à travers le monde montrent par ailleurs que la durabilité des systèmes socio-écologiques (SSÉ) est souvent dépendante de la capacité de la structure du système de gouvernance à inclure divers groupes, notamment ceux qui s'avèrent parfois marginalisés, ainsi qu'à favoriser les coopérations et les échanges de connaissances entre tous (Ostrom, Walker et al. 1992, Olsson, Folke et al. 2004, Tyler 2006). C'est ainsi que des structures en cogestion, où des acteurs de différents milieux participent activement à la prise de décision, sont souvent préconisées. Entre les acteurs, au fil des collaborations qui se font et se défont, des réseaux parfois denses et aux structures complexes, émergent. Ceux-ci peuvent être étudiés de manière qualitative (Marsden, Murdoch et al. 1983, Law 1986, Law 1992, Murdoch 1994, Bryant 2001, Doyon 2009) ou quantitative par des mesures issues de la théorie des réseaux (Berkes, Hughes et al. 2006, Bodin and Crona 2009, Crona and Bodin 2010, Marín and Berkes 2010, Matouš and Todo 2015). L'approche structurale quantitative, celle qui nous intéresse ici, a notamment mené à identifier une série de caractéristiques structurales favorisant la résilience et la durabilité des SSÉ (chapitre 2).

Certaines de ces caractéristiques sont toutefois contradictoires par nature et la projection d'une topologie de coopérations idéale, incluant ces mesures favorisant la résilience et la durabilité des SSÉ, est donc particulièrement floue. À ma connaissance, aucune étude ne s'est encore penchée sur l'ampleur des contradictions entre ces mesures dans le cadre de réseaux d'acteurs, ni sur l'identification formelle des compromis structurellement possibles entre elles. Par conséquent, aucune mesure quantifiant la qualité globale des réseaux de cogestion n'a encore été proposée. C'est ce manque qui constitue la motivation de cette thèse.

1.2. OBJECTIFS ET PLAN DE LA THÈSE

L'objectif général de cette thèse est de créer une mesure quantitative du niveau auquel un réseau d'acteurs contribue, de par la topologie des collaborations en son sein, à la résilience du SSÉ dans lequel il s'inscrit. Cet objectif est rempli à travers quatre chapitres numérotés de 2 à 5. Dans le chapitre 2, nous présentons (j'utiliserai la première personne du pluriel lorsque je me référerai aux chapitres, car ils ont été rédigés en collaboration avec ma directrice Lael Parrott) une revue de la littérature à partir de laquelle nous identifions une série de mesures structurales favorisant la résilience des SSÉ.

Dans le chapitre 3, nous nous penchons sur l'analyse d'un réseau empirique mesuré spécifiquement pour cette thèse en 2012 sur la Péninsule d'Eyre en Australie-Méridionale. La fonction du réseau d'acteurs est de favoriser et promouvoir la conservation de la biodiversité sur la péninsule. Il comprend 129 individus organisés dans 24 groupes à travers 18 municipalités. Nous y analysons les liens éventuels entre géographie et topologie à l'intérieur du réseau, la capacité relative des groupes à relier d'autres groupes potentiellement marginalisés, et proposons une méthode pour projeter — à partir du réseau existant — des topologies alternatives favorisant la résilience du système.

Dans le chapitre 4, nous construisons, à l'aise d'un algorithme d'optimisation de type recuit simulé (*simulated annealing*), un réseau d'acteurs théorique dont la topologie correspond à un des compromis possibles entre quatre mesures favorisant la résilience des SSÉ. Cet archétype de réseau d'acteurs est utilisé comme étalon avec lequel d'autres réseaux, dont notre réseau empirique étudié au chapitre précédent, sont comparés. La distance structurelle entre ces réseaux et notre archétype constitue une mesure globale du niveau auquel un réseau contribue à la résilience de son SSÉ.

Dans le cinquième et dernier chapitre, nous prolongeons la recherche du chapitre précédent en améliorant significativement l'algorithme de recuit simulé. Alors que l'algorithme proposé au chapitre 4 n'optimisait qu'un des multiples compromis possibles entre les quatre mesures utilisées, nous proposons ici une méthode permettant d'explorer de manière formelle l'espace multidimensionnel des objectifs.

Tous les chapitres ont été écrits sous la forme d'articles publié, soumis ou en préparation pour une soumission prochaine. Je suis le premier auteur et ma directrice de recherche Lael Parrott est la deuxième auteure pour l'ensemble des articles. Mon codirecteur de recherche Wayne Meyer est troisième auteur pour le chapitre 3.

PARAGRAPHE D'INTRODUCTION AU CHAPITRE 2

L'article présenté dans le chapitre qui suit est une revue de la littérature sur la théorie des réseaux utilisée pour l'analyse de la résilience dans les SSÉ. Il a été réalisé en collaboration avec Lael Parrott. J'ai effectué la recherche bibliographique et rédigé le manuscrit dans son entièreté. L. Parrott a agi à titre de superviseure en m'apportant idées et recommandations tout au long du travail de recherche. Elle a également amélioré le manuscrit par ses ajouts, conseils et corrections.

Ce chapitre est publié sous forme d'article dans *Geography Compass*:

Gonzalès, R., and Parrott, L. (2012). Network Theory in the Assessment of the Sustainability of Social–Ecological Systems. Geography Compass, 6(2), 76-88.

2. NETWORK THEORY IN THE ASSESSMENT OF THE SUSTAINABILITY OF SOCIAL-ECOLOGICAL SYSTEMS

R. Gonzalès and L. Parrott

2.1. ABSTRACT

As human activities increasingly threaten the ecosystems on which they depend, one of the main questions our societies are facing is related to the resilience – seen as a necessary element of sustainability – of social–ecological systems (SES). SES are composed of many heterogeneous elements including human actors such as institutions and resource users, and natural components such as land patches or animal species. The numerous relationships between these different entities shape complex, dynamic networks of social–ecological interdependencies. Once described as networks, SES can be analyzed using a variety of network metrics, which may potentially help to better quantify and evaluate the resilience of SES to external or internal perturbations. In this paper, we provide a broad overview of the latest progress in network theory as applied to SES and discuss how network metrics may be used to assess the sustainability of an SES.

2.2. 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 (SES) (Ostrom 2007, Becker 2012) or coupled human and natural systems (Liu, Dietz et al. 2007, Stevenson 2011) serve as a starting point for these frameworks (Ostrom 2007). 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, Kay et al. 2008).

Many approaches, either qualitative or quantitative, have been used to assess SES sustainability (Bell and Morse 2008). Recently, a structural approach based on describing the interactions of human and natural elements has been proposed (Janssen, Bodin et al. 2006, Cumming, Bodin et al. 2010); as SES 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 towards assessing SES' sustainability in this manner, using the broad set of metrics from network theory.

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

2.3. RESILIENCE IN THE CONTEXT OF SEN

2.3.1. 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, or parks and tourism. 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, or to resource extraction from the natural world to human subsystems. Real-world SES are typically complex adaptive systems: they are dynamic (in that the amounts of matter, information or energy flowing through SES 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 several decades of research and is rich with many powerful and versatile tools, each crafted to describe and quantify a particular aspect of a network (Scott and Carrington 2011). 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, Mehra et al. 2009) or to study social structures related to resource management (Crona 2006, Ernstson, Barthel 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, Tscharntke et al. 2007, Berlow, Dunne et al. 2009) and habitat fragmentation (Bodin, Tengö et al. 2006, Baranyi, Saura et al. 2011) [for an overview of the last 10 years in network research, please refer to Barabási (2009)]. Within the natural and social sciences, applications in geography are also numerous (Barthélemy 2011, Cumming 2011). However, if network analysis has been widely used for both social and ecological systems, it has only recently been applied to SES (Cumming, Bodin et al. 2010).

2.3.2. SOCIAL-ECOLOGICAL SYSTEMS MODELLED AS SOCIAL-ECOLOGICAL NETWORKS

It is now commonly accepted that network theory may contribute a wide range of tools and concepts to the study of sustainability in SES (Bodin 2006, Janssen, Bodin et al. 2006, Cumming, Bodin 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, Bodin et al. 2006, Webb and Bodin 2008), help identify structures favouring sustainable natural resource management (Bodin 2006) and provide a framework to compare SES' structures despite the large differences between systems (Janssen, Bodin 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, to name but a few) might become nodes, and edges may explicitly show selected linkage between these nodes (such as energy transfer between species, information and knowledge sharing between human components). This approach raises a lot of questions, conceptual concerns and challenges, as discussed below.

Network Simplification and Boundary Setting

A 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, Graves et al. 2009), the inclusion or exclusion of potential nodes and edges, the level of aggregation of the elements, and the temporal and spatial scales to consider must therefore be clearly defined. As it is practically impossible to include all elements directly or indirectly connected to each other in an 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 an SES, evaluate their power and level of interest (Prell, Hubacek 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 an 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.

2.4. NETWORK THEORY METRICS TO HELP ASSESS THE RESILIENCE OF SEN

2.4.1. WHAT IS A RESILIENT SEN?

Social–ecological system 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 and Salt 2012).

In its simplest terms, however, a part of what sustainability represents is the capacity of a system to persist in time (Costanza and 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 reorganize in a changing socio-economical or environmental setting (Carpenter, Walker et al. 2001, Folke, Carpenter et al. 2002, Carpenter and Brock 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, Walker et al. 1997, Carpenter, Walker 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 SES' Resilience

If resilience is a useful concept in the study of SES' dynamics, it cannot easily be directly measured in SEN. 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)", 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." (Jen 2003)

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 and Erlebach 2005, Webb and Bodin 2008). This is close to both the definition of resilience and of system robustness.

2.4.2. LINKING ROBUSTNESS TO NETWORK THEORY METRICS

While there is not a unique formula for measuring robustness in an SES, some important particularities of a robust system have been identified in the literature (Carpenter, Walker et al. 2001, Perrings 2006). Most particularly, Webb and Bodin (2008) provide a detailed review of some of the methods used to assess robustness in SES 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. However, it is important to note that most of the research connecting the topology of SES to their outcomes in terms of resilience is based on theoretical work only. As such, these relationships have not yet been formally tested empirically, and should be considered as strong assumptions at this point.

2.4.2.1. Diversity and Redundancy

It is commonly admitted that a high diversity of components within a system helps build robustness (Ehrlich and Walker 1998, Webb and Bodin 2008, Norberg and Cumming 2013). 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 SES (Walker 1995, Carpenter, Walker et al. 2001, Scheffer, Carpenter et al. 2001, Folke, Carpenter et al. 2002, Janssen, Bodin 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 us 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 us 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 α, β, γ, δ, ε, ζ and θ). 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 us 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 α and γ fulfilled by a and c cannot be replaced and the system is likely to endure severe structural damage.

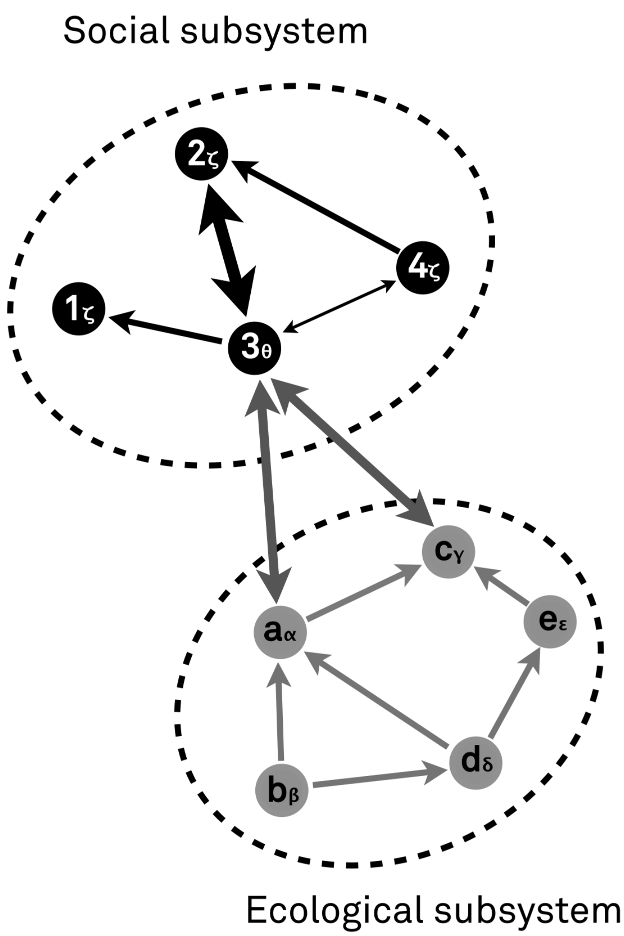


Figure 2.1 — Imaginary fishery-oriented integrated SEN where a human subsystem is in interaction with an ecological sub-system. Nodes 1, 2, 3 and 4 represent four human groups (three institutions and one industry represented by node 3). Nodes a, b, c, d and f represent an ecosystem in which a and b are 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.

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 (2013) 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 2013). 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 SEN 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 an SEN.

Simpson's Diversity Index

Simpson's diversity index can be calculated with Equation 2.1:

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

Equation 2.1 — Simpson diversity index.

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 Equation 2.2.

$$H = -\sum_{n=1}^{S} p_i \ln(p_i)$$

Equation 2.2 — Shannon's diversity index.

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 (Equation 2.2 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.

2.4.2.1. 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 and Carrington 2011). As Webb and 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, Bodin 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 instance, in an ecological network focusing on habitat connectivity, a highly connected landscape can often improve chances for a species to survive landscape fragmentation (Baranyi, Saura 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 and 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:

$$d = \frac{e}{\frac{n(n-1)}{2}}$$

Where d is the density of the network, e 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 0, while a clique (a network or sub-network where every node is connected to every other node) would score 1.

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, Bodin 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 2012).

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, Sörlin et al. 2008, McAllister, Cheers et al. 2008, Bodin and Crona 2009, Prell, Hubacek et al. 2009, Reed, Graves et al. 2009, Crona and Bodin 2010, Marín and Berkes 2010, Newig, Günther 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 and Bodin 2008, Zetterberg 2009, Cinner and Bodin 2010, Baranyi, Saura 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 and Carrington 2011).

2.4.2.1. Evaluating the Modularity of the Structure and the Control of the Flow

Webb and Levin (2005) identify a set of mechanisms characterizing robust SES when considered more particularly through the lens of network analysis: control of flow and modular structure. These two characteristics are central to robustness in SES 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 whole system's structure. According to (Webb and 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 2.2.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 and 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 2.2.b and 2.2.d are simple examples of systems with this kind of trade off).

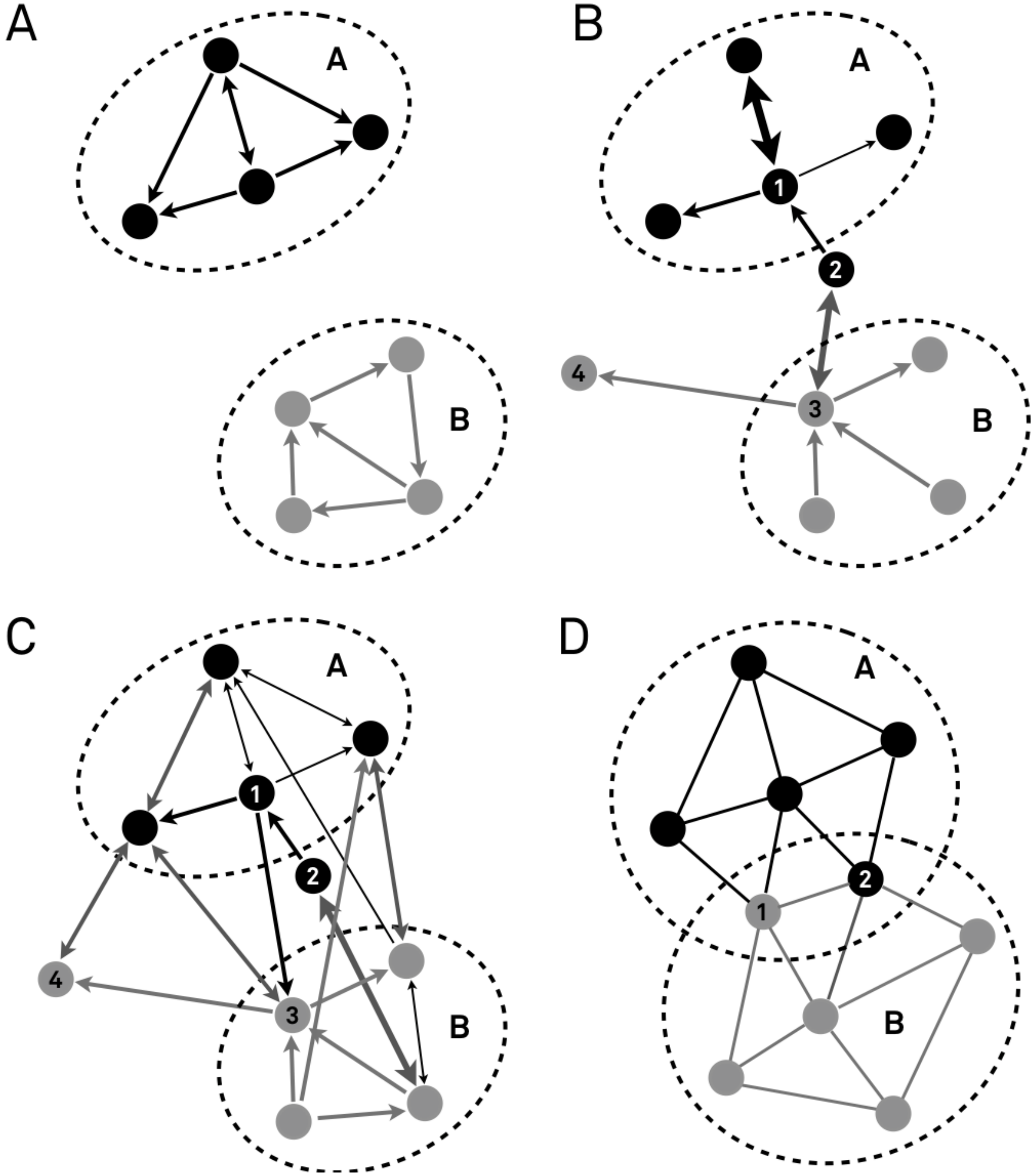


Figure 2.2 — Three examples of networks. A) Modular structure consisting of distinct modules or clusters. In B), the two clusters are connected to each other. We can describe four different noticeable nodes in B): nodes 1 and 3 could be considered as "peaks" of the system (they are connected to more 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. Examples of C) low modularity and D) overlapping groups.

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 2012), and involve measures of clustering, often done through a hierarchical clustering procedure, or dendrogram (Scott 2012), "clique" and "blockmodeling". For a detailed review of these methods, see Scott (Scott 2012). 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 2.2.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, 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 2012). Nodes with a high level of betweenness centrality act as intermediaries within the system, and therefore hold a very important role in the network (Scott 2000). As such, they often manifest themselves as "bridges" (node 2 in Figure 2.2.b) or as nodes belonging to two or more overlapping groups at the same time (nodes 1 and 2 in Figure 2.2.d). Betweenness centrality can be complicated to quantify; (Scott 2012) 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 2.2.b) are removed, the whole structure would be separated into different modules and its function would likely be destroyed.

2.5. DISCUSSION

2.5.1. COUPLING SOCIAL AND ECOLOGICAL NETWORKS

As SEN are typically built from edges and nodes that are potentially heterogeneous, coupling the social and ecological parts of an 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 and Bodin (2008) also point out that while a lot of research is being done towards understanding robustness of individually considered SEN, the robustness of SEN is still not well understood. More recently, Cumming et al. (2010) identified several kinds of couplings, including (i) analysing each sub-network independently and (ii) 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 SEN 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 (Cumming, Bodin et al. 2010).

2.5.2. SOCIAL-ECOLOGICAL NETWORKS CHANGE OVER TIME

Another important characteristic of robust SES is their capacity to change and adapt over time. This is one of the fundamental characteristics of the adaptive cycle in system resilience (Gunderson 2001). 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 (ibid.), 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 top(Leskovec, Kleinberg et al. 2005, Palla, Barabási et al. 2007, McCulloh and Carley 2008, Top 2009, Mucha, Richardson et al. 2010, Szell, Lambiotte et al. 2010).

2.6. CONCLUSION

In this paper, we have explored how some characteristics of SES' sustainability could be quantitatively assessed in SES 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 SES, 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’ SES were defined, and some of these characteristics were linked to quantitative network analysis metrics.

Despite its advantages, a network approach to analyzing the sustainability of SES 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 SES is still in the early stages of development. Despite certain limitations, which requires more theoretical work (e.g. dynamic integrated SEN), 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 SES.

PARAGRAPHE DE LIAISON A

Le chapitre 3 s'articule autour de trois axes. Le premier décrit la construction d'un réseau d'acteurs impliqués dans divers projets de conservation de la biodiversité sur la péninsule d'Eyre, en Australie-Méridionale. J'ai conduit les travaux de terrain entre 2011 et 2012 par une série d'entrevues et de questionnaires en ligne. Le second est une analyse de la structure de ce réseau utilisant le formalisme de la théorie des réseaux. Le troisième, partiellement fondé sur les mesures décrites dans le chapitre précédent, propose une méthode permettant de projeter le réseau empirique dans des états alternatifs où certains aspects de leur structure, liés à la résilience de leur SSÉ, sont optimisés. Ce chapitre propose également deux nouvelles mesures permettant de quantifier le degré global de marginalisation des groupes composant le réseau, ainsi que le niveau auquel chaque acteur contribue à établir des liens entre d'autres acteurs appartenant à des groupes différents.

Contributions personnelles

Ce chapitre est en préparation pour soumission, sous forme d'article, à *Ecology and Society*. La recherche dont il rend compte a été réalisée en collaboration avec Lael Parrott et Wayne Meyer. J'ai effectué la recherche et rédigé le manuscrit dans sa majorité. Lael Parrott et Wayne Meyer ont agi à titre de superviseurs en m'apportant idées et recommandations tout au long du travail de terrain et de recherche. Lael Parrott a également amélioré le manuscrit par ses nombreux ajouts, conseils et corrections.

3. RURAL LANDSCAPES, STAKEHOLDER NETWORKS AND BIODIVERSITY CONSERVATION: A STRUCTURAL ANALYSIS ON THE EYRE PENINSULA IN SOUTHERN AUSTRALIA

R. Gonzalès, L. Parrott and W. Meyer

3.1. ABSTRACT

Studying the ways in which natural resource management (NRM) stakeholders interact with each other is essential to fully understand NRM outcomes. Network theory, by providing a framework to quantify patterns of interactions has become a popular tool to analyse the topologies of collaborating stakeholders. This article uses the framework provided by network theory to analyse a stakeholder network in rural Southern Australia, where human-driven transformations of the region's landscapes, as well as climate changes, are eroding biodiversity. This article is divided in three parts. First, we explain how we reconstructed the network of interactions between stakeholders in the study area. Then, we describe the patterns through which stakeholders organize and collaborate to improve biodiversity in their region. Finally. we use an optimisation algorithm to project alternate states in which new collaborations could improve topological features related to resilience-building in SES. For the purpose of our analysis and optimizations, we also propose two new network metrics which can be used in other analyses: one designed to measure the level to which groups are marginalized at the network level, and the other to measures the capacity of an individual to serve as a bridge, or broker, between otherwise separated stakeholders. While our results are focused on a specific case study, the methods and approach described in this article are easily generalizable to many similar natural resource management systems.

3.2. INTRODUCTION

Natural resource management, and most particularly in co-management settings, involves a variety of stakeholders from different horizons (Bouwen and Taillieu 2004, Reed, Graves et al. 2009). As in any human system, these interacting stakeholders form a complex adaptive system (CAS) (Buckley 2008). CAS are composed of heterogeneous elements in interaction, from which higher scale patterns emerge (Sawyer 2005, Parrott, Chion et al. 2012) which, in turn, influence the way individuals interact through feedback loops. Local interactions are therefore central to understanding emergent human dynamics, as well as their outcomes in terms of how the human system interacts with the natural resource and the environment upon which both depend.

In many cases, lower hierarchical levels in CAS can appropriately be formalized as graphs, or networks (Wasserman and Faust 1994), in which individual elements are modelled as vertices (or nodes, as we will call them thereafter), and where interactions between pairs of nodes are represented by edges. Patterns of connections (or lack thereof) in networks can be identified and measured with the wealth of metrics developed in network theory (Scott and Carrington 2011). Not only can these measures shed light on a system's fundamental structural properties, but they can also help elaborate relationships between network topologies and network functions (Newman 2003). As collaborations and information-sharing between stakeholders are central to the success of natural resource co-management (Armitage, Plummer et al. 2008), network theory offers an opportunity to look at these interactions from a quantitative, structural point of view. As a framework, it has become a valuable tool in assessing the qualities of NRM co-management (Bodin, Crona et al. 2006, Bodin and Crona 2009, Ernstson, Barthel et al. 2010). Furthermore, it is widely argued (see Chapters 2 and 4 for a review) that the topology of these networks (that is, the patterns with which nodes connect with each other) are related to resilience-building in social-ecological systems (SES).

In this manuscript, we analyse the structural properties of a stakeholder network dedicated to conserving and improving biodiversity in a rural region of Southern Australia. It is divided into three parts. In the first part, we describe how the stakeholder network was reconstructed from field and online surveys. Secondly, we employ network theoretic tools to describe the patterns through which stakeholders organize and collaborate, focusing more particularly on the capacity of stakeholders, and of the groups they belong to, to serve as bridges in the network. Thirdly, we project, using an optimization algorithm, new collaboration opportunities that improve topological features related to resilience-building in SES. In the process, we develop two novel network metrics. The first measures a group's level of marginalization in a stakeholder network, while the second measures the capacity of an individual to serve as a bridge, or broker between otherwise distant stakeholders.

3.2.1. CASE STUDY EYRE PENINSULA

The case study is set on the Eyre Peninsula (EP) (Figure 3.1), a region in South Australia located 250 km, as the crow flies, west of the State Capital city of Adelaide. The large triangle-shaped peninsula is bordered to the south, east, and west by the Southern Ocean. The climate of the EP varies greatly, according to a south–north gradient, from a Mediterranean-type climate in the southern tip to a semi-arid climate in the north (where rainfall is highly variable at around 250 mm/year). The economy of the region is primarily based on agriculture, mainly grain and grazing, and the landscape is therefore largely rural. Apart from fields and pasture, around 12% of the peninsula was still covered with native vegetation in 2001. This percentage was divided between 729,000 ha on public land and 230,000 ha on privately owned land (Matthews, Oppermann et al. 2001).

As in many agricultural systems across the world, the environment of the peninsula is subject to anthropogenic pressures. The EP counts several threatened, endangered, or vulnerable native plant and animal species (Matthews, Oppermann et al. 2001). These species are affected by a variety of factors (*ibid*), including the fragmentation of their habitats, which is related to land-cover change on privately owned land (clearance of native vegetation for agriculture, as well as over grazing, plays a large part in these perturbations) (Figure 3.2). This issue is even more sensitive in a context of climate change on the EP (Thomas, Cameron et al. 2004, Heller and Zavaleta 2009, Shoo, O'Mara et al. 2014) for which models project decreased and more variable rainfall (Hughes 2003), which will put further pressure on already stressed ecosystems.

In order to preserve the natural environment and the ecological services it produces, a Natural Resources Management Act was passed in 2004 by the South Australian government. This piece of legislation, which included a wide set of social-ecological targets and goals for the following 20 years, served as a base, and led the way to the creation of regional natural resources management (NRM) boards across South Australia, as well as plans to address environmental management and conservation in a fashion that would integrate human and environmental factors. Among the priorities identified by the NRM boards, biodiversity is a strong focus of concern on the EP.

Conserving and augmenting biodiversity in the region may provide increased ecological resilience in the landscape and increase the capacity of ecological systems on the peninsula to adapt to environmental changes. Biodiversity on the EP partly depends on the protection and improvement of the many and scattered native vegetation patches on privately owned land (Meyer 2013) (Figure 3.2). However, farmers and other landowners on the EP have somewhat contrasting views of the importance of biodiversity (Ward and MacDonald 2009), which means that biodiversity conservation on the EP is not without challenges. Natural resource managers, working in collaboration with a broad range of different actors and stakeholders, must therefore develop innovative programs that take into account both environmental and socioeconomic constraints (Parrott and Meyer 2012).

Figure 3.1 — Map of the Eyre Peninsula in relation to Australia (credit: Marc Girard).

As part of the regional NRM plan to restore native species habitats, a variety of conservation efforts have been put into place on the EP. These initiatives, designed and promoted by natural resource management entities, NGO and grassroots initiatives alike, are diverse in nature. They include workshops aimed at promoting better land management planning among farmers, direct seeding of native vegetation, fencing remnant vegetation bushes to protect against over grazing, and problem animal poisoning campaigns. A large number of individuals, acting under a variety of formal institutions or community initiatives, have taken part in these initiatives. They have been sharing their time, energy and knowledge to work toward a set of common biodiversity-related goals. Over the years, from these many interactions, a dense and complex stakeholder network has been shaped.

The objective of our study was to describe and explore how the structure of this stakeholder network contributes to the sharing and co-production of knowledge about biodiversity conservation initiatives on the EP. We hypothesized that a well-connected and appropriately structured stakeholder network may enhance the social-ecological resilience of the natural resource and conservation management system on the EP. We thus assessed the degree to which the topology of the EP stakeholder network exhibited properties known to enhance resilience in social-ecological systems, and sought to make recommendations on how the structure of the EP network could be modified through the addition of new collaborations to increase overall system resilience.

Figure 3.2 — Satellite imagery from Cleve district Council on the Eyre Peninsula. While the distribution of remnant vegetation on the Peninsula varies greatly along a South-North gradient, this image illustrates the sparse distribution of remnant vegetation used as habitat by many species in agricultural areas (credit: Spot Image 2015).

3.3. METHODS

3.3.1. CONSTRUCTION OF THE STAKEHOLDER NETWORK

In order to analyse the patterns of connection between stakeholders, we constructed a network of EP-centered, biodiversity-related collaborations. This was achieved in 2012 in two main steps: first by identifying the system's key stakeholders through a stakeholder analysis, then by documenting how each of these individuals interact with each other using a survey approach. We describe these two steps separately in the following sections[2].

[2] Each of these steps were conducted according to University of Montreal's ethics committee approval number CERFAS- 2011-12-146-A

3.3.1.1. Stakeholder Analysis: Setting the Units, Types of Relations and Network Boundaries

Network analysis usually starts with the sensitive step of clearly defining the relevant units and types of connections that will be taken into account (Prell, Hubacek et al. 2009, Reed, Graves et al. 2009). In our case, we decided to focus on any stakeholders (i.e. anyone having an interest in biodiversity conservation on the EP and actively acting on this interest), as individuals working within groups of governmental or non-governmental organizations, that either:

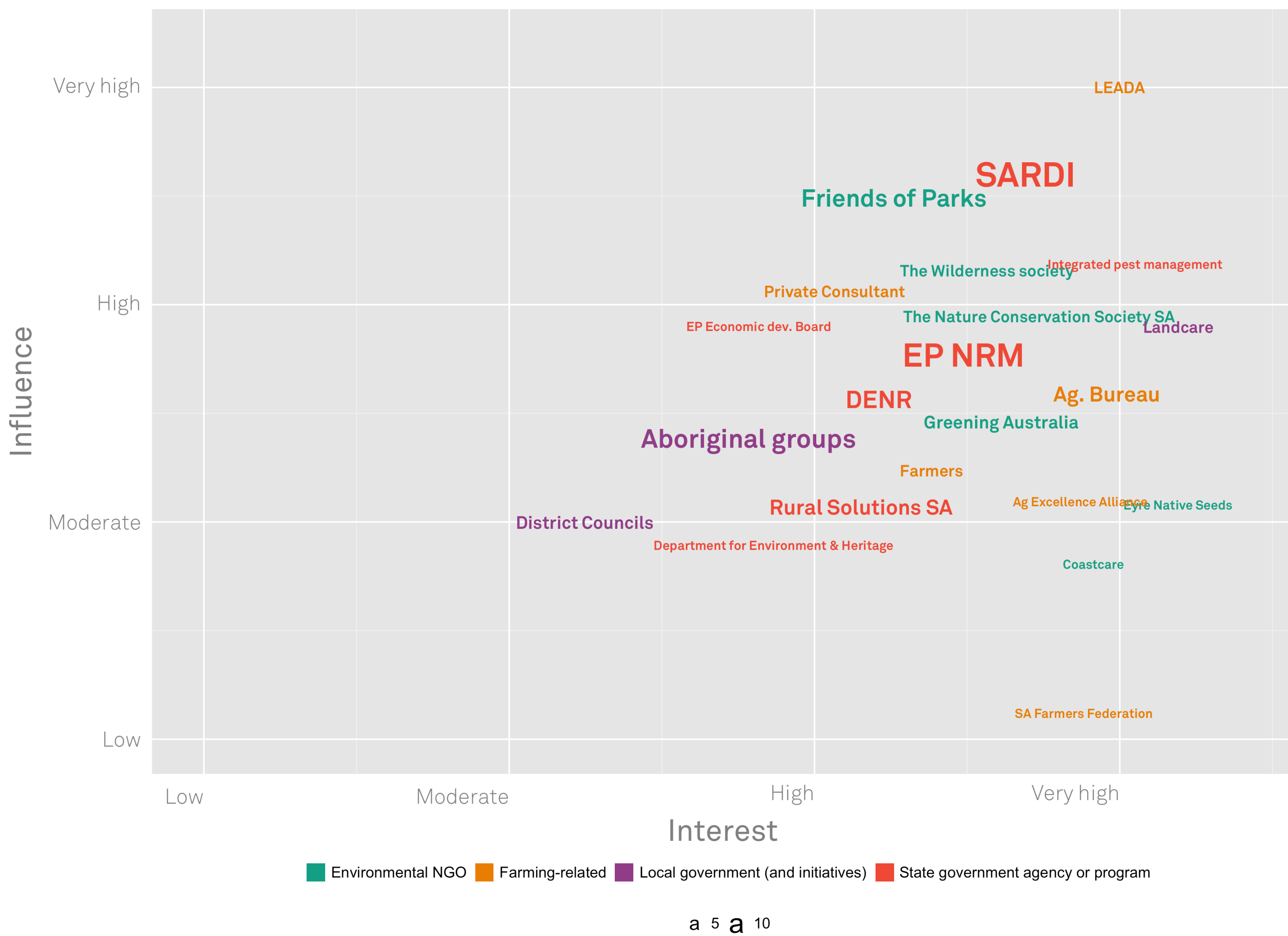
- Promote conservation programs (e.g.. governmental agencies, some non-governmental organizations), or
- Implement conservation programs (e.g. farmers, local associations, NGOs).

This list of stakeholders was produced by conducting a stakeholder analysis (Grimble and Wellard 1997, Prell, Hubacek et al. 2009, Reed, Graves et al. 2009, Lienert, Schnetzer et al. 2013). It involved contacting a list of six key individuals from the EP, and building with them a list of potential stakeholders. The six interviewees were asked to rate each of the stakeholders in the list along three axes (Annex 1): 1. their level of interest in biodiversity conservation (from "Very high: biodiversity-related issues are a matter of livelihood to this stakeholder" to "Very low: this stakeholder has only a remote or unclear interest in this matter), 2. their strength of influence in comparison to other stakeholders when it comes to decision-making related to biodiversity conservation on the EP (from "Among the most influential" to "Among the least influential"), and, 3. the number of times a specific stakeholder was mentioned by our interviewees. In order to avoid circumscribing our description of the system to particular geographic or expertise areas, the key individuals selected to participate in the analysis worked in different places around the EP, and represented expertise in specific domains related to the subject. These individuals were:

- Eyre Peninsula Natural Resources Management's (EP NRM) general manager in EP's main city Port Lincoln;
- A project manager at EP NRM in Elliston (about 170 km North of Port Lincoln);

- An employee of Rural Solutions SA in Adelaide, South Australia's Capital city;
- A program manager for aboriginal programs at EP NRM in Port Lincoln;
- A grain farmer outside of Port Penny (about 70 km North of Elliston on the EP);
- An EP NRM board member in Streaky Bay, on the Northwest coast of the EP.

The analysis identifies 24 groups and organizations, which are aggregated in Table 1 and visualized in Figure 3.3. This figure displays groups of stakeholders along the two axes (interest vs. influence), hence defining the institutional boundaries of the network. The size of characters, representing the number of times the group was mentioned by an interviewee, is of the upmost importance in this figure: while SARDI and EP NRM both appear less influential than LEADA according to the axes, the latter was only mentioned once, and its influence might have been involuntary exaggerated. However, despite the qualitative nature of the ratings, both Table 1 and Figure 3.3 constitute a sound base upon which to start documenting the relationships between stakeholders.



Influence
Very high
High
Moderate
Low
Interest
Low
Moderate
High
Very high
LEADA
SARDI
Friends of Parks
The Wilderness society
Integrated pest management
Private Consultant
The Nature Conservation Society SA
Landcare
EP Economic dev. Board
EP NRM
DENR
Ag. Bureau
Greening Australia
Aboriginal groups
Farmers
Rural Solutions SA
Ag Excellence Alliance
Eyre Native Seeds
District Councils
Department for Environment & Heritage
Coastcare
SA Farmers Federation
Environmental NGO
Farming-related
Local government (and initiatives)
State government agency or program
a 5
a 10

Figure 3.3 — Stakeholder groups' influence and interest on subjects related to biodiversity conservation on the EP. Colours represent the broad category the stakeholder group was given. The size of the text gives an indication of the number of times it was mentioned by interviewees.

Table 3.1 — List of groups working in biodiversity conservation on the Eyre Peninsula, SA, and their corresponding categories and functions regarding biodiversity conservation.

Group name	**Acronym**	**Category**	**Function**
Aboriginal community members & focus group		Local initiatives	Promote & implement
Ag Excellence Alliance		Industry	Implement
Ag. Bureau		Industry	Implement
Australian Wildlife Conservancy		Environmental NGO	Promote
Commonwealth Scientific and Industrial Research Organisation	CSIRO	Australian government agency or program	Research
Conservation Council SA		Environmental NGO	Promote
Department for Environment and Natural Resources	DENR	State governmental agency or program	Coordinate
Eyre Peninsula Natural Resource Management	EP NRM	State governmental agency or program	Promote, implement & coordinate
Friends of Parks		Environmental NGO	Promote
Future Farming Industries CRC		Industry	Implement
Greening Australia		Environmental NGO	Promote & implement
Landcare		• State governmental agency or program • Local initiatives	Promote & implement
Local governments		Local initiatives	Promote & implement
Lower Eyre Agriculture Development Association	LEADA	• Local initiatives • Industry	Promote
Lower Eyre Pest Management Group Member		Industry	Implement

Group name	Acronym	Category	Function
Nature Conservation Society of South Australia		Environmental NGO	Promote
Other Australian Government agencies		Governmental agency or program	Promote & implement
Private Consultant		Industry	Promote
Progress Associations		Local initiatives	Promote & implement
Rural Solutions SA (Primary Industry & Regions South Australia)	PIRSA	• Governmental agency or program • Industry	Promote & implement
SA Farmer Federation		Industry	Implement
South Australia Research & Development Institute (Primary Industry & Regions South Australia)	SARDI	• Governmental agency or program • Industry	Promote & implement
The Wilderness Society		Environmental NGO	Promote
University of Adelaide		Academia	Promote
University of South Australia		Academia	Promote

3.3.1.2. Quantifying Stakeholder Interactions: Network Survey

To build the stakeholder network, we developed and conducted a structured survey based on Table 3.1. The survey (Annex 2) was divided into two main parts. The first part focused on nodes (the surveyees), from whom we asked factual information, including the full list of groups and organizations to which the surveyee belonged, as well as the types of projects in which they were involved and the geographical locations of these projects. The second part focused on listing edges connecting this particular node to others. It is itself divided by groups, and consisted of the following name-generator question:

> "On the issue of biodiversity conservation on the Eyre Peninsula, who do you share information or otherwise collaborate with?"

For each of the identified individuals, surveyees were asked to choose the kinds of interactions (or edges) that tied them to the new node, as well as the direction of the edges.

The choices were a) “I provide information to this person”, b) “I gain information from this person”, c) “We collaborate on program promotion”, and/or d) “We collaborate on on-the-ground implementation”. Additionally, the weight of the edge was inferred by asking the frequency of any given interactions. The choices were a) “Daily”, b) “Weekly”, c) “Fortnightly”, d) “Monthly”, e) “Yearly”. A final question documented in which of the 11 district councils the interactions were happening (see Table 2 for survey questions and drop-down options).

The survey was first filled out in person with 16 stakeholders in order to identify and fix clarity issues. We then sent the survey by email as an online questionnaire (https://www.surveymonkey.com/r/?sm=nEyXq0r65A4Dx6b%2fO4WNF5XJU2jwumP4MxyS%2fIz6gaE%3d) to all identified stakeholders, with an introductory video that explained the objectives of the research, as well as providing a clear tutorial on how to fill out the survey (https://www.youtube.com/watch?v=eVorfxqDq2k). We obtained a response rate of 48% after filtering (see next section). Interestingly, while surveyees had the choice to specify if interactions were directed or undirected, only 5% of interactions were reported as directed.

Setting weights for edges in the network was a matter of converting a frequency of interactions into a number which we could work with for our analysis. We chose to weight each edge as a fraction of daily interactions (Equation 3.1 and Table 3.3).

Table 3.2 — Survey questions and drop-down options.

Survey questions	Drop-down options
Stakeholder	Stakeholder’s name and group
Information and knowledge sharing on biodiversity-related issues	• I provide information/knowledge • I gain information/knowledge • All of the above
Collaboration on biodiversity-related programs	• We collaborate on program promotion • We collaborate on on-ground implementation • All of the above

Survey questions	Drop-down options
On average over the last 3 years, how often do you collaborate with this person?	• Daily • Weekly • Fortnightly • Monthly • Every 4 to 6 months • Every 7 to 9 months • Once a year or more
Which District Council are the projects situated in?	• None in particular • Ceduna • Cleve • Others (11 councils in all)

Table 3.3 — Conversion table between raw survey data related to frequency of interactions, and edge weights in the network.

Frequencies of interactions	Nbr. days	Weights
Daily	1	1
Weekly	7	0.14
Fortnightly	14	0.07
Monthly	30	0.03
Every 4 to 6 months	152	0.006
Every 7 to 9 months	244	0.004
Once a year or more	365	0.003

$$w = \frac{1}{f}$$

Equation 3.1 — Conversion between frequency (f) of interactions in days and edge weight (w).

3.3.1.1. Filtering the Network

While more than 230 stakeholders were initially identified through the survey, some of the collected information was found to be inconsistent between surveyees. To cope with this problem, we set up an index of "fuzziness", or "relationship uncertainty". Setting the index at zero for each relationship, we checked for discrepancies in the raw data, and incremented the index according to a set of rules: discrepancy on the fact that a relationship was directed vs. undirected incremented the index by one; for directed edges, a discrepancy on the direction of the interaction added another increment to the index; a relationship between two stakeholders mentioned by one surveyee while unmentioned by the other added yet another increment. Additionally, a relationship we weren't able to confirm by one of the pair added two to the index. At the end of this assessment, edges scoring 3 or higher were removed. Lone nodes which were mentioned by only one surveyee and whom we were unable to reach for confirmation were also removed. 129 names were kept, as well as 1180 weighted and directional edges of any type.

The resulting network, represented using a force-directed layout (Kobourov 2012) (Figure 3.4 with its corresponding legend in Table 4), shows weighted collaborations (information and knowledge exchange) between all 129 stakeholders retained for further analysis. While a quantitative analysis will give a more accurate assessment of the structure, a few elements may already be noted from the visualisation shown in Figure 3.4. First, the density of the network is rather high (a large number of all possible connections between nodes seems to be realized), indicating potential low average path length (Gulyás, Horváth et al. 2011). Secondly, we observe that stronger ties seem to occur within nodes belonging to similar groups (nodes of the same colour, see Figure 3.4 - details). This could indicate that the network is somewhat modular, and that the formation of communities could be correlated to group membership. Looking at centrality at the node scale, we notice a few nodes showing large betweenness centrality, which measures "the frequency with which a point falls between pairs of other points on the shortest or geodesic paths connecting them" (Freeman 1979). This indicates that a limited number of nodes are very central to the network's topology and contribute to a large extent to the connectivity of the whole network. This is an important structural feature since if these nodes were to disappear, the network's connectivity would most likely be greatly diminished. A few nodes (the ones represented with the largest circles) hold particularly important positions in the network, for at least two reasons: 1) they are topologically very central nodes (Freeman 1979), meaning that they greatly contribute to the overall connectivity of the network. Removing these nodes from the network would contribute more to reducing the connectivity than removing any other node in this network (Iyer, Killingback et al. 2013), and 2) although the density of connections makes visualizing the network structure difficult, these more topologically central nodes seem to be connecting several groups (EP NRM, SARDI, academics, members of farming industry), hence serving as bridges between groups in the network. These observations provide points of departure for further investigation of the network structure.

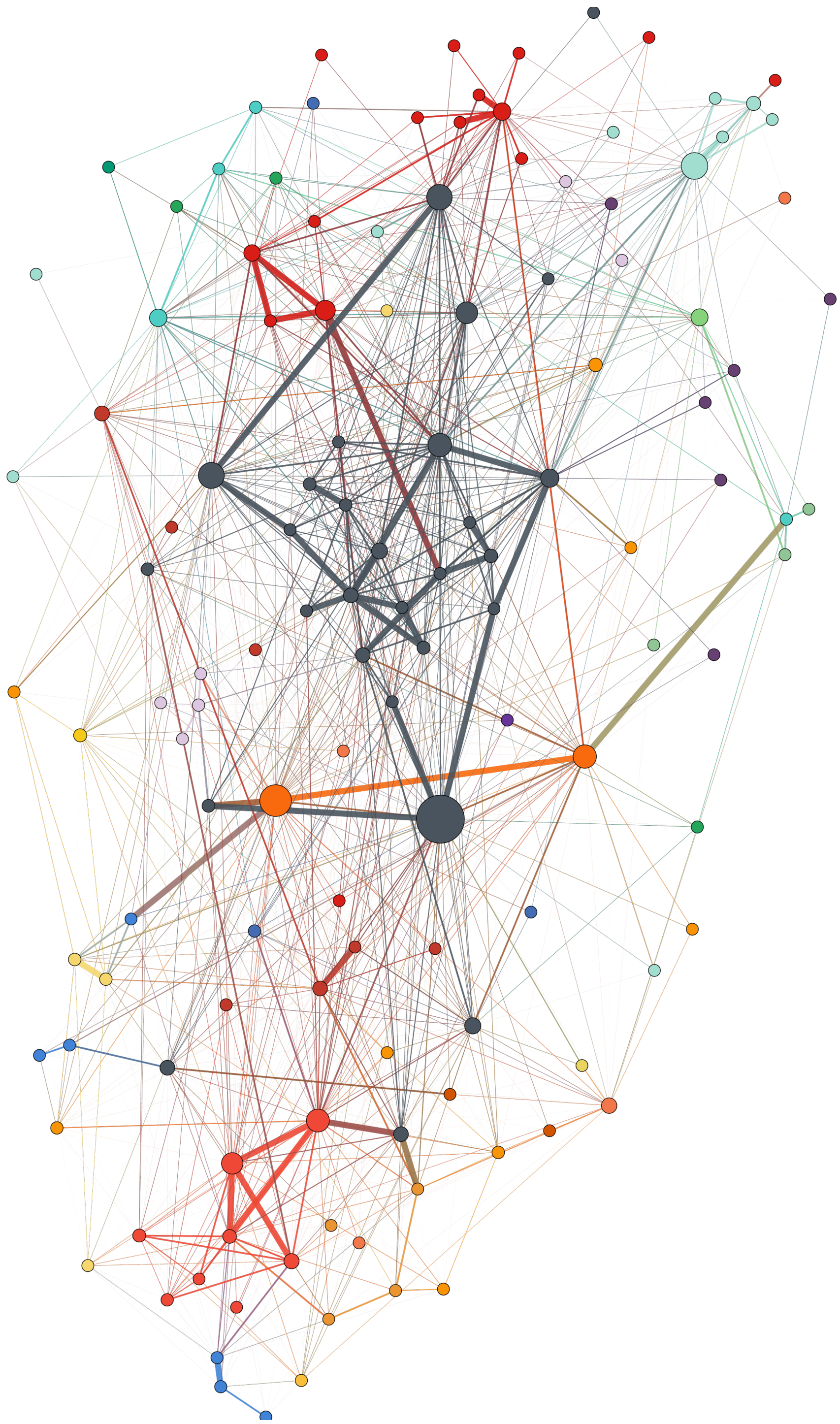


Figure 3.4 — EP stakeholder network. Each node is a stakeholder and edges represent undirected interactions between stakeholders. Node sizes are relative to their betweenness centrality, and colours represent the stakeholder group to which the node belongs. Edges are weighted according to interaction frequencies, indicated by line thickness. See Table 3.4 for colour coding.

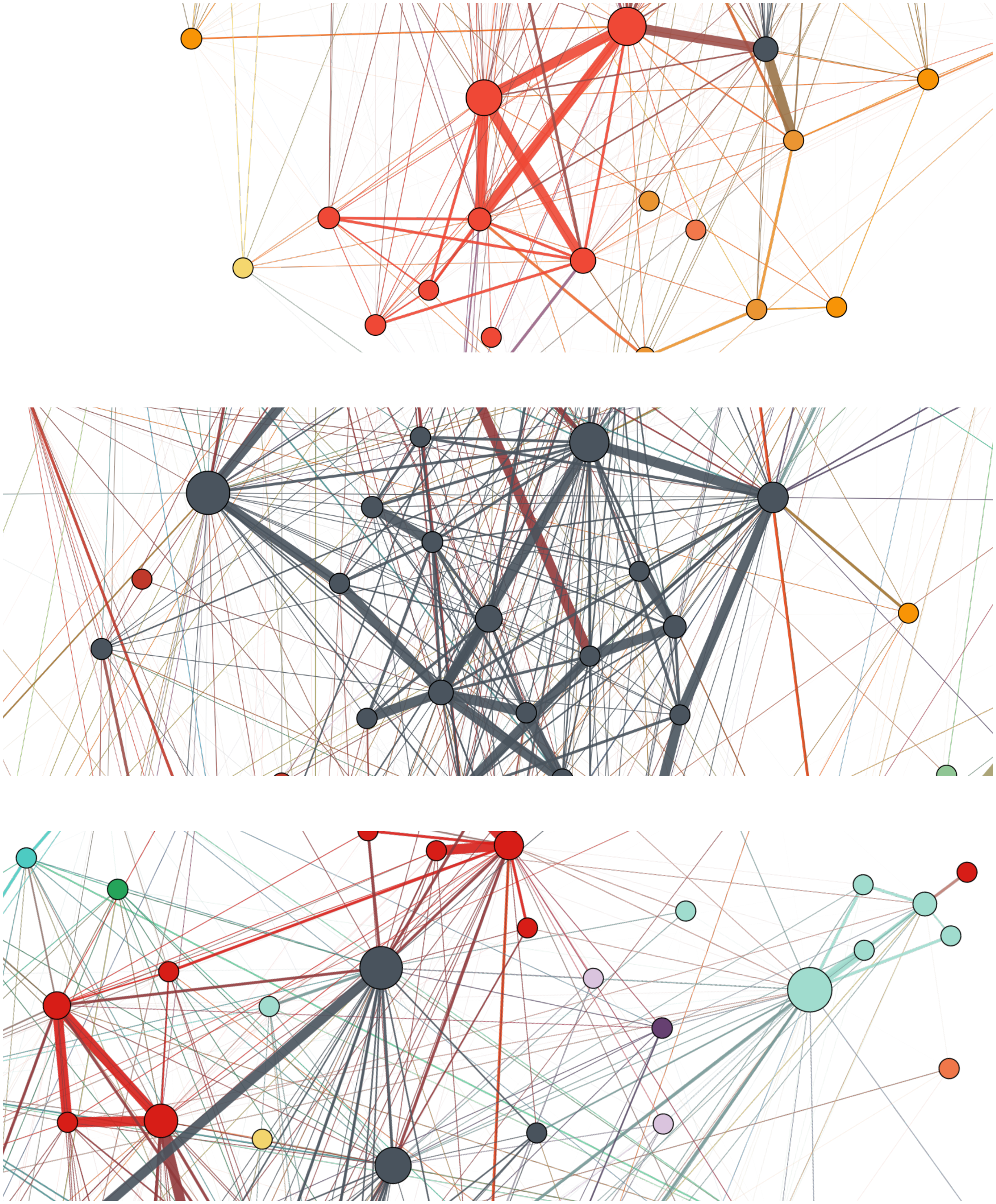


Figure 3.4 (details) — Details of the EP stakeholder network focusing on a selection of group clusters. Top: Cluster of individuals from SARDI (orange) showing strong links among themselves and with an EP NRM individual (grey). Middle: Very strong and dense interactions

among EP NRM individuals (grey), making this group particularly densely connected. Bottom: A state government agency (red) and a federal government agency (blue) interacting among themselves and with an EP NRM individual (grey).

Table 3.4 — Colour coding for Figure 3.4

Stakeholder categories	**Colour shades**
Farming-related groups	Orange
environmental groups	Green
local government (and initiatives)	Purple
federal government agencies	Blue
Academics	Yellow
State government agencies	Red
EP NRM	Grey

3.3.2. NETWORK ANALYSIS

A number of structural analyses were performed on the stakeholder network to identify how network typology contributes to facilitating or impeding communication and information exchange about biodiversity conservation initiatives on the EP.

Geography vs. Topology

While modern technologies provide opportunities to communicate in a way that should transcend geographic distances, a number of studies show that distance still very much matters in explaining human interactions (Goldenberg and Levy 2009, Onnela, Arbesman et al. 2011, Illenberger, Nagel et al. 2013). We used the stakeholder network to explore how physical distance relates to the frequency of interactions. For this, each stakeholder was given a set of geographic coordinates corresponding to his or her primary workplace. We then calculated the orthodromic (as the crow flies) length of each edge in the network, and looked at the distribution of weighted frequencies of edge lengths. In order to test if geographically-driven communities emerge from the collaborations, we also reconstructed the network by gathering nodes working from the same place into a single node. Next, we tested for a relationship between geographical and topological centralities in the network. For this, we looked for a correlation between nodes' geographic distance from Port Lincoln (EP's administrative regional centre) and their topological (betweenness) centrality in the network.

Assessment of Groups' Topological Centrality and Reaching Capacity

Stakeholders may have different roles within the network (Ostrom 2007). While some groups focus on implementing projects on site, others, often government agencies, coordinate programs. The latter can often serve as bridges between communities. They are boundary spanners, as they can reach far across the network topology to spread information and help connect potentially marginalized groups. However, bridges can also be in *de facto* privileged positions of control. In some circumstances, this can lead to negative outcomes in adaptive NRM co-management (Crona and Bodin 2010). We used two different metrics to assess nodes' bridging capacity:

- Betweenness centrality, which measures (at the node level) the topological centrality (as the frequency of a given node to fall on shortest paths between pairs of other nodes) (Equation 3.2);

- Group betweenness (GB) centrality, which measures the capacity of a node to connect different groups (more precisely, it is the frequency that a given node falls on shortest paths between pairs of other nodes belonging to different groups, see Equation 3.3). We propose GB as a measure of the relative capacity of a network's nodes to connect stakeholders with potentially different values, opinions and knowledge. A node's GB should only depart from its betweenness if its bridging capacity is mainly effective among nodes belonging to the same groups. It is to be seen as a complement to betweenness centrality.

$$B_v = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Equation 3.2 — Betweenness centrality as defined in (Freeman 1979). V is the ensemble of nodes in the network, v is the node for which we measure the centrality, s and t are two nodes from the network, $\sigma_{st}(v)$ is the number of shortest paths on which v can be found, while σ_{st} is the total number of shortest paths between s and t.

$$GB_v = \sum_{s \neq v \neq t \,\&\, G_s \neq G_t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Equation 3.3 — Group betweenness as a modified betweenness centrality. V is the ensemble of nodes in the network, v is the node for which we measure the group betweenness, s and t are two nodes from the network, G_s and G_t are the groups to which s and t belong, $\sigma_{st}(v)$ is the number of shortest paths on which v can be found, while σ_{st} is the total number of shortest paths between s and t.

3.3.3. IMPROVING RESILIENCE-BUILDING WITH NETWORK OPTIMIZATIONS

Edge rewiring (the action of removing an edge and adding a new one) is commonly used to manipulate random networks in order to improve their topology according to a criterion of interest (Watts and Strogatz 1998, Beygelzimer, Grinstein et al. 2005, Rad, Jalili et al. 2008, Zeng and Liu 2012, Sydney, Scoglio et al. 2013). In this section, we will explore how a sequence of rewiring can improve the topology of our empirical network. The improvements will be done according to several metrics known to improve, when measured on stakeholder networks, resilience-building in SES.

Metrics

Among the many network metrics, a number have been identified as favourable to resilience in SES (Bodin and Crona 2009). In this section, we measure the EP stakeholder network's average path length (APL) (Scott and Carrington 2011), its synchronizability

(Kelly and Gottwald 2011), and its modularity (Newman and Girvan 2004). The value of using these metrics in the context of resilience in SES is described in Chapter 4, and summarized in Table 3.5.

To these three metrics, we propose a fourth, which we call the "group marginalization index" (GMI). While a network can be highly modular and synchronizable, as well as having a short average path length, it can also display a highly asymmetrical structure in terms of group involvement. This can lead to marginalization of stakeholder groups, and make for a system prone to unfair, or unbalanced, co-management (Tompkins and Adger 2004). GMI is the spread of node degrees calculated for each of the network's groups (Figure 3.5), and is meant to quantify the level of asymmetry of interactions at the group-level. This involves a two step process. The first step consists in creating a new, aggregated network merging all nodes belonging to the same group into a single node. This new network has a number of nodes equal to the total number of groups in the stakeholder network. The edges of this new, "stakeholder groups" network are weighted as the sum of all edges' weights existing between individuals of different groups. The second step is to compute the spread of the weighted degree distribution in the aggregated network. This spread is calculated as the inter-quartile range of weighted degrees divided by the median (a non-parametric analog to the coefficient of variance) (Equation 3.4).

We will use these metrics to successively optimize our EP network.

$$GMI = \frac{Q_3 - Q_1}{\tilde{d}}$$

Equation 3.4 — Calculation of the Group Marginalization Index (GMI) as a group-level degree spread. GMI is the ratio of inter-quartile range (Q3-Q1) and median ($\tilde{d}$) of all weighted degrees measured on the network at group level (Figure 3.5).

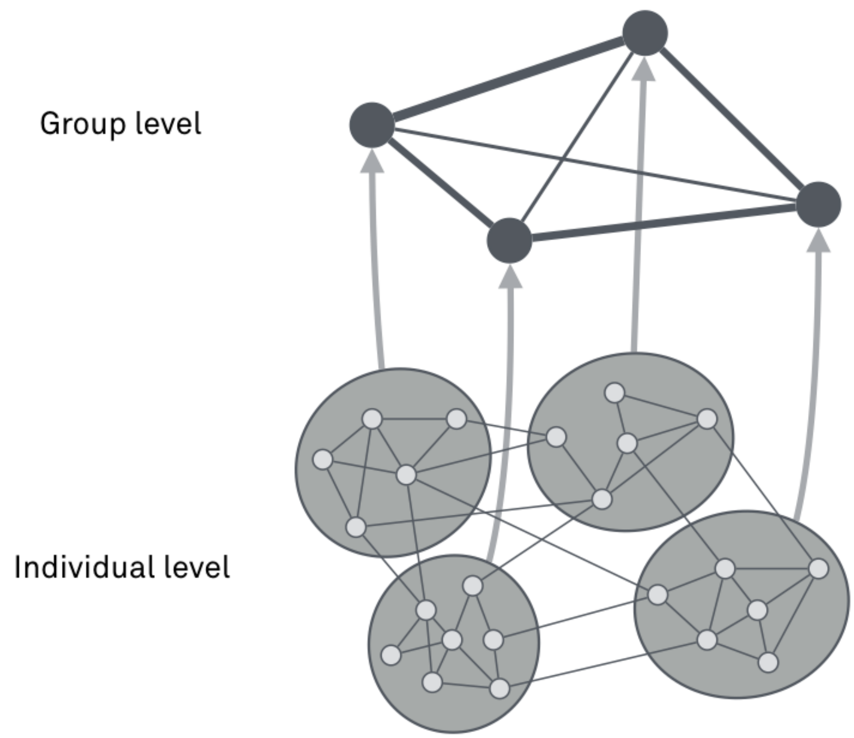


Figure 3.5 — Schematic representation of a level of node aggregation. The individual level represents the 129 nodes of the empirically constructed stakeholder network. The group level is an aggregated version of the same network, where all individuals belonging to the same group (as listed in Table 3.3) are contracted into one node. In this aggregated network, edges exist if at least one edge exists between two nodes of different groups at the individual level. Their weights (represented as width in this figure) is the sum of all edges' weights between nodes at the individual level.

Table 3.5: Network metrics favouring resilience building in SES

Metric	Description	How it connects to resilience-building
Robustness	Counts the number of nodes that need to be removed (according to a removal strategy) before the network splits in two unconnected subnetworks. The removal strategies are: randomly, by descending order of degrees.	Test the capacity of the network to withstand stakeholder disinvolvement.

Metric	Description	How it connects to resilience-building
Average path length (APL)	The average number of nodes separating every pair of nodes in the network.	Low APL helps achieve quick and efficient transmission of information and ideas through the network, and promotes social capital, trust, and better cooperation.
Synchronizability	The speed to which the network's nodes (modelled as originally asynchronous oscillators whose phases are influenced by neighbouring nodes) converge to a common phase.	Relates to the capacity of a social network to reach consensus despite originally diverging values.
Modularity	Quantifies the level to which members of a group are relatively more strongly connected within their groups than with members of other groups.	High modularity ensures that groups of special interests and specialized knowledge can efficiently develop solutions close to their own stakes and values. High modularity helps promote the emergence of novel ideas, which is particularly important to cope with social or environmental uncertainty.
Group marginalization index (GMI)	The group-level degree spread.	Measures the marginalization of stakeholders groups within the network.

Simulated Annealing

The chain of successive edge rewiring (edge removal, addition, and edge weight alteration, as shown in Equation 3.5) best improving the set of metrics relevant to resilience building (Table 3.5) in the EP is found with a simulated annealing optimization algorithm (Kirkpatrick 1984).

$$p = \Big[\underbrace{\big[\underbrace{(v_1^\alpha, v_1^\beta)}_{a}, \underbrace{(v_1^\gamma, v_1^\delta}_{b}, \underbrace{w_1)}_{c} \big]}_{d}, \big[(v_2^\alpha, v_2^\beta), (v_2^\gamma, v_2^\delta, w_2)\big], \ldots, \big[(v_n^{\omega-1}, v_n^{\omega-1}), (v_n^\omega, v_n^\omega, w_n)\big] \Big]$$

Equation 3.5 — Chain of graph edits (p) providing a path between the original and optimized version of the EP network. The optimized graph-edit chain is encoded as a series of 100 steps (i.e., d is one step), each containing three actions: a) remove an edge between two nodes, b) add an edge between two other nodes, and give it a weight (c).

Simulated annealing (SA) is a type of algorithm designed to explore large solution spaces in order to find the lowest scoring candidate (SA traditionally tries to lower a candidate solution's score). Practically, our SA (described in Figure 3.6) is initialized with a randomly generated rewiring chain (described in Equation 3.5). The EP stakeholder network is rewired according to the chain, and an initial score (Equation 3.6) is computed. The score is a composite of resilience-enhancing network metrics described in Table 3. From this initial state, the simulation enters an iterative process of 6000 small chain rearrangements (one chain link —noted "d" in eq. 3.5— is removed, and replaced by a new, randomly generated one) and a new score is calculated. If the new score is better (lower) than the previous step's score, it is accepted as the new best solution. If, on the other hand, it scores higher (worse), it is either accepted or rejected according to a probability which decreases exponentially as the SA's iterations progress. At the end of the 600,000 iterations, a chain of edits best improving the EP stakeholder network (within the number of iterations set) is found.

We replicated the simulations five times for improved modularity, APL, synchronizability, and GMI (we successively set Equation 3.6's weights to 0 or 1 in order to optimize particular metrics). The average of the five runs was calculated and used for subsequent analyses.

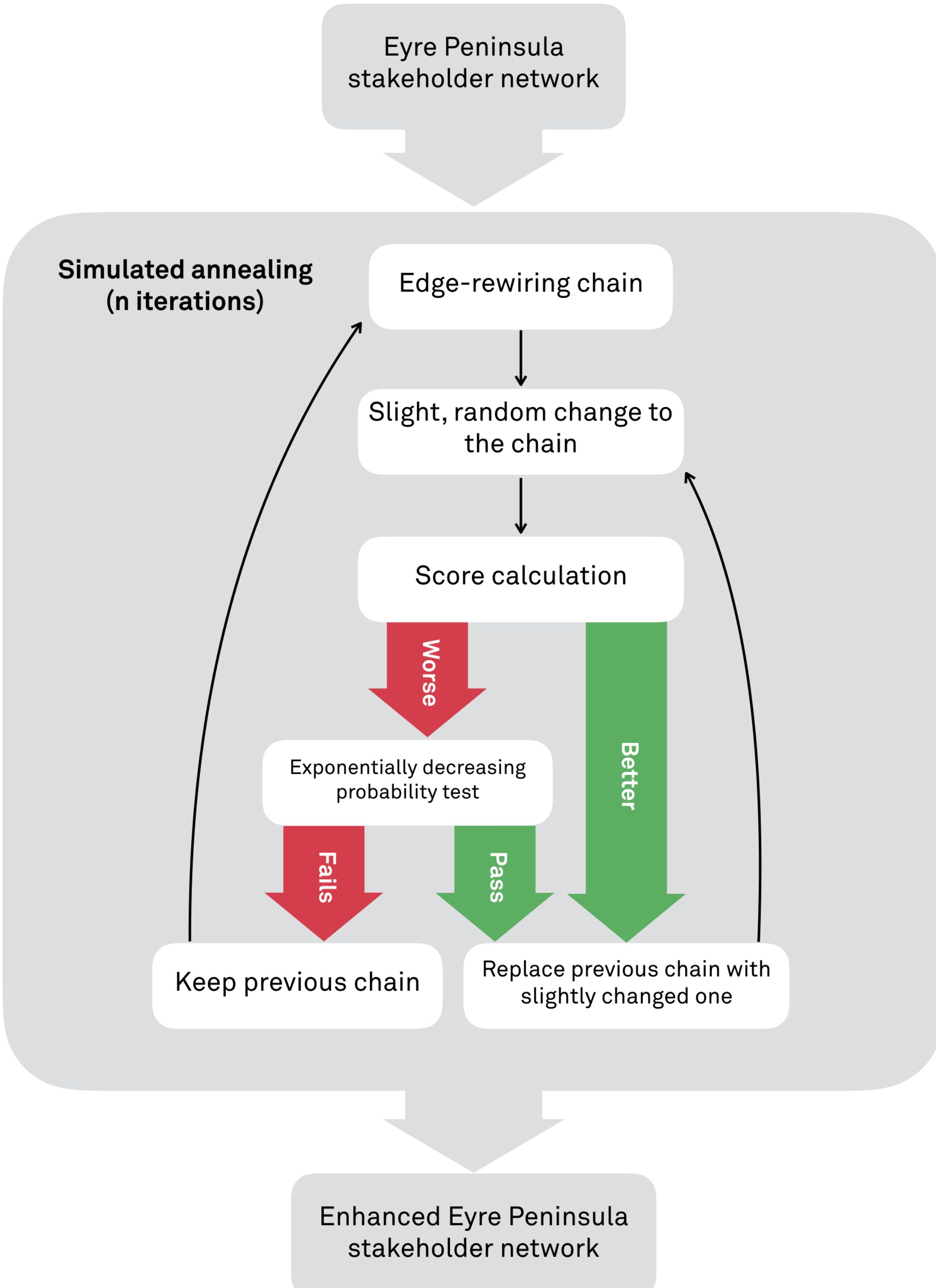


Figure 3.6 — Simulated annealing flowchart.

$$s = \frac{w_1 \times m + w_2 \times \dfrac{-d}{d_M} + w_3 \times \dfrac{r}{N} + w_4 \times \lambda_2 + w_5 \times gmi}{w_1 + w_2 + w_3 + w_4 + w_5 + w_6}$$

Equation 3.6 — Score composite (s) used in the simulated annealing. Each new solution is evaluated as a weighted (w1 to w6) average of normalized metrics, namely modularity (m), average path length (d), normalized over the longest path in the network (d_M), robustness to highest degree-targeted node removal (r), normalized over the total number of nodes in the network (N), synchronizability (λ_2), Group Marginalization Index (gmi).

3.4. RESULTS AND DISCUSSION

3.4.1. EP Stakeholder Network Analysis

Is there a Typical Distance Between Interacting Stakeholders?

We used each stakeholder's main work address to plot a weighted histogram of geographic distances separating stakeholders (edge orthodromic length in kilometres) in the network (Figure 3.7). A clear tendency for very local interactions emerges from the network as 53% of all weighted interactions take place between stakeholders working in the same locality (or within 10 km of each other). Another peak emerges at around 250 km, which incidentally is the average distance between stakeholder's locations on the EP (with a standard deviation of 90 km). It is interesting to note that at a time of inexpensive and fast long distance communications, very short physical distances remains a strong structuring driver for stakeholder interactions in our case study.

Figure 3.9 gives a different perspective of how geography may drive collaborations beyond immediately local interactions. The figure represents an agglomerated version of the EP network where individual nodes are contracted as per their cities or towns of residence. Node colours indicate community membership calculated with a community detection algorithm (Blondel, Guillaume et al. 2008), where nodes belong to the same communities if they are more connected among each other than they are with nodes belonging to other communities. Three communities were found by the algorithm (albeit with the relatively small modularity score of 0.13, see the *Modularity* section in Chapter 4 for more information about this algorithm): the first one, represented in orange, gathers nodes that are, all but one (Brisbane), situated on the upper West coast of the peninsula, which can be explained by the existence of important conservation projects (such as Chain of Bays: http://www.chainofbays.com.au). The second community, in blue, covers most of the central and eastern part of the EP. While this group is somewhat spatially linked to the East coast of the Peninsula, it also includes towns from the center of the EP, as well as Adelaide. It is therefor difficult to draw any firm conclusions about this group. The last one, in green, draws a line from the Western, northern part to the center of the EP. These three groups of towns and cities indicate that while most of the collaborations (green community) aren't conclusively geography-driven, at least some others (the orange community in particular) most likely are.

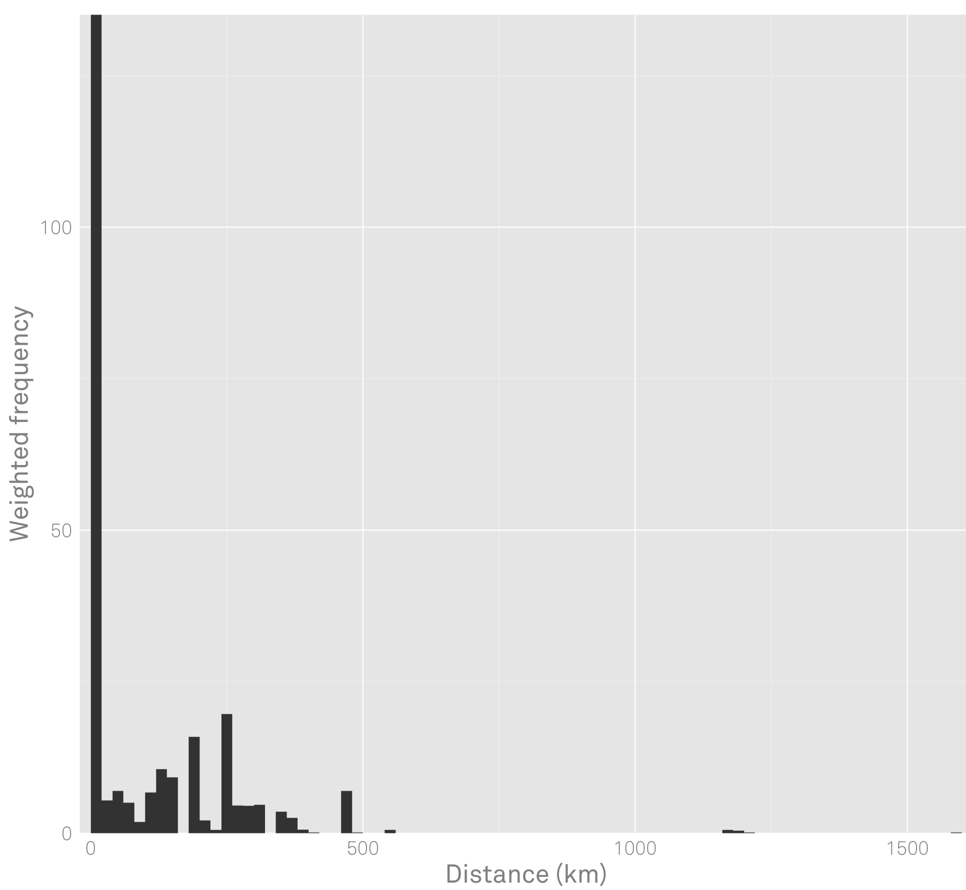


Figure 3.7 — Weighted distribution of edges vs. orthodromic edges length (as the crow flies) for the EP stakeholder network. This distribution, weighted according to edge weights, shows that a large majority of interactions between stakeholders happen when individuals are geographically very close to each other.

Is Port Lincoln a Topological Centre as well as an Administrative One?

Port Lincoln is EP's main city. It is the place, on the peninsula, where the main State government offices are. This central situation should therefore be seen in our data. In Figure 3.9, node sizes demonstrate the diversity of topological betweenness centralities among cities. It shows that while Port Lincoln is in fact the network's most central city, it is closely followed by two others: Adelaide and, to a slightly lesser extent, Streaky Bay. This pattern is also noticeable in Figures 3.8.a and 3.8.b, where these three cities form a strong axis across the EP. This can be explained by the fact that two of these cities are strong administrative hubs, while the third, Streaky Bay, hosts a variety of stakeholders (from DENR and EP NRM, as well as from environmental NGOs). This diversity of stakeholders most likely increases the chances of more intense interactions far across the network.

Returning to node-level centrality, Figure 3.10 scatters the nodes of the stakeholder network along two axes: the orthodromic distance (as the crow flies) from Port Lincoln, and the nodes' betweenness centrality. The figure shows that the proximity of stakeholders to Port Lincoln constitutes a strong geographical driver of the structure of the network: 1) while 27% of all stakeholders work from Port Lincoln, 43% of the weighted interactions happen in this city, 2) all topologically very central outliers work in Port Lincoln, and 3) the betweenness centrality slowly decreases as the distance from Port Lincoln increases. This goes to show that the city of Port Lincoln, while geographically off-centred, effectively acts as a strong knowledge-sharing hub on the peninsula.

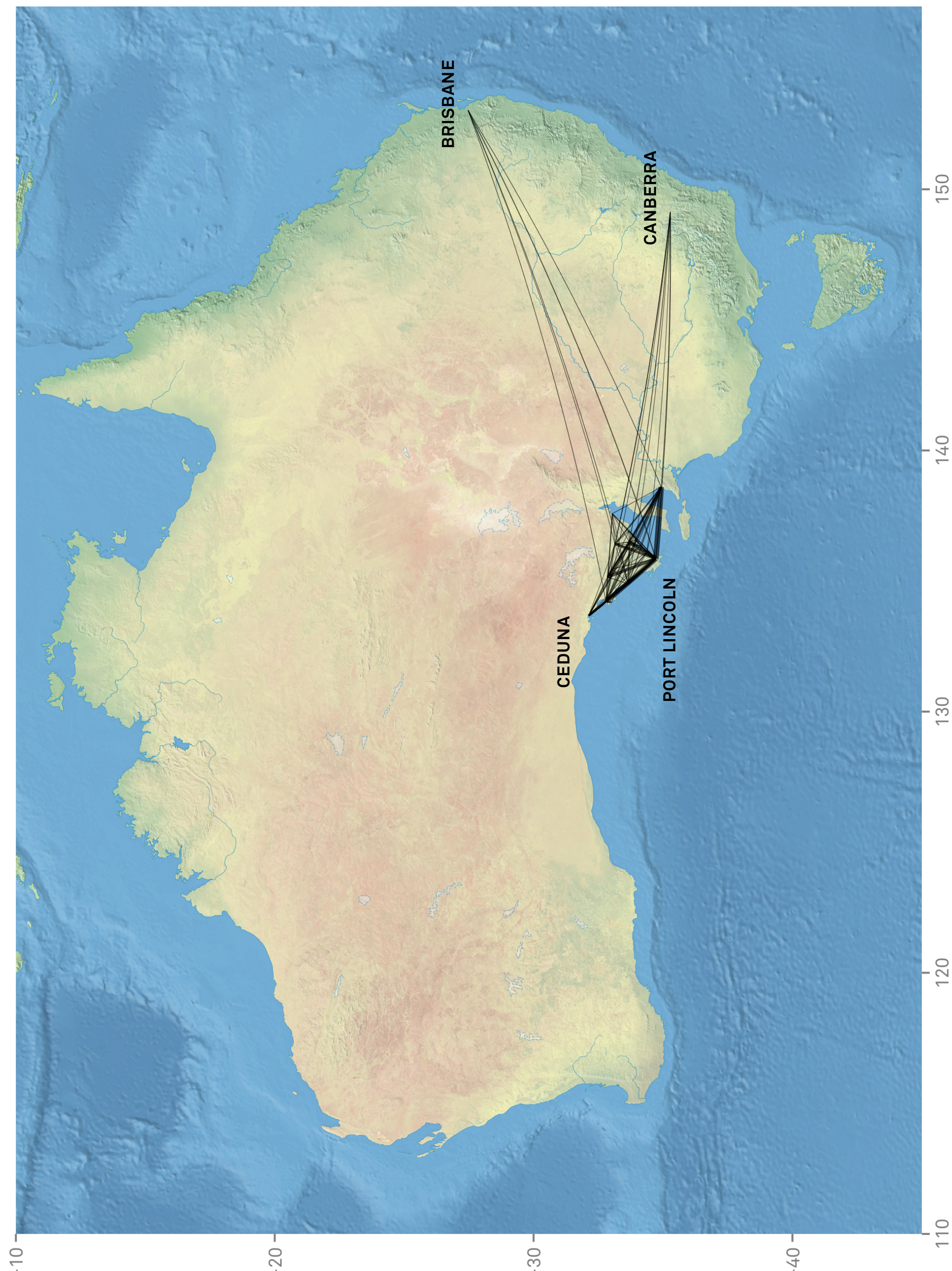


Figure 3.8.a — Geographical visualization of the stakeholder network. Orthodromic lines represent interactions between stakeholders. The width of the line represents the cumulative strength of all connections from one place to another.

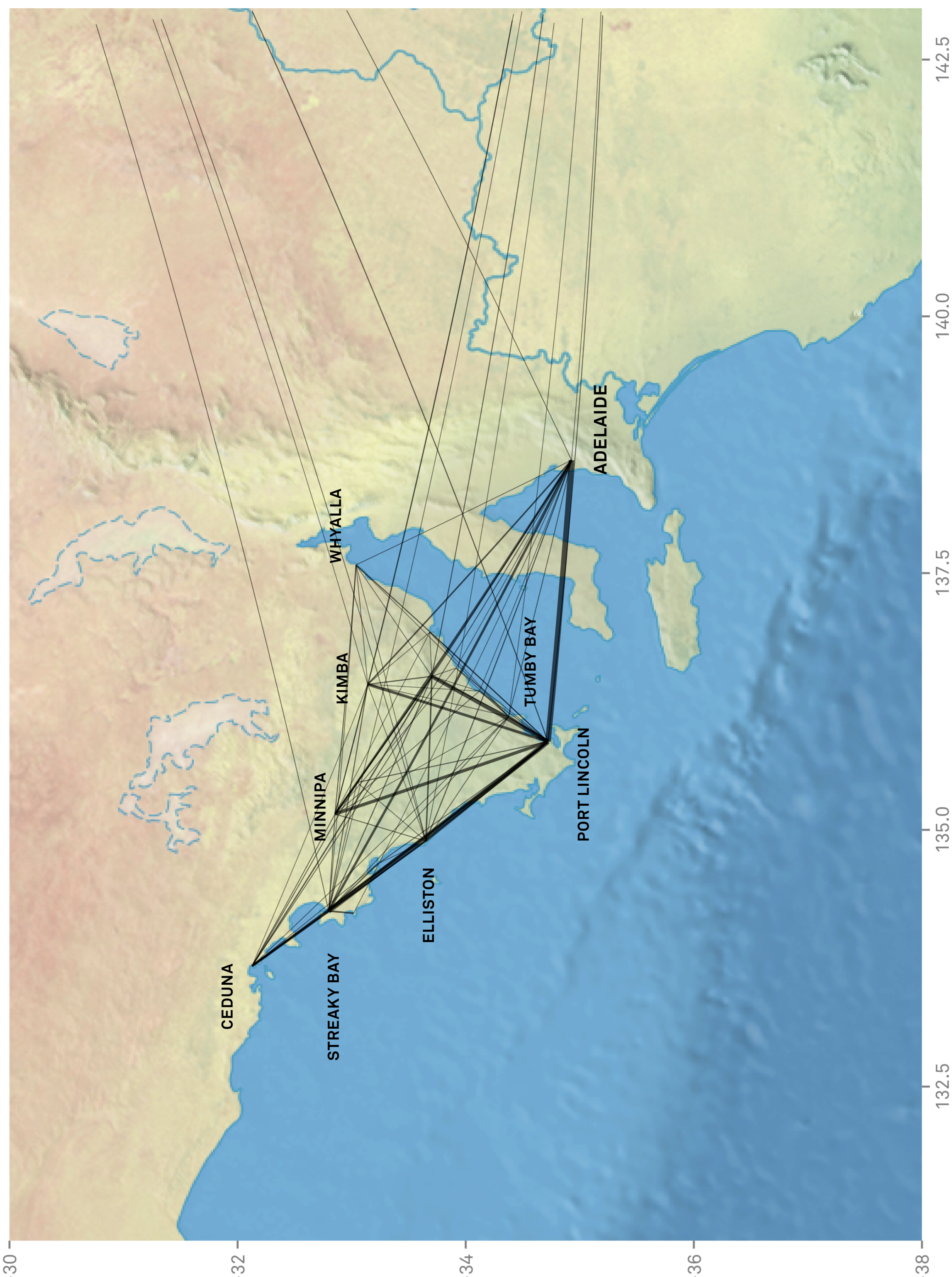


Figure 3.8.b — *Ibid (detail)*.

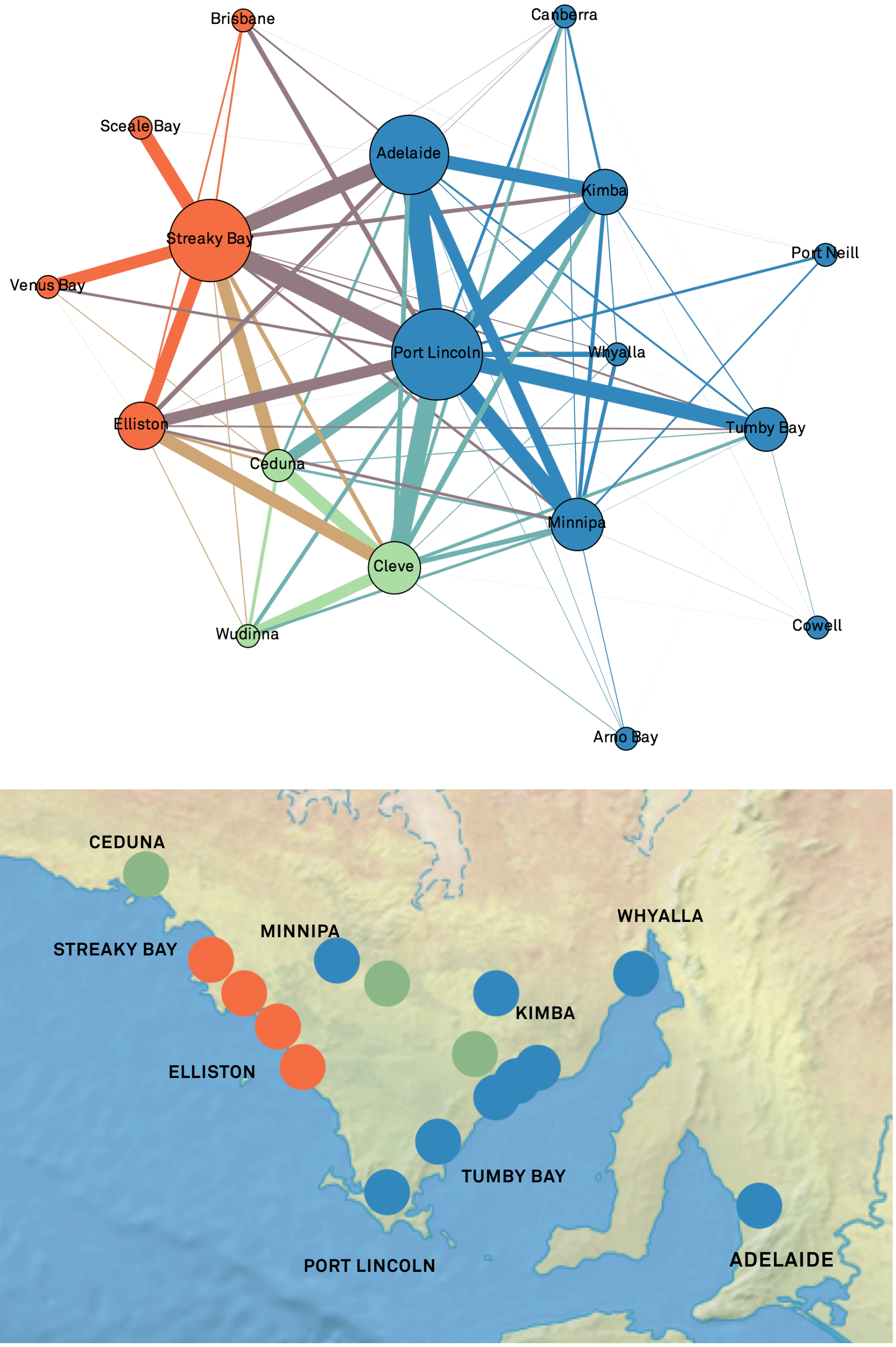


Figure 3.9 — Representation of the EP stakeholder network where all nodes belonging to the same place are contracted into the same node (top). Edge size represents the summation of all edges connecting nodes belonging to each place. Node size represents the level of betweenness centrality in this newly created network. Node colours were attributed using a community de-

tection algorithm. Spatial distribution of the communities (detected according to stakeholders interactions) (bottom).

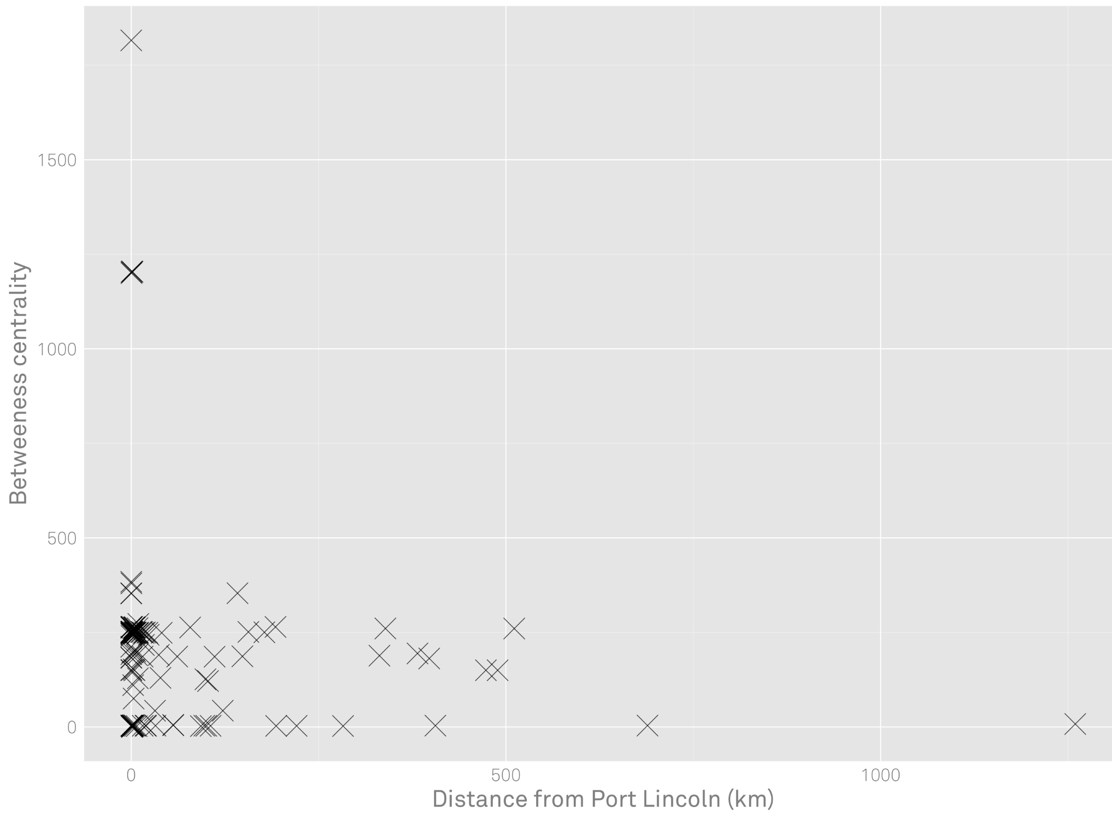


Figure 3.10 — Scatter plot of node's betweenness centrality vs. orthodromic distance from Port Lincoln. This plot shows that all the highly central stakeholders (topologically speaking) work in Port Lincoln.

3.4.2. COORDINATION IN THE NETWORK

Topological Centrality and Reaching Capacity

The betweenness centrality of nodes, that is, their capacity to reach far across the network, and act as bridges between other stakeholders, is visualized at the group level in Figure 3.11 and summarized in Figures 3.12.a and 3.12.b. Figure 3.12.a shows that two groups account for a large share of the total betweenness centrality: South Australia Research & Development Institute (SARDI), which is a State governmental agency (Primary

Industry & Regions South Australia) conducting agricultural research as well as running an experimental farm, and Eyre Peninsula Natural Resource Management (EP NRM). This in confirmed by Figure 3.12.b, which shows that State government agencies dominate betweenness centralities in the network.

SARDI is an interesting case as it is located in Minnipa (250 km by roads north of Port Lincoln, very close to EP's northern marginal agricultural lands), far from the geographical centre described above. However, being as much a research centre as a farm, SARDI is topologically close to both farming and state agency circles, which places it at a central, bridging position in the network. We note also that, while our survey only accounted for quantitative relationships, the stakeholders we interviewed face to face on the EP were eloquent about SARDI, and unanimously seemed to hold this group in high esteem. This qualitative observation is supported by our quantitative assessment of influence based on betweenness centrality as well as on GB.

EP NRM ranks first in median of GB and second in betweenness centrality. This group also hosts the network's most central individuals (see outliers and upper inner whiskers in Figures 3.12.a and 3.13.a). EP NRM's structurally very central position is in accordance with its institutional role of coordinating and implementing NRM programs and projects in the region (Spekkink and Boons 2015). On a structural point of view, EP NRM not only managed to reach far in the network (high betweenness centrality), but also to reach and connect stakeholders belonging to different groups (high GB). This fundamental quality to fulfill a role of coordination is well illustrated by Figure 3.11. The figure shows how groups connect with each other in the network, with node size corresponding to betweenness centrality, and colours showing communities as detected by the same algorithm used for Figure 3.9. The figure clearly demonstrates EP NRM's central position between two large groups composed mainly of environmental NGOs (in green) on one side, and of industry/academia/research groups (orange) on the other. The wide spread of betweenness scores among members of EP NRM can be explained by the fact that this group includes administrators, project managers, and board members, who have very different roles within the organization. Lastly, Figures 3.12.b and 3.13.b show that state government agencies rank the highest for their bridging capacity. This confirms this group's function as a broker.

Farming groups are very heterogeneous in terms of betweenness centrality, but some groups such as the "Agricultural Bureau" and "Consultants" perform fairly well in this regard. In terms of GB, the farming industry ranks high. Once again, this is mainly due to consultants (private or from Rural Solutions SA), who succeed in connecting not only with the industry as their function suggests, but also with academic and environmental groups.

Academia and research have a relatively low centrality. It can be argued that universities', and research centres such as CSIRO's, way to communicate is mainly, while not exclusively, done through academic articles and reports, which are useful to local projects and long-term programs, but difficult to account for in our network.

The Department of Environment and Natural Resources (DENR), while ranking rather high in betweenness centrality (Figure 3.12.a), ranks much lower in GB, which suggests that most of its betweenness score accounted for connections among members of the same groups. Additionally, while some environmental groups like Greening Australia rank very high in both GB and betweenness centrality (hence taking an important coordination role), others like Friends of Parks rank lower in GB than in betweenness centrality. This is consistent with Friends of Parks' focus on local projects.

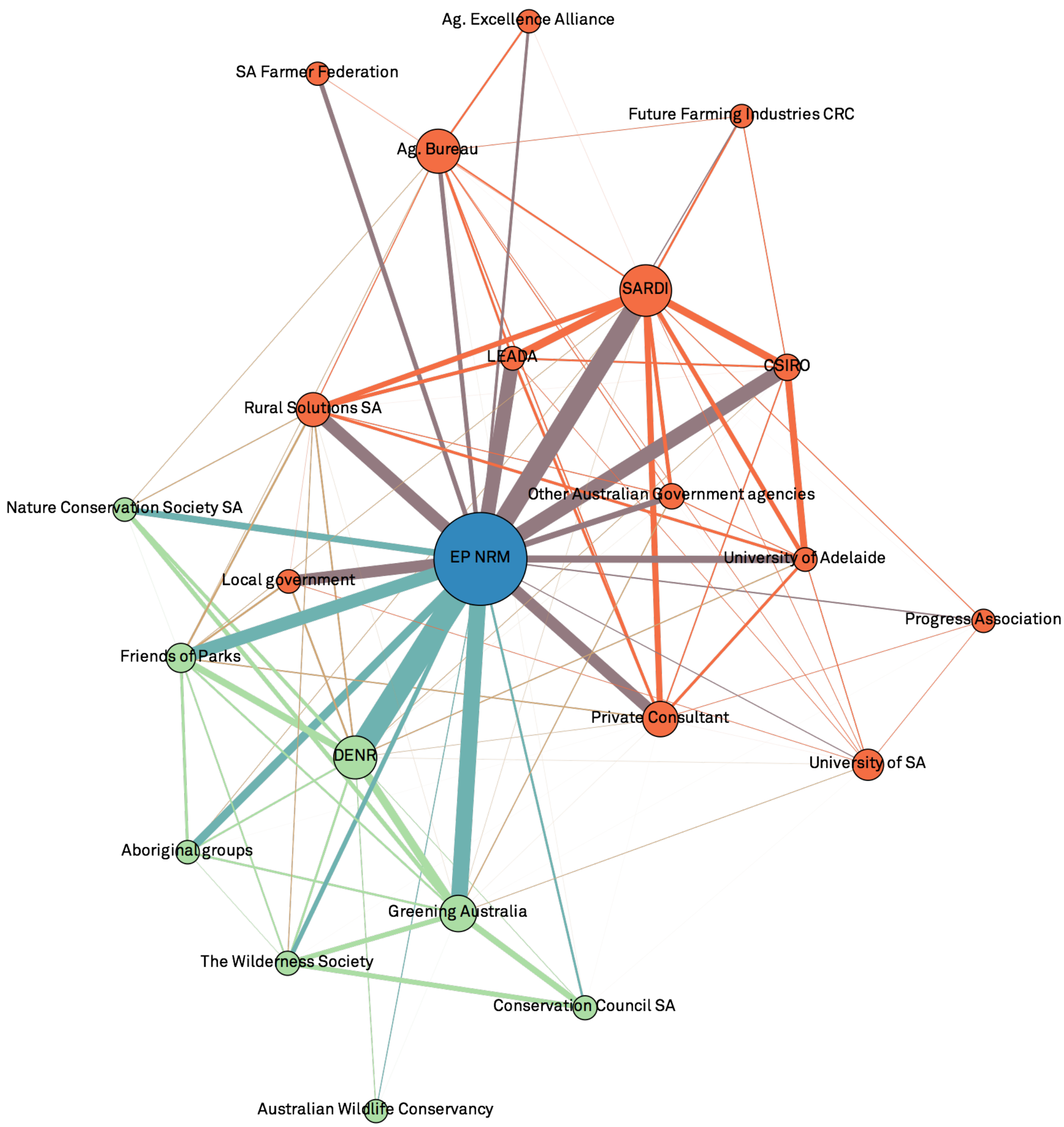


Figure 3.11 — Representation of the stakeholder network where all nodes belonging to the same group are contracted into the same node. Edge size represents the summation of all edges connecting nodes belonging to each group. Node size represents the level of betweenness centrality in this newly created network. Node colours were attributed using a community detection algorithm (Blondel, Guillaume et al. 2008), except for EP NRM which, while detec-

ted as belonging to the orange community, was forced to blue for illustration purposes in order to highlight its bridging position.

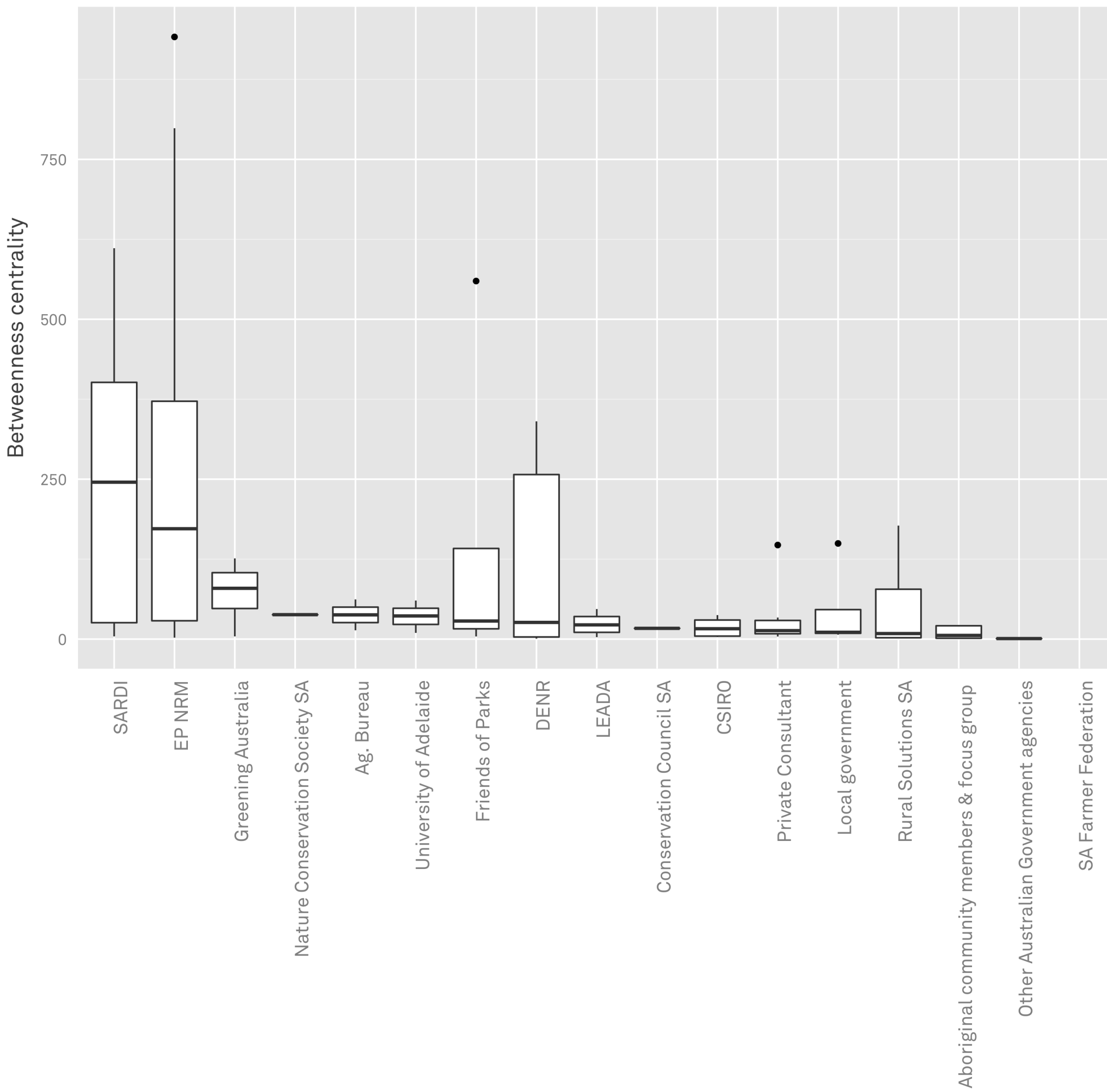


Figure 3.12.a — Betweenness centrality of stakeholder groups in the EP network. Groups are ordered on the abscissa by decreasing median betweenness centrality. The whiskers are set at 1.5 interquartile.

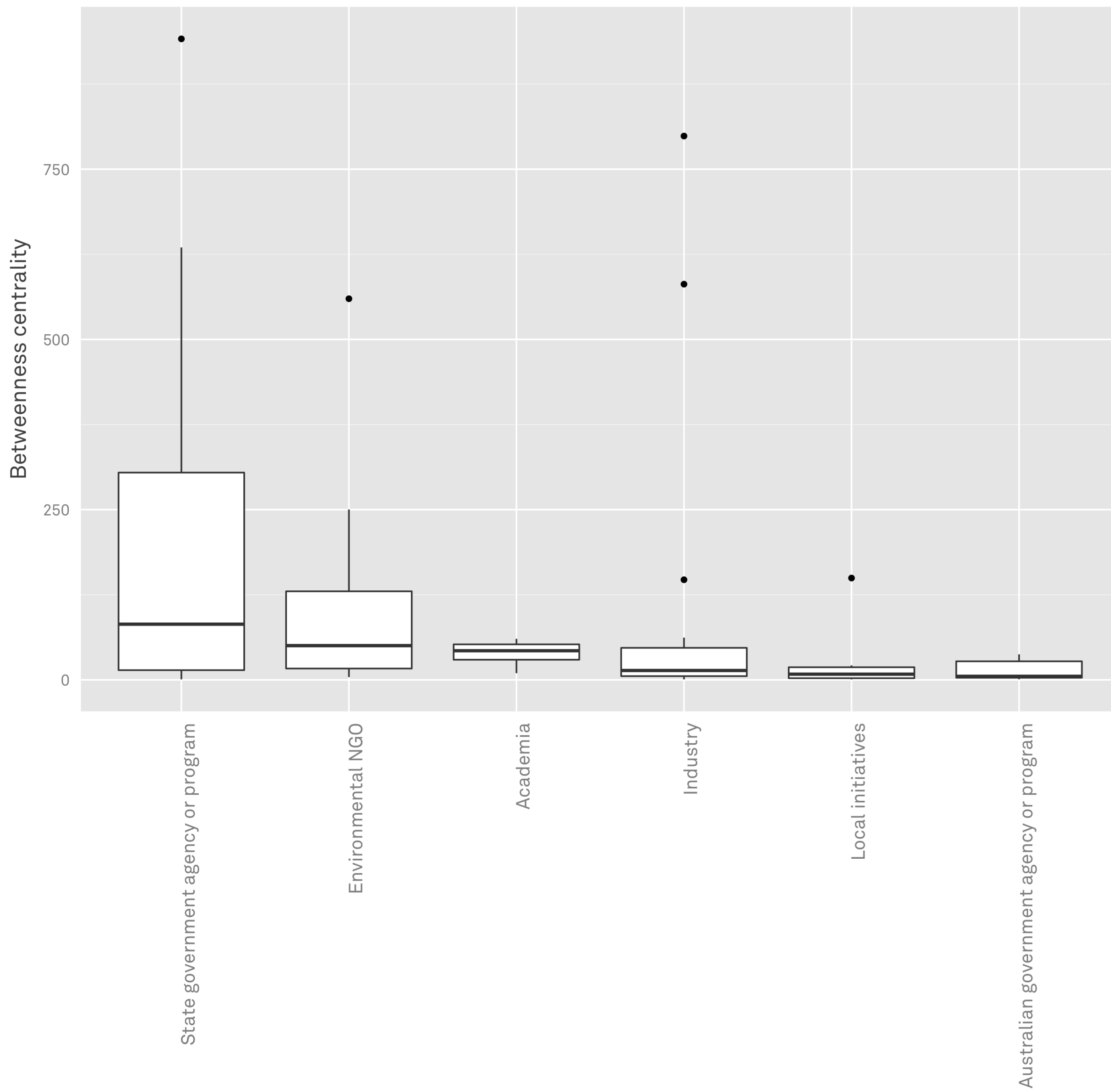


Figure 3.12.b — Betweenness centrality of stakeholder categories in the EP network.

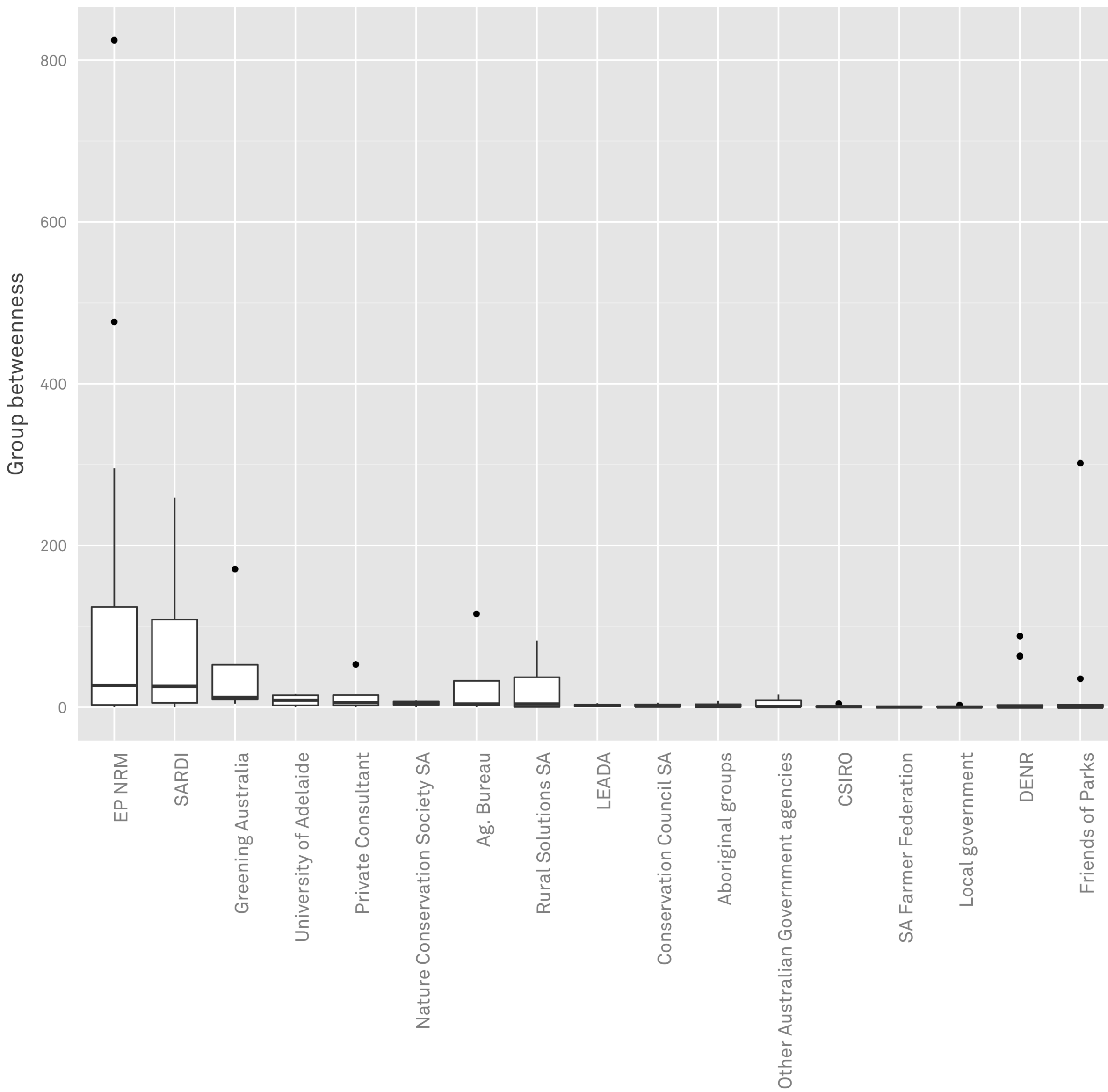


Figure 3.13.a — Group Betweenness (GB) of stakeholder groups in the EP network. Groups are ordered on the abscissa by decreasing median of group betweenness. The inner whiskers are set at 1.5 interquartile.

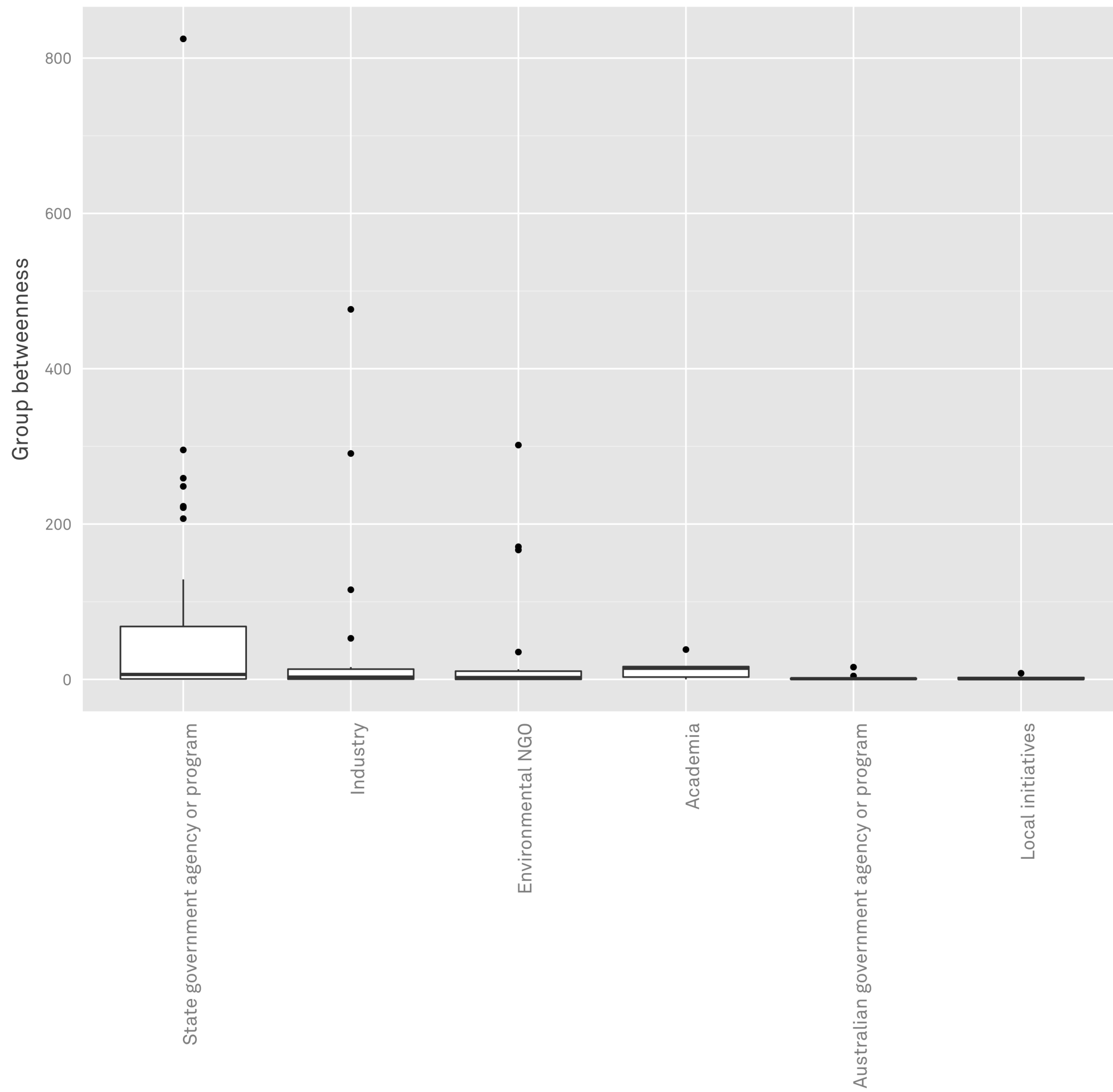


Figure 3.13.b — Group Betweenness (GB) of stakeholder categories in the EP network.

3.4.3. OPTIMIZED REWIRING FOR IMPROVED RESILIENCE-BUILDING

We altered our empirical EP's stakeholder network according to an optimized sequence of 100 rewirings. Our optimization algorithm was set to improve, at the end of these 100 alterations, four network metrics related to resilience-building in SES: modularity, average path length (APL), synchronizability and the group marginalization index (GMI). While such an exercise is purely hypothetical, and would be difficult to impose on the real-world network, it can provide insight into the types of new collaborations that should be nurtured so as to promote system resilience and social adaptive capacity through increased coordination and information sharing between stakeholders. Such insight could be used by umbrella organizations such as the EP NRM board, for example, to prioritize programs that would contribute to building and strengthening such links. The 100 steps are summarized, for each metric separately, in Figures 3.14.a/b to 3.17.a/b. Each “a” Figure only shows edges added during rewiring in order to help focus on the collaborations that should be promoted. “B” Figures show, at the category level, which inter-category interactions should be promoted to improve the network (see Annex 3 for more detailed group-level matrices). Negative scores indicate a negative balance between edge creation and deletion, while positive scores indicate a positive balance.

Figure 3.14.a and b show that favouring intra-category collaborations (nodes of the same colour shade in “a”, and the matrix’s diagonal in “b”) is the most efficient way to improve modularity in the network (purple in Figure 3.14.a). There are two exceptions however: the network’s modularity would gain from stronger collaborations between environmental NGOs and local initiatives (such as local governments, aboriginal communities, and progress associations), as well as collaborations between farming groups and academia.

As opposed to modularity-optimization, APL and synchronizability aren’t improved by intensifying short, local interactions, but by the addition of farther-reaching edges connecting remote stakeholders across the network. This is in accordance with the literature on small-world networks (Watts and Strogatz 1998). However, while APL and synchronizability are correlated, their optimization requires sightly different modifications to our EP network:

- Improving APL comes down to increasing collaborations between environmental NGOs and three other categories of stakeholders (farming groups, State government agencies, and Australian government agencies);
- Increasing synchronizability requires more collaborations between farmer groups and

local initiatives, environmental NGOs and state government agencies. For both APL and synchronizability, NGOs and the farming industry are important categories to focus on.

Improving GMI in the network produces a similar chain of rewiring as improving synchronizability. This means improving synchronizability also reduces group marginalization in the EP stakeholder network. Intuitively, the two measures may indeed be correlated in some types of topologies, but this need to be further investigated.

Altogether, the four optimized chains of rewiring do not lead to strong, definitive recommendations, likely due to the complexity of the optimization problem (i.e., attempting to find solutions that reconcile trade-offs between four different metrics in a high dimensional space). However, they do provide some directions on first steps to take in order to build better conditions for more effective and fairer co-management of biodiversity on the EP. For instance, all network figures show that very few EP NRM nodes (in grey) are newly connected, which can be explained by the predominance of this stakeholder in the original network, and by the necessity to focus on other stakeholders. Instead, the need for more collaborations involving two categories of stakeholders stand out:

- Farming industry (farmer groups, consultants) and environmental NGOs for better APL/synchronizability/GMI, and
- Intra-category cooperations for better modularity.

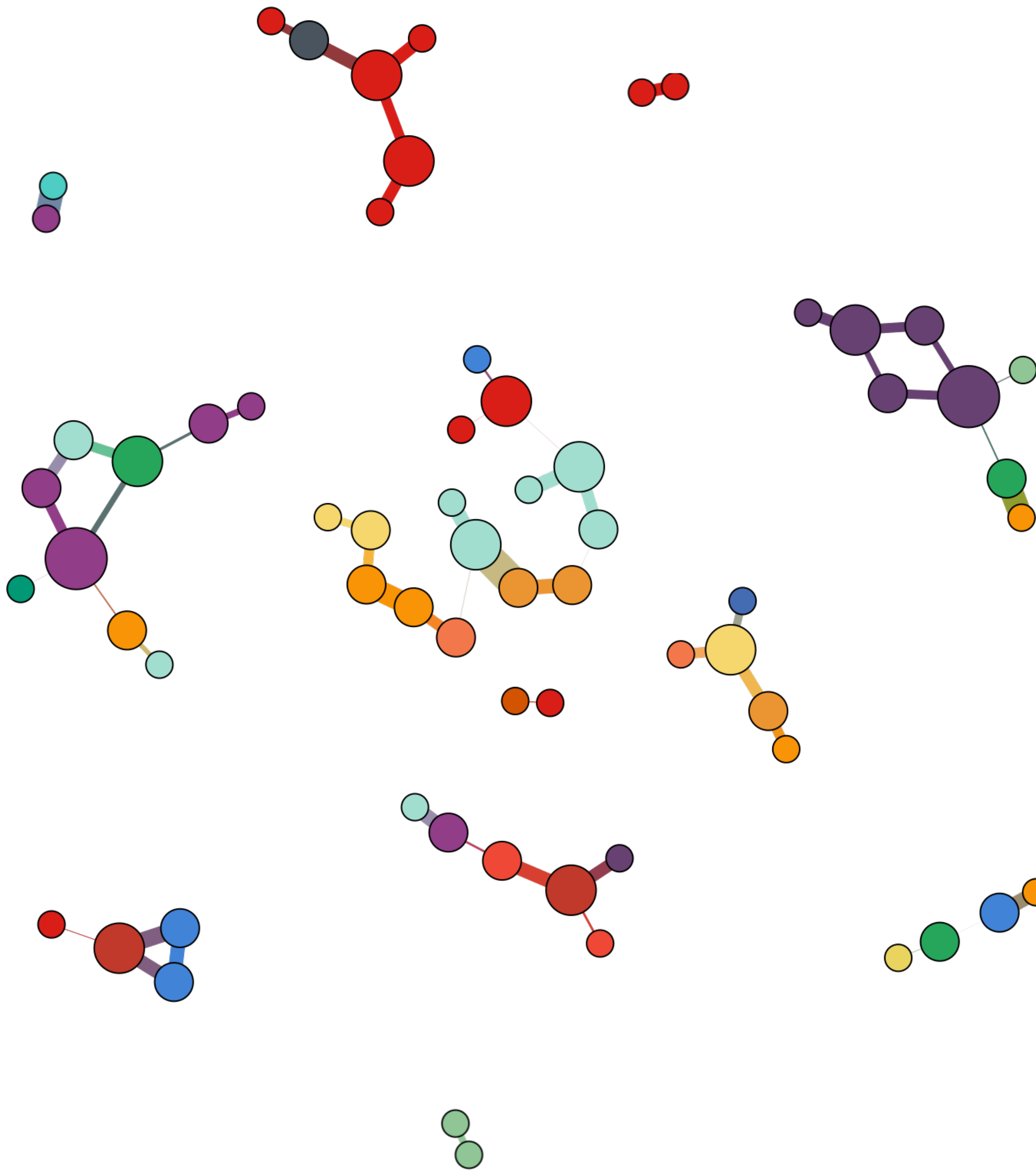


Figure 3.14.a — Edges added to the EP stakeholder network during the modularity-optimized rewiring sequence. The width of edges corresponds to the strength of the relationship. See Table 3.3 for colour coding.

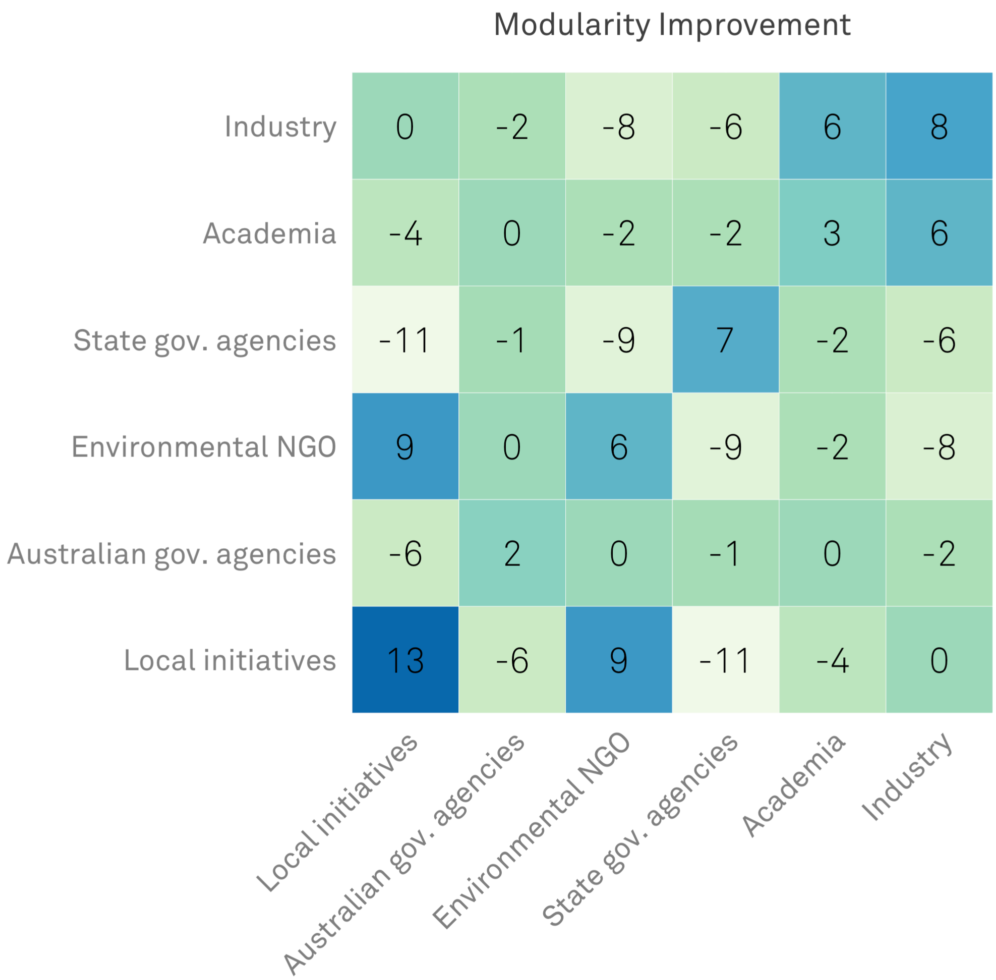


Figure 3.14.b — Balance of edge additions and deletions between stakeholder categories in the EP network as optimized for best modularity with the simulated annealing (average of five runs). Each cell contains the balance of node creations and node deletions during rewiring.

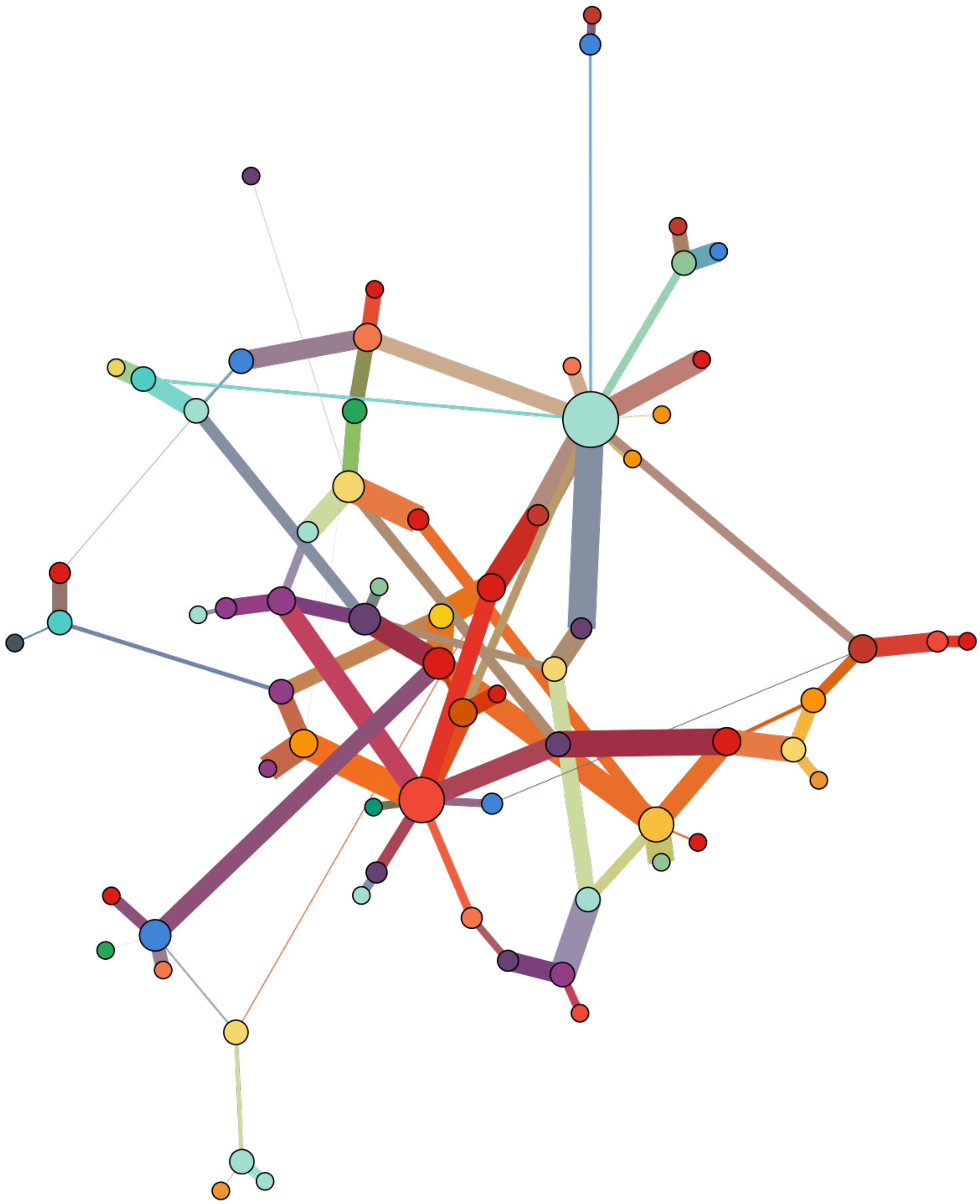


Figure 3.15.a — Edges added during the average path length-optimized rewiring sequence. The width of edges corresponds to the strength of the relationship. See Table 3.3 for colour coding.

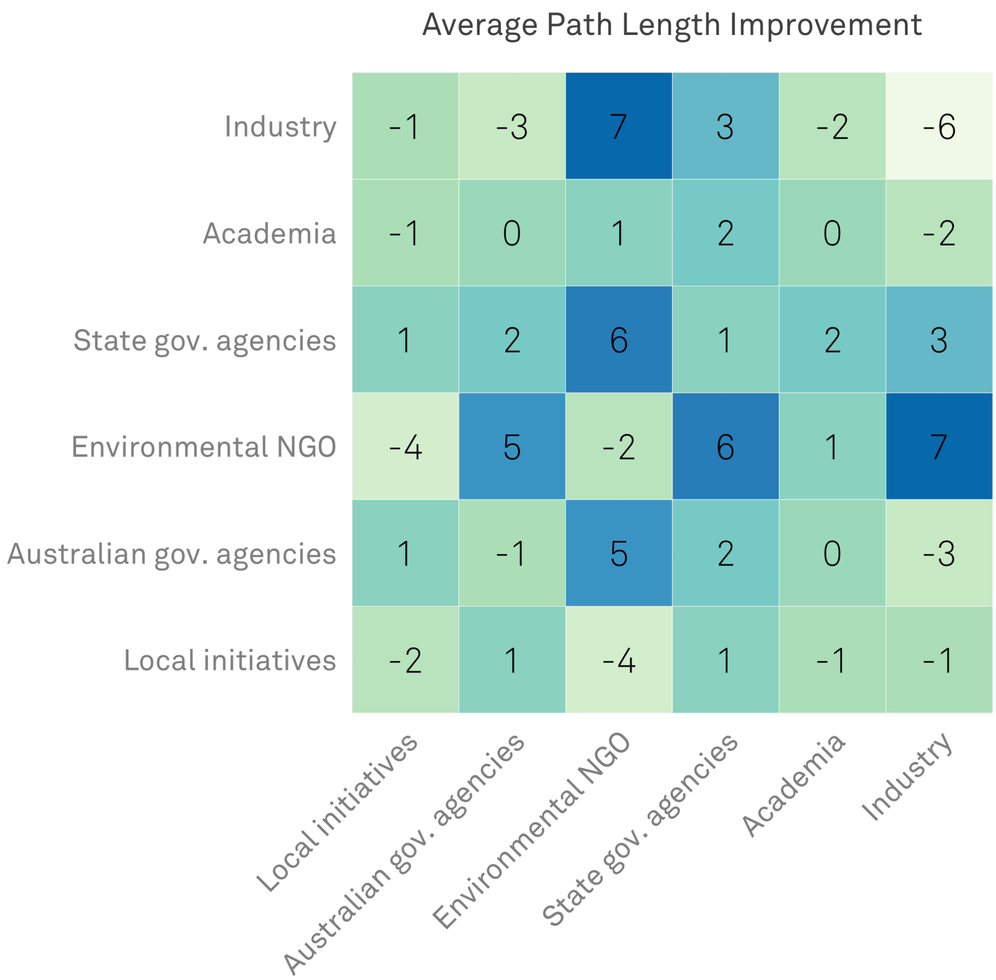


Figure 3.15.b — Balance of edge additions and deletions between stakeholder categories in the EP network as optimized for best average path length (average of five runs).

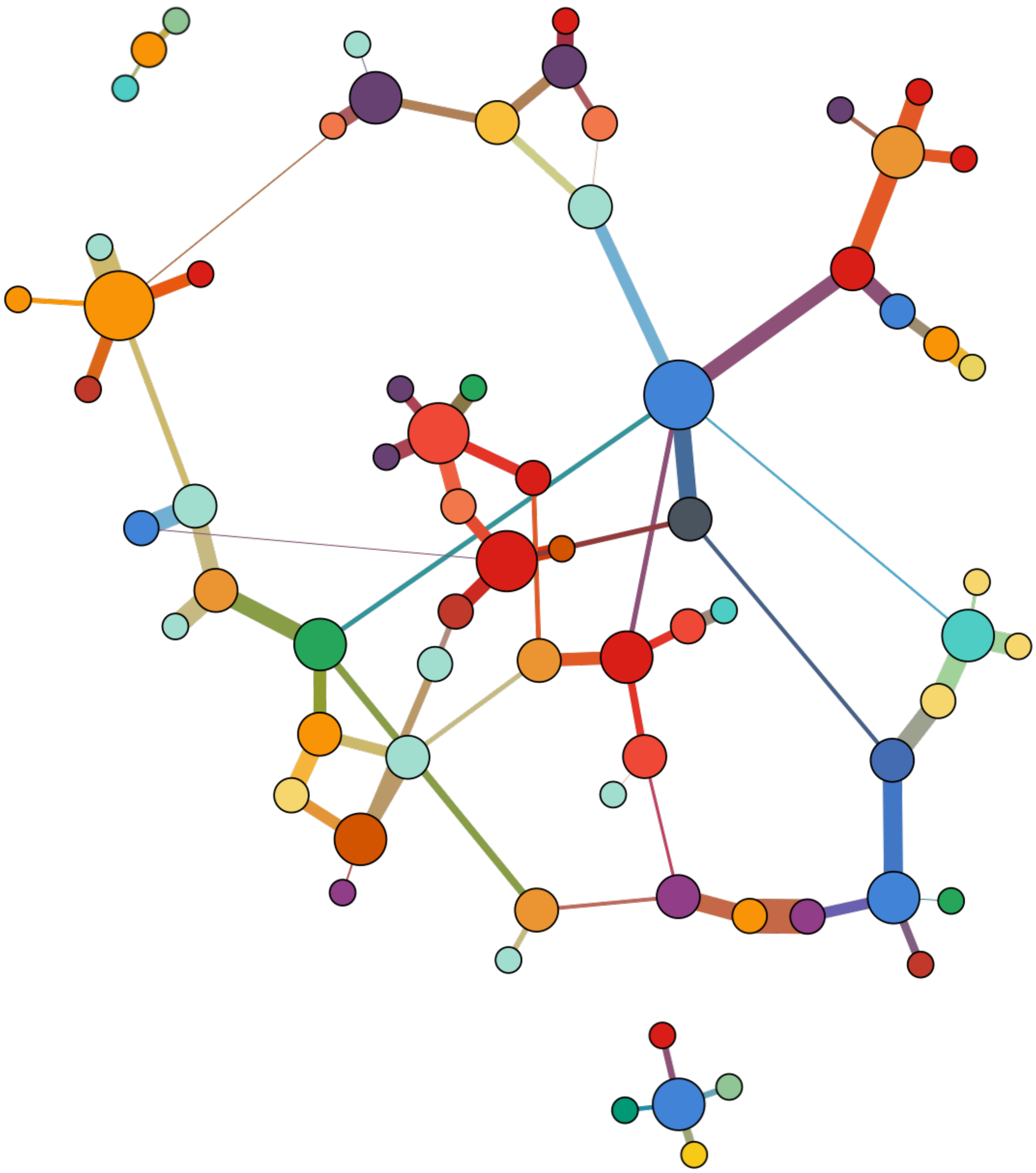


Figure 3.16.a — Edges added during the synchronizability-optimized rewiring sequence. The width of edges corresponds to the strength of the relationship. See Table 3.3 for colour coding.

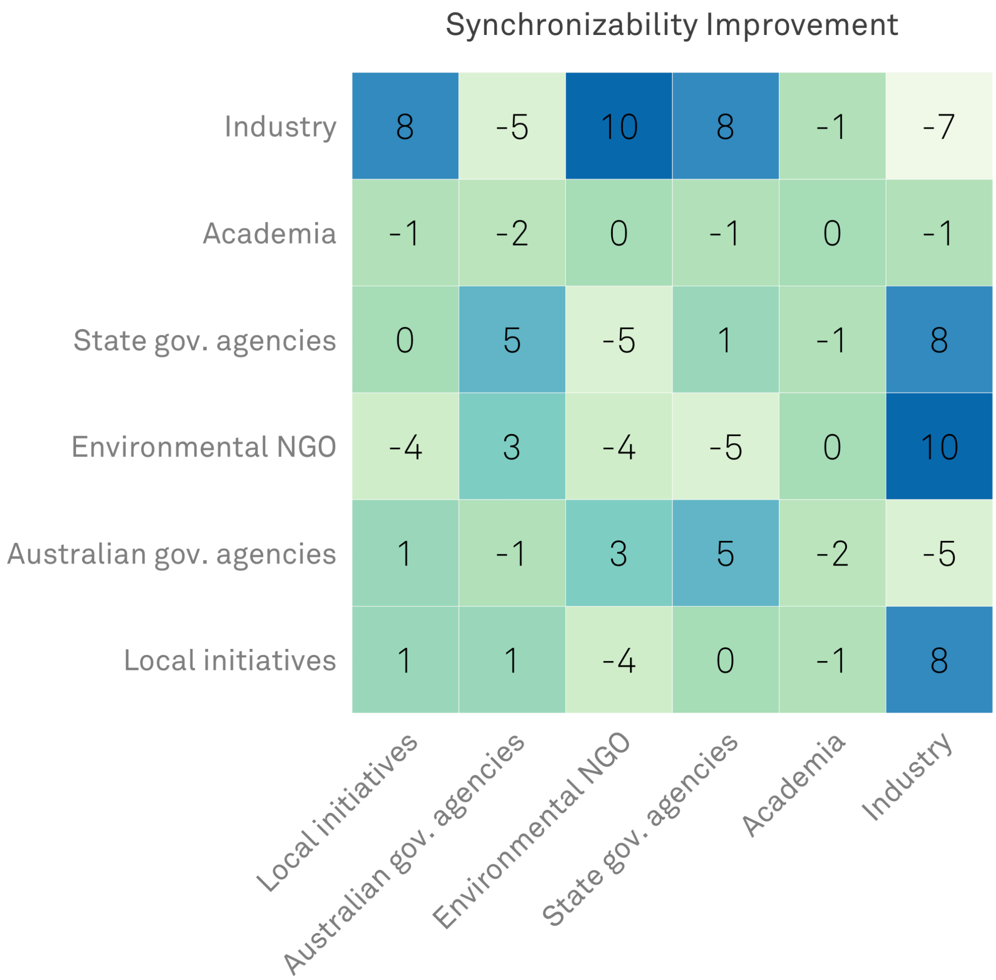


Figure 3.16.b — Balance of edge additions and deletions between stakeholder categories in the EP network as optimized for best synchronizability (average of five runs).

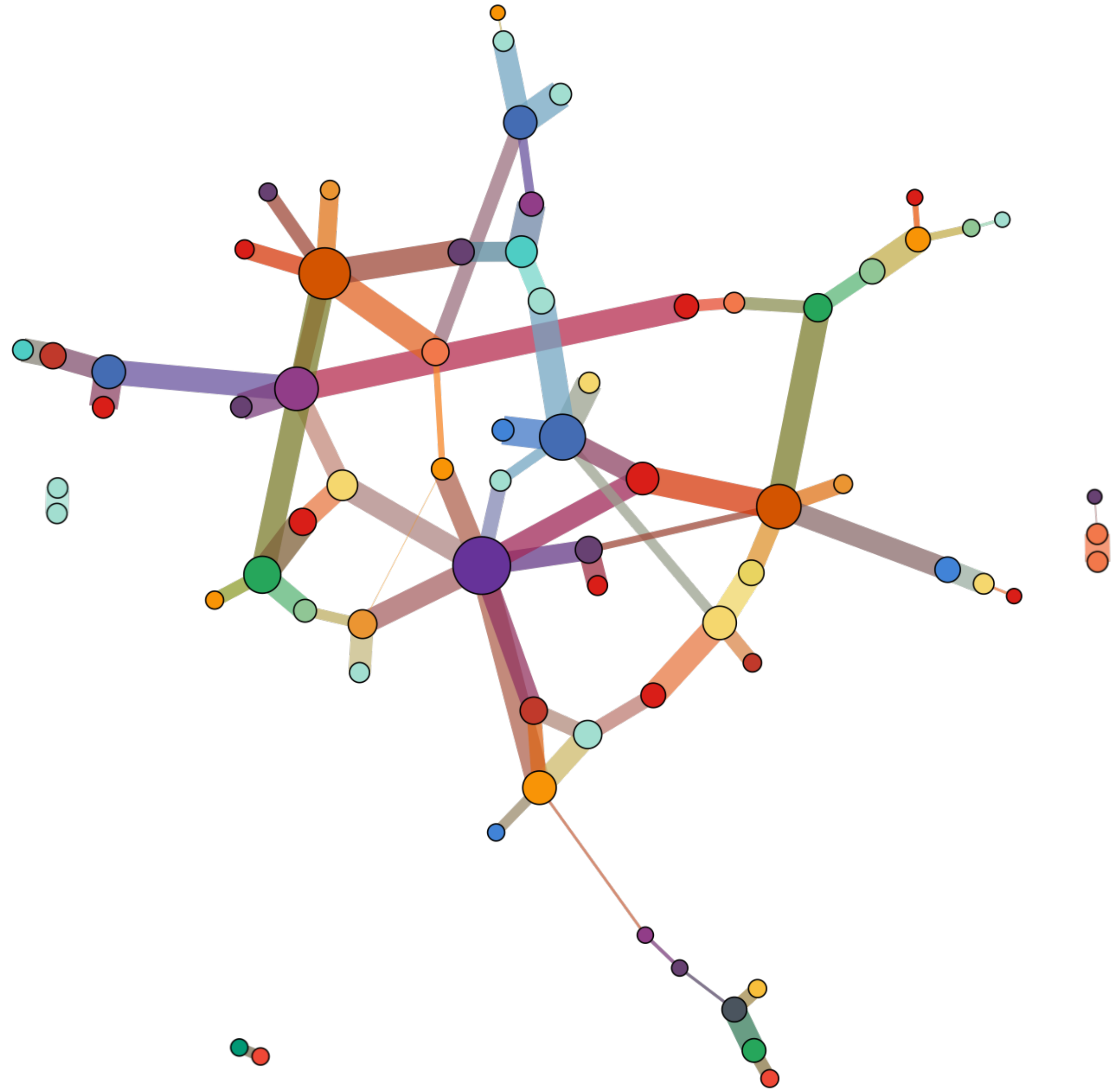


Figure 3.17.a — Edges added during the optimization for best group marginalization index (GMI). The width of edges corresponds to the strength of the relationship. See Table 3.3 for colour coding.

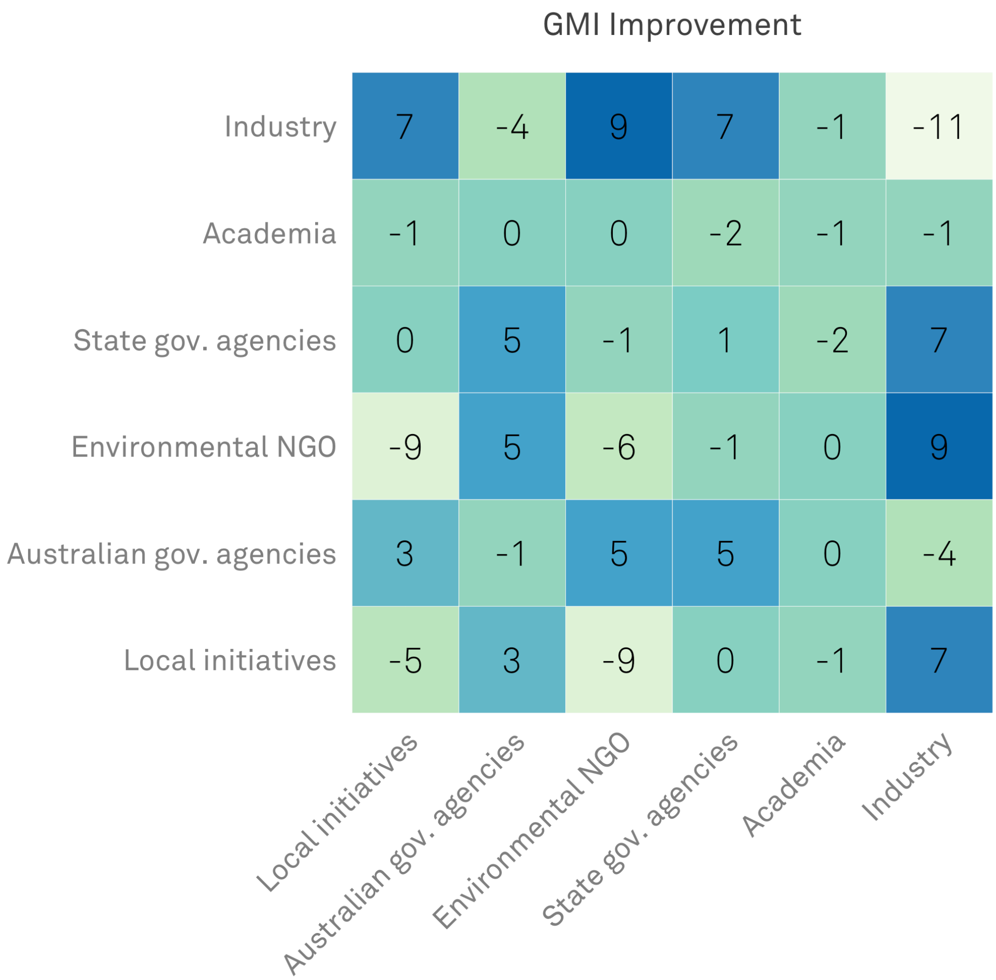


Figure 3.17.b — Balance of edge additions and deletions between stakeholder categories in the EP network as optimized for best group marginalization index (GMI) (average of five runs).

3.5. LIMITATIONS

Selecting the nodes to include is a very sensitive step of any network analysis. In our case, stakeholders' dynamics are often shaped by either clear or underlying power dynamics, and while some interests, often from recurrently marginalized populations, may be involuntary omitted, others may be overrepresented. The misrepresentation of just a few bridging nodes can lead to very different structures, and caution must therefore be used when finding the network boundaries and sampling the interactions. In this study, we partially addressed this issue by filtering the network according to an *ad-hoc* index of fuzziness which allowed us to discard nodes or edges we suspected could be inaccurate. However, we have no ways to account for nodes we may have missed during the survey. Additionally, this means that nodes that weren't interviewed could still be included in the network (their presence being inferred from interviews with several people mentioning their names). This raises some important limitations: firstly, people who weren't interviewed but had been included in the network have their number of connections potentially underestimated; secondly, these individuals couldn't participate in the snowball sampling, which could have artificially limited the boundary of the network; thirdly, their presence is less legitimate than the one that were interviewed. However, our knowledge of the system made us confident in the fact that these individuals were indeed stakeholders in the system, and that not including them could biais the structure towards already strong players. This "fuzziness" in the data should be taken into consideration with regards to any conclusions or recommendations drawn from the network analyses.

In section 3.3.3, we are employing a set of measures which have been identified as favorable to improving resilience in SES. An important limitation of this part of the work is that while these metrics are strongly believed to improve resilience, very little empirical evidence has been published at this point. These metrics do however remain highly valuable as our best indication of the connection between stakeholder collaboration structures and positive outcomes in ecosystems.

In section 3.8, we show matrices of graph edits (edge removals and edge creations between categories of stakeholders). While edge removals are indeed relevant to improving the network (more interactions does not necessarily mean better outcomes) (Borgatti and Foster 2003), practical and ethical considerations led us to decide that we cannot suggest that some collaborations should be deliberately refrained. We addressed this issue by not focusing on which interactions should be discarded, and by proposing instead that the balance of edge creations and removals should indicate a level of priority in promoting collaborations between the corresponding categories.

3.6. CONCLUSION

In this article, we explored the structural properties of an empirical stakeholder network related to biodiversity conservation on the Eyre Peninsula, in Southern Australia. We proceeded in three main parts.

In the first part, we described how we reconstructed, through a stakeholder analysis and a series of face-to-face and online surveys, a stakeholder network of 129 individuals acting through 24 groups across 18 towns and cities. We also show how the network was filtered as to exclude some potential inaccurate data. In a second part, we focused on the topological qualities of the network. We showed the extent to which geography drives collaborations in the network, with larger cities like Port Lincoln and Adelaide acting as strong centres around which other interactions articulate themselves. We also identified how some groups of stakeholders act as bridges between other groups which focus on more local collaborations. In this part, we introduced group-betweenness centrality, a node-level metric specifically designed to measures the capacity of a stakeholder to act as a bridge between stakeholder belonging to different groups. In a third and last part, we explored how a sequence of edge rewiring optimized with a simulated annealing algorithm could improve metrics related to resilience-building in the network. For this, we introduced another novel metric which quantifies group marginalization at the network scale. We showed, for instance, that increased collaborations between the grain and grazing industry and environmental NGOs could help foster a more efficient and collaborative network.

Among all of the stakeholder groups identified in the study, the state-run Eyre Peninsula Natural Resources Management (EP NRM) board was shown to be greatly influential in coordinating and communicating information about biodiversity conservation efforts on the Peninsula. Regional NRM boards were created by the state of South Australia as part of legislation passed in 2004 within the Natural Resources Management Act. This initiative resulted from an effort to remove silos between government agencies representing different environmental resource sectors on the landscape (e.g., agriculture, biodiversity, freshwater, marine) so as to better coordinate and manage land and water resources. The creation of the NRM boards is in accordance with frequent recommendations in the scientific literature calling for coordinated planning of multiple resources on the landscape. The results of the analyses performed as part of the present study underline the success of this initiative, clearly identifying the important and central role played by the EP NRM, and supporting continued efforts to integrate resource management by government agencies in Australia and elsewhere.

Extensive analyses of case studies from around the world show that effective and sustainable natural resource management and conservation is dependent upon a well-structured governance system that promotes information sharing and collaboration amongst stakeholders (Ostrom, Walker et al. 1992, Olsson, Folke et al. 2004, Ostrom 2007). Our study provides a concrete example of how a multi-institutional stakeholder network can be analyzed to assess 1) the degree to which it meets the structural requirements necessary for effective information sharing and collaboration and 2) to determine what changes might be made to improve the structure. Being able to assess and improve the structure of stakeholder networks ultimately leads to increased resilience and adaptive capacity within the social-ecological system in which they are embedded and is key to the sustainable management and governance of natural resources. The methods and approach described here, while focused on a specific case study, are generalizable to many similar natural resource management systems and can be used as a basis to make recommendations for how the structure of those networks could be modified to improve communication and adaptive capacity within the system.

PARAGRAPHE DE LIAISON B

Le chapitre 4 poursuit l'analyse du réseau d'acteurs de la péninsule d'Eyre et propose une méthode quantitative permettant de mesurer le niveau auquel un réseau d'acteurs contribue, par la structure même des collaborations en son sein, à la résilience d'un SSÉ. La méthode utilisée est articulée autour de deux axes : d'une part la création, par recuit simulé (*simulated annealing*), d'un réseau archétypique dont la structure représente un compromis entre quatre caractéristiques (parfois conflictuelles) favorisant la résilience des SSÉ (décrite dans le chapitre 2), et d'autre part sur une mesure de similarité entre les représentations spectrales des réseaux (la densité des valeurs propres des matrices laplaciennes normalisées). La plupart des méthodes actuelles pour estimer la résilience des SSÉ est fondée sur l'analyse de mesures individuelles, et donc partielles. La méthode décrite dans ce chapitre permet au contraire une quantification globale, car fondée sur un compromis entre des caractéristiques conflictuelles, des qualités structurales d'un réseau d'acteurs pour augmenter la résilience du SSÉ dans lequel il s'inscrit.

Contributions personnelles

Ce chapitre a été soumis, et est actuellement en révision pour publication sous forme d'article dans *Plos One*. Il a été réalisé en collaboration avec Lael Parrott. J'ai effectué la recherche et rédigé le manuscrit dans sa majorité. Lael Parrott a agi à titre de superviseure en m'apportant idées et recommandations tout au long du travail de recherche. Elle a également rédigé certains paragraphes et a, d'une manière générale, largement amélioré le manuscrit par ses ajouts, conseils et corrections.

4. A QUANTITATIVE APPROACH TO ASSESS THE CONTRIBUTION OF STAKEHOLDER NETWORKS TO THE RESILIENCE OF SOCIAL-ECOLOGICAL SYSTEMS

R. Gonzalès and L. Parrott

4.1. ABSTRACT

The structure of interactions between stakeholders (human actors and institutions) governing a natural resource can greatly affect the resilience of the social-ecological system in which they are embedded, however, few methods exist to quantify this relationship. We present a robust quantitative approach that can be used to assess the structure of a stakeholder interaction network against an ideal, resilience-enhancing archetype. Our method is two-fold: first, we craft a class of archetypal networks whose structure demonstrates a compromise on a set of features known to enhance innovation, learning and adaption, and therefore resilience, within stakeholder networks. Secondly, we demonstrate how to measure the structural differences between these archetypal networks and empirical stakeholder networks. This approach provides a rigorous quantitative method to assess how the network of interactions between stakeholders should be structured to enhance system resilience and sustainability, thus responding to a key challenge faced in many contemporary studies of social-ecological systems.

4.2. INTRODUCTION

In a context of increasing human pressures on natural environments, many ecosystems around the world are degraded to the point of becoming unable to provide the services needed for the livelihood and well-being of local human communities (Berkes, Folke et al. 2000, Olsson, Folke et al. 2004, Diamond 2005). As natural resource management (NRM) governance systems struggle to achieve resilience and sustainability to avoid reaching these critical ecological thresholds, local stakeholders may organize, either formally or informally, to produce knowledge about the problems they are facing, find suitable solutions, and ultimately build more resilient social-ecological systems (SES). These repeated collaborations between stakeholders eventually shape networks, where nodes represent either individuals holding a stake in the sustainability of a resource of interest, and where edges represent one or several interactions between stakeholders (e.g. information exchange, collaborations on projects, or other resource transfers). Network theory is therefore becoming a popular tool to model and describe interactions between resource users and other stakeholders in SES. Many contributions, both empirical and theoretical, emphasize resilience building in the system as a means to achieve better sustainability (Adger 2000, Gallopín 2006, Bottom, Jones et al. 2009, Turner 2010), and employ the abundance of network metrics to both assess the extent to which the NRM stakeholder networks contribute to resilience (Bodin and Crona 2009, Prell, Hubacek et al. 2009, Reed, Graves et al. 2009, Gonzalès and Parrott 2012), and to better understand the relationships between stakeholder network structures and their functions in the broader SES context (Janssen, Bodin et al. 2006, Matous and Todo 2015). However, while it is generally accepted that a well-connected stakeholder network is key to building trust and reaching consensus (Provan and Kenis 2008, Carpenter 2014), it has also been shown that networks of high connectivity may lead to uniformity and hinder innovation in natural resource management (Borgatti and Foster 2003). There is thus a delicate balance to be found between a network structure that fosters communication, information sharing, and innovation, and a structure that is over-connected, leading to a lack of diversity and possibly reduced adaptive capacity (Gonzalès and Parrott 2012). While this relationship between network structure and function is recognized in the literature, there exists no general model describing what the ideal structure of a stakeholder network should be so as to promote resilient and sustainable NRM.

In this paper we propose an optimization method to produce archetypal networks having an idealized structure that promotes resilience in SES. We then show how these archetypal networks can be used as a basis for comparison with empirical stakeholder networks. By assessing the degree to which empirical networks achieve this idealized structure, our methods provide a rigorous approach to quantifying the contribution of stakeholder networks to the resilience of natural resource management systems.

4.3. METHODS

Our methods involve first identifying the most important structural features of networks that, for a group of stakeholders, would be linked to the ability of the group to collaborate, share information, adapt, innovate and learn. We hypothesize that promoting these features in a stakeholder network would contribute to enhancing the resilience of the social-ecological system in which the stakeholders are embedded. Next, we seek the optimal combination of structural features in a resilience-enhancing stakeholder (RES) network, and develop an archetypal model of RES networks. Lastly, we compare the properties of our RES network model with an empirical stakeholder network and several well-known theoretical network models, and quantify the structural distances between these networks.

4.3.1. STRUCTURAL FEATURES OF RESILIENCE-ENHANCING STAKEHOLDER NETWORKS

Resilience is a broad concept holding many definitions depending on the field in which it is used (Bruneau, Chang et al. 2003, Folke 2006). Broadly, it can be defined as "the magnitude of disturbance that can be absorbed [by a system] before [it] changes to a radically different state, as well as the capacity to self-organize and the capacity for adaptation to emerging circumstances" (Adger 2006). The main qualities of a resilient SES thus reside in withstanding different kinds of disturbances (such as environmental changes, market fluctuations, pest outbreaks or resource scarcities, to name but a few), partly through corrective measures and adaptation on the part of its NRM governance system (Olsson, Folke et al. 2004, Folke, Hahn et al. 2005). The latter's capacity to promote learning and innovation in a robust social environment is therefore central to the resilience of a SES. Resilience of a SES is thus closely linked to human agency, and to the ability of stakeholders to learn, re-organize, and adapt in response to change (Magis 2010, Berkes and Ross 2013). It is increasingly understood that effective learning and capacity for adaptation and innovation at the regional scale is highly dependent on the structure of the stakeholder interaction network (Benz and Fürst 2002, Bristow and Healy 2014). In this work, we focus our attention on this particular aspect of social-ecological resilience. We study how, and through which topological structures, a set of interacting stakeholders of different governance levels, views, and motivations can best collaborate, develop knowledge and innovate in the face of unforeseen disturbances in order to better contribute to their SES's resilience.

The literature in network theory applied to natural resource management suggests a number of structural properties of networks which should promote resilience in SES, namely: robustness, average path length, and modularity. As these structural properties are difficult to test empirically, they remain assumptions, albeit strong and well-accepted.

Robustness

The robustness of the network, that is, its capacity to stay connected as one component under node failures or targeted node removals, is an important feature of stakeholder networks. It ensures that if some nodes were to fail or be deliberately removed from the network, the whole structure would hold its integrity, provide alternative routes for information to flow across, and keep all groups of stakeholders in the collaboration loops. The robustness of a graph can be measured by counting how many nodes need be removed for the structure to split into at least two separate networks. In the present work, we measure the robustness of networks first to random node removal by counting how many nodes are removed until the network fragments, then by targeting nodes according to their number of direct neighbours (which corresponds to their degree centrality), in descending order, where degree centrality is re-computed at each removal step (Holme, Kim et al. 2002). The theoretically least robust network would need only one node removal to fragment the structure into at least two parts, while the most robust would need close to 100% of all nodes to be removed. Additionally, the evolution (the rate of increase or decrease) of other structural characteristics favouring resilience, as nodes are removed from the network, is explored; the slower the rate, the more robust the network.

Average Path Length

A second important characteristic of a resilient network is its efficiency of information flow, which can be measured with the average path length (APL). APL is the average number of nodes (or steps) that separate every pair of nodes in the network. A short APL promotes social capital, trust, and better cooperation (Bailón 2006) as it helps achieve quick and efficient transmission of information and ideas through the network. Additionally, crossing few intermediaries keeps information deterioration to a minimum, while potentially reducing the chances of information retention in the network. APL is a common and relatively easily computable metric (Scott and Carrington 2011). APL isn't bounded; in the best case scenario (a completely connected network) the APL would be 1 (only one step is needed to reach any other node of the network), while the largest possible value depends on the network's size.

Moreover, APL is often correlated to the synchronizability of the network (Kelly and Gottwald 2011). A highly synchronizable network provides a structure where nodes (therein modelled as oscillators, with a phase of their own) quickly converge to a state where all nodes' phases become, and stay, synchronized (Watts and Strogatz 1998, Kocarev 2013). This characteristic has been used to measure the capacity of a social network to reach consensus despite originally divergent values (Pluchino, Latora et al. 2005) or to quickly and collectively find solutions to different problems (Mason, Jones et al. 2008). Synchronizability is not easily measurable via network metrics. However, it has been shown to be correlated to the Laplacian spectrum of the network (the distribution of eigenvalues computed on the network's Laplacian matrix) through its first non-trivial value, λ_2, also referred to as the algebraic connectivity (Holroyd and Kincaid 2006, Yang, Jia et al. 2013). As the Laplacian spectrum is bounded between 0 and 2, so is the algebraic connectivity. More precisely, λ_2 is most often found to be in a range slightly above 0, where synchronizability is very poor, and below 1 where synchronizability is very good.

However, a highly efficient flow (i.e., a short average path length), as well as a high synchronizability, can lead to homogeneity in the network (Borgatti and Foster 2003), hence potentially hindering innovation and the emergence of original solutions to unpredictable social or environmental stressors. A stakeholder network promoting resilient SESs should therefore also promote diversity of interest and expertise.

Modularity

In this regard, the modularity of the stakeholder network, that is, the level to which a network is structured around smaller communities of relatively more strongly connected nodes, is also central to improving resilience in SES. A high modularity is thought to better promote the emergence of novel ideas in contexts of social or environmental uncertainty. The rationale is that original solutions to complex social or environmental problems are most likely to emerge from independently, potentially more specialized, working groups. A modular structure also ensures a more polycentric governance, where groups of special interests can develop solutions close to their own stakes and values (Ghimire, McKey et al. 2004, Bodin, Crona et al. 2006, Schlüter, Biggs et al. 2015).
Modularity is more a concept than a precise measure, and many methods in network analysis attempt to encapsulate it (Fortunato 2010). We chose to use the Louvain community detection algorithm (Blondel, Guillaume et al. 2008), a method well suited for fast computations. All modularity measures with the Louvain community detection method fall between 0 and 1, where a complete network would score 0 and a perfectly modular network would score close to 1.

While a stakeholder network promoting better SES resilience should display a structure in which the above-described characteristics coexist, some of these features are contradictory by definition. For instance, networks cannot be all at once very connected and display a strongly modular structure. We thus need to find the vicinity, between best modularity, best robustness and best APL, where this compromise would sit.

4.3.2. FINDING A TRADE-OFF BETWEEN CONFLICTING NETWORK FEATURES

We produced, using a simulated annealing optimization method described in the next section, a large number of networks with modularity ranging from 0.30 to 0.70 (with increments of 0.02) and APL ranging from 1.90 and 2.40 (with increments of 0.05). 10

replicates of each of these networks were produced, corresponding to a total of 2310 networks. This matrix of networks with different values of modularity and APL was in turn optimized for best robustness to targeted node removal as described below. Considering the high number of possible combinations of networks, as well as the time required to optimize each one of them, the fourth metric, synchronizability, was not considered during this optimization phase, although it was assessed for the resulting networks at the end. We instead focused on the trade-offs in network structure along the three dimensions of APL, modularity, and robustness.

Figure 4.1 shows a heat map plot of the trade-offs involved in the multi-objective optimization of resilience-enhancing networks. In this 3-dimensional space, we are seeking the best compromise between small APL, high modularity and high robustness to targeted node removal. A front (marked by a dotted line on Figure 4.1) clearly separates two zones: Zone A, where the robustness is high, and Zone B, where it is low. An ideal compromise would then sit on this front, as high as possible on the X (modularity) axis, and as low as possible on the Y (APL) axis.

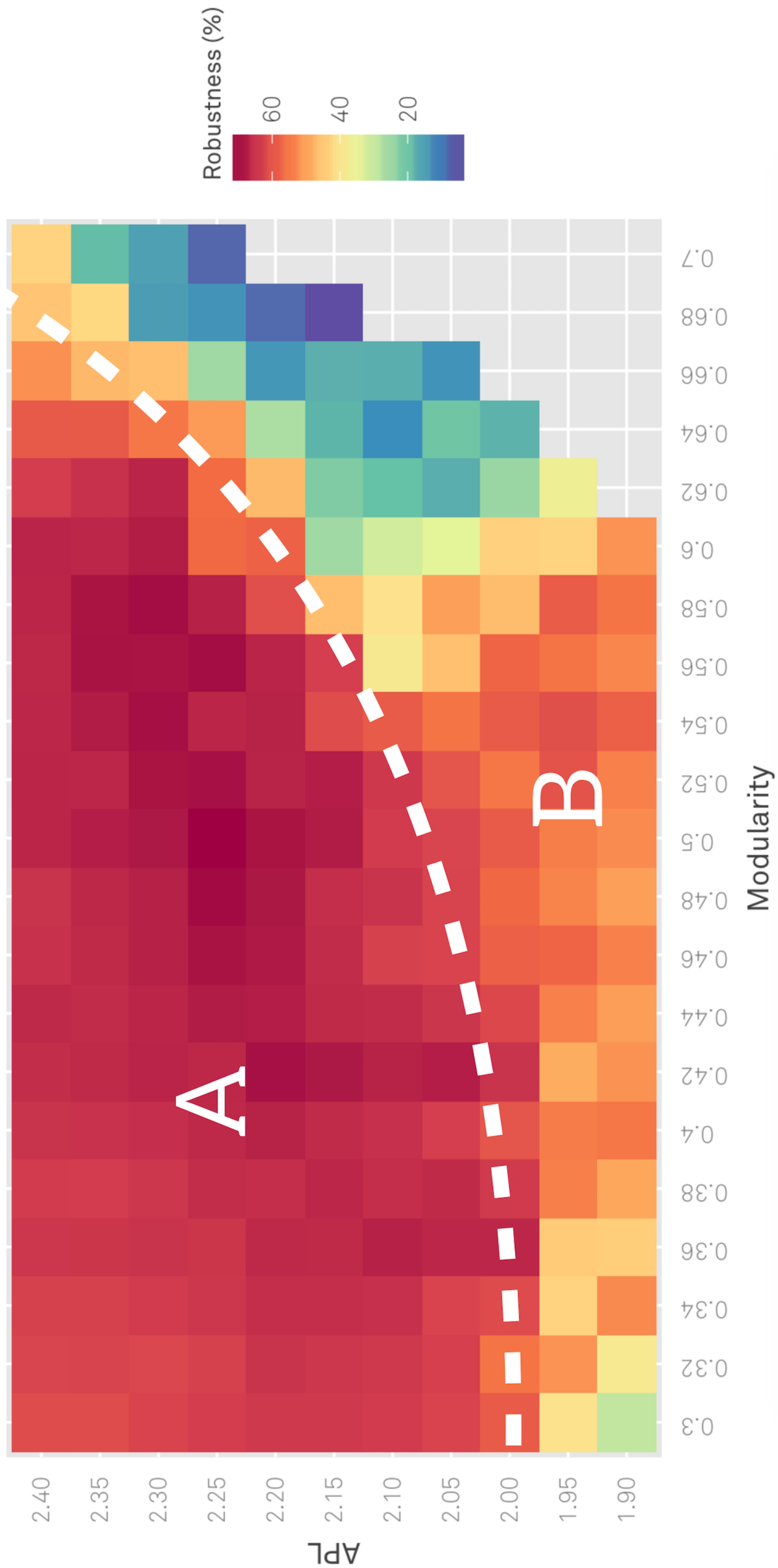

Robustness (%)
60
40
20
APL
2.40
2.35
2.30
2.25
2.20
2.15
2.10
2.05
2.00
1.95
1.90
Modularity
0.3
0.32
0.34
0.36
0.38
0.4
0.42
0.44
0.46
0.48
0.5
0.52
0.54
0.56
0.58
0.6
0.62
0.64
0.66
0.68
0.7
A
B

Figure 4.1 — Representation of the trade-offs between high modularity, low average path length (APL) and high robustness to targeted attacks (targeted by node degree) optimized in networks. Each cell represents the average robustness of 10 optimized networks. A front (white dotted line, added for clarity) emerges from this plot. We chose our ideal compromise on this line.

The strategy is to find the best spot along this front that satisfies both the constraints of low APL and high modularity. For demonstration purposes, we decided to work with optimized networks located near the middle point of the front, having a modularity of 0.52. This value of modularity was chosen for being sensibly higher than our comparison models described below, yet not so high as to negatively impact the trade-off with APL and robustness.

4.3.3. GENERATION OF OPTIMIZED STAKEHOLDER NETWORKS

Here we describe the method used to generate archetypal networks having topologies that are optimized to achieve trade-offs between APL, modularity, robustness and synchronisabilty. A number of existing models permit the generation of networks having specific topologies. Some produce random, statistically uniform networks given a probability of connection between each node, such as the random attachment model (Erdős and Rényi 1961), while others generate complex topologies aimed at better representing the structure of real-world networks. From the latter category, the most well known are the preferential attachment model (Barabási and Albert 1999) producing semi-random networks displaying scale-free topologies (where the distribution of node degrees follows a power law), and the small-world model (Watts and Strogatz 1998) reproducing the so-called small-world effect, where local clustering and short average path length occur in conjunction. Other models, such as Klemm and Eguiluz's (2002) aim at reproducing several traits in conjunction.

These models can each produce networks that approximate some of the structural features often seen in empirical networks. However, they cannot specifically reproduce the particular set of features needed to better promote resilience in SES, i.e., networks that are highly modular, have a short average path length, are robust to node removal and display high synchronisability. We thus implemented an algorithm to generate idealized networks fulfilling this combination of characteristics by searching for suitable networks within the space of all possible networks of a set number of nodes and edges. This space is very large. For example, for networks with 100 nodes and a density of 12% (approximately 1200 edges; this is the network size we are working with in this article), the number of possible, non-isomorphic networks to choose from is approximately 2×10^{700}. A systematic combinatory search is therefore unmanageable, and we choose to tackle this problem with an optimization method called simulated annealing (SA) (Kirkpatrick 1984). SA is an algorithm inspired by the metallurgy process of the same name, which aims at improving the structural properties of metals through heating and slow, carefully controlled, cooling. A simulated annealing algorithm builds on this analogy and attempts to crystallize a problem's solution into its best possible configuration, by progressively decreasing the "temperature" (that is, the probability of the process to tolerate worse solutions) of the simulation as the space of solutions is searched.

Practically, our simulated annealing is initialized with a random network (using Erdös-Rényi's random attachment model) consisting of 100 nodes, with a density of 12%. From this initial state, the simulation enters an iterative process of 1.6 million steps of exponentially decreasing temperature (Equation 4.1). At each step, a new candidate network is produced as a slightly altered version of the previous iteration's candidate network (one random edge permutations is performed). The new candidate is evaluated and given a score which is an addition of modularity (distance from a target value; here set to 0.52 based on the analysis of trade-offs shown in Figure 4.1), normalized APL (minimized), synchronisability, and normalized robustness towards targeted node removal (by descending order of degree) (Equation 4.2). What constitutes an appropriate score for multi-objective optimization with a simulated annealing algorithm is an ongoing research problem. While true Pareto-based multi-objective implementations are possible (Smith 2006), simpler weighted composite functions also show good results (ibid). We tested both approaches in this study, and our best and faster-converging results were found with a weighted energy score.

Candidates with better scores are accepted as the new reference for the next iteration, while candidates with worse scores are either rejected or accepted according to a probability related to how poor the score is, and how high the temperature of the simulation is (Equation 4.3). High temperatures are tolerant to worse solutions in order to avoid trapping the optimization at a local minimum too early. As the temperature decays, a proportionally decreasing number of worse solutions are accepted, which allows the algorithm to progressively focus on optimizing the current best solution (see annex 1 for the Python code used). We applied this method 100 times to produce 100 resilience-enhancing stakeholder networks (RES networks). All networks were then ranked from best (1) to worse (100, the total number of networks to rank) independently for each of their four metrics. This gave each network a vector of 4 ranks, which were averaged to make an overall rank. The 50 best scoring networks were selected (refer to annex 2 for the Python code used to rank networks). An example of one of these networks is shown in Figure 2.

$$T = T_M \times e^{-\ln(\frac{T_M}{T_m}) \times \frac{i}{i_M}}$$

Equation 4.1 — Calculation of current annealing temperature (T). At each step, a new temperature is calculated according to the current step of the optimization process. TM is the temperature at the beginning of the annealing process, Tm is the final temperature of the annealing process, i is the current step of the simulation, and iM is the total number of iterations planed for the SA

$$\begin{cases} s = -\dfrac{w_1 * m + w_2 * \frac{-d}{d_M} + w_3 * \frac{r}{N} + w_4 * \lambda_2}{w_1 + w_2 + w_3 + w_4} & \text{when } m \geq t \\ s = -\dfrac{w_1 * m + 5 * w_2 * \frac{-d}{d_M} + w_3 * \frac{r}{N} + w_4 * \lambda_2}{w_1 + w_2 + w_3 + w_4} & \text{when } m < t \end{cases}$$

Equation 4.2 — Calculation of a conditional, weighted composite score (s) for a candidate solution. Each new solution is evaluated as a conditional weighted (w1 to w4) and normalized average of metrics, namely modularity (m), average path length (d), normalized over the longest path in the network (dM), robustness to highest degree-targeted node removal (r), normalized over the total number of nodes in the network (N), and synchronizability (λ_2). As long as the simulated annealing hasn't found a candidate scoring a minimum threshold (t) in modularity, the score is biased towards improving this metric. For this study we used t = 0.52.

$$p = e^{\frac{-(s_{i+1} - s_i)}{T}}$$

Equation 4.3 — Probability of accepting worse solutions. The score of the current candidate network is noted s_{i+1} while the last accepted network is noted s_i. T is the current annealing temperature.

4.3.4. MEASURING DIFFERENCES BETWEEN NETWORKS

Quantifying differences between networks is a difficult task in most situations. It is often performed by algorithms searching for the so-called "graph edit distance" between two networks (Sanfeliu and Fu 1983, Gao, Xiao et al. 2010). These algorithms find the minimum number of alterations (node/edge insertion or node/edge removal, node re-labeling) one of the networks must undergo for the two networks to become isomorphic. The computing complexity is high and best suited for much smaller networks than the ones we are using here. However, an accurate proxy to proper edit distance can by employed using normalized Laplacian spectra (Wilson and Zhu 2008).

The spectrum of a network is the distribution of all eigenvalues calculated on its normalized Laplacian matrix. The normalized Laplacian matrix has been shown to provide valuable information on the global structure of a network. Importantly, it provides, in all practicalities, a unique signature for individual networks (de Lange, de Reus et al. 2013). Wilson and Zhu (2008) show that past the size of 11 nodes, two non-isomorphic networks have a very low chance of having the same normalized Laplacian spectra, and that the edit distance between two graphs can be approximated by the Euclidian distance between the two eigenvalue vectors representing the spectra. Additionally, the Laplacian spectrum holds important advantages for comparing networks' structures. For instance, no matter the structure or the size of a network, Laplacian matrices' eigenvalues always fall between 0 and 2 (this is not the case for non-normalized Laplacian, or for the adjacency matrices), which makes the spectrum well suited for comparison between networks of different sizes. Moreover, the shape of a spectrum is not dependent on node labeling: two identically-structured networks will therefore show similar eigenvalue distributions regardless of how nodes are named or numbered. This approach thus provides a quantitative measure by which to compare structural differences between networks, and will here be used to assess the distance between our class of optimized stakeholder networks and a set of three benchmark networks.

4.3.5. NETWORKS USED FOR COMPARISON

Empirical Network

Our empirical network is a natural resource management stakeholder network related to biodiversity conservation on the Eyre Peninsula (EP), a 48,000 square kilometre region in the state of South Australia, Australia. While tourism is on the rise, the economy of the EP is still primarily based on dryland agriculture (grain and grazing), which relies on rainfall alone. The landscape, therefore largely rural, is home to several native threatened, endangered or vulnerable plant and animal species (Matthews, Oppermann et al. 2001). These species are affected by a variety of factors (ibid, p. 139), including the connectivity of their habitats, which is related to land-cover change on privately owned land. A variety of conservation initiatives are being carried out on the peninsula. They aim at restoring native species' habitats through programs promoting more biodiversity-friendly practices on the part of farmers, including fencing of remnant vegetation to protect from grazing by livestock, revegetation through planting native trees as windbreaks, and using perennial bush for grazing. The network we are studying represents individuals working, through government agencies, private companies or NGO, on improving biodiversity. The links between these individuals represent exchanges in knowledge or direct collaborations on biodiversity-enhancing programs. The data were collected in 2011 and 2012 through questionnaires that asked stakeholders to identify the frequency with which they exchanged information on biodiversity conservation programs with other stakeholders in the network. It features 136 nodes, has a density of 16%, is directed, and weighted according to the frequency of information exchange in the network. For the present purposes of this research, and due to computational time constraints, a minimum threshold on the edge weights was set to reduce the number of connected nodes to 100 (density thereby falling to 12%). Weights and directions have also been discarded in order to only focus on the most basic, underlying structural features of the network.

Theoretical Network Models

In addition to the empirical network, three well documented models are used as structural benchmarks: 1) Erdös-Rényi's random attachment model (Erdős and Rényi 1961), where each pair of nodes is connected according to a probability of 0.12 (density of 12%); 2) Barabási-Albert's scale-free model (Barabási and Albert 1999), which reproduces the commonly observed phenomenon of scale invariance in natural and social networks. We used iGraph's "Barabasi game" algorithm (Csardi and Nepusz 2006) to generate the networks, adding 7 new edges at each time-step of the growing process. The final scale-free networks reach a density of 12%; and 3) Watts-Strogatz's small-world model (Watts and Strogatz 1998) which reproduces another commonly observed phenomenon in natural and social networks: the "small-world" effect where few nodes have long-reaching edges connecting parts of the network previously far apart. iGraph's small-world algorithm was parameterized with a rewiring probability of 5% and a neighbourhood of 6, leading to a network density close to 12% (while several sets of parameters were used, this set provided the best results in our studied metrics).

All generated networks have 100 nodes and have a density close to 12% as per the empirical and RES network. For each of these models, a series of 50 networks was produced.

4.4. RESULTS

4.4.1. NETWORK COMPARISONS: METRICS ASSOCIATED WITH RESILIENCE IN SES

Figure 3 shows the average path length (APL; the average distance between two randomly chosen nodes in the network), the modularity (calculated using the Louvain algorithm, value ranges between 0 and 1, where 1 is high), the synchronizability (value between 0 and 1) and the robustness (percent of nodes removed before the network fragments into two connected components), computed for the 5 classes of networks (random, scale-free, small-world, RES network and the empirical case study from the Eyre Peninsula). Results demonstrate that while the RES network performs well, yet not best, in APL (lowest is best), and synchronizability (highest is best), it largely out-performs all others in modularity (highest is best) and robustness to targeted node removal (highest is best). Compared to the other network models, the RES network has a structure that appears to have the best compromise between these competing features.

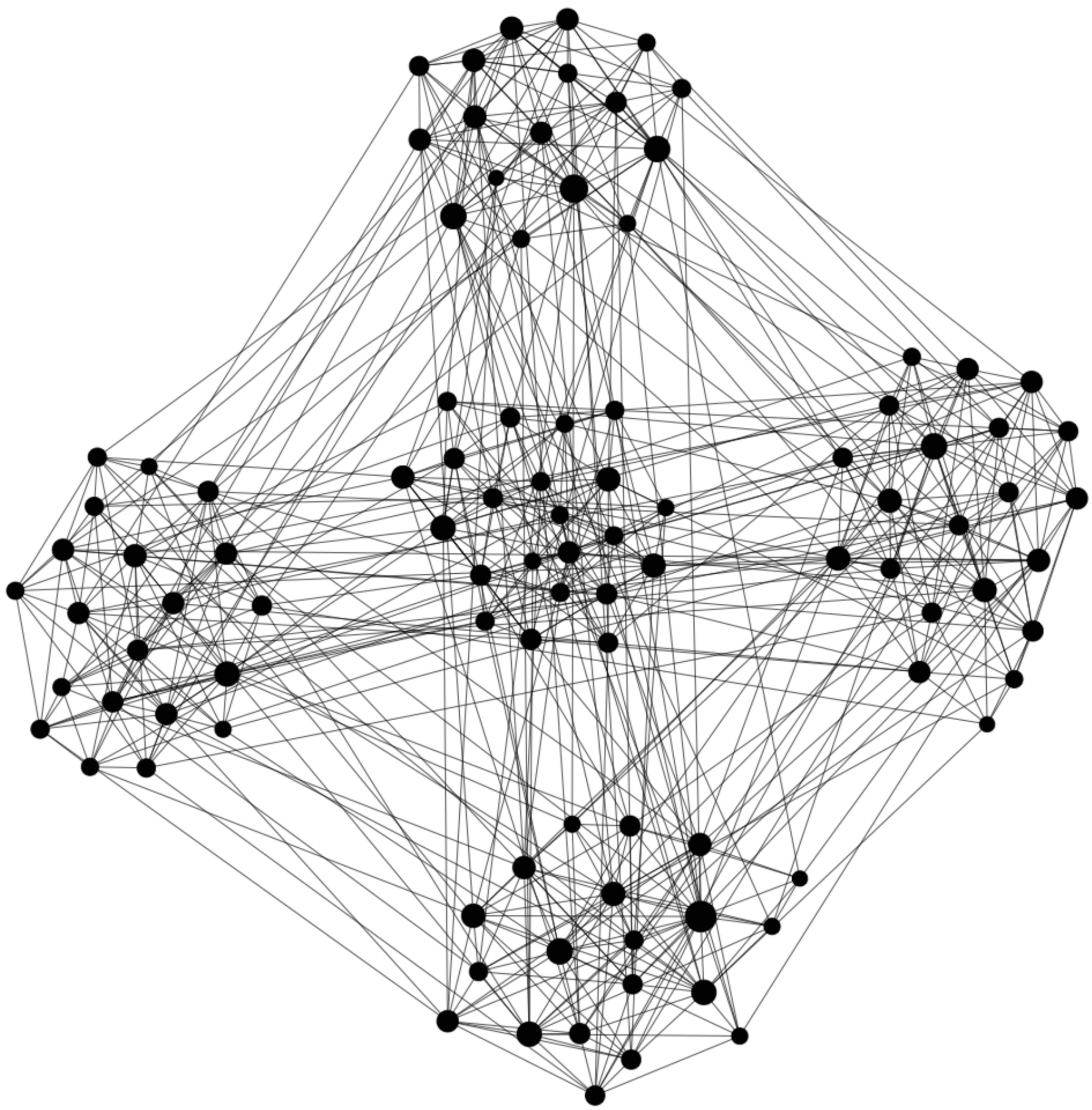


Figure 4.2 — Force-based layout (Kobourov 2012) of one of the 50 resilience-enhancing stakeholder (RES) networks produced by our simulated annealing algorithm. The size of nodes represents their degree (or number of direct connections). A visual examination hints at high modularity with quite distinct highly connected communities, short average path length with many links reaching far across the structure, and a decentralized structure where the distribution of degrees is somewhat even across the network.

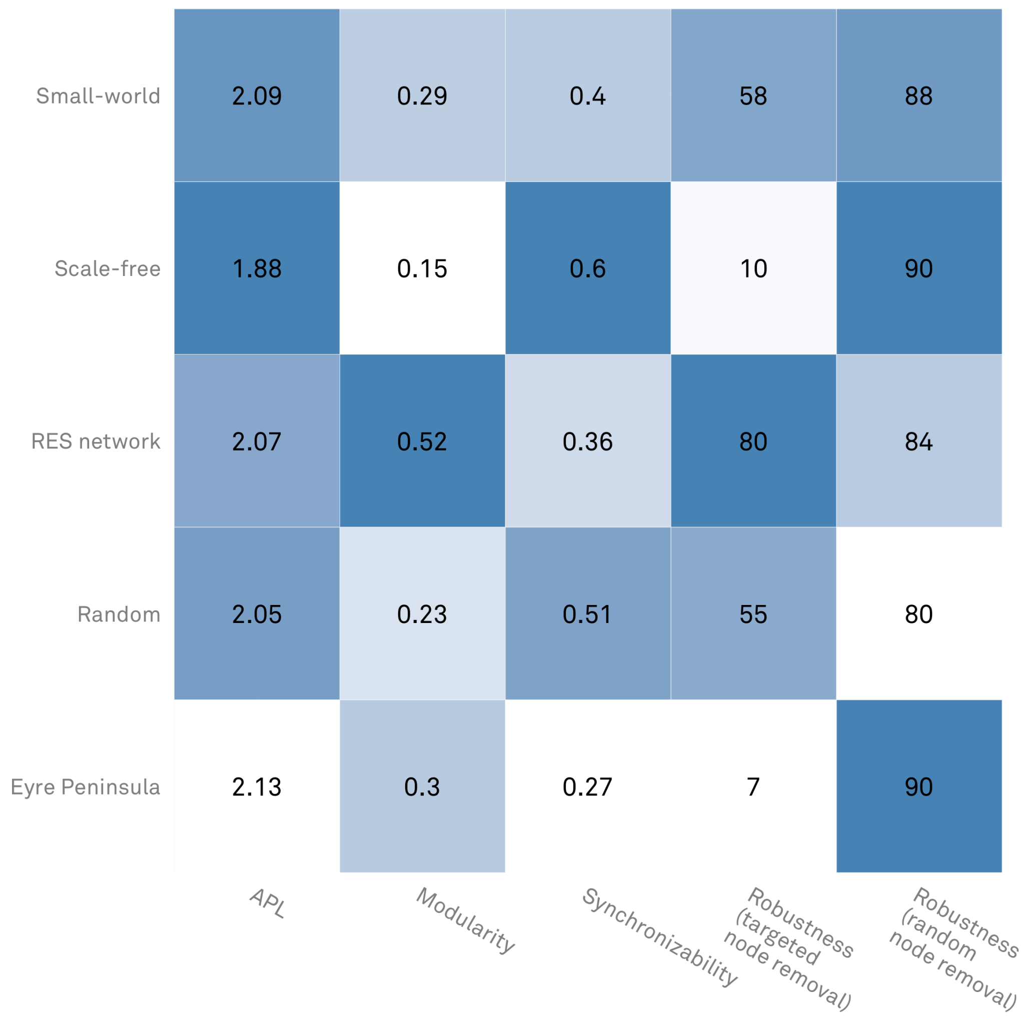


Figure 4.3 — Values of structural measures for the 5 classes of networks studied. Lower APL, higher modularity, higher synchronizability, and higher robustness are best. While the RES network performs well, but not best, in APL and synchronizability, it largely out-performs all others on modularity and robustness to targeted node removal. Values provided are averaged over 50 networks for each network class, except for the empirical EP network (only one instance exists). The colour indicates how good a given model performs, per column, compared to all other models (darker is better).

Moreover, we find that the RES network's degree distribution (Figure 4) is very different from scale-free models, which are known to accurately represent the degree distribution of many empirical networks (Ravasz and Barabási 2003). Degree centrality, that is, the number of direct connections a node has, is one of many centrality measures available, and is often used to identify potentially influential and powerful individuals in a network. While scale-free networks show a power-law distribution of degrees, where few nodes hold the most “powerful” positions in the network, and where the vast majority of nodes reside in less favorable positions, our RES networks distribute degrees more evenly, as a small-world network would, allowing most nodes to reside close to the network’s average degree. Degree distribution was not taken into account while optimizing network structure, and this characteristic most likely emerged as a corollary to what a resilience-enhancing stakeholder network should be. Most particularly, the optimization of the network’s robustness to targeted node removals, which hindered the creation of hubs within the network, could account in a large part for this structure. This is a welcomed characteristic as it can be argued, especially in co-management settings, that a structure displaying a more equal share of potential power, where possible abuse of dominant positions within the network is kept minimal, could favour more democratic solutions to social-ecological issues.

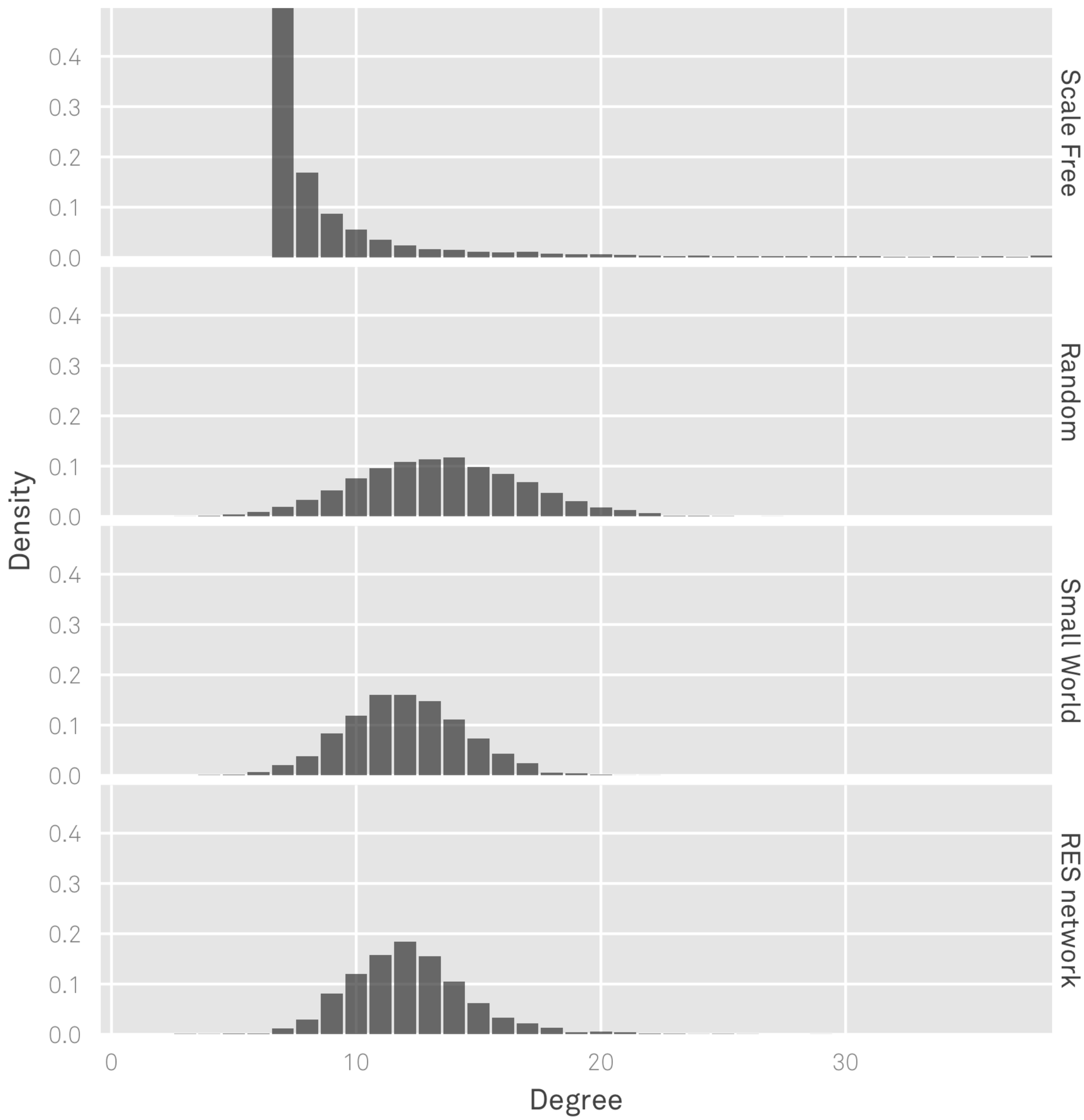


Figure 4.4 — Degree distribution of four network models. The RES network shows a degree distribution where, while few nodes hold positions of relatively higher degree (around 20), most nodes are averagely connected. This demonstrates a more equitable power distribution than scale-free structures which are often observed in natural and social networks, where most nodes are poorly connected while a few nodes share the majority of the network's total connections.

4.4.1. NETWORK COMPARISONS: ROBUSTNESS TO NODE REMOVAL

Focusing on the evolution of our selected metrics as nodes are removed from the networks, Figure 5 shows, as expected, that the scale-free network is quite robust against error (random node removal) as it takes on average about 90% of node removal to break the network into at least two separate networks (Figure 3). In addition, the APL is almost unchanged as nodes are randomly removed. On the other hand, the scale-free model is very weak against targeted attacks (when nodes are removed in descending order of degree), as only about 10% of high degree nodes need be removed for the network to become disconnected. This can be explained by the inherent formation of relatively few, highly connected hubs in scale-free structures. These features are shared by the Eyre Peninsula empirical network, which is also robust to random node removal but highly vulnerable to targeted node removal. The random and small-world models respond similarly to node removals. In both cases, targeted attacks fragment the networks faster than random attacks, as about 60% of higher degree nodes need to be removed to fragment the network compared to about 80% of randomly selected nodes. In comparison, our RES networks, while highly modular (hence potentially prone to contain hubs) are almost as robust against targeted attacks as they are against random node removal (80% of higher degree nodes need to be removed compared to about 84% of randomly selected nodes). Additionally, the increasing or decreasing rates of change of APL, modularity and synchronizability as nodes are removed, are either comparable or slower than for the other networks (Figure 5). Our RES networks thus maintain their key resilience-enhancing structures even as nodes are removed. Through their combination of a modular structure with short average path lengths, our networks are thus the most robust of all network models overall, resisting well to both targeted and random attacks.

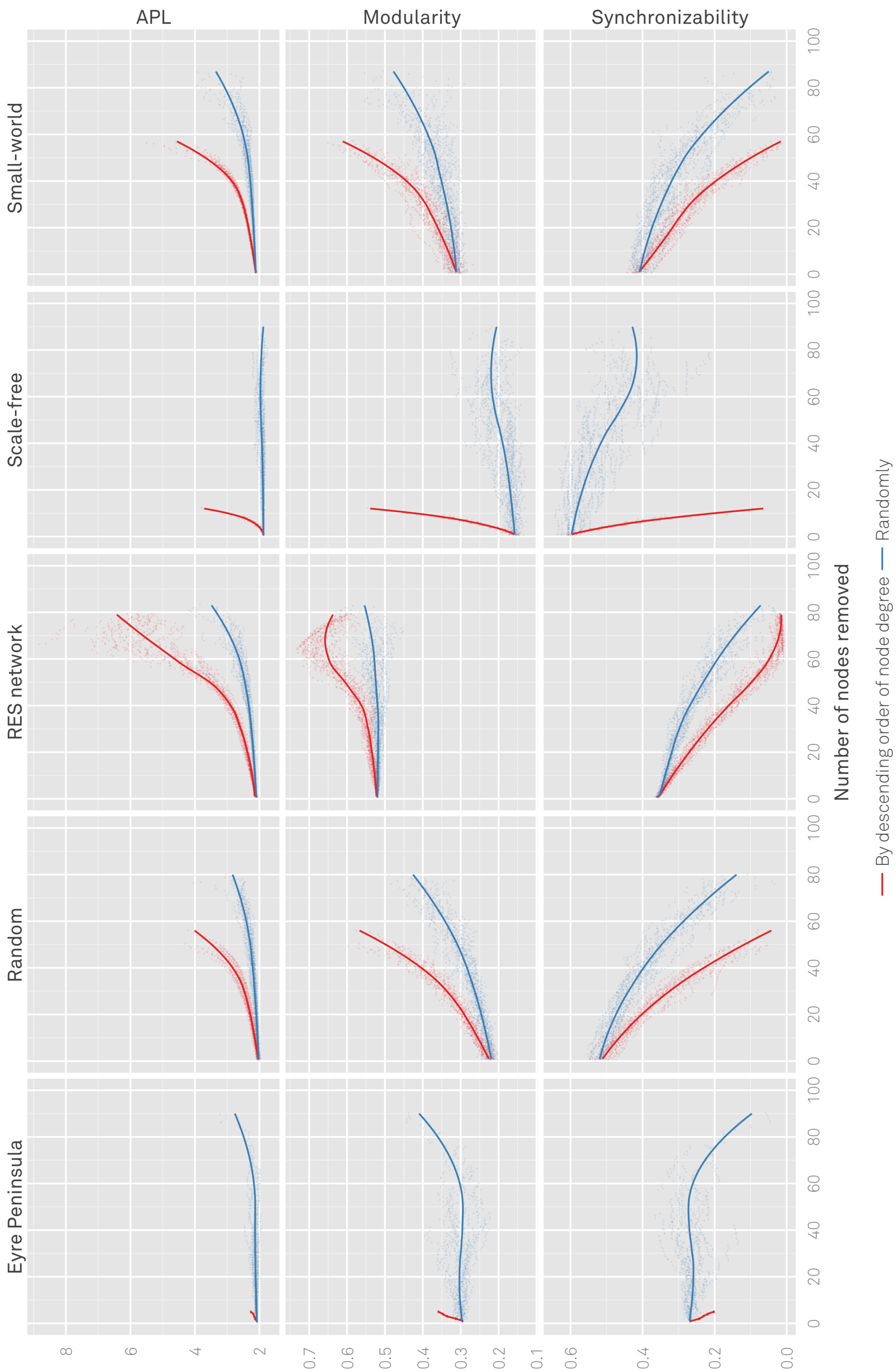

APL
Modularity
Synchronizability
Small-world
Scale-free
RES network
Random
Eyre Peninsula
Number of nodes removed
By descending order of node degree
Randomly

Figure 4.5 — Robustness of five network models. This figure shows the robustness of three network metrics seen as important for resilience-enhancement in SES, namely the average path length and modularity, on three network models (Random, Scale-free, and small-world), our RES network, and one empirical network. The length of smoothed lines shows how many node-removals each network can withstand on average before breaking into at least two modules. The blue line represents node-removal in random order, while the red line represents node-removal in order of best degree centrality. All networks show a sensibly equivalent average path length before node removal begins. However, modularity is very different from one model to another (RES networks showing the best modularity at 0.52 while small-world, the second best, has 0.40, see Figure 3). Similarly, our optimized networks display a strong capacity to withstand node removal in both random and targeted situations, a characteristic lacking from other networks.

4.4.2. LAPLACIAN SPECTRA AND DISTANCE BETWEEN NETWORKS

As described earlier, the Euclidian distance between each vector of eigenvalues representing the Laplacian spectrum is used as a proxy to graph edit distance. Figure 4.6 shows the Laplacian spectrum of each network studied. The random network displays its typical half-circle shape around eigenvalue 1. The scale-free network also displays a symmetrical shape, but elongated at eigenvalue 1. The small-world network displays a skewed shape towards higher eigenvalues, as well as an increased density around eigenvalue 0.4, a characteristic of modular structures. In general, density of all of these networks increases around eigenvalue 1 (hinting at a structure where duplication of motifs plays a large role). The RES network displays a significantly different, “M” shape, where density decreases around eigenvalues 1 and where a sharp peak appears around eigenvalue 0.35, suggesting a quite different structural topology which is not investigated at this point.

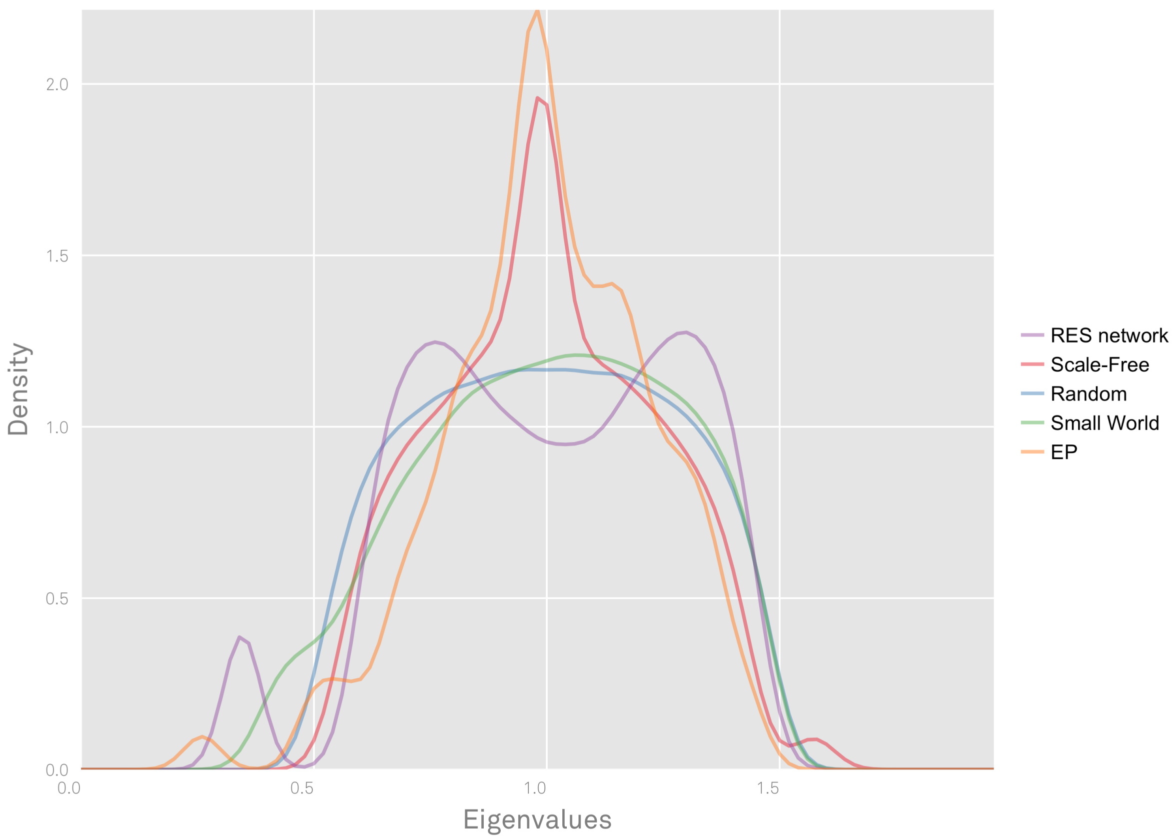


Figure 4.6 — Laplacian spectra of three network models, the RES network, and an empirical stakeholder network from the Eyre Peninsula. The normalized Laplacian spectra are averaged over 50 iterations of each of the network models, except for the EP network, which is unique. They are calculated as densities. Additionally, the plotted spectra have been filtered by convolution through a Gaussian kernel (with a width of 1) to decrease noise.

In Table 4.1, we compute this distance between all considered networks, and find that all networks are unequally distant from each other. They can be ranked, from closest to most remote, to the RES network: 1) random, 2) small-world, 3) scale-free, 4) Eyre Peninsula empirical network. A random network in first position may seem counter intuitive, however, this distance does not formally provide a « resilience-enhancing » rank, but rather an insight into how much a network needs to be altered (via edge edits) to become isomorphic to our idealized structure. We can also note that the empirical network from the Eyre Peninsula is, in accordance to the literature on scale-free networks (Barabási and Albert 1999), more similar to a scale-free structure than any other network we compared it to. It is also the most dissimilar to our optimized networks. These two points confirm our qualitative comprehension of the EP network, where a few stakeholders hold hub positions (as a scale-free network would) which puts them in situations of de facto information control, and makes the network prone to fragmentation (Meyer 2013). It also stresses that changes to the structure of collaborations between stakeholders should be promoted in order to decrease its distance to the optimized network.

Table 4.1 — Distance matrix between all 5 network models considered. Matrix of distances between graphs as measured using the Euclidian distance between each pair of eigenvalues' vectors.

	Scale-free	**Random**	**Small world**	**RES network**	**Eyre Peninsula**
Scale-free	0.00				
Random	3.30	0.00			
Small world	3.38	1.39	0.00		
RES network	4.25	2.50	2.65	0.00	
Eyre Peninsula	2.65	4.83	4.49	5.72	0.00

4.5. DISCUSSION AND CONCLUSION

It is increasingly recognized that the resilience of social-ecological systems, communities, and regions is determined by the structure of their governance systems, and the ability of these systems to learn, innovate, and adapt. This adaptive notion of resilience requires that social actors and institutions (stakeholders) involved in regional governance or natural resource management collaborate and interact, so as to innovate and learn in response to change. Understanding how this stakeholder network should be structured to best contribute to innovation and learning, and therefore system resilience, is an open question in the study of social-ecological systems, and is ultimately linked to the sustainability of regions.

In this article, we address this question by proposing an archetypal class of networks that are built to optimize a set of key structural properties (modularity, average path length, synchronizability and robustness) known to critically influence how effectively a governance or stakeholder network can adapt, innovate, and learn. These resilience-enhancing stakeholder (RES) networks, while only caricatures of real networks, can provide us with a rigorous quantitative method to assess the level to which an empirical stakeholder network contributes to the resilience of a SES. We demonstrate how this can be done by quantifying the differences between this new class of networks and an empirical stakeholder network built from a survey conducted on the Eyre Peninsula in the State of South Australia.

We also demonstrate that existing models used to represent complex systems do not adequately encapsulate all of the key features known to be important to system resilience. Compared to the well-known scale-free and small-world network models, our RES network model performs particularly well in terms of robustness towards not only random loss of components but also to targeted node removal (targeted by descending order of degree). The RES network model also performs much better than any of the other studied models in terms of modularity, a feature important in promoting diversity and innovation in stakeholder networks. Modularity is a particularly sensitive feature to optimize as, inherently producing cliques and bottlenecks, it hinders other structural features such as robustness and APL. The high modularity in the RES network models, however, contributed to the overall structural quality of these networks.

Limitations must be stated. Firstly, we optimized our networks to score best in four different metrics. Resilience being such a complex concept, with potential different meanings depending on the particularities of each case study, other measures could have been included. Moreover, particular political contexts or cultural differences could surely lead to adjustments in what is possible or desirable to achieve in term of idealized collaboration structures. However, our method is designed to be flexible enough to address such contextual adjustments through a redefinition of the nature of some metrics, or in their weighting during the optimization phase.

Finding the edit distance (i.e. the number of alterations needed for one network to be isomorphic with the other) between large networks is almost always an issue in terms of computer's CPU time. Choosing to use a proxy (the Euclidean distance between graph spectra, which involves the eigenvalue distribution of normalized Laplacian matrices of the networks) instead of graph-edit distance may be somewhat problematic. The explicative capacity of distances between the Laplacian spectra could be blurred by a tendency of these spectra to keep, in their shapes, parts of their evolutionary history, such as motif duplication (Banerjee 2012). Our method of producing optimized resilient networks being very different to how both real networks evolve into their current states, and how algorithms grow scale-free and small-world networks, a certain amount of noise is to be expected in the resulting distances. Despite possible inaccuracies in the estimates of edit distances, the method provides a reliable assessment of the relative distance between networks, and is useful for the comparison of several networks to a selected archetype.

Additionally, SES evolve in time, and their resilience is tightly linked to their capacity to bounce back from perturbation, and quickly re-organize after disturbance or stress events (Bruneau, Chang et al. 2003, Folke 2006). Our method, while capturing the important structural features of a stakeholder network that facilitate this re-organization, lacks this temporal dimension, and is therefore, for instance, unable to assess resilience in the context of a SES's trajectory on the adaptive cycle. We note, however, that most empirical studies of social networks are based on data extracted from questionnaires that aim at reconstructing networks as a snapshot of their state as they evolve in time. Our method, used within the boundaries of this important limitation, can therefore safely be used to assess, at a point in time only, where an empirical network stands compared to its ideal version.

These limitations stated, our methodology remains both intuitive and rigorous in assessing the structure of stakeholder interaction networks in the context of SES's resilience. Our resilience-enhancing network model can serve as a benchmark against which to compare different real-world stakeholder networks (and thus compare the vulnerability of different regions). It can also allow for a quantitative assessment of the degree to which different community-building initiatives or government programs, for example, might increase the resilience, of an SES. Social agency and human interactions are likely one of the strongest contributors to the resilience of communities whose livelihoods are dependent on natural resources; the methods proposed here are a step towards better understanding how to structure those interactions to enhance community resilience to change, and, ultimately, to ensure the sustainability of the entire SES.

PARAGRAPHE DE LIAISON C

L'archétype proposé dans le chapitre 4 est produit par un algorithme d'optimisation fondé sur un score aggloméré de quatre mesures. Ce score projette ainsi quatre objectifs à l'intérieur d'un seul. S'il s'avère performant pour produire une des nombreuses solutions possibles, il ne permet pas une exploration formelle des compromis qui sous-tendent la plupart des problèmes d'optimisation multiobjectif (la frontière formée par le sous-ensemble des solutions dites "non-dominées"). Dans le chapitre suivant, je propose une adaptation simple et intuitive de l'algorithme de recuit simulé présenté dans le chapitre 4. Cet algorithme modifié permet l'utilisation d'un score réellement multiobjectif, et fournit l'ensemble des solutions non-dominées trouvées lors du processus d'optimisation. Ainsi, il permet, en tenant compte de certaines limitations liées à la puissance des ordinateurs utilisés, un emploi plus souple de la méthode présentée dans le chapitre 4.

Contributions personnelles

Ce chapitre est actuellement en préparation afin d'être proposé pour publication dans un journal à comité de lecture. Il a été réalisé en collaboration avec Lael Parrott. J'ai effectué la recherche et rédigé le manuscrit dans sa majorité. Lael Parrott a agi à titre de superviseure en m'apportant idées et recommandations tout au long du travail de recherche. Elle a également amélioré le manuscrit par ses ajouts, conseils et corrections.

5. DOMINANCE-BASED SIMULATED ANNEALING TO OPTIMIZE NETWORKS' TOPOLOGIES ALONG MULTIPLE OBJECTIVES

R. Gonzalès and L. Parrott

5.1. ABSTRACT

Optimizing network topology is almost always a matter of searching a space of solutions so vast that a systematic search is infeasible, and the use of stochastic optimization algorithms is instead required. Among all the available methods, simulated annealing algorithms are often preferred for optimizing network topology. However, they usually only allow for the optimization of either one objective at a time, or a composite of several scores, which makes searching for topologies representing trade-offs difficult. To solve this problem, we developed a modified simulated annealing algorithm designed to search solution spaces for optimized networks whose structure meets several objectives simultaneously. We first describe how we constructed a score for solutions based on dominance, which reflects the multi-dimensional nature of the optimization problem. We then optimize three random networks of 50 nodes to make them fit desired topological characteristics, and discuss the trade-offs at work within these networks. This article demonstrates that dominance-based, multi-objective simulated annealing can be easily and intuitively implemented. However, the time required for optimization greatly increases with the number of objectives optimized, thus optimization approaches based on composite scores may still be preferred in some cases.

5.2. INTRODUCTION

A number of algorithms exists to create networks having specific known topologies (e.g., Erdos-Renyi's random attachment model, Watts and Strogatz's small-world, Barabási and Albert's scale-free model), but constructing a network whose topology simultaneously meets multiple criteria cannot be achieve by such straightforward methods. The problem is complicated by the fact that these criteria are often competing with each other, and cannot all be fully satisfied at once in a single structure. For example, in the study of social networks, the ideal topology to promote innovation and transfer of knowledge involves both high connectivity and high modularity; two competing characteristics. In our research, we are interested in networks of stakeholders managing natural resources. These networks also must meet specific structural requirements in order to enhance resilience and sustainability. They need to be all at once modular, well connected, provide a structure favouring synchronizability, and be robust to targeted node removal (Chapter 4). This constitutes a multiple-objective optimization problem for a very vast solution space.

This category of problems can be addressed with a variety of methods, including evolutionary algorithms such as genetic algorithms (Reeves, 2003), swarm intelligence algorithms such as ant colony optimization and particle swarm optimization (Beni and Wang 1993, Ashlock 2006), and other meta-heuristics such as simulated annealing (Kirkpatrick 1984, Černý 1985). While some are preferred to others for specific applications (Ross 2005), the literature on network optimization suggests that simulated annealing (SA) is often preferred for network topology optimizations (Donetti, Hurtado et al. 2005, Rad, Jalili et al. 2008, Guang-Yu, Li et al. 2012, Pal, Ray et al. 2012).

A simulated annealing (SA) algorithm searches for a problem's close-to-optimal solution by iterating through a few simple steps. It first produces a random solution, copies it and randomly modifies the copied solution. It then compares the two copies (pre and post-modification) by attributing a score to each of the two. The algorithm then decides to keep one or the other for the next iteration according to the following rules: if the new, modified solution 1) scores better, or 2) passes a probabilistic test, it is used as the new best solution. The modified copy is otherwise discarded. The probability test takes two parameters into account: 1) the step the simulation is at (early steps are more tolerant to worse solutions) through a variable called “temperature” by convention (referring to the thermodynamic inspiration of SA) which exponentially decreases as the simulation progresses, and 2) how much worse the modified solution is compared to its previous version (Equation 5.1). This is SA’s strength, as it allows for a wide search of the solution space at the early stage of the simulation (hence avoiding early local optima traps), and focuses on improving the best-found optimum later in the simulation (see Figure 3.6 “Simulated annealing flow chart” in chapter 3). If a solution has been accepted, it is used as the current best solution and tested against a new modified copy of itself in the next iteration. The SA stops at the end of a set number of iterations, and returns the best found solution.

$$p = e^{-\frac{\delta S}{T}}$$

Equation 5.1 — Probability p to accept a worse score (S) according to the current temperature (T) of the simulated annealing.

Unlike genetic algorithms however (Deb, Agrawal et al. 2000), SA have a major drawback regarding multi-objective optimization problems. The score used to discriminate solutions is a single scalar, as opposed to a vector of scores which would better reflect the multi-objective nature of the problem. This limitation can be addressed by building a composite score, which often is a weighted average of the scores for each objective towards which the solution is to be improved. This works well in many cases (Smith 2006, Gonzalès and Parrott 2015), albeit with some important drawbacks: 1) some objectives, if correlated with each-other, tend to bias the score towards the structural characteristic the objectives are correlated to (like synchronizability, average path length and efficiency, for instance, which —despite subtile and important particularities— all assess a level of network connectivity). While this can be addressed through further weighting adjustments in the composite score, it often requires time-consuming trial and error; 2) only one solution is produced (the one best improving the composite score), leaving aside all other non-dominated solutions (NDS).

NDS are all the solutions which are not dominated by any other found solutions. A solution dominates the other if it is strictly better in at least one of the objectives, while being at least as good in all objectives. In an ideal situation, the non-dominated set approaches the Pareto frontier (which is, in essence, the analytical representation of the trade-offs in a multi-objective problem). As there is no objective way to decide which non-dominated solution is preferable to any other, a multi-objective optimization should not only result in one optimized solution, but in the full set of NDS.

In this article, we implement a modified SA designed to address this problem and perform true multi-objective simulated annealing (MOSA). While other solutions have been proposed (Czyzżak and Jaszkiewicz 1998, Smith 2006), we aimed at simplicity and efficiency for the particular case of network topology optimization. We will present the principles behind our MOSA, and show results for three optimization problems of increasing objective dimensions. We will discuss the trade-offs at work during optimization, as well as the advantages and limitations of this method compared to the composite score-based SA used in previous work (e.g, Chapter 4).

5.3. METHOD

We optimized random networks (Erdős and Rényi 1961) of 50 nodes and around 146 edges (density close 12%, although each run of the algorithm producing the original random network provides a slightly different density), so that their topologies are improved on two, three, or four topological characteristics: modularity (the level to which a network is organized around communities of more densely connected nodes) (Newman and Girvan 2004, Blondel, Guillaume et al. 2008); efficiency, which is a measure of how efficient the flow of information —or whatever the network is modelled to convey— is in the network (Latora and Marchiori 2001). Efficiency is strongly correlated to the average path length of a network (the average shortest number of edges separating all pairs of nodes in a network), but unlike it, it is normalized between 0 and 1. We also use synchronizability, which measures the capacity of a network's topology to foster fast and stable convergence towards synchrony of dynamic nodes originally oscillating at different frequencies (Pecora and Carroll 1990, Watts and Strogatz 1998, Kocarev 2013). Synchronizability is measured through the algebraic connectivity (λ_2), which is the lowest non-trivial eigenvalue calculated on the network's Laplacian matrix. Finally, we measure the robustness of a network, which we define as the number of nodes (and connected edges) that need to be removed in descending order of degree (a nodes' number of connected edges) before the network splits into at least two parts (Albert, Jeong et al. 2000). The motivation behind using these metrics is related to assessing resilience in social-ecological systems. Their characteristics are further discussed in section 4.3.1.

Starting with the general concept of SA, we focus on finding a method of calculating a network's score that better reflects the multidimensional nature of the problem. Instead of calculating scores as scalars (a composite of network metrics in our case), that the algorithm would try to lower, we calculate each potential solution as coordinates in the *n*-dimensional objective space (*n* being the number of objectives to optimize). We then measure the distance between this solution and the surface shaped by the NDS found so far (Box A in Figure 5.2). The score of a given solution is thus a dynamically changing value that is dependant upon the evolving set of NDS.

Figure 5.1 demonstrates a simplification in two dimensions of this score calculation. A and A' are two solutions that need to be compared. d_1 and d_2 are the shortest distances measured between a candidate solution and the closest segments from the non-dominated solutions. In this case, d_2 is shorter than d_1 since A' is closer than A from the NDS. A' is therefore accepted as the next iteration's current solution. If A' were farther than A from the NDS, it would be either accepted or discarded according to Equation 5.1, where $\delta S = d_1 - d_2$. Solution B illustrates the case where a modified copy of the solution is undominated by any other solution found yet, and is therefore located beyond the current NDS. In this case, the algorithm does not compute the distance but instead automatically accepts it as part of the new NDS. In other words, respective distances to the surface shaped by NDS are used as a proxy to score calculations.

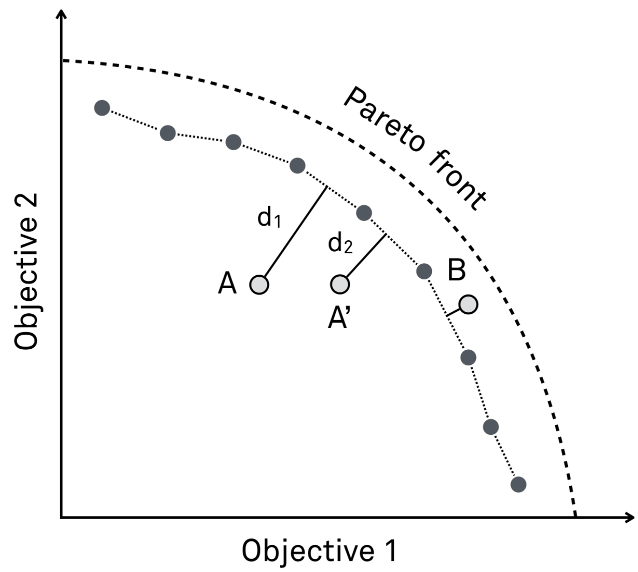


Figure 5.1 — Two-dimensional distance to a non-dominated set. Dark points are part of the non-dominated set. The dotted line is the theoretical Pareto front. A is the system's current solution while A' is a slightly modified version of A. d_1 and d_2 are the distances, measured perpendicularly, to the non-dominated solution set's closest line segment. B is yet another solution, but unlike A and A', it is undominated and resides outside of the non-dominated set.

This score is intrinsically based on dynamically changing list of current NDS. The list is empty at the beginning of the simulation. The initial solution, as well as its first modified copy (second iteration) are automatically added to the list, forming a first NDS segment from which the distance to the second mutated clone will be calculated. Between the third and last iterations every non-dominated solution is added to the NDS (Box C in Figure 5.2).

Additionally, the algorithm keeps a count of the number of consecutive solutions it discards (Box B in Figure 5.2). If the count raises above a specified threshold (which would mean the current solution does not manage to improve its distance to NDS in its neighbourhood, and that the simulation may be trapped in a meta-stable state), the algorithm replaces the current solution by a non-dominated solution randomly selected from the NDS. This allows the algorithm to further explore the boundary of non-dominated solutions, and potentially push it further towards the Pareto front.

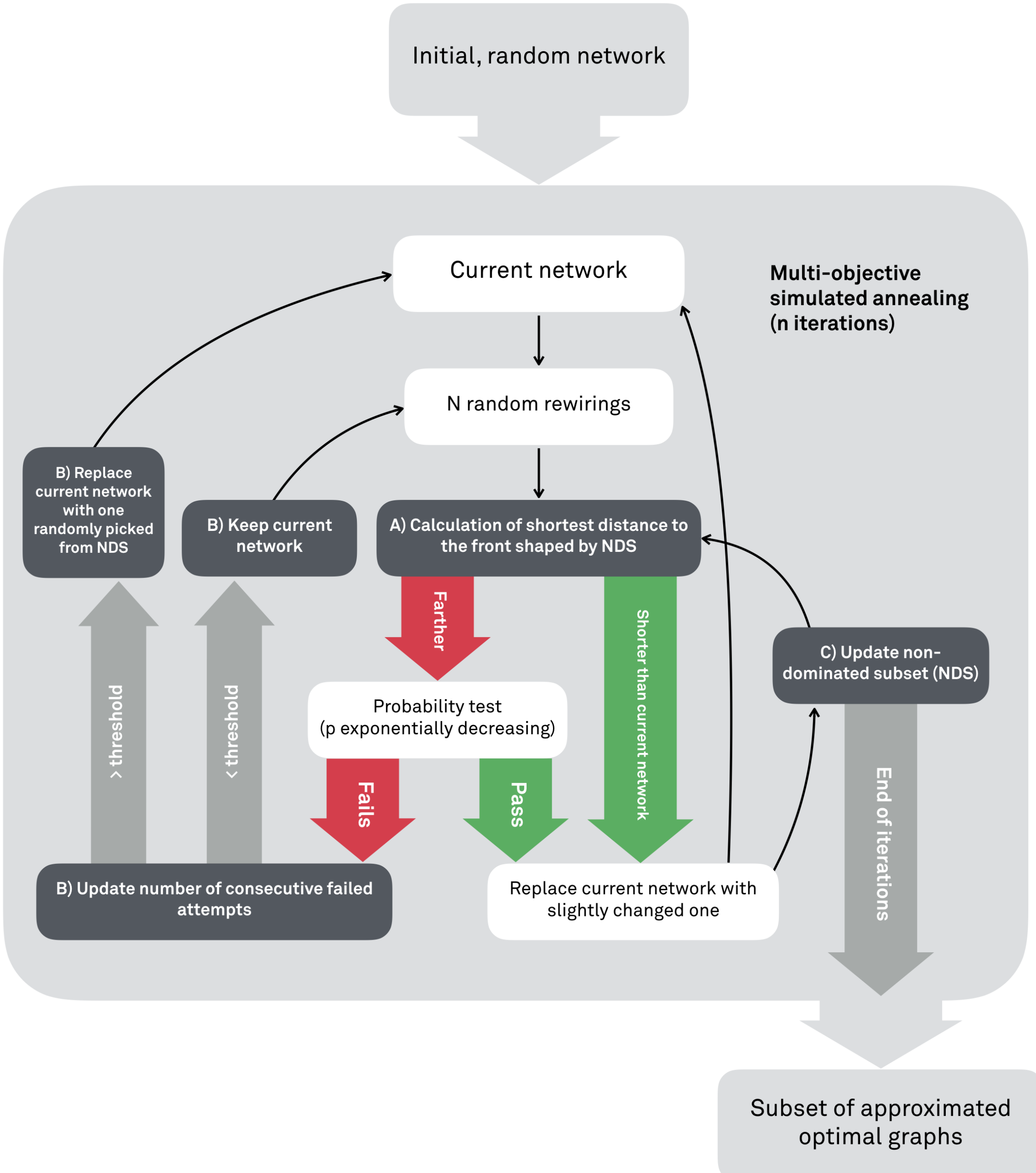


Figure 5.2 — Multi-objective simulated annealing flow chart. The darker boxes represent our addition to regular SA that allows for multi-objective optimization.

5.4. RESULTS

5.4.1. TWO-OBJECTIVE OPTIMIZATION

Starting with a randomly wired network, we ran our optimization for 20,000 iterations. Figure 5.3 shows locations of solutions optimized by our MOSA for modularity and efficiency in the two-dimensional objective space. Each non-dominated solution found during the simulation is recorded by the script and marked as a dot. The colours provide insight on how the algorithm works: blue shades, indicating NDS found earlier in the simulation, are —as expected— clustered and located away from the boundary, while red shaded solutions are spread along a curve: the frontier of non-dominated solutions (NDS). The NDS shapes a Pareto-like frontier, which represents the best compromises found by the algorithm. It provides a clear visual representation of the conflict between the optimization of each objective: one cannot improve modularity without hindering efficiency, and *vice-versa*.

Figure 5.4 shows three points out of the 148 found by the MOSA as part of the final set of NDS. Network “a” was sampled at the top-left of the front (low in modularity but high in efficiency). It shows the algorithm found a star-like topology, where one highly central node serves to dispatch the flow to other nodes. Network “c”, sampled at the other end of the NDS, is high in modularity and low in efficiency. The algorithm found a structure where five communities of highly connected nodes weakly connect with each other. In between these two extreme topologies, sits network “b”. It constitutes one compromise between the two objectives, where quite distinct communities of nodes strongly connect with each other.

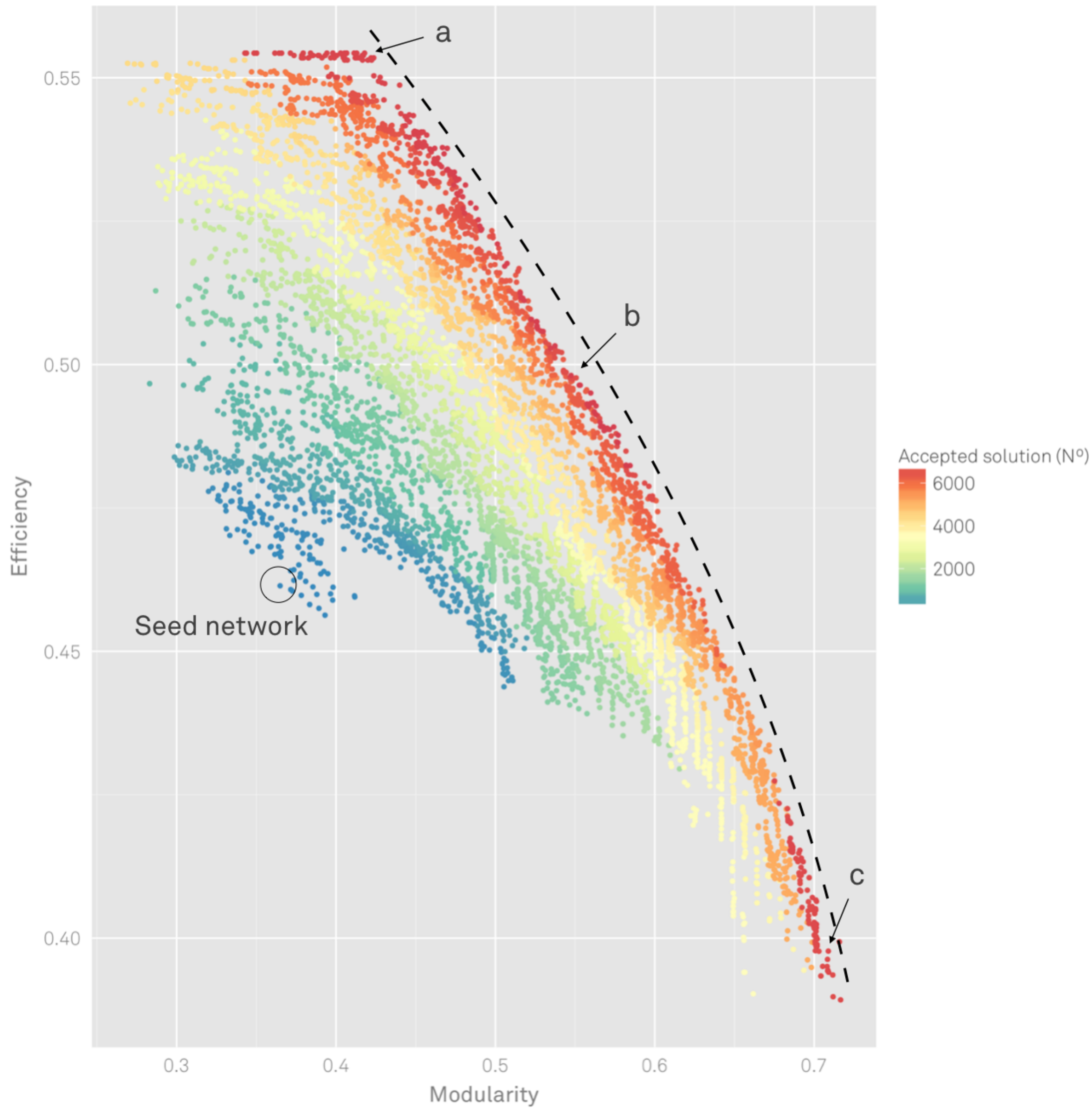


Figure 5.3 — Visualization of the evolution of one run of a MOSA optimizing two objectives: modularity, and efficiency (in both cases, higher is better). Each coloured dot is a non-dominated (accepted) solution (NDS) found during the 20,000 iterations (dominated solutions are not shown in this figure). The colour indicates when the solutions were found (blue indicates early-found solutions, while red indicates most recent, and best, solutions). The dotted line was added in order to highlight the front of all NDS found during the simulation. The letters correspond to sampled points used in the making of Figure 5.4.

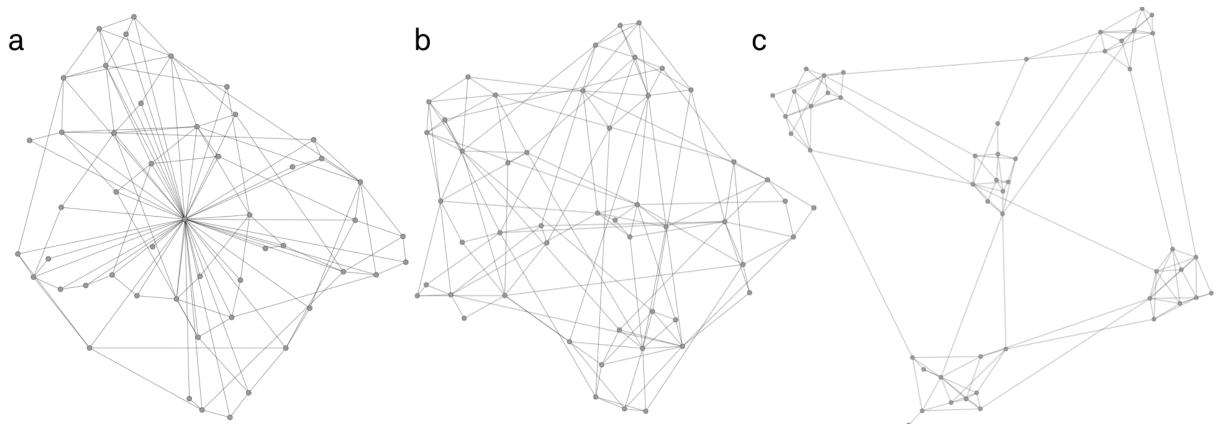


Figure 5.4 — Force-based layout representation of networks sampled among the non-dominated set (NDS) at points a, b and c in Figure 5.3.

5.4.1. THREE-OBJECTIVE OPTIMIZATION

In order to test our MOSA for three-objective optimization, we ran two simulations: the first one optimizing modularity, efficiency and synchronizablity of networks (Figure 5.5), and the second one optimizing modularity, efficiency and robustness of networks (Figure 5.7). As increasing the number of dimensions increases computation time non-linearly, we settle for only 10,000 iterations, for this case. While this number of iterations is certainly not enough to fully explore the space of solutions (hence the generally weaker scores found while optimizing three objectives instead of two), this number suffices for demonstration purposes. The MOSA could easily be run for more iterations for specific applications requiring highly optimized outcomes.

Modularity, Efficiency and Synchronizability

Figure 5.5 shows the three-dimensional objective space as a series of two-dimensional projections: one for each of the combinations. As for Figure 5.3, modularity and efficiency are in conflict. A very similar NDS front also emerges between modularity and synchronizability, which can be explained by the fact that efficiency and synchronizability are highly correlated. This correlation is, again, clearly shown in the bottom subplot of Figure 5.5, where the optimization of efficiency and synchronizability converge into a very short front. While synchronizability and efficiency are different in concept, such a short front could makes these two objectives easily reconcilable for some applications.

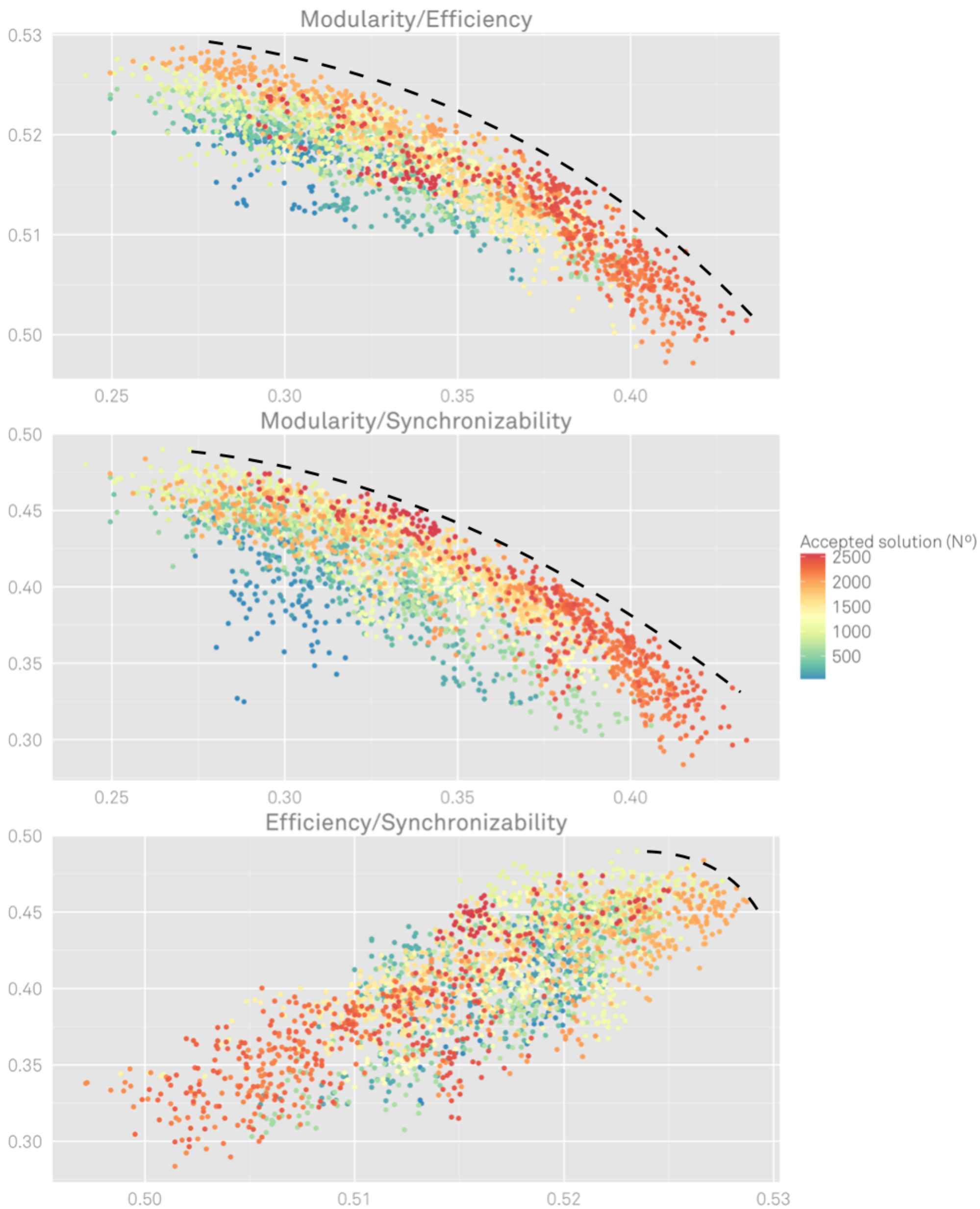


Figure 5.5 — Visualization of the evolution of one run of a MOSA optimizing three objectives (modularity, efficiency and synchronizability). Each subplot shows a projection (or “slice") in two dimensions of the three-dimensional space, providing all combination of the three metrics optimized: modularity, synchronizability, and efficiency (in all cases, higher is better). Each coloured dot is a non-dominated (accepted) solution found during the 10,000 iterations (dominated solutions are not recorded). The colour indicates when the solution was found (blue

indicates early-found solutions, while red indicates most recent, and best, solutions). The dotted line was added to highlight the front of all NDS found during the simulation.

Modularity, Efficiency and Robustness

Figure 5.6, visualizing the trade-offs between modularity, efficiency and robustness in the solution space for optimized networks, effectively recreates Figure 4.1 from Chapter 4. If, as expected, increasing modularity does hinder robustness, the front is much shorter than between modularity and efficiency, and between efficiency and robustness. A compromise could hence be found without gravely hindering either modularity or robustness (as Chapter 4 demonstrated using a different method). However, the optimization of efficiency and robustness is indeed more conflictual and shapes a wide front. The topological difference is visually demonstrated for sample network solutions in Figures 5.4.a/5.7.a (both showing a topology of high efficiency) when compared with Figure 5.7.b (which shows high robustness). In the latter case, the "star-like" topology is avoided as to not make the structure weak to the removal of any particularly central nodes. Instead, the highly robust structure shares node degrees more evenly. Figure 5.7.d shows a compromise between the three objectives: while some communities seems to emerge, the connectivity between them is strong, which improves efficiency without generating highly central nodes (as in the star-like topology).

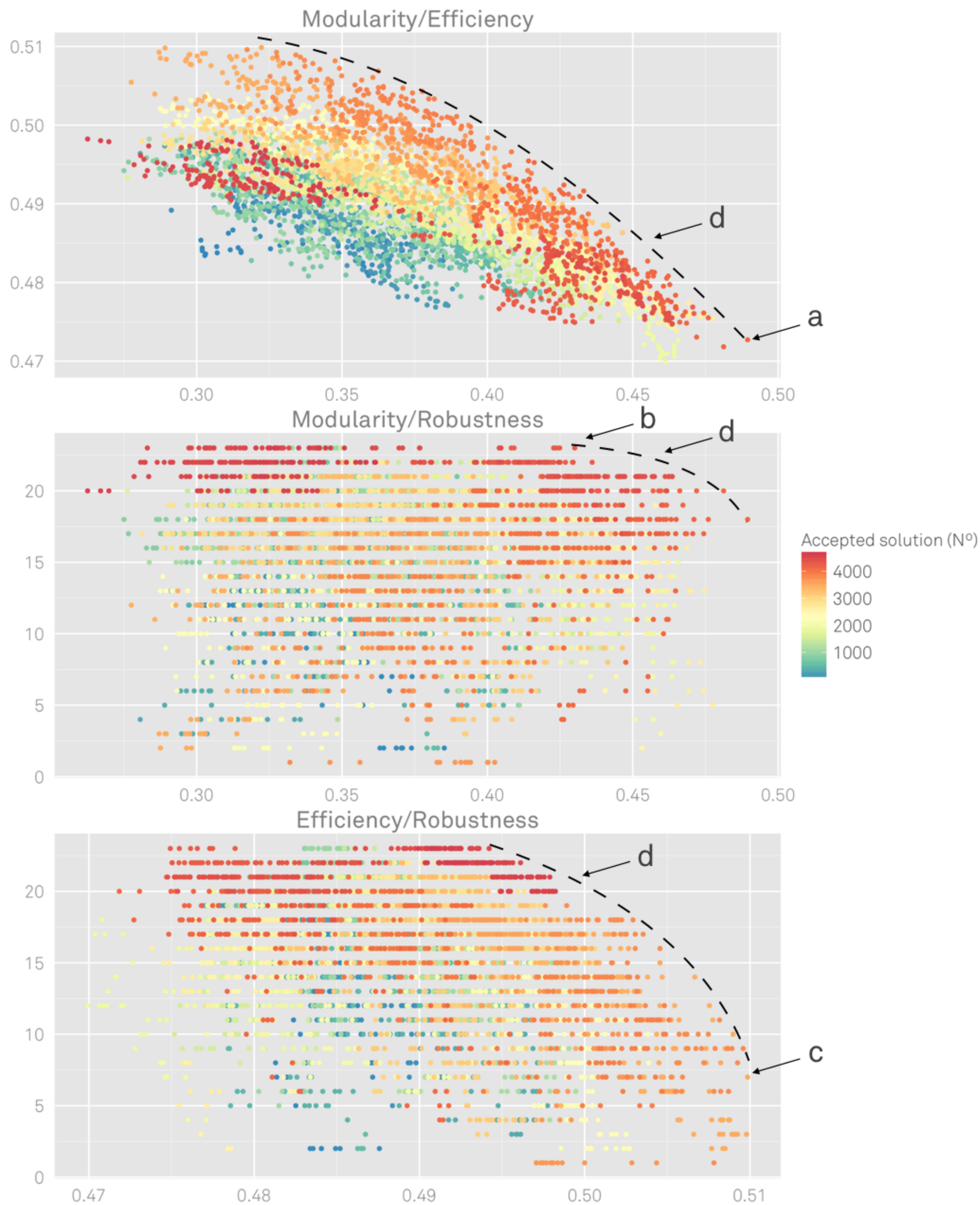


Figure 5.6 — Visualization of the evolution of one run of a MOSA optimizing three objectives (modularity, efficiency and robustness). Each subplot shows a projection (or "slice") in two dimensions of the three-dimensional space, providing all combinations of the three metrics optimized (in all cases, higher is better). Each coloured dot is a non-dominated solution found

during the 10,000 iterations (dominated solutions are not recorded). The colour indicates the step at which the solution was found (blue indicates early-found solutions, while red indicates most recent, and best, solutions).

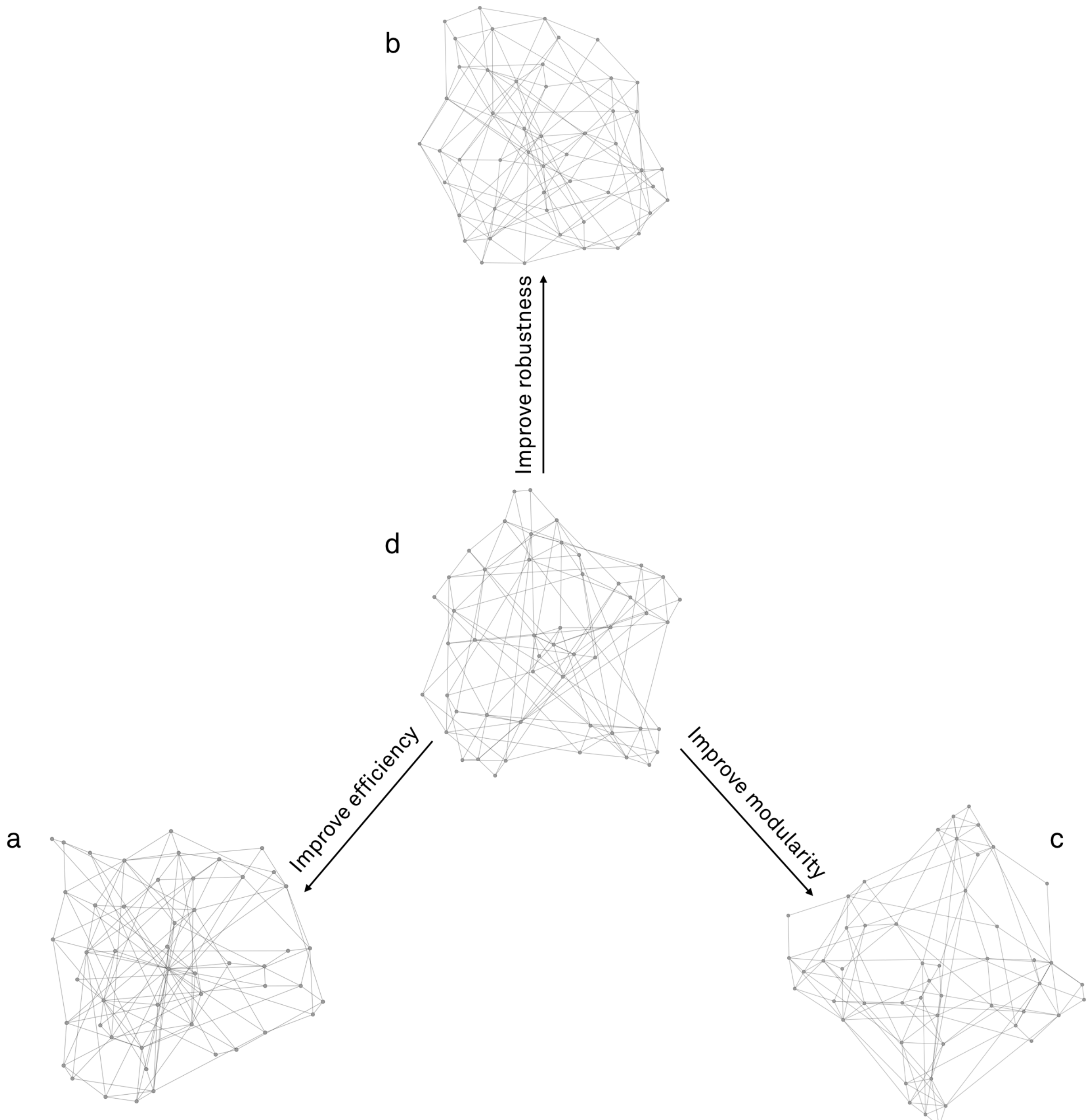


Figure 5.7 — Force-based layout representations of four networks sampled among the 358 present in the final non-dominated set when optimizing for three objectives (see points a, b, c

and d in Figure 5.6). The middle network noted d demonstrates one of the possible trade-offs between modularity, efficiency and robustness.

5.5. LIMITATIONS AND RECOMMENDATIONS

While our MOSA provided satisfying results, a number of limitations need be stated. First, each of our runs produced a unique NDS, which indicates that an Pareto-optimal set of solutions was not found using this algorithm (and given the number of iterations). While this is expected considering the large number of possible non-isometric networks which can be built from 50 nodes and 146 edges (estimated 7×10^{131} combinations), and the relatively short optimization time, it is important to keep this limitation in mind while planing optimization times. On the subject of optimization time (arguably one of the most sensitive points for any optimization method), our MOSA's main drawback is that the filtering of the NDS, which needs to be made at each iteration, becomes very time consuming as its size augments. While optimizing for two objectives produce a NDS list of around 25 entries, three objectives provides around 600 solutions and four objective above 900. This makes for a sizeable time difference between simulations depending on their objective dimensions.

As for any simulated annealing optimization, performance is tightly connected to parameters choices. In our case, we found that starting and ending temperatures should 1) be close to each other, and 2) be relatively low, making for a rather greedy optimization (Cormen 2009). We also found that smaller amounts of random rewiring at each step shapes NDS fronts more quickly than by performing larger numbers of random rewirings. However, too few rewirings hinder the capacity of the algorithm to fully explore solution spaces, instead causing the algorithm to randomly find a topology scoring high in one of the parameters, and then only slightly modifying this topology to rather poorly improve on the other objectives. Our experiments showed that rewiring 1 to 2% of the total number of edges in the network provided satisfying results. As for the MOSA's total number of iterations, higher is always better. However, as stated above, NDS filtering is very time consuming. It is therefore advised to aim for a large number of iterations, while programming the algorithm to regularly export —as the MOSA keeps running— the ensemble of networks included in the NDS.

Table 5.1 — Multiple-objective simulated annealing, parameter recommendations.

	Recommended setting	Effect
Starting temperature	Low so as to reject a large portion of worse solutions	Makes for a rather "greedy" algorithm.
End temperature	Very low so as to reject a large portion of worse solutions	
Extent of the random rewiring	1 to 2% of all edges	Makes sure the algorithm does explore truly different topologies.
Number of steps	At least 20,000	

5.6. DISCUSSION AND CONCLUSION

While using a composite score of weighted objectives can provide solutions performing better, for each objectives, than the ones produced here (see for example the large network optimized in Chapter 4), the multi-objective method is arguably advantageous for several reasons. Firstly, instead of providing one output solution (as a SA using a composite score would), a MOSA make all non-dominated solutions available. Our algorithm explores multi-objective spaces (we experimented with two, three and four objectives —the latter is provided in Annex 7 as it is largely redundant from the results already described here) from which clear non-dominated fronts emerge. As there is no formal way to discriminate between solutions residing on these fronts, it is important to keep them for later analysis on which compromises are required for a given application. Secondly, our MOSA permits a much better understanding of the system's tradeoffs. In Chapter 4, we had to resort to optimizing robustness for all combinations of modularity and average path length is order to obtain the necessary insights about the trade-offs at work between our objectives. The method presented here inherently deals with these trade-offs. Thirdly, potential problems related to objectives being correlated with each other do not bias results with a MOSA as a composite score would. For instance, for a three-objective optimization for which two of the three objectives are perfectly correlated, our MOSA would simply produce a NDS shaped as a curved line instead of a surface.

The approach presented here provides a true, simple and intuitive multi-objective optimization applied to network structure using simulated annealing. The MOSA approach provides an elegant method to explore the space of solutions when seeking to generate networks whose topology meets desired criteria, and is especially applicable to cases for which there are competing objectives that impose trade-offs in network structure. The approach allows us to explore the range of non-dominated solutions in the multi-dimensional objective space, and provides a multi-dimensional front against which empirical or simulated networks may be compared. The approach thus also contributes to advancing the field of network analysis, by creating a well-defined theoretically optimal surface in objective space for a desired network structure, the distance from which can be quantified for a network under study. We are optimistic that this demonstration of MOSA for network topology will be further developed and may be widely applicable to a variety of practical applications.

6. CONCLUSION GÉNÉRALE

6.1. CONTRIBUTIONS

Cette thèse compte quatre contributions notables pour la recherche sur la résilience dans les systèmes socio-écologiques.

Exploration formelle des compromis structuraux permettant l'amélioration de la résilience des SSÉ

Les structures actorielles favorisant la résilience des SSÉ sont complexes et constituent un compromis entre plusieurs topologies parfois contradictoires. Cette thèse identifie quatre mesures réputées favoriser la résilience des SSÉ, et explore leurs contradictions. La Figure 4.1 d'une part, mais surtout les Figures 5.3, 5.5, 5.6 et Annexe 7, montrent que ces contradictions sont contrastées. On y voit que si le degré de modularité d'un réseau est, de par la longueur et la pente du front des solutions non-dominées (SND), très clairement en conflit avec sa connectivité (volets supérieurs des Figures 5.3, 5.5, 5.6), ce n'est pas le cas entre la connectivité et la synchronisabilité, ni entre la modularité et la robustesse, qui convergent vers un front très court. Ceci ne signifie pas que ces mesures à « court front » de SND sont équivalentes, mais qu'il est possible de trouver une structure les satisfaisant en même temps, ou presque. Il s'agit toutefois de demeurer vigilant. Par exemple, si le front entre connectivité (par *average path length* ou *efficiency*) et synchronisabilité (par λ_2) est court, ses extrêmes peuvent déboucher sur des structures tout à fait différentes, où d'un côté la distribution des degrés dans le réseau est proche d'une loi de puissance (faisant émerger une hiérarchie à l'intérieur du réseau), et de l'autre quasi normale et plus égalitaire en termes de distribution de pouvoirs (Figure 4.4). Toutefois, le plus important compromis réside entre deux topologies : d'un côté une topologie fortement modulaire, qui favorise le développement de solutions originales et innovantes face à des défis écosystémiques complexes (et donc souvent imprévisibles), et une topologie fortement connectée qui facilite le partage d'informations (donc la capacité d'apprentissage) et la confiance entre tous les acteurs d'un réseau. La question de quelle mesure doit être

favorisée pour mesurer la résilience de réseaux empiriques relève certainement du contexte politique, géographique, social et historique de chaque étude de cas.
Cette thèse constitue la première étude quantitative complète sur les compromis complexes qui contribuent à améliorer la résilience des système humain-nature couplés.

Développement de deux nouvelles mesures de réseau.

Les recherches de cette thèse ont mené à la création de deux nouvelles mesures de réseau. La première, le *Group Marginalization Index* (GMI) est une mesure de l'équilibre entre les relations inter-groupes (équation 3.4). Elle permet de mesurer le degré auquel un réseau marginalise certains groupes au profit d'autres entre lesquels les relations seraient plus denses. La seconde est la *group-betweenness centrality* (équation 3.3), qui mesure la capacité d'un nœud à servir de pont entre d'autres nœuds appartenant à des groupes différents. Ces deux mesures sont facilement et directement utilisables dans d'autres études de cas, et augmentent la boite d'outils disponibles pour l'analyse des relations de pouvoir au sein de réseaux sociaux.

Développement d'une mesure structurale du degré auquel un réseau d'acteurs contribue à la résilience de son SSÉ

La mesure proposée utilise le concept de similitude structurale (distance euclidienne entre les spectres laplaciens) entre un réseau empirique et un réseau archétypique représentant le compromis idéal entre plusieurs topologies contradictoires (réseau RES). Plus la distance résultante est faible, plus le réseau empirique ressemble, structurellement, à un réseau idéal. Deux méthodes sensiblement différentes sont utilisées dans cette thèse afin de créer ces réseaux RES : la première, proposée dans le chapitre 4, est un algorithme d'optimisation de type « recuit simulé » fondé sur un score aggloméré qui représente les quatre objectifs à la fois (modularité, connectivité, synchronisabilité et robustesse) (équation 4.2). S'il s'avère performant en termes de vitesse d'optimisation (y compris pour des réseaux denses et de taille relativement grande), il ne fournit qu'un seul résultat et ne permet donc pas une exploration formelle des compromis discutés plus haut. La seconde méthode, proposée dans le chapitre 5 est une adaptation simple et intuitive de l'algorithme de recuit simulé précédent. Dans cette méthode, le score unique aggloméré est remplacé par la distance entre une solution et la surface multidimensionnelle des SND (Figure 5.1). Ce score réellement multiobjectif fournit l'ensemble des solutions non-dominées trouvées lors du processus d'optimisation. Il permet, en tenant compte de certaines limitations liées à la puissance de l'ordinateur utilisé (augmenter le nombre d'objectifs augmente également les temps de calcul), un emploi moins rigide de notre mesure.

Toutefois, la mesure de « similitude spectrale » proposée n'est pas normalisée, il est donc difficile de l'utiliser sans ordre de comparaison. Elle se révèle néanmoins véritablement utile lorsqu'il s'agit de comparer des réseaux empiriques entre eux (par leurs distances respectives par rapport au réseau RES), de suivre l'évolution dans le temps d'un réseau d'acteurs, ou de tenter de projeter ses états alternatifs souhaitables.

Il est désormais possible d'analyser une étude de cas à la lumière des deux premiers points. Nous avons choisi un réseau d'acteurs impliqués dans divers projets de conservation de la biodiversité sur la péninsule d'Eyre (EP), en Australie-Méridionale. Si le cas particulier de la biodiversité est sans doute un peu restrictif, il est probable que d'autres problématiques activent les mêmes relations, et que des réseaux similaires en émergent (même si cela n'est pas vérifié dans le cadre de cette étude). Le chapitre 4 quantifie la contribution de ce réseau empirique à la résilience du SSÉ, et compare le score obtenu à d'autres topologies largement étudiées dans la littérature (Tableau 4.1).

Le réseau RES constitue le premier exemple publié de topologie représentant un compromis entre plusieurs caractéristiques reconnues pour améliorer la résilience des SSÉ. Comme décrit, l'utilisation de ce réseau archétypique, en combinaison avec la mesure de distance spectrale, fourni une méthode quantitative pour des études sur la résilience des SSÉ. Un seul réseau empirique a été étudié dans cette thèse, la méthode demeure cependant identique pour un grand nombre d'autres réseaux d'acteurs, et ouvre ainsi la voie à d'autres études sur le sujet.

Démonstration de l'importance de groupes construisant des ponts collaboratifs dans un réseau d'acteurs empirique

Le chapitre 3 est consacré à une analyse générale du réseau EP, et permet une compréhension plus profonde des éléments contextuels de l'étude de cas. L'analyse met en lumière plusieurs points : le contexte institutionnel d'une part, et géographique de l'autre, sont des éléments profondément structurants de l'organisation des acteurs. Les Figures 3.7, 3.8, 3.9 et 3.10 montrent clairement l'impact de la géographie sur les relations. Elles sont de trois ordres : 1) les relations sont très largement locales, et de plus rares relations de longues distances permettent d'élargir la portée spatiale du réseau des acteurs (Figure 3.7) ; 2) le réseau montre une agglomération spatiale forte sur la côte ouest de la péninsule alors que les relations entre les autres acteurs sont moins géographiquement marquées (Figure 3.9) ; 3) deux villes rassemblent les acteurs possédant les plus fortes *betweenness centralities* et *group-betweenness centralities* : Adélaïde et Port Lincoln. Ce résultat n'est pas une véritable surprise, car ce sont des centres administratifs importants où résident les groupes institutionnels dominants du réseau, il confirme toutefois l'importance des grands centres administratifs dans les structures de communication. Les Figures 3.11, 3.12, et 3.13 mettent en lumière le caractère structurant de ces institutions. On y voit se démarquer EP-NRM (institution relativement jeune issue d'une volonté politique de décloisonner les relations entre les acteurs traditionnels) comme un puissant outil institutionnel de mise en relation des acteurs, quel que soit leur groupe d'origine (forte *group-betweenness*). Ces deux points démontrent une nouvelle fois l'importance du contexte politique et géographique dans la compréhension des dynamiques d'acteurs.

6.1. OUVERTURE DE RECHERCHE

Le travail présenté dans cette thèse se concentre sur la partie humaine des SSÉ. En proposant une mesure quantitative reliée à la résilience, il constitue un pas important vers d'autres mesures plus globales et holistiques. Des telles mesures doivent cependant s'affranchir de plusieurs obstacles. Ceux-ci constituent la suite logique des recherches de cette thèse.

Preuves empiriques des théories avancées

Si les mesures de réseaux utilisées dans ce manuscript sont issues de travaux largement acceptés, elles demeurent toutefois seulement théoriques pour le moment. Il n'existe pas, ou très peu, de preuves empiriques que ces mesures, et à forcerie un compromis entre ces mesures, aident effectivement à augmenter sensiblement la résilience des SSÉ. Un des obstacles majeurs à une application pratique de ces recherches réside dans ce manque qui pourrait être comblé par des recherches pluri-disciplinaires sur une plus longue période de temps. Période durant laquelle des séries temporelles (dans les sous-systèmes sociaux et écologiques) pourront être collectées et analysées.

Contexte des SSÉ

Le concept de résilience est large et parfois flou. Dans la multitude des SSÉ à travers le monde, il existe une grande diversité de contextes, de perturbations internes ou externes, de services écosystémiques en jeu, et de solutions d'adaptations acceptables (culturellement et économiquement). Tous ces éléments doivent être pris en compte lorsque l'on tente de mesurer la résilience dans les SSÉ, ou de comparer différents réseaux d'acteurs entre eux. Ces différences impliquent que certaines topologies d'interactions peuvent contribuer différemment à la résilience d'un système en fonction dans son contexte. La mesure présentée ici est souple et facilement adaptable à d'autres objectifs que la modularité, la connectivité, la synchronisabilité et la robustesse. Toutefois, comparer deux études de cas où chacun des scores serait calculé selon des objectifs différents pourrait être conceptuellement problématique. Une clarification des limites liées à cette diversité de contextes constituerait une contribution importante.

La dimension temporelle

Les SSÉ évoluent dans le temps, passent par des cycles, et voient certains liens s'éteindre puis se réactiver en cas de besoin. L'étude de la résilience dans les SSÉ tirerait bénéficie de l'ajout de la dimension temporelle (avec, par exemple, une approche utilisant des diagrammes de récurrence). Cet ajout permettrait également de prendre formellement en compte la phase, dans le cycle d'adaptation (Gunderson 2001), dans laquelle l'étude de cas se situe, et permettant ainsi d'ajuster les objectifs structurels en fonction d'elle (par exemple, chaque phase implique un niveau différent de connectivité). En plus des travaux de terrain de type sociométriques tels que je les ai conduits pour ce travail, l'inclusion de la dimension temporelle demande une recherche historique poussée, ce qui pourrait compliquer la collecte de données.

Divergences graves d'intérêts

Les types de relations inclus dans ce travail sont uniquement positifs. Toutefois, certains acteurs, dans leur diversité d'intérêts, de valeurs et de motivations, peuvent être hostiles au but fixé pour l'étude de cas. Ces acteurs peuvent s'organiser en réseaux et agir de leur côté à des objectifs différents, voire opposés. Comment ces divergences d'intérêts et de pouvoir affectent-elles la résilience des SSÉ ? Comment collecter ces données de la manière la moins biaisée possible, et comment les inclure dans une mesure globale ?

Intégration des sous-systèmes humains et naturels au sein d'un même réseau.

Finalement, est-il possible, pour analyser les SSÉ de manière holistique, d'intégrer simplement et intuitivement les réseaux écosystémiques liés aux réseaux sociaux ? Certains obstacles se posent, parmi lesquels i) la définition de ce qui doit transiter dans le RSÉ modélisé (quels types de flux sont adaptés à la fois aux relations sociales et aux relations écosystémiques ?), et ii) l'asynchronie entre processus humains et processus bio-physiques.

Ces quelques ouvertures de recherche mèneraient vers une compréhension plus profonde des relations socio-écologiques, de leurs dynamiques à travers le temps, et des rétroactions entre les sous-systèmes humains et naturels. À une époque où les conséquences des activités anthropiques se font durablement et profondément sentir dans les paysages et parmi les individus qui les habitent, ces éléments de compréhension fondamentaux constituent certainement une des clés vers des relations socio-écologiques plus équilibrées.

7. BIBLIOGRAPHIE

Adger, W. (2000). Social and ecological resilience: are they related?. *prog hum geogr*, 24(3), pp.347-364.

Adger, W. (2006). Vulnerability. *Global Environmental Change*, 16(3), pp.268-281.

Albert, R., Jeong, H. and Barabási, A. (2000). Error and attack tolerance of complex networks. *Nature*, 406(6794), pp.378-382.

Armitage, D., Plummer, R., Berkes, F., Arthur, R., Charles, A., Davidson-Hunt, I., Diduck, A., Doubleday, N., Johnson, D., Marschke, M., McConney, P., Pinkerton, E. and Wollenberg, E. (2008). Adaptive co-management for social–ecological complexity. *Frontiers in Ecology and the Environment*, 7(2), pp.95-102.

Ashlock, D. (2006). *Evolutionary computation for modeling and optimization*. New York: Springer.

Bailón, S. (2006). The Role of Dynamic Networks in Social Capital : a Simulation Experiment. *Papers: revista de sociologia*, (80), pp.171-194.

Banerjee, A. (2012). Structural distance and evolutionary relationship of networks. *Biosystems*, 107(3), pp.186-196.

Barabasi, A. (2009). Scale-Free Networks: A Decade and Beyond. *Science*, 325(5939), pp. 412-413.

Barabási, A. and Albert, R. (1999). Emergence of Scaling in Random Networks. *Science*, 286(5439), pp.509-512.

Baranyi, G., Saura, S., Podani, J. and Jordán, F. (2011). Contribution of habitat patches to network connectivity: Redundancy and uniqueness of topological indices. *Ecological Indicators*, 11(5), pp.1301-1310.

Barthélemy, M. (2011). Spatial networks. *Physics Reports*, 499(1-3), pp.1-101.

Becker, E. (2012). Social-ecological systems as epistemic objects. In: M. Glaser, G. Krause, B. Ratter and M. Welp, ed., *Human-Nature Interactions in the Anthropocene: Potentials of Social-Ecological Systems Analysis*, 1st ed. London: Routledge.

Bell, S. and Morse, S. (2008). Sustainability indicators: measuring the immeasurable?. *Choice Reviews Online*, 46(03), pp.46-1433-46-1433.

Beni, G. and Wang, J. (1993). Swarm intelligence in cellular robotic systems. In: P. Dario, G. Sandini and P. Aebischer, ed., *Robots and Biological Systems: Towards a New Bionics?*, 1st ed. II Ciocco, Toscana, Italy.

Benz, A. and Furst, D. (2002). Policy Learning in Regional Networks. *European Urban and Regional Studies*, 9(1), pp.21-35.

Berkes, F., Hughes, T., Steneck, R., Wilson, A., Bellwood, D., Crona, B., Folke, C., Gundersen, L., Leslie, H. and Norberg, J. (2006). Globalization, Roving Bandits, and Marine Resources. *Science*, 311(5767), pp.1557-1558.

Berkes, F. and Ross, H. (2013). Community Resilience: Toward an Integrated Approach. *Society & Natural Resources*, 26(1), pp.5-20.

Berkes, F., Folke, C. and Colding, J. (2000). *Linking social and ecological systems*. Cambridge, U.K.: Cambridge University Press.

Berlow, E., Dunne, J., Martinez, N., Stark, P., Williams, R. and Brose, U. (2009). Simple prediction of interaction strengths in complex food webs. *Proceedings of the National Academy of Sciences*, 106(1), pp.187-191.

Beygelzimer, A., Grinstein, G., Linsker, R. and Rish, I. (2005). Improving network robustness by edge modification. *Physica A: Statistical Mechanics and its Applications*, 357(3-4), pp.593-612.

Blondel, V., Guillaume, J., Lambiotte, R. and Lefebvre, E. (2008). Fast unfolding of communities in large networks. *J. Stat. Mech.*, 2008(10), p.P10008.

Bodin, Ö. (2006). *A network perspective on ecosystems, societies and natural resource management*. Ph.D. Stockholm University.

Bodin, Ö. and Crona, B. (2009). The role of social networks in natural resource governance: What relational patterns make a difference?. *Global Environmental Change*, 19(3), pp.366-374.

Bodin, Ö. and Norberg, J. (2005). Information Network Topologies for Enhanced Local Adaptive Management. *Environmental Management*, 35(2), pp.175-193.

Bodin, Ö., Crona, B. and Ernstson, H. (2006). Social networks in natural resource management: what is there to learn from a structural perspective?. *Ecology and Society*, 2(11).

Bodin, Ö., Tengö, M., Norman, A., Lundberg, J. and Elmqvist, T. (2006). The Value Of Small Size: Loss Of Forest Patches And Ecological Thresholds In Southern Madagascar. *Ecological Applications*, 16(2), pp.440-451.

Borgatti, S. and Foster, P. (2003). The Network Paradigm in Organizational Research: A Review and Typology. *Journal of Management*, 29(6), pp.991-1013.

Borgatti, S., Mehra, A., Brass, D. and Labianca, G. (2009). Network analysis in the social sciences. *Science*, 323(5916), pp.892-895.

Bottom, D., Jones, K., Simenstad, C. and Smith, C. (2009). Reconnecting social and ecological resilience in salmon ecosystems. *Ecology and Society*, 1(14).

Bouwen, R. and Taillieu, T. (2004). Multi-party collaboration as social learning for interdependence: developing relational knowing for sustainable natural resource management. *J. Community. Appl. Soc. Psychol.*, 14(3), pp.137-153.

Bowler, I. (2001). From system to networks in the exploration of rural sustainability. In: *Developing Sustainable Rural Systems*, 1st ed. Pusan, Korea: Pusan National University Press, pp.1-9.

Brandes, U. and Erlebach, T. (2005). *Network analysis*. Berlin: Springer.

Bristow, G. and Healy, A. (2014). Building Resilient Regions: Complex Adaptive Systems and the Role of Policy Intervention. *Raumforsch Raumordn*, 72(2), pp.93-102.

Bruneau, M., Chang, S., Eguchi, R., Lee, G., O'Rourke, T., Reinhorn, A., Shinozuka, M., Tierney, K., Wallace, W. and von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, 19(4), pp.733-752.

Bryant, C., Allie, L., Des Roches, S., Buffet, K. and Granjon, D. (2001). A framework to quantitatively assess and enhance the seismic resilience of communities. In: *Reshaping of Rural Ecologies, Economies and Communities (Conference Proceedings, Commission on the Sustainability of Rural Systems, I.G.U.)*, 1st ed. Burnaby, BC: Simon Fraser University, Department of Geography.

Buckley, W. (2008). *Society-- a complex adaptive system*. [Australia]: Gordon and Breach.

Carpenter, A. (2014). Resilience in the social and physical realms: Lessons from the Gulf Coast. *International Journal of Disaster Risk Reduction*, 14, pp.290-301.

Carpenter, S. and Brock, A. (2008). Adaptive capacity and traps. *Ecology and society*, 2(13).

Carpenter, S., Walker, B., Anderies, J. and Abel, N. (2001). From Metaphor to Measurement: Resilience of What to What?. *Ecosystems*, 4(8), pp.765-781.

Černý, V. (1985). Thermodynamical approach to the traveling salesman problem: An efficient simulation algorithm. *J Optim Theory Appl*, 45(1), pp.41-51.

Cinner, J. and Bodin, Ö. (2010). Livelihood Diversification in Tropical Coastal Communities: A Network-Based Approach to Analyzing 'Livelihood Landscapes'. *PLoS ONE,* 5(8), p.e11999.

Cormen, T. (2009). *Introduction to algorithms*. Cambridge, Mass.: MIT Press.

Costanza, R. and Patten, B. (1995). Defining and predicting sustainability. *Ecological Economics,* 15(3), pp.193-196.

Crona, B. (2006). *Of mangroves and middlemen: a study of social and ecological linkages in a coastal community*. Ph.D. Department of Systems Ecology, Stockholm University.

Crona, B. and Bodin, Ö. (2010). Power asymmetries in small-scale fisheries: a barrier to governance transformability. *Ecology and Society*, 4(15).

Crutzen, P. (2002). Geology of mankind. *Nature*, 415(6867), pp.23-23.

Csardi, G. and Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal, Complex Systems*, 5(1695), pp.1-9.

Cumming, G. (2011). *Spatial resilience in social-ecological systems*. Dordrecht: Springer.

Cumming, G., Bodin, Ö., Ernstson, H. and Elmqvist, T. (2010). Network analysis in conservation biogeography: challenges and opportunities. *Diversity and Distributions*, 16(3), pp.414-425.

Czyzżak, P. and Jaszkiewicz, A. (1998). Pareto simulated annealing—a metaheuristic technique for multiple−objective combinatorial optimization. *J. Multi−Crit. Decis. Anal.*, 7(1), pp.34-47.

de Lange, S., de Reus, M. and van den Heuvel, M. (2013). The Laplacian spectrum of neural networks. *Front. Comput. Neurosci.*, 7.

Diamond, J. (2005). *Collapse*. New York: Viking.

Donetti, L., Hurtado, P. and Muñoz, M. (2005). Entangled Networks, Synchronization, and Optimal Network Topology. *Phys. Rev. Lett.*, 95(18).

Doyon, M. (2009). *La dynamique actorielle dans la construction des espaces périurbains : les cas de Montpellier (France) et de Montréal (Québec)*. Ph.D. Département de géographie, Université de Montréal.

Ehrlich, P. and Walker, B. (1998). Rivets and Redundancy. *BioScience*, 48(5), pp.387-387.

Erdős, P. and Rényi, A. (1961). On the strength of connectedness of a random graph. *Acta Mathematica Academiae Scientiarum Hungaricae*, 12(1-2), pp.261-267.

Ernstson, H., Barthel, S., Andersson, E. and Borgström, S. (2010). Scale-crossing brokers and network governance of urban ecosystem services: the case of Stockholm. *Ecology and Society*, 4(15).

Ernstson, H., Sörlin, S. and Elmqvist, T. (2008). Social movements and ecosystem services—The role of social network structure in protecting and managing urban green areas in Stockholm. *Ecology and Society*, 2(13).

Estrada, E. and Bodin, Ö. (2008). USING NETWORK CENTRALITY MEASURES TO MANAGE LANDSCAPE CONNECTIVITY. *Ecological Applications*, 18(7), pp.1810-1825.

Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change*, 16(3), pp.253-267.

Folke, C., Carpenter, S., Elmqvist, T., Gunderson, L., Holling, C. and Walker, B. (2002). Resilience and Sustainable Development: Building Adaptive Capacity in a World of Transformations. *AMBIO: A Journal of the Human Environment*, 31(5), p.437.

Folke, C., Hahn, T., Olsson, P. and Norberg, J. (2005). Adaptive governance of social-ecological systems. *Annu. Rev. Environ. Resour*, (30), pp.441-473.

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, 486(3-5), pp. 75-174.

Freeman, L. (1979). Centrality in social networks conceptual clarification. *Social Networks*, 1(3), pp.215-239.

Gallopín, G. (2006). Linkages between vulnerability, resilience, and adaptive capacity. *Global Environmental Change*, 16(3), pp.293-303.

Gao, X., Xiao, B., Tao, D. and Li, X. (2010). A survey of graph edit distance. *Pattern Anal Applic*, 13(1), pp.113-129.

Ghimire, S., McKey, D. and Aumeeruddy-Thomas, Y. (2004). Heterogeneity in ethnoecological knowledge and management of medicinal plants in the Himalayas of Nepal: implications for conservation. *Ecology and Society*, 3(9).

Goldenberg, J. and Levy, M. (2009). Distance is not dead: Social interaction and geographical distance in the internet era. *arXiv preprint arXiv:0906.3202.*.

Gonzalès, R. and Parrott, L. (2012). Network Theory in the Assessment of the Sustainability of Social-Ecological Systems. *Geography Compass*, 6(2), pp.76-88.

Grimble, R. and Wellard, K. (1997). Stakeholder methodologies in natural resource management: a review of principles, contexts, experiences and opportunities. *Agricultural Systems*, 55(2), pp.173-193.

Guang-Yu, K., Li, X., Lu, Z. and Su, Y. (2012). Synchronizability Optimization for Tree-structured Deterministic Small-world Network with Modified Simulated Annealing Algorithm. In: *Second International Conference on Instrumentation, Measurement, Computer, Communication and Control*. IEEE.

Gulyás, L., Horváth, G., Cséri, T. and Kampis, G. (2011). An Estimation of the Shortest and Largest Average Path Length in Graphs of Given Density. *arXiv*, (1101.2549).

Gunderson, L. and Holling, C. (2001). *Panarchy*. Washington, DC: Island Press.

Heller, N. and Zavaleta, E. (2009). Biodiversity management in the face of climate change: A review of 22 years of recommendations. *Biological Conservation*, 142(1), pp.14-32.

Holling, C. (1973). Resilience and Stability of Ecological Systems. *Annu. Rev. Ecol. Syst.*, 4(1), pp.1-23.

Holme, P., Kim, B., Yoon, C. and Han, S. (2002). Attack vulnerability of complex networks. *Physical Review E*, 65(5).

Holroyd, M. and Kincaid, R. (2006). Synchronizability and Connectivity of Discrete Complex Systems. In: *International Conference on Complex Systems*. Williamsburg, Virginia, United States: The College of William & Mary in Virginia.

Hughes, L. (2003). Climate change and Australia: Trends, projections and impacts. *Austral Ecology*, 28(4), pp.423-443.

Illenberger, J., Nagel, K. and Flötteröd, G. (2013). The Role of Spatial Interaction in Social Networks. *Networks and Spatial Economics*, 13(3), pp.255-282.

Iyer, S., Killingback, T., Sundaram, B. and Wang, Z. (2013). Attack Robustness and Centrality of Complex Networks. *PLoS ONE*, 8(4), p.e59613.

Janssen, M., Bodin, Ö., Anderies, J., Elmqvist, T., Ernstson, H., McAllister, R., Olsson, P. and Ryan, P. (2006). Toward a network perspective of the study of resilience in social-ecological systems. *Ecology and Society*, 1(11).

Jen, E. (2003). Stable or robust? What's the difference?. *Complexity*, 8(3), pp.12-18.

Kelly, D. and Gottwald, G. (2011). On the topology of synchrony optimized networks of a Kuramoto-model with non-identical oscillators. *Chaos*, 21(2), p.025110.

Kirkpatrick, S. (1984). Optimization by simulated annealing: Quantitative studies. *Journal of Statistical Physics*, 34(5-6), pp.975-986.

Klemm, K. and Eguíluz, V. (2002). Growing scale-free networks with small-world behavior. *Physical Review E*, 65(5).

Kobourov, S. (2012). Spring embedders and force directed graph drawing algorithms. *arXiv*, (1201.3011).

Kocarev, L. (2013). *Consensus and synchronization in complex networks*. Berlin: Springer.

Latora, V. and Marchiori, M. (2001). Efficient behavior of small-world networks. *Physical review letters*, 19(87), pp.198701-1.198701-4.

Law, J. (1986). *Power, action, and belief*. London: Routledge & Kegan Paul.

Law, J. (1992). Notes on the theory of the actor-network: Ordering, strategy, and heterogeneity. *Systems Practice*, 4(5), pp.379-393.

Leskovec, J., Kleinberg, J. and Faloutsos, C. (2005). Graphs over time: densification laws, shrinking diameters and possible explanations. In: *The Eleventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. Chicago, Illinois, USA: ACM.

Levin, S. (1998). Ecosystems and the Biosphere as Complex Adaptive Systems. *Ecosystems*, 1(5), pp.431-436.

Levin, S. (2008). Foreword. In: J. Norberg and G. Cumming, ed., *Complexity theory for a sustainable future*, 1st ed. Columbia University Press.

Lienert, J., Schnetzer, F. and Ingold, K. (2013). Stakeholder analysis combined with social network analysis provides fine-grained insights into water infrastructure planning processes. *Journal of Environmental Management*, 125, pp.134-148.

Liu, J., Dietz, T., Carpenter, S., Alberti, M., Folke, C., Moran, E., Pell, A., Deadman, P., Kratz, T., Lubchenco, J., Ostrom, E., Ouyang, Z., Provencher, W., Redman, C., Schneider, S. and Taylor, W. (2007). Complexity of Coupled Human and Natural Systems. *Science*, 317(5844), pp.1513-1516.

Ludwig, D., Walker, B. and Holling, C. (1997). Sustainability, stability, and resilience. *Conservation ecology*, 1(1), p.7.

Magis, K. (2010). Community Resilience: An Indicator of Social Sustainability. *Society & Natural Resources*, 23(5), pp.401-416.

Magurran, A. (2013). *Ecological diversity and its measurement*. Princeton, N.J.: Princeton University Press.

Marín, A. and Berkes, F. (2010). Network approach for understanding small-scale fisheries governance: The case of the Chilean coastal co-management system. *Marine Policy*, 34(5), pp.851-858.

Marsden, P. (1990). Network data and measurement. *Annual review of sociology*, 16, pp. 435-463.

Marsden, T., Murdoch, J., Lowe, P., Munton, R. and Flynn, A. (1993). *Constructuring The Countryside*. Florence: Taylor and Francis.

Mason, W., Jones, A. and Goldstone, R. (2008). Propagation of innovations in networked groups. *Journal of Experimental Psychology: General*, 137(3), pp.422-433.

Matous, P. and Todo, Y. (2015). Exploring dynamic mechanisms of learning networks for resource conservation. *Ecology and Society*, 20(2).
Matous, P. and Todo, Y. (2015). Exploring dynamic mechanisms of learning networks for resource conservation. *Ecology and Society*, 20(2).
Matthews, E., Oppermann, A. and Inns, R. (2001). *Biodiversity Plan for the Eyre Peninsula*. Adelaide, South Australia, Australia: Department for Environment and Heritage, South Australia.

McAllister, R., Cheers, B., Darbas, T., Davies, J., Richards, C., Robinson, C., Ashley, M., Fernando, D. and Maru, Y. (2008). Social networks in arid Australia: a review of concepts and evidence. *Rangel. J.*, 30(1), p.167.

McCulloh, I. and Carley, K. (2008). Social network change detection. *Carnegie-Mellon University, Pittsburgh School of Computer Science*.

Meyer, W., Bryan, B., Gonzalès, R., King, D., Lyle, G., Moon, T., Summers, D. and Turner, D. (2013). *Climate Change, Communities and Environment. Technical Report*. Adelaide: University of Adelaide.

Mucha, P., Richardson, T., Macon, K., Porter, M. and Onnela, J. (2010). Community Structure in Time-Dependent, Multiscale, and Multiplex Networks. *Science*, 328(5980), pp.876-878.

Murdoch, J. (1994). Weaving the seamless web: a consideration of network analysis and its potential application to the study of the rural economy, Centre for Rural Economy. *Department of Agricultural Economics and Food Marketing, University of Newcastle upon Tyne*.

Newig, J., Günther, D. and Pahl-Wostl, C. (2010). Synapses in the network: learning in governance networks in the context of environmental management. *Ecology and Society*, 4(15).

Newman, M. (2003). The structure and function of complex networks. *arXiv*, (0303516v1).

Newman, M. and Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, 69(2).

Norberg, J. and Cumming, G. (2013). *Complexity theory for a sustainable future*. New York: Columbia University Press.

Olsson, P. and Folke, C. (2001). Local Ecological Knowledge and Institutional Dynamics for Ecosystem Management: A Study of Lake Racken Watershed, Sweden. *Ecosystems*, 4(2), pp.85-104.

Olsson, P., Folke, C. and Berkes, F. (2004). Adaptive Comanagement for Building Resilience in Social?Ecological Systems. *Environmental Management*, 34(1).

Onnela, J., Arbesman, S., González, M., Barabási, A. and Christakis, N. (2011). Geographic Constraints on Social Network Groups. *PLoS ONE*, 6(4), p.e16939.

Ostrom, E. (2007). A General Framework for Analyzing Sustainability of Social-Ecological Systems. *Science*, 325(5939), pp.419-422.

Ostrom, E., Walker, J. and Gardner, R. (1992). Covenants With and Without a Sword: Self-Governance is Possible. *The American Political Science Review*, 86(2), p.404.

Pal, A., Ray, B., Zakaria, N. and Sarma, S. (2012). Comparative Performance of Modified Simulated Annealing with Simple Simulated Annealing for Graph Coloring Problem. *Procedia Computer Science*, 9, pp.321-327.

Palla, G., Barabási, A. and Vicsek, T. (2007). Quantifying social group evolution. *Nature*, 446(7136), pp.664-667.

Parrott, L. and Meyer, W. (2012). Future landscapes: managing within complexity. *Frontiers in Ecology and the Environment*, 10(7), pp.382-389.

Parrott, L., Chion, C., Gonzalès, R. and Latombe, G. (2012). Agents, Individuals, and Networks: Modeling Methods to Inform Natural Resource Management in Regional Landscapes. *Ecology and Society*, 17(3).

Pecora, L. and Carroll, T. (1990). Synchronization in chaotic systems. *Physical review letters*, 8(64), p.821.

Perrings, C. (2006). Resilience and sustainable development. *Envir. Dev. Econ.*, 11(04), p. 417.

Pluchino, A., Latora, V. and Rapisarda, A. (2005). Changing opinions in a changing world: a new perspective in sociophysics. *Int. J. Mod. Phys. C*, 16(04), pp.515-531.

Prell, C., Hubacek, K. and Reed, M. (2009). Stakeholder Analysis and Social Network Analysis in Natural Resource Management. *Society & Natural Resources*, 22(6), pp. 501-518.

Provan, K. and Kenis, P. (2008). Modes of Network Governance: Structure, Management, and Effectiveness. *Journal of Public Administration Research and Theory*, 18(2), pp. 229-252.

Rad, A., Jalili, M. and Hasler, M. (2008). Efficient rewirings for enhancing synchronizability of dynamical networks. *Chaos*, 18(3), p.037104.

Ravasz, E. and Barabási, A. (2003). Hierarchical organization in complex networks. *Physical Review E*, 2(67), p.026112.

Reed, M., Graves, A., Dandy, N., Posthumus, H., Hubacek, K., Morris, J., Prell, C., Quinn, C. and Stringer, L. (2009). Who's in and why? A typology of stakeholder analysis methods for natural resource management. *Journal of Environmental Management*, 90(5), pp.1933-1949.

Ross, P. (2005). Hyper-heuristics. In: F. Glover and G. Kochenberger, ed., *Search methodologies*, 1st ed. New York, NY, USA: Kluwer Academic, pp.529-556.

Sanfeliu, A. and Fu, K. (1983). A distance measure between attributed relational graphs for pattern recognition. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-13(3), pp.353-362.

Sawyer, R. (2005). *Social emergence*. Cambridge: Cambridge University Press.

Scheffer, M., Carpenter, S., Foley, J., Folke, C. and Walker, B. (2001). Catastrophic shifts in ecosystems. *Nature*, 413(6856), pp.591-596.

Schlüter, M., Biggs, R., Schoon, M., Robards, M. and Anderies, J. (2015). 10 - Reflections on building resilience – interactions among principles and implications for governance. In: R. Biggs, M. Schlüter and M. Schoon, ed., *Principles for Building Resilience - Sustaining Ecosystem Services in Social-Ecological Systems*, 1st ed. Cambridge University Press, pp.251-282.

Scott, J. (2012). *Social network analysis*. London: SAGE Publications.

Scott, J. and Carrington, P. (2011). *The SAGE handbook of social network analysis*. London: SAGE.

Shoo, L., O'Mara, J., Perhans, K., Rhodes, J., Runting, R., Schmidt, S., Traill, L., Weber, L., Wilson, K. and Lovelock, C. (2014). Moving beyond the conceptual: specificity in regional climate change adaptation actions for biodiversity in South East Queensland, Australia. *Regional Environmental Change*, 14(2), pp.435-447.

Simpson, E. (1949). Measurement of Diversity. *Nature*, 163(4148), pp.688-688.

Smith, K. (2006). *A study of simulated annealing techniques for multi-objective optimisation*. Ph.D. University of Exeter, UK.

Spekkink, W. and Boons, F. (2015). The Emergence of Collaborations. *Journal of Public Administration Research and Theory*, 15(1), pp.1-15.

Stevenson, R. (2011). A revised framework for coupled human and natural systems, propagating thresholds, and managing environmental problems. *Physics and Chemistry of the Earth, Parts A/B/C*, 36(9-11), pp.342-351.

Sydney, A., Scoglio, C. and Gruenbacher, D. (2013). Optimizing algebraic connectivity by edge rewiring. *Applied Mathematics and Computation*, 219(10), pp.5465-5479.

Szell, M., Lambiotte, R. and Thurner, S. (2010). Multirelational organization of large-scale social networks in an online world. *Proceedings of the National Academy of Sciences*, 107(31), pp.13636-13641.

Thomas, C., Cameron, A., Green, R., Bakkenes, M., Beaumont, L., Collingham, Y., Erasmus, B., De Siqueira, M., Grainger, A. and Hannah, L. (2004). Extinction risk from climate change. *Nature*, 427(6970), pp.145-148.

Tompkins, E. and Adger, W. (2004). Does adaptive management of natural resources enhance resilience to climate change?. *Ecology and society*, 2(9).

Top, N. (2009). Counterterrorism's new tool: "metanetwork" analysis. *Science*, 325, pp. 409-411.

Turner II, B. (2010). Vulnerability and resilience: Coalescing or paralleling approaches for sustainability science?. *Global Environmental Change*, 20(4), pp.570-576.

Tyler, S. (2006). *Comanagement of natural resources*. Ottawa: International Development Research Centre.

Tylianakis, J., Tscharntke, T. and Lewis, O. (2007). Habitat modification alters the structure of tropical host–parasitoid food webs. *Nature*, 445(7124), pp.202-205.

Walker, B. (1995). Conserving Biological Diversity through Ecosystem Resilience. *Conservation Biology*, 9(4), pp.747-752.

Walker, B. and Salt, D. (2012). *Resilience thinking*. Washington, DC: Island Press.

Waltner-Toews, D., Kay, J. and Lister, N. (2008). *The ecosystem approach*. New York: Columbia University Press.

Ward, J. and MacDonald, D. (2009). *Encouraging landholder participation in natural resource incentive programs on the Eyre Peninsula*. Port Lincoln: Eyre Peninsula Natural Resources Management Board.

Wasserman, S. and Faust, K. (1994). *Social network analysis*. Cambridge: Cambridge University Press.

Watts, D. and Strogatz, S. (1998). Collective dynamics of "small-world" networks. *Nature*, 6684(393), pp.440-442.

Webb, C. and Bodin, Ö. (2008). A network perspective on modularity and control of flow in robust systems. In: J. Norberg and G. Cumming, ed., *Complexity theory for a sustainable future*, 1st ed. New York, NY, USA: Columbia University Press, pp.85-118.

Webb, C. and Levin, S. (2005). Cross-system perspectives on the ecology and evolution of resilience. In: E. Jen, ed., *Robust Design: A Repertoire of Biological, Ecological, and Engineering Case Studies*, 1st ed. Oxford University Press.

Wilson, R. and Zhu, P. (2008). A study of graph spectra for comparing graphs and trees. *Pattern Recognition*, 41(9), pp.2833-2841.

Yang, C., Jia, Q. and Tang, W. (2013). Enhancing Synchronizability of Complex Networks via Optimization. In: L. Kocarev, ed., *Consensus and Synchronization in Complex Networks*, 1st ed. New York, NY, USA: Springer, pp.155-183.

Zeng, A. and Liu, W. (2012). Enhancing network robustness against malicious attacks. *Physical Review E*, 85(6).

Zetterberg, A. (2009). *Network based tools and indicators for landscape ecological assessments, planning, and design*. Licentiate. Department of Land and Water Resources Engineering Royal Institute of Technology (KTH), Sweden.

ANNEXE 1 — Tableau utilisé pour l'analyse des acteurs

This spreadsheet is meant to identify a comprehensive list of actors (groups and individuals) influencing decision making regarding biodiversity conservation on the Eyre Peninsula. This list is divided in two main parts.

1) The first part is the "stakeholders as groups" section, which lists stakeholders groups that, you consider, are affecting or being affected by matters related to biodiversity conservation on the EP. These stakeholders can be, without being limited to, government agencies, NGO's, and consultancy enterprises (even one-man enterprises).

2) The second part, "Individual actors involved within this stakeholder group" lists individual actors working under the corresponding stakeholder group. As an example, we started filling the table with stakeholder groups and individuals working on the WildEyre project. We see that a row is dedicated to each individual, working on this particular project, listed on the right side of the table. When there is more than one individual associated with a stakeholder group, insert a new row and just fill in the individual details on the right side of the table - the stakeholder group detail only needs to be entered once .

To help develop a comprehensive understanding of who is affected, who is influencing and who is deciding, it is important that we get this listing as complete as possible. Please fill the table to the best of your knowledge, adding as many stakeholder groups and actors' names as you think are relevant.

We greatly appreciate your help. Please contact us if you have any concerns or questions. *** Please note that any information you provide and its source will be treated confidentially. Material which may be published from this study will be modified to protect confidentiality of source and individual identity.

Note: 1). there are comments associated with the column headings - hovering over the cell will bring this information up. 2). A number of the columns e.g. Category have an imbedded list of options that will help describe the stakeholder or strength of influence for example. To activate the pop up list, highlight the cell, click on the arrow on the right hand side of the highlighted cell and the list will appear - then click on the best description. If the list does not have the description you think is appropriate you can type in an alternative.

Groups of stakeholders				**Stakeholders as individuals**			
Name	Category	Level of interest in biodiversity issues	Strength of influence in comparison to most other	Name	Specific involvement regarding biodiversity issues	Geographic location of this individual's involvement	Contact

This table was set up with drop-down choice on some cell. For “category”, choices included: “Aboriginal groups”, “Industry (farming)”, “Local governments”, “NGO and local initiatives” and “Private agronomist”. Choices for “Level of interest in biodiversity issues on the Eyre Peninsula”: “Very high (these issues are a matter of livelihood to this stakeholder)”, “High”, “Moderate”, “Low”, “Very low (this stakeholder has only remote or unclear interest in this matter)”. Choices for “Strength of influence in comparison to most other” were: “Among the most influential”, “Higher than average”, “Average”, “Lower than average”, “Among the least influential”.

ANNEXE 2 — Tableau utilisé pour la collecte des données de réseau

SURVEY n°

Focus of the study. This questionnaire is part of a University of Adelaide and University of Montreal (Canada) project dealing with climate change, communities and environment. It focuses on **assessing the structures of interactions** between formal institutions, community initiatives and independent advisors **in biodiversity conservation efforts** on the Eyre Peninsula (EP). This specific part of the project is being conducted by PhD candidate Rodolphe Gonzales under the supervision of University of Adelaide Professor Wayne Meyer.

Research goal. A dense and intricate social network is shaped by stakeholders' collaborative efforts to promote and implement biodiversity conservation programs on the EP. This questionnaire will allow us to study the large-scale structural qualities of this complex network. Based on the data collected here, we will conduct a series of **network analyses that will inform stakeholders on the strength and ability of this structure to continue looking after the valuable biodiversity assets** of EP in a changing environment.

Targeted surveyees. We are hoping to reach **anyone who has, in the last 3 years, been involved in any project or program, directly or indirectly, related to biodiversity conservation on the EP** (that is: directly if biodiversity conservation is considered a first goal of the program or indirectly if it is one of its positive outcomes). Your participation in this research, through the completion of this questionnaire (**which should take you less than a half hour: there are many pages to this survey, but not all of them are likely to apply to you**), is highly important to us.

Applicable programs & projects. We include in "biodiversity conservation effort" any program or project which could benefit biodiversity conservation on the EP, even if it's not the project's first goal. In general, these initiatives include land management efforts such as **fencing remnant vegetation**, **planting windbreaks**, **controlling pests and weeds in native vegetation areas**, some **coastal management programs**, etc. but could also include other activities and programs, such as **land use planning**, **carbon sequestration projects**, **saltbush forage systems**, which can also have an impact on habitats and biodiversity. Please ask us if you aren't sure if the programs you are involved in relate to biodiversity conservation.

Privacy protection. We would like to emphasis that **the information gathered here, as well as its sources, will be treated confidentially** (see declaration of consent at the end of this questionnaire). For this social network analysis to be meaningful, it is very important to identify the role and interactions of individuals shaping conservation initiatives network on the EP. However, material that may be published from this study will be modified to strictly protect confidentiality, and **AT NO TIME WILL ANY INFORMATION REGARDING AN INDIVIDUAL BE MADE AVAILABLE TO THEIR ORGANISATION OR ANY OTHER ORGANISATION OR PERSONS**. This research has received University of Montreal's ethics comittee approval number: CERFAS-2011-12-146-A. Please contact us if you have any questions or concerns in this regard: [redacted]

SURVEY n°

Questionnaire, Part I: Information about yourself

Your email address	....
What is your age group?	❍ 20-30 years ❍ 31-40 years ❍ 41-50 years ❍ 51-60 years ❍ 60+ years
Please indicate your gender	❍ Male ❍ Female
What is your highest completed level of education?	❍ Completed year 10/Form 4 ❍ Completed year 11/Form 5 ❍ Completed year 12/Form 6 ❍ Technical/trade ❍ Tertiary agriculture ❍ Tertiary environment ❍ Other Tertiary ❍ Postgraduate agriculture ❍ Postgraduate environment ❍ Other postgraduate
What is your occupation?	....
Are you involved in any natural resource or agricultural based organisation? Possible answers include: "independent adviser", "EP NRM", "Agricultural bureau", "Local gov.", "Landcare group", etc.	1. .... 2. .... 3. .... 4. .... 5. ....
How important do you rate biodiversity conservation to be on the EP?	☐ It should be regarded as a major issue ☐ It is important but other issues are more pressing (please precise: ____________________ ☐ It is not an important issue
What is your main position or role in each of the above-mentioned organisations? Please indicate the roles or positions in the same order as above.	1. .... 2. .... 3. .... 4. .... 5. ....
How long (in years) **have you lived on the EP?**	____ years
How long (in years) **have you been involved in NRM or land management programs on the EP?**	____ years

What proportion of your time (in %) do you dedicate to NRM or land management on **privately owned land?**	____ %
What proportion of your time (in %) do you dedicate to NRM or land management on **public land?** (public parks, conservation reserves, etc.)	____ %
Which geographical area do you mainly work from? Please check one box corresponding to the location of your offices/workplace, or add another location if no option applies.	❍ District Council of Ceduna ❍ District Council of Cleve ❍ District Council of Elliston ❍ District Council of Franklin Harbour ❍ District Council of Kimba ❍ District Council of Lower EP ❍ City of Port Augusta ❍ City of Port Lincoln ❍ District Council of Streaky Bay ❍ District Council of Tumby Bay ❍ Wudinna District Council ❍ City of Whyalla ❍ City of Adelaide ❍ Other:____________________

Which areas are your projects located in? Please check the corresponding box or add another location. **For the selected areas, what types of biodiversity-related conservation program(s) or project(s) are you involved with?**	☐ District Council of Ceduna ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation, creeks); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ District Council of Cleve ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ District Council of Elliston ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ District Council of Franklin Harbour ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ District Council of Kimba ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ District Council of Lower EP ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ District Council of Streaky Bay ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ District Council of Tumby Bay ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ Wudinna District Council ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________ ☐ Other:__________ ☐ Habitat restoration (e.g. tree or other vegetation planting); ☐ Habitat protection (e.g. fencing of remnant vegetation); ☐ Pest and weed control in native vegetation areas; ☐ Other:__________

Part II: Who do you interact with?

This section is composed of tables dedicated to different stakeholders groups. Each row of each table holds a commonly cited name within the group. In order to describe your interactions regarding biodiversity-related issues on the EP, please check:

☑ **I provide information to this person** if the corresponding individual has regularly contacted you for information and advice in the last 3 years. Information/advice may be about:

- Reasons to participate in a particular program (environmental benefits of the program, on-ground economical relevance, etc.);
- The practicalities of getting involved in a particular program;
- How to better design, promote or implement programs;
- Contextual elements, general or specific knowledge about the system, data;
- Etc.

☑ **I gain information from this person** if you contact the corresponding individual for the same kind of information and advice listed above.

☑ **We collaborate on program promotion** if you interact with the corresponding individual to promote programs that are beneficial to biodiversity on the EP.

These promotional activities can, for instance, take the form of:

- Organising workshops;
- Producing brochures and reports to inform stakeholders
- Collaborating on scientific publications informing on these issues;
- Etc.

☑ **We collaborate on on-ground implementation** if you interact with the corresponding individual on implementing programs that are beneficial to biodiversity on the EP.

These promotional activities can, for instance, take the form of:

- Planting perennial trees or other vegetation for windbreaks/habitat restoration
- Fencing of remnant vegetation;
- Controlling pests and weeds;
- Etc.

Example. If you interact weekly with Joe Bloggs on implementing a perennial tree planting project around Streaky Bay, as well as providing him with advice on why this is important economically and for the environment, please check the following boxes:

Example stakeholder group				
Name of individual	What type of collaboration typically happens between you and this individual? (You can check several boxes)	**How often** do you collaborate with this person?	Which District Council are the projects situated in?	
Joe Bloggs	☑ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☑ We collaborate on on-ground implementation	❍ Never ❍ Daily, ⦿ Weekly ❍ Monthly+ ❍ Other	☐ None in particular ☐ Ceduna ☐ Cleve ☐ Elliston ☐ Franklin Harbour ☐ Kimba	☐ Lower EP ☐ Port Lincoln ☑ Streaky Bay ☐ Tumby Bay ☐ Wudinna ☐ Other:........

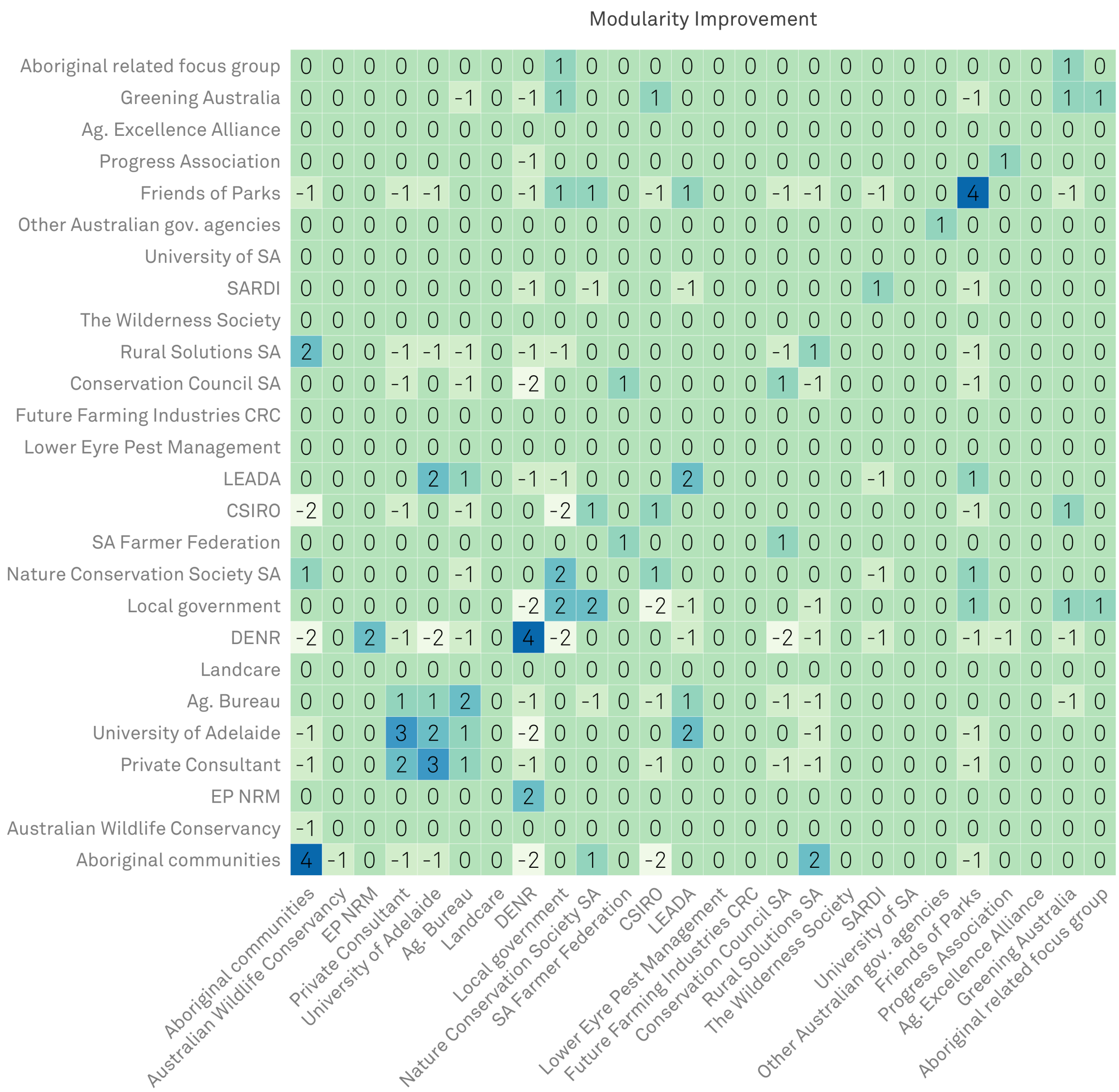
Section 1: Formal Institutions

EP Natural Resource Management (EP NRM)			
Name of Individual	What type of collaboration typically happens between you and this individual? (You can check several boxes)	**How often** do you collaborate with this person?	Which District Council are the projects situated in?
[redacted]	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Lower EP ☐ Ceduna ☐ Port Lincoln ☐ Cleve ☐ Streaky Bay ☐ Elliston ☐ Tumby Bay ☐ Franklin Harbour ☐ Wudinna ☐ Kimba ☐ Other:__________
[redacted]	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Lower EP ☐ Ceduna ☐ Port Lincoln ☐ Cleve ☐ Streaky Bay ☐ Elliston ☐ Tumby Bay ☐ Franklin Harbour ☐ Wudinna ☐ Kimba ☐ Other:__________
[redacted]	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Lower EP ☐ Ceduna ☐ Port Lincoln ☐ Cleve ☐ Streaky Bay ☐ Elliston ☐ Tumby Bay ☐ Franklin Harbour ☐ Wudinna ☐ Kimba ☐ Other:__________
[redacted]	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Lower EP ☐ Ceduna ☐ Port Lincoln ☐ Cleve ☐ Streaky Bay ☐ Elliston ☐ Tumby Bay ☐ Franklin Harbour ☐ Wudinna ☐ Kimba ☐ Other:__________
[redacted]	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Lower EP ☐ Ceduna ☐ Port Lincoln ☐ Cleve ☐ Streaky Bay ☐ Elliston ☐ Tumby Bay ☐ Franklin Harbour ☐ Wudinna ☐ Kimba ☐ Other:__________
[redacted]	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Lower EP ☐ Ceduna ☐ Port Lincoln ☐ Cleve ☐ Streaky Bay ☐ Elliston ☐ Tumby Bay ☐ Franklin Harbour ☐ Wudinna ☐ Kimba ☐ Other:__________

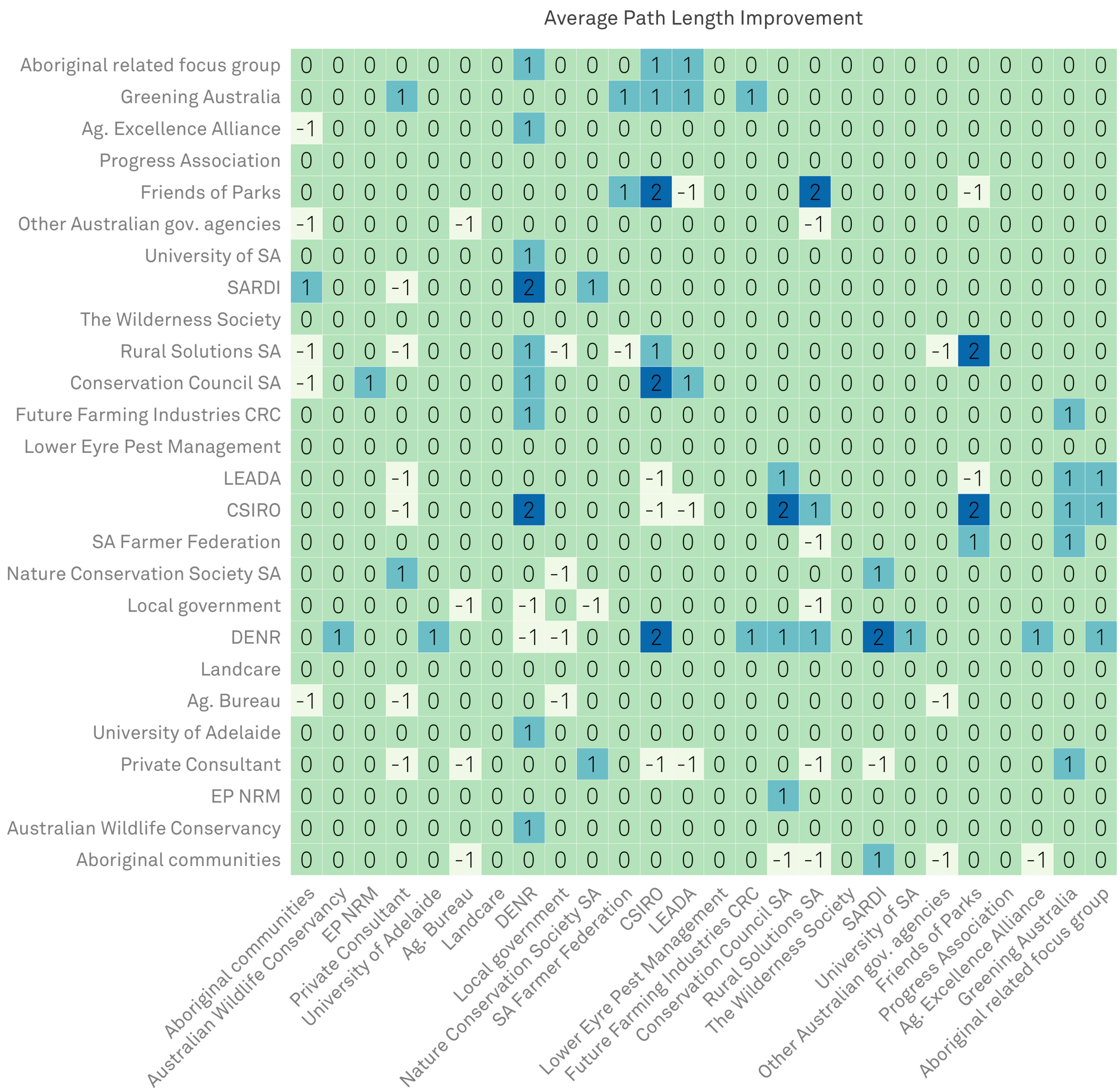
[redacted]	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Ceduna ☐ Cleve ☐ Elliston ☐ Franklin Harbour ☐ Kimba	☐ Lower EP ☐ Port Lincoln ☐ Streaky Bay ☐ Tumby Bay ☐ Wudinna ☐ Other:__________
Other individuals from this group with whom you collaborate				
Name______________________ Email______________________ Phone#_____________________	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Ceduna ☐ Cleve ☐ Elliston ☐ Franklin Harbour ☐ Kimba	☐ Lower EP ☐ Port Lincoln ☐ Streaky Bay ☐ Tumby Bay ☐ Wudinna ☐ Other:__________
Name______________________ Email______________________ Phone#_____________________	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Ceduna ☐ Cleve ☐ Elliston ☐ Franklin Harbour ☐ Kimba	☐ Lower EP ☐ Port Lincoln ☐ Streaky Bay ☐ Tumby Bay ☐ Wudinna ☐ Other:__________
Name______________________ Email______________________ Phone#_____________________	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Ceduna ☐ Cleve ☐ Elliston ☐ Franklin Harbour ☐ Kimba	☐ Lower EP ☐ Port Lincoln ☐ Streaky Bay ☐ Tumby Bay ☐ Wudinna ☐ Other:__________
Name______________________ Email______________________ Phone#_____________________	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Ceduna ☐ Cleve ☐ Elliston ☐ Franklin Harbour ☐ Kimba	☐ Lower EP ☐ Port Lincoln ☐ Streaky Bay ☐ Tumby Bay ☐ Wudinna ☐ Other:__________
Name______________________ Email______________________ Phone#_____________________	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Ceduna ☐ Cleve ☐ Elliston ☐ Franklin Harbour ☐ Kimba	☐ Lower EP ☐ Port Lincoln ☐ Streaky Bay ☐ Tumby Bay ☐ Wudinna ☐ Other:__________
Name______________________ Email______________________ Phone#_____________________	☐ I provide information to this person ☐ I gain information from this person ☐ We collaborate on program promotion ☐ We collaborate on on-ground implementation	☐ Never ☐ Daily ☐ Weekly ☐ Monthly+ ☐ Other (#/3y)____	☐ None in particular ☐ Ceduna ☐ Cleve ☐ Elliston ☐ Franklin Harbour ☐ Kimba	☐ Lower EP ☐ Port Lincoln ☐ Streaky Bay ☐ Tumby Bay ☐ Wudinna ☐ Other:__________

ANNEXE 3 — Matrices D’optimisation à l'échelle du groupe

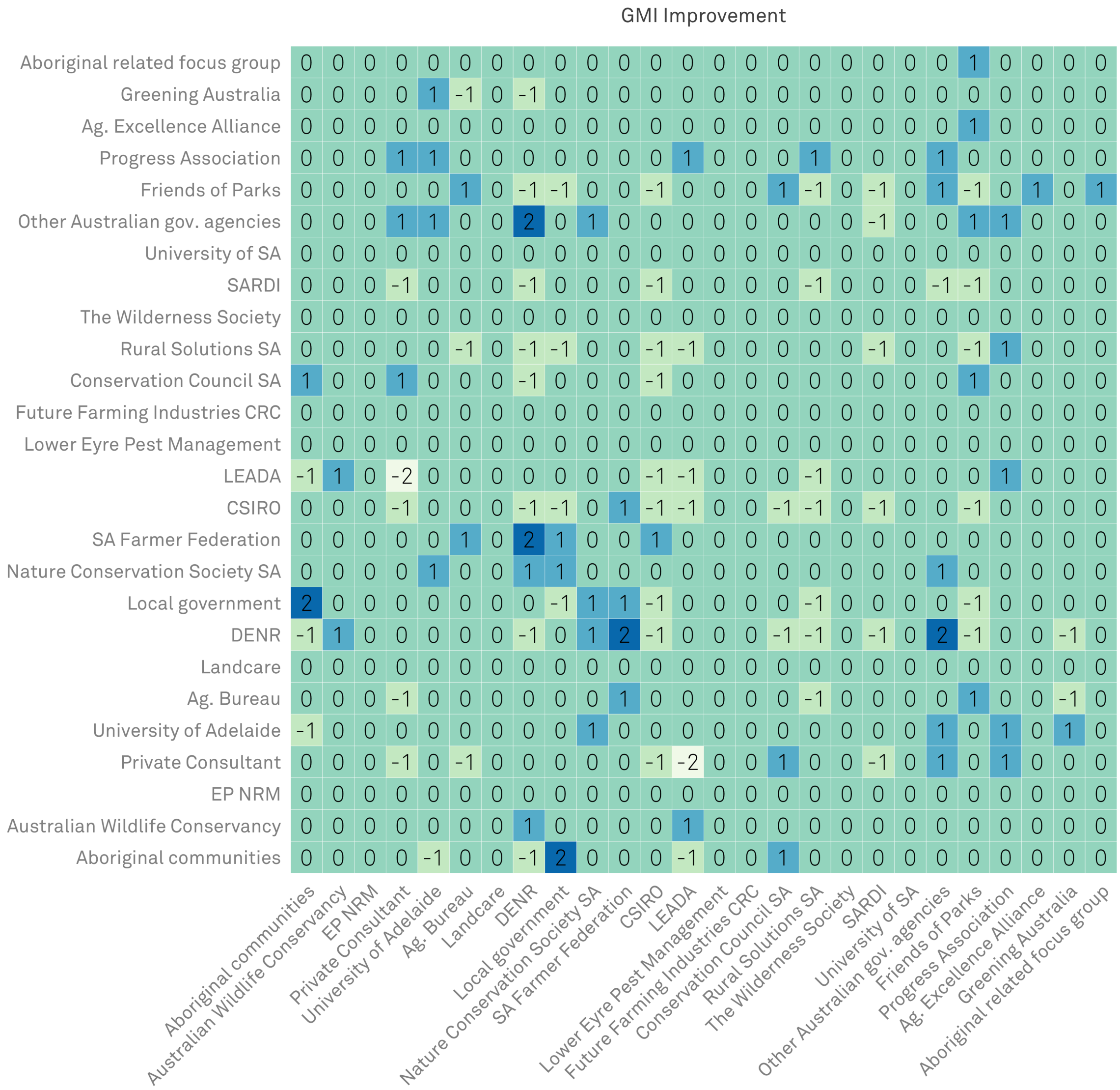
Modularity optimization



Average Path Length optimization



Group marginalization index optimization



Group synchronizability index optimization

Synchronizability Improvement

	Aboriginal communities	Australian Wildlife Conservancy	EP NRM	Private Consultant	University of Adelaide	Ag. Bureau	Landcare	DENR	Local government	Nature Conservation Society SA	SA Farmer Federation	CSIRO	LEADA	Lower Eyre Pest Management	Future Farming Industries CRC	Conservation Council SA	Rural Solutions SA	The Wilderness Society	SARDI	University of SA	Other Australian gov. agencies	Friends of Parks	Progress Association	Ag. Excellence Alliance	Greening Australia	Aboriginal related focus group
Aboriginal related focus group	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Greening Australia	0	0	0	1	1	0	0	-1	0	0	0	1	1	0	0	0	0	0	0	0	0	-1	0	0	0	0
Ag. Excellence Alliance	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Progress Association	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Friends of Parks	0	0	0	1	1	0	0	-3	-1	-1	1	2	3	0	1	-1	0	0	2	0	0	-1	0	0	-1	0
Other Australian gov. agencies	0	0	0	0	0	0	0	-1	0	-1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
University of SA	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SARDI	2	0	0	0	0	0	0	4	0	1	0	-1	-1	0	0	1	0	0	0	0	0	2	0	0	0	0
The Wilderness Society	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rural Solutions SA	-1	0	0	-2	-1	-1	0	0	0	-1	-1	-1	0	0	0	-1	0	0	0	0	0	0	0	0	0	0
Conservation Council SA	-1	0	0	0	0	0	0	-1	0	-1	0	0	0	0	0	0	-1	0	1	0	0	-1	0	0	0	0
Future Farming Industries CRC	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Lower Eyre Pest Management	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LEADA	2	0	0	-1	0	-1	0	5	0	1	0	-2	0	0	0	0	0	0	-1	0	0	3	0	0	1	0
CSIRO	1	0	0	-1	-1	-1	0	7	1	2	-1	-1	-2	0	0	0	-1	0	-1	0	0	2	0	0	1	0
SA Farmer Federation	0	0	0	0	0	0	0	2	1	0	0	-1	0	0	0	0	-1	0	0	0	1	1	0	0	0	0
Nature Conservation Society SA	0	0	0	0	0	0	0	-1	-1	0	0	2	1	0	0	-1	-1	0	1	0	-1	-1	0	0	0	0
Local government	-1	0	0	-1	0	-1	0	-1	-1	-1	1	1	0	0	0	0	0	0	0	0	0	-1	0	0	0	0
DENR	-1	0	0	2	0	1	0	-2	-1	-1	2	7	5	0	0	-1	0	0	4	-1	-1	-3	0	0	-1	0
Landcare	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ag. Bureau	0	0	0	0	0	0	0	1	-1	0	0	-1	-1	0	0	0	-1	0	0	0	0	0	0	0	0	0
University of Adelaide	0	0	0	-1	0	0	0	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	1	0	0	1	0
Private Consultant	0	0	0	0	-1	0	0	2	-1	0	0	-1	-1	0	0	0	-2	0	0	0	0	1	0	0	1	0
EP NRM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Australian Wildlife Conservancy	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Aboriginal communities	-1	-1	0	0	0	0	0	-1	-1	0	0	1	2	0	1	-1	-1	0	2	0	0	0	0	0	0	0

ANNEXE 4 — Script Python "RES_Network_Simulated_annealing.py"

```
"""Python code for the simulated annealing algorithm producing archetypal, resilience-en-
hancing, stakeholder networks"""
from igraph import * #Csardi G, Nepusz T: The igraph software package for complex network
research, InterJournal, Complex Systems 1695. 2006. http://igraph.org
from random import *
import numpy as np # Stéfan van der Walt, S. Chris Colbert and Gaël Varoquaux. The NumPy
Array: A Structure for Efficient Numerical Computation, Computing in Science & Engineering,
13, 22-30 (2011), DOI:10.1109/MCSE.2011.37
import copy
from igraph import *
from random import *
import numpy as np
import copy

def Deg_Node_Cut(G):
    g = G.as_undirected()
    n = 0
    while g.is_connected() == True and len(g.vs) > 2:
        degree = g.vs.degree()
        degreeDict = {}
        vc = 0
        for v in degree:
            degreeDict[vc] = degree[vc]
            vc += 1
        degree = sorted(degreeDict.iteritems(),
                        key=operator.itemgetter(1), reverse=True)
        strongestNode = degree[0][0]
        g.delete_vertices(g.vs(strongestNode))
        n = n + 1
    return n
def energy(g):
    """Computes the energy score the SA aims at minimizing"""
    if isinstance(g, list):
        g = edgelist2graph(g)

    modu = g.modularity(g.community_multilevel(
        return_levels=False), weights=None)
    mnc = float(Deg_Node_Cut(g)) / nbr_nodes
    apl = 1 - (g.average_path_length() / g.diameter())
    fiedler = sorted(np.linalg.eigvals(
        g.laplacian(normalized=True)).tolist())[1]
    if g.is_connected() == False:
        e = 0
    if modu <= .52:
        fModu = 5
    else:
        fModu = 1

    return -(fModu * modu + mnc + apl + fiedler)

def move(g, T):
    """Randomly swaps two edges"""
    r = g.get_edgelist()[randrange(len(g.get_edgelist()))]
    g.delete_edges(r)

    v1, v2 = randint(0, nbr_nodes - 1), randint(0, nbr_nodes - 1)
```

```
    while g.are_connected(v1, v2):
        v1, v2 = randint(0, nbr_nodes - 1), randint(0, nbr_nodes - 1)
    g.add_edge(v1, v2)
    return r, (v1, v2)

def annealing():
    """original, random, state of the network"""
    state = Graph.Erdos_Renyi(nbr_nodes, dens, directed=False, loops=False)

    print
state.modularity(state.community_multilevel(return_levels=False),weights=None),Deg_Node_-
Cut(state),state.average_path_length(),sorted(np.linalg.eigvals(
                    state.laplacian(normalized=True)).tolist())[1]

    for step in range(1, steps):
        T = Tmax * math.exp(Tfactor * step / steps)
        prev_state = copy.deepcopy(state)
        prev_energy = energy(prev_state)
        move(state, T)
        new_energy = energy(state)
        dE = new_energy - prev_energy
        if dE < 0 or (dE >= 0 and math.exp(-dE / T) > random()):
            if dE >= 0:
                print step, "Accepted (uphill)"
            else:
                print step, "Accepted (downhill)"
        else:
            state = copy.deepcopy(prev_state)

    return state

if __name__ == '__main__':
    nbr_nodes, dens = 50, .12

    """annealing schedule"""
    steps = 1600000
    Tmax = 2.5
    Tmin = 2.2e-07
    Tfactor = -math.log(Tmax / Tmin)
    optimized_network = annealing()
    print optimized_network.modularity(optimized_network.community_multilevel(re-
turn_levels=False),weights=None),Deg_Node_Cut(optimized_network),optimized_network.aver-
age_path_length(),sorted(np.linalg.eigvals(
                optimized_network.laplacian(normalized=True)).tolist())[1]
```

ANNEXE 5 — Script Python “Best_archetypes_selection.py”

```
"""Python code for selecting the best archetype produced with simulated annealing """

from igraph import * # Csardi G, Nepusz T: The igraph software package for complex network
research, InterJournal, Complex Systems 1695. 2006. http://igraph.org
import csv
from operator import itemgetter
import numpy as np # Stéfan van der Walt, S. Chris Colbert and Gaël Varoquaux. The NumPy
Array: A Structure for Efficient Numerical Computation, Computing in Science & Engineering,
13, 22-30 (2011), DOI:10.1109/MCSE.2011.37
from itertools import groupby
import math
import datetime
from collections import Counter

dens = .12
weights = [1, 1, 1, 1]

def Deg_Node_Cut(G):
    g = G.as_undirected()
    n = 0
    while g.is_connected() == True and len(g.vs) > 2:
        degree = g.vs.degree()
        degreeDict = {}
        vc = 0
        for v in degree:
            degreeDict[vc] = degree[vc]
            vc += 1
        degree = sorted(degreeDict.iteritems(),
                        key=operator.itemgetter(1), reverse=True)
        strongestNode = degree[0][0]
        g.delete_vertices(g.vs(strongestNode))
        n = n + 1
    return n

path = '/'

for i in os.listdir(path):
    # find all network gml files starting with name 'Arch_network_'
    if os.path.isfile(os.path.join(path, i)) and 'Arch_network_' in i:
        files.append(i)
data = []
c = 0

for file in files:
    c += 1
    G = read(path + file)
    try:
        ac = sorted(np.linalg.eigvals(
            G.laplacian(normalized=True)).tolist())[1]
    except:
        ac = 0.000001
    data.append([
        file,
        round(G.density(), 2),
        round(G.modularity(G.community_multilevel(
            return_levels=False), weights=None), 2),
        round(ac, 2),
        round(-G.average_path_length(), 2),
        Deg_Node_Cut(G)])
```

```
for p in range(4):
    sorted_data = sorted(data,  key=itemgetter(p + 2), reverse=True)
    rank = 0
    for _, grp in groupby(sorted_data, key=lambda xs: xs[p + 2]):
        r = rank + 1
        for x in grp:
            x.append(r)
            rank += 1
for i in data:
    i[4] = -i[4]
    i.append((float(i[6]) * weights[0] + float(i[7]) * weights[1] + float(i[8]) * weights[
             2] + float(i[9]) * weights[3]) / (weights[0] + weights[1] + weights[2] +
weights[3]))
df = []

for i in data:
    df.append([i[0], i[2], i[3], i[4], i[5], i[6], i[7], i[8], i[9]])

sorted_data = sorted(data,  key=itemgetter(6), reverse=False)

print "best modu:", sorted_data[0][2], "(", sorted_data[0][0], ")", ", worse modu", sort-
ed_data[len(sorted_data) - 1][2], "(", sorted_data[len(sorted_data) - 1][0], ")"
file = path + str(sorted_data[0][0]) + ".gml"

sorted_data = sorted(data,  key=itemgetter(7), reverse=False)
print "best mec:", sorted_data[0][3], "(", sorted_data[0][0], ")", ", worse mec", sorted_-
data[len(sorted_data) - 1][3], "(", sorted_data[len(sorted_data) - 1][0], ")"

sorted_data = sorted(data,  key=itemgetter(8), reverse=False)
print "best apl:", sorted_data[0][4], "(", sorted_data[0][0], ")", ", worse apl", sorted_-
data[len(sorted_data) - 1][4], "(", sorted_data[len(sorted_data) - 1][0], ")"

sorted_data = sorted(data,  key=itemgetter(9), reverse=False)
print "best deg_mc:", sorted_data[0][5], "(", sorted_data[0][0], ")", ", worse deg_mc",
sorted_data[len(sorted_data) - 1][5], "(", sorted_data[len(sorted_data) - 1][0], ")"

sorted_data = sorted(data,  key=itemgetter(10), reverse=False)
print "best score:", sorted_data[0]
sorted_data = sorted(data,  key=itemgetter(10), reverse=False)
print "second best score:", sorted_data[1]
sorted_data = sorted(data,  key=itemgetter(10), reverse=False)
print "third best score:", sorted_data[2]
sorted_data = sorted(data,  key=itemgetter(10), reverse=False)
print "worse score:", sorted_data[len(data) - 1]
```

ANNEXE 6 — Script Python "RES_Network_Multi-Objective-Simulated_annealing.py"

```
# -*- coding: utf-8 -*-

"""Python code for multiple objective simulated annealing (MOSA) """

from igraph import * # Csardi G, Nepusz T: The igraph software package for complex network
research, InterJournal, Complex Systems 1695. 2006. http://igraph.org
from random import *
import copy
import numpy as np
from multiprocessing import Pool
import csv
import numpy as np # Stéfan van der Walt, S. Chris Colbert and Gaël Varoquaux. The NumPy
Array: A Structure for Efficient Numerical Computation, Computing in Science & Engineering,
13, 22-30 (2011), DOI:10.1109/MCSE.2011.37
from pickle import dumps, loads
import cPickle
import shapely.geometry as geom
import itertools
import operator

""" NDS calculations """
def select_dominated(a,b):
    ge = all(map(operator.ge, a[0], b[0]))
    le = all(map(operator.le, a[0], b[0]))
    return b if ge else a if le else 'indifferent'

def dominate(a,b):
    ge = all(map(operator.ge, a, b))
    le = all(map(operator.le, a, b))
    return True if ge else False if le else 'indifferent'

def dominate_all(a,NDS):
    c = 0
    for b in NDS:
        if dominate(a,b) == True or dominate(a,b) == 'indifferent':
            c += 1
    if c == len(NDS):
        return True
    else:
        return False

def NDSFront(a):
    b = copy.deepcopy(a)
    if len(a) > 1:
        for i in range(len(a)):
            for j in range(i,len(a)):
                if i != j:
                    try:
                        b.remove(select_dominated(a[i],a[j]))
                    except:
                        ""
    return b

""" start util """
def column(matrix, i):
    return [row[i] for row in matrix]
""" end util """
```

```
def dist2NDS2(NDS,candidate):
    if len(NDS) >= 2:
        line = []
        for p in NDS:
            if len(p) == 3:
                line.append((p[0],p[1],p[2]))
            else:
                line.append((p[0],p[1]))
        line = geom.LineString(line)
        point = geom.Point(candidate[0], candidate[1])
        return point.distance(line)
    else:
        return 0

""" Efficiency calculation """
def efficiency(G):
    avg = 0.0
    n = len(G.vs)
    for node in G.vs:
        path_length = G.shortest_paths(node)
        avg += sum(1.0/v for v in path_length[0] if v !=0)
    avg *= 1.0/(n*(n-1))
    return avg

""" Robustness to targeted node removal calculation """
def Deg_Node_Cut(G):
    g = G.as_undirected()
    n = 0
    while g.is_connected() == True and len(g.vs) > 2:
        degree = g.vs.degree()
        degreeDict = {}
        vc = 0
        for v in degree:
            degreeDict[vc] = degree[vc]
            vc += 1
        degree = sorted(degreeDict.iteritems(), key=operator.itemgetter(1),reverse=True)
        strongestNode = degree[0][0]
        g.delete_vertices(g.vs(strongestNode))
        n = n + 1
    return n

"""Calculates metrics"""
def energy(g):

    modu = g.modularity(g.community_multilevel(return_levels=False),weights=None)
    mnc = Deg_Node_Cut(g)
    eff = efficiency(g)
    try:
        sync = sorted(np.linalg.eigvals(g.laplacian(normalized=True)).tolist())[1]
    except:
        sync = float(0)
    if sync == 0:
        return [0,0,0]
    else:
        return [modu,eff,mnc]

"""Rewire N times"""
def move(g,N):
    nbrEs = len(g.es())
    for i in range(N):
        c = 0
        while c == 0 or g.is_connected() == False:
```

```
            c += 1
            r = g.get_edgelist()[randrange(len(g.get_edgelist()))]
            s1 = r[0]
            g.delete_edges(r)
            v1, v2 = randint(0,nbr_nodes-1),randint(0,nbr_nodes-1)
            while g.are_connected(v1, v2):
                v1, v2 = randint(0,nbr_nodes-1),randint(0,nbr_nodes-1)
            g.add_edge(v1, v2)
    return r,(s1,v2)

def MOSA(nbr_nodes,dens,steps,Tmin,Tmax,Tfactor,jumpThresh,jumpThresh2,saveStep):

    """ create a random, seed network """
    state = Graph.Erdos_Renyi(nbr_nodes, dens, directed=False, loops=False)
    state.simplify(multiple = True,loops = True)

    """ Set empty lists and variables """
    NDS = []
    NDSF = []
    NDS2 = []
    NDS2Export = []
    NDSF2 = []
    NDSF2Export = []
    accepted = 0
    acceptedD = 0
    refused = 0
    refusedUD = 0
    save = 0
    fileName = "NDS.p"


    """ start simulaiton """
    for step in range(1,steps):

        T = Tmax * math.exp(Tfactor * step / steps)

        prev_state = copy.deepcopy(state)
        prev_energy = energy(prev_state)

        N = choice([2,3,4])
        move(state,N)

        new_energy = energy(state)

        if new_energy != [0,0,0]:
            NDS.append([new_energy,dumps(state)])

        NDS = NDSFront(copy.deepcopy(NDS))

        d1 = dist2NDS2(column(NDS, 0),new_energy)
        d2 = dist2NDS2(column(NDS, 0),prev_energy)

        if dominate_all(new_energy,column(NDS, 0)) or d1 < d2:
            dE = -1
            refused = 0
        else:
            dE = d2 - d1
            refused += 1

        if dE < 0 or (dE >= 0 and math.exp(-dE / T) > random()):
            if dE >= 0:
                accepted += 1
            else:
```

```
                acceptedD += 1
        else:
            state = copy.deepcopy(prev_state)
            refusedUD += 1

        if refused > jumpThresh:
            N = int(random()*100)
        if refused > jumpThresh2:
            state = loads(choice(NDS)[1])

        save += 1

        if save == saveStep:
            print int((float(step)/steps)*100),"%,","Non dominated set:",len(NDS)

            save = 0
            accepted = 0
            acceptedD = 0
            refusedUD = 0
            Nmoy = 0
            cPickle.dump(NDS, open(fileName, "wb"))

    cPickle.dump(NDS, open(fileName, "wb"))


if __name__ == '__main__':

    """ Set parameters """
    nbr_nodes, dens = 50, .09

    steps = 2000000

    Tmin = 1e-10
    Tmax = .001
    Tfactor = -math.log(Tmax / Tmin)

jumpThresh = 100
    jumpThresh2 = 1000

    saveStep = 100

    MOSA(nbr_nodes,dens,steps,Tmin,Tmax,Tfactor,jumpThresh,jumpThresh2,saveStep)
```

ANNEXE 7 — Optimisation d'un réseau par recuit simulé pour quatre objectifs