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Towards a Framework to Guide and Facilitate Interdisciplinary Social-Ecological System Research in Practice

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A whole is more than

the sum of its parts.

ARISTOTLE

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Acknowledgments

This study is the result of a wonderful three-year journey, along which I have had the pleasure to meet some amazing souls and minds. This time was filled with many experiences that challenged me, brought me to my personal and intellectual limits, and made me learn and grow as a person and as a researcher. I was also presented with many fantastic opportunities, and for that I am very grateful. Many people have played important roles in and contributed to my life and my PhD process, and I would like to thank them here, in no particular order.

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Glossary

Domain	A knowledge sphere; a body of scientific (sub-)disciplines that study a certain topic or system.
Framework	An analytical tool with several variations and contexts. It is used to make conceptual distinctions and organise ideas.[a]
Interdisciplinarity	Involvement of several unrelated academic disciplines in a way that forces them to cross subject boundaries in order to create new knowledge and theory and solve a common research goal.[b]
Model	A (coherent) representation of a system and/or the processes therein, which may consist of words, graphs, or equations.[c]
Multidisciplinarity	Involvement of several academic disciplines with multiple, disciplinary goals in parallel, often with the purpose of comparison, but does not cross subject boundaries or aim for any form of integration.[b]
Research Practice	A set of sayings or doings by individuals or groups for a particular purpose. Commonly each discipline has its own established research practices.[e]
Social-Ecological System	A coherent system of biophysical and social factors that regularly interact in a resilient, sustained manner; a system that is defined on several spatial, temporal, and organisational scales, which may be hierarchically linked; a perpetually dynamic, complex system with continuous adaptation.[e]
Social-Ecological System Research	Research that clearly links the social and the ecological system, with the aim to understand relationships between social and ecological conditions, interactions, and outcomes. Always requires an inter- or transdisciplinary approach.[f]
Transdisciplinarity	Interdisciplinarity with additional involvement of non-academic participants that work towards a common goal in order to create new knowledge and theory through a collaborative and participatory approach.[b]

[a] Ravitch and Riggan 2012
[b] Tress et al. 2005a
[c] Hart and Reynolds 2008
[d] National Academy of Sciences 1992; Castán Broto et al. 2009
[e] Redman et al. 2004
[f] Ostrom 2009; Cumming 2014; Binder et al. 2013

Summary

Social-ecological systems (SES) consist of a social and an ecological system that are linked through a complex interplay of social and ecological processes. SES can be studied through SES research, which has become increasingly important because it is thought that it can potentially address and solve many societal challenges, such as climate change, resource scarcity, and habitat degradation. SES research investigates the relationships between social and ecological conditions, interactions, and outcomes, and requires an integrative, i.e. interdisciplinary or transdisciplinary approach, because one discipline alone cannot study the complex interactions within SES. This makes SES research particularly challenging and practical real-world barriers continue to hinder integration and progress in the field. Yet, the challenges and practical barriers for interdisciplinary SES research have hardly been explored, while practical guidance on how to conduct SES research is generally lacking.

As a first step to explore interdisciplinary SES research practices, a preliminary study is conducted with the aim to develop a framework that can guide researchers on how to conduct interdisciplinary SES research in practice. A preliminary framework is developed through a review and synthesis of various strands of literature and empirical experiences.

The framework provides ten design principles to guide the different phases of the interdisciplinary SES research process: the orientation phase—for problem identification, the preparation phase—for identifying relevant disciplines and team members, and the analysis and integration phase—for analysis, integration, and knowledge production. In addition, common practical challenges when implementing each of the design principles are outlined, while suggestions for practical coping strategies are provided to prevent or overcome these challenges. Three selected coping strategies proposed by the framework are demonstrated through practical examples, showing the application in practice of a particular methodology suitable to implement the respective coping strategy.

The preliminary framework could be applied by different users for various purposes, but its main intent is to make the SES research process easier on a practical level. The framework serves as a first step towards guiding and facilitating interdisciplinary SES research, from where an adjustment of the framework through co-creation with potential users or an expansion of the framework to guide transdisciplinary SES research, can be potential avenues for future research.

List of Papers

Paper 1:

Syed, S. & Weber, C.T. (2018). Using Machine Learning to Uncover Latent Research Topics in Fishery Models. *Reviews in Fisheries Science & Aquaculture*, 26(3), 319-336.
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Paper 2:

Weber, C.T. & Syed, S. Interdisciplinary Optimism? Sentiment Analysis of Twitter Data. Under review at *Royal Society Open Science*.

Paper 3:

Weber, C.T., Borit, M. & Aschan, M. An Interdisciplinary Insight into the Human Dimension in Fisheries Models. A Systematic Literature Review in a European Union Context. Accepted. Under second stage review at *Frontiers of Marine Science*.

Co-Author Contributions:

	Paper 1	**Paper 2**	**Paper 3**
Concepts and idea	CTW, SS	CTW	CTW, MB, MA
Literature study and references	CTW, SS	CTW	CTW, MB
Study design and methods	CTW, SS	CTW, SS	CTW, MB
Data gathering	SS	CTW, SS	CTW
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Manuscript preparation and writing	CTW, SS	CTW, SS	CTW, MB
Inputs to the manuscript writing	CTW, SS	CTW, SS	CTW, MB, MA

Abbreviations for author names:
CTW – Charlotte Teresa Weber
MA – Michaela Aschan
MB – Melania Borit
SS – Shaheen Syed

Summary of the Papers

Paper 1. Using Machine Learning to Uncover Latent Research Topics in Fishery Models. Modelling has become the most commonly used method in fisheries science, with numerous types of models and approaches available. The large variety of models, and the overwhelming amount of scientific literature published yearly, can make it difficult to effectively access and use the output of fisheries modelling publications. In particular, the underlying topic of an article cannot always be detected using keyword searches. As a consequence, identifying the developments and trends within fisheries modelling research can be challenging and time-consuming. This paper utilises a machine-learning algorithm to uncover hidden topics and subtopics from peer-reviewed fisheries modelling publications and identifies temporal trends using 22,236 full-text articles extracted from 13 top-tier fishery journals from 1990 to 2016. Two modelling topics were discovered: estimation models (a topic that contains the idea of catch, effort, and abundance estimation) and stock assessment models (a topic on the assessment of the current state of a fishery and future projections of fish stock responses and management effects). The underlying modelling subtopics have shown a change in the research focus of modelling publications over the last 26 years.

Paper 2. Interdisciplinary Optimism? Sentiment Analysis of Twitter Data. Interdisciplinary research can face many challenges, from institutional and cultural, to practical ones, while it has also been reported as a "career risk" and even as "career suicide" for researchers pursuing such an education and approach. Yet, the propagation of the challenges and risks can easily lead to a feeling of anxiety and disempowerment in researchers, which we think is counterproductive to improving interdisciplinarity in practice. Therefore, in the search of 'bright spots', which are examples where people have had positive experiences with interdisciplinarity, this study assesses the perceptions of researchers on interdisciplinarity on the social media platform Twitter. The results of this study show researchers' many positive experiences and successes of interdisciplinarity, and as such document examples of bright spots. These bright spots can give reason for optimistic thinking, which can potentially have many benefits for researchers' well-being, creativity, and innovation, and may also inspire and empower researchers to strive for and pursue interdisciplinarity in the future.

Paper 3. An Interdisciplinary Insight into the Human Dimension in Fisheries Models. Fisheries are complex adaptive social-ecological systems (SES) that consist of interlinked human and ecosystems. Thus far, they have mainly been studied by the natural sciences. However, the understanding and sustainable management of fisheries will require an expansion of the study of the human element in order to reflect the SES perspective. Models are currently the most common method used to provide management advice in fisheries science, and these, in particular, will have to expand to include the human dimension in their assessment of fisheries. The human dimension is an umbrella term for the complex web of human processes within a social-ecological system, and, as such, it is captured by disciplines from the social sciences and humanities. Consequently, capturing and synthesising the variety of disciplines involved in the human dimension, and integrating them into fisheries models, will require an interdisciplinary approach. This study, therefore, attempts to address the current shortcomings associated with the modelling of fisheries in the European Union and advises on how to include the human dimension and increase the interdisciplinarity of these models. We conclude that there is potential for the expansion of the human dimension in fisheries models. To reach this potential, consideration should be given to some aspects, e.g. early involvement in model development of all relevant disciplines, and the formulation of operationalisable theories and data from the human dimension. We provide recommendations for interdisciplinary model development, communication, and documentation in support of sustainable fisheries management.

1 Introduction

1.1 Motivation for this Study

Social-ecological systems (SES) are complex integrated systems in which humans are linked with nature through a complex interplay of social and ecological processes (Berkes 2011). SES consist of a social system and an ecological system that regularly interact in a dynamic and complex manner (Berkes and Folke 1998). The social system refers to the 'human system', which includes all human processes of economic, political, social, and cultural nature, as well as management and governance aspects. The ecological system refers to the biophysical system, including ecological processes, organisms, and communities that interact with each other and their environment. SES function in a two-way feedback loop, in which a change in one subsystem can impact the other, and vice versa (Berkes et al. 2006; Levin et al. 2012; Leenhardt et al. 2015).

At the core of the dynamic and complex interactions of SES lie many of today's complex problems and societal challenges. For example, climate change, biodiversity loss, resource scarcity, and habitat degradation are all complex problems that are driven by human activities and social dynamics (Binder et al. 2013; Fang et al. 2018). Yet, mankind depends on the natural world for life support, and it is, therefore, of importance to address and solve these complex problems and societal challenges for a sustainable future and human well-being (Redman et al. 2004; Ostrom 2009; Cumming 2014; Guimarães et al. 2018). Subsequently, there is a need for better understanding and the study of SES (McGinnis et al. 2012; Leslie et al. 2015).

SES can be studied through what is termed Social-Ecological System Research, or SES research in short (Cumming 2011; McGinnis et al. 2012). SES research has become increasingly important because it is thought that it can potentially address and solve many societal challenges, which are often both, ecological *and* social (Berkes and Folke 1998; Levin et al. 2012). SES research has a socio-ecological core (Cumming 2014), which means that it clearly links the social and ecological systems by investigating the relationships between social and ecological conditions, interactions, and outcomes (Ostrom 2009; Binder et al. 2013). Note that SES can also be studied in their separate parts, in which one or more disciplines investigate only one of the subsystems (either the social or the ecological system) or a single study object within a subsystem (e.g. the study of fish stock recruitment in a fishery system). Such studies can take any form, from a mono-, to a multi-, inter-, or transdisciplinary approach (for definitions of these concepts, see the Glossary). Yet, studies lacking a clear link between the social and ecological system are considered not to be SES research.

SES research requires an integrative research approach (Redman et al. 2004; Stephenson et al. 2017; Dressel et al. 2018; Markus et al. 2018), because one discipline alone cannot study the complex interactions to address its social-ecological core (Collins et al. 2011; Cumming 2014; Guimarães et al. 2018). Integrative approaches, i.e. inter- and transdisciplinary, offer a synthesis from several disciplines and can incorporate the humanities, natural, economic, and social sciences, as well as non-academic stakeholders and knowledge bodies. Integrative approaches are inherently complex because both interdisciplinary and transdisciplinary research requires an integration of different knowledge bodies and disciplines. It is certainly not an easy task to integrate concepts, methodologies, procedures, terminologies, or data from different disciplines, especially when these are very disparate and have different ways of working, e.g. Biology and Anthropology (Apostel et al. 1972). Additionally, integrative research requires researchers to pay attention to many other aspects besides integration itself, for example, the choice of appropriate disciplines, the process by which they work together, and to ensure that individuals do not withdraw when conflicts arise (Pretty 2011). Additionally, interdisciplinary and transdisciplinary research faces many challenges, from structural and institutional challenges (Buanes and Jentoft 2009), to cultural (Chiu et al. 2013), and practical challenges (Lang et al. 2012; Pischke et al. 2017). As a result, a large body of literature has been developed in an attempt to help researchers in the study of SES.

Much of the SES literature has focused on the concepts and methodological approaches for the analysis of SES (Ravitch and Riggan 2012; Binder et al. 2013; Cumming 2014), while increasing numbers of SES case studies are being conducted within different domains (McGinnis et al. 2012; Hinkel et al. 2015; Partelow 2015; Liehr et al. 2017). Yet, despite the great interest of the research community in the study of SES, the interface between integrative approaches and SES research has hardly been explored (Cumming 2014). As such, the literature currently lacks guidance for integrative research dynamics in practice (Cumming 2014; Brown 2018). As a result, real-world barriers continue to hinder integration and challenge progress in the field (Redman et al. 2004).

A lack of integration is a major limitation for a research domain that intends to build "a strong interdisciplinary science of complex, multilevel systems[...]" (Ostrom 2007), because integration lies at the core of SES research and the field cannot progress nor advance without it. The widely dispersed literature on inter- and transdisciplinary research further hinders researchers from acquainting themselves with integrative concepts and applying them in practice (Lang et al. 2012).

Thus, the integration of different disciplines constitutes the weakest link in SES research (Cumming 2014), and there remains a general lack of practical recommendations to help researchers conducting inter- and transdisciplinary SES research. Hence, there is a need for practical approaches that can guide and facilitate the integration in SES research to lower the barriers for interdisciplinary and transdisciplinary SES research processes. Guiding principles could help researchers understand how to conduct integrative SES research in practice, i.e. how to *do* this type of research. For this purpose, it is thought that learning from the lessons of real-world interdisciplinary and transdisciplinary collaborations will identify and provide practical approaches for integrative SES research (Redman et al. 2004).

Investigations into *interdisciplinary* SES research practices and processes are needed as a first attempt towards guiding and facilitating SES research. Once guiding principles for an interdisciplinary SES research process have been identified and developed, they can then be expanded to a *transdisciplinary* approach. As such, guiding principles for *interdisciplinary* SES research can lay a foundation for any future guiding principles for the practice of *transdisciplinary* SES research.

1.2 Scope and Research Questions

As a first step to investigate and support interdisciplinary SES research practices, the objective of this study is to develop a preliminary framework that can guide researchers on how to conduct interdisciplinary SES research in practice. To do so, the preliminary framework provides guiding principles for an interdisciplinary SES research process. In addition, the framework aims to facilitate this research process by raising awareness of common challenges within the research process and by providing practical coping strategies to prevent and overcome these challenges. The main research question (MRQ) for this study was formulated as follows:

MRQ: *How can interdisciplinary SES research be guided and facilitated in practice?*

This main research question was divided into the following research questions (RQ):

RQ1: *What are the design principles for an interdisciplinary SES research process in practice?*

RQ2: *What are the practical challenges when complying with the design principles for interdisciplinary SES research in practice?*

RQ3: *What are the coping strategies to prevent or overcome the practical challenges of interdisciplinary SES research in practice?*

RQ4: *How to demonstrate selected coping strategies to prevent or overcome practical challenges of interdisciplinary SES research?*

RQ1 supports the MRQ by identifying how to *guide* interdisciplinary SES research in practice, whereas RQ2 and RQ3 support the MRQ by identifying what impedes and what *facilitates* interdisciplinary SES research in practice.

To ensure that the preliminary framework can support the *practical* challenges of interdisciplinary SES research, the framework is not only based on the theory of interdisciplinary and SES research, but also on the 'lessons learned' in empirical case studies with demonstrated successes and failures. The preliminary framework was developed via a literature review approach, as well as from the inclusion of the practical lessons-learned from two EU-funded projects—ClimeFish (2016) and SAF21 (2015) (see section 2.2.9 for more information on the projects).

To address RQ4, Papers 1–3 demonstrate three selected coping strategies of the preliminary framework in practice by applying an explicit methodology and providing concrete results. One of the papers (Paper 2) is applied to the academic context but without a domain-specific focus. Two of the papers (Paper 1 and Paper 3) are applied into the domain of fisheries research, in particular into the fisheries modelling domain, for the following reasons: (i) Fishery systems have been recognised as SES (Ostrom 2009), which makes fisheries a suitable research domain to demonstrate the coping strategies of the framework; (ii) modelling is the most commonly used method in fisheries science (Jarić et al. 2012) and amongst the most commonly used methods to study SES (Rissman and Gillon 2017); and (iii) this study is part of the project SAF21—Social Science Aspects of Fisheries for the 21^{st} Century (SAF21 2015)—which has the particular aim to improve the understanding of fisheries as SES.

1.3 Structure of the Study

The remainder of this study is structured as follows: Section 2 provides the scientific underpinnings of the study by addressing the concepts 'social-ecological systems' and 'interdisciplinarity', and a brief description of the EU projects ClimeFish and SAF21. Section 3 presents the methodology applied during the research. In Section 4, the results of the study are presented, followed by a discussion of the findings in Section 5 and conclusions in Section 6. The study ends with a self-assessment in Section 7, which provides an opportunity for critical evaluation and self-reflection regarding this study.

2 Background and Scientific Underpinnings of the Research

2.1 Social-Ecological Systems

2.1.1 Social-Ecological Systems Concept and Background

Social-ecological systems (SES) are complex integrated systems that consist of a social system and an ecological system, which interact in a dynamic and complex manner (Berkes and Folke 1998). The social system refers to the 'human system', which includes all human processes of an economic, political, social, and cultural nature, as well as management and governance aspects. The ecological system refers to the biophysical system, including ecological processes, organisms, and communities that interact with each other and their environment (Berkes 2011).

SES are understood as complex adaptive systems (Levin et al. 2012), and as such, the SES concept draws heavily on systems ecology and complexity theory (Cumming 2011). SES are **complex** due to the complex processes and behaviours that merge from the dynamic interaction between the social system and the ecosystem. Complexity is created through factors such as uncertainty, nonlinear feedback, cross-scale interactions, self-organisation, and emergence. SES are considered **adaptive** because they have the capacity to respond to their environments through self-organisation (Cumming 2011). As such, adaptation or adaptive capacity can be understood as "the improvement of fit between a system component or entire system and its environment. In evolutionary biology, adaptation is considered to be a passive process, in the sense that adaptation occurs through the action of selection on diversity. In social systems, a form of active adaptation, through decision making and proactive responses to environmental change, may be possible" (Cumming 2011).

Uncertainty is caused by the **non-linear relationship** between cause and effect in SES (Cumming 2011). Hence, nonlinearity is related to inherent uncertainty, as SES components interact in nonlinear ways that make responses and the effects of change difficult to predict (Levin et al. 2012).

Feedbacks, or feedback loops, describe a situation in which an effect influences its cause

(Cumming 2011). SES function in a two-way feedback loop, in which a change in one subsystem can impact the other, and vice versa (Berkes et al. 2006; Levin et al. 2012; Leenhardt et al. 2015). These feedbacks can be either positive, with an amplifying effect, or negative, with a dampening effect.

Self-organisation relies on the basic idea that open systems are able to reorganise themselves at critical points of instability. It is a process by which a system can modify its own internal structures and behaviours, often in response to external change (Cumming 2011). This principle is operationalised through feedback mechanisms within the system. However, the direction of the system under change is path dependent, as directions of change depend on, for example, the history of the system, and are therefore difficult to predict (Berkes et al. 2003).

Emergence, or emergent properties, result from critical relationships such as feedback and dependencies among components within SES, which cannot be understood by examining individual components (Knoot et al. 2010). Examples of emergent properties in SES include sustainability, or resilience, because these system properties arise from the interactions of a number of system components with one another and with their environment. These system components have the ability to process information and respond to internal and external change through action, adaptation, or learning (Cumming 2011).

Other important aspects in SES are **hierarchy** and **scale**. In this sense, SES are hierarchic, wherein every subsystem is nested within a larger subsystem (Berkes et al. 2003). Both the social system and ecosystem are nested. Hierarchical levels within a social system are, for example, governmental institutions on city level, provincial level, or national level. Whereas, Adriatic Sea, Mediterranean, North Atlantic, depicts a nested ecosystem with subsystems of different spatial scales (Cumming 2011). From such an understanding, scale and hierarchy can be defined as 'the spatial, temporal, quantitative, or analytical dimensions used to measure a phenomenon' (Berkes 2011). Studies of a particular SES will usually have to make a subjective choice regarding on which scale the analysis should take place (Cumming 2011). Phenomena within SES tend to have their own emergent properties and can occur at each level of these scales; the different levels may be coupled through feedback relationships (Berkes et al. 2003), with the levels being defined as 'the units of analysis located at different positions on a scale' (Berkes 2011). SES processes commonly occur over a wide range of scales, which result in **cross-scale interactions**. This means that social and ecological processes can be coupled at each scale, smaller processes are embedded in larger ones, and larger-scale processes can also influence the smaller ones (Liu et al. 2007).

Modularity describes the degree to which the system's components may be separated and recombined, which is crucial for preventing harmful properties spreading throughout the system during the phase of change, and provides the building blocks with which to reorganise the system (Levin et al. 2012). Hence, modularity can be understood as the compartmentalisation of the system in space, in time, or in organisational structure. In this context, compartments are subsystems in which interactions between components are stronger than their interactions with system components outside the compartment (Cumming 2011).

Resilience is also an important concept for complex systems and SES. Resilience refers to the system's ability to continue functioning when exposed to either intrinsic or extrinsic disturbances. A system can thus be considered robust if it is resistant to change or able to reorganise after change (Levin et al. 2012). Many different definitions of resilience have been discussed but generally, resilience tries to capture the idea about the ability of a complex system to persist. However, resilience is not always necessarily a good characteristic or trait. Systems can be locked in a resilient state that is, from a human perspective, undesirable (Cumming 2011). Competing terms for resilience include robustness, sustainability, vulnerability, and fragility. However, as Cumming (2011, p.13) puts it: "Some scientists have tried to delineate minor differences between these different terms. In my opinion, such differences are more reflective of differences in the ways that different research groupings have approached the same problem than of fundamental differences in the nature of the problem being addressed".

2.1.2 Defining Social-Ecological Systems

The social-ecological systems concept is based on the understanding that humans are an integral part of all ecosystems, thus acknowledging the interconnectedness of humans and the environment. The term itself—'Social-Ecological System'—is meant to emphasise the co-equal interaction of the forces operating within the two systems (Redman et al. 2004). Based on Redman et al. 2004, SES can be described though a four-pronged definition as follows:

- A coherent system of biophysical and social factors that regularly interact in a resilient and sustained manner;
- A system that is defined at several spatial, temporal, and organisational scales, which may be hierarchically linked;
- A set of critical resources (natural, socioeconomic, and cultural), of which the flow and use are regulated by a combination of ecological and social systems; and
- A perpetually dynamic, complex system with continuous adaptation.

In short, a social-ecological system can be understood as the interconnection of a human system and an ecosystem, which interact in a dynamic and complex manner over several scales.

2.1.3 Examples of the Social-Ecological Systems Concept Applied in Different Contexts

Generally, SES are investigated to understand certain drivers and interactions between system components, sudden events, and extensive, pervasive, and subtle change (Collins et al. 2011). As such, the SES concept can be applied to different contexts and case studies, which is why the conceptualisations of SES differ depending on the analytical focus and research question of the approach. Below, brief examples of SES case studies are provided, with the aim to facilitate a better understanding of the SES concept through real-world examples, and to demonstrate how conceptualisations, interactions, and system components differ, depending on the system under investigation and the purpose of the study. Additionally, figures of the conceptual SES under investigation are shown to allow for a visual representation of the interactions and feedbacks within the SES.

Land-use. Gardner et al. (2013) conducted an SES research study on land-use in Eastern Brazil Amazonia. The landscape provides significant benefits for human well-being through economic goods such as timber, and through ecosystem services such as climatic regulation. However, the area has also been under severe pressure through forest clearance, deforestation, and overexploitation, which poses a potential risk for irreversible damage to both the social and ecological system. Therefore the study aimed to identify the problems within the system that should be addressed first and assessed the long-term implications of land-use alternatives in the landscape.

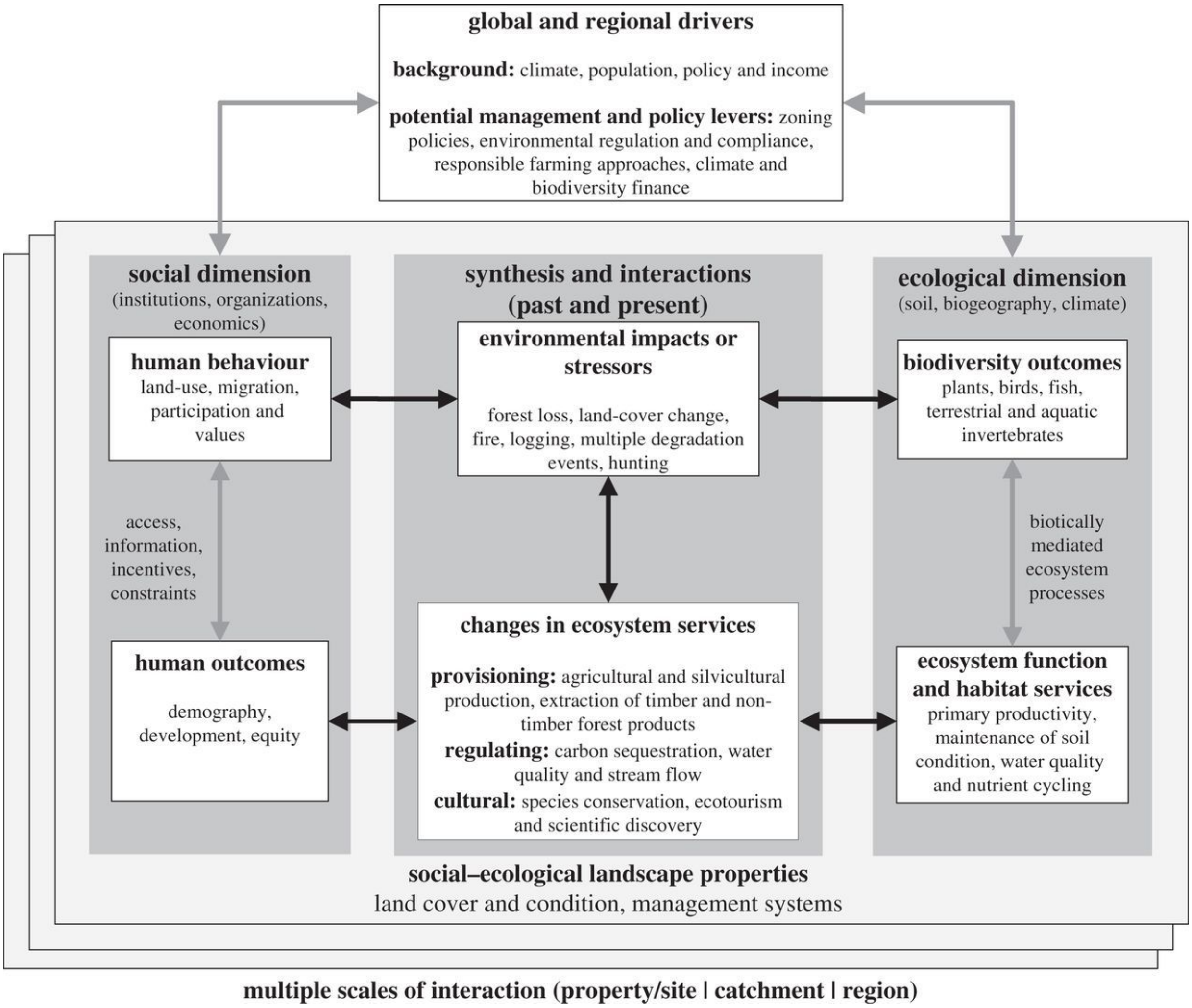

Figure 1 – Conceptual diagram of the social-ecological system of the landscape and its properties in Eastern Brazil Amazonia. The figure shows the interactions between system components, the social and ecological processes, the cause-effect relationships, feedbacks, and impacts. The social-ecological landscape properties, such as land cover and condition, are changes in landscape features that emerge, and that mediate relationships between social and ecological phenomena. System dynamics play out across multiple spatial scales. All the variables listed in the figure have been studied in this case study. Image from Gardner et al. (2013).

The SES approach was applied to identify the consequences of deforestation, forest clearance and degradation, and agricultural change on the system, to identify the factors within the system that can help explain the observed ecological condition, such as changes in biodiversity and soil chemicals, and to examine patterns of land use and farmers' well-being.

The conceptualisation of the case study SES as shown in Figure 1, highlights the drivers and interactions within the system: The dynamics of the ecological system are driven by the environmental impacts or stressors, which, in turn, are influenced or caused by human behaviour. Over time, the interactions of environmental impacts or stressors alter biodiversity outcomes and influence ecosystem functions and habitat services. Ultimately, this changes quantity and quality of ecosystem services that humans gain (human outcomes). Changes in human outcomes can affect human behaviour. For more info on this case study, see Gardner et al. (2013).

Agriculture & livestock production. In a study by Tenza et al. (2018), the social-ecological system under investigation is the oasis of Comondú in Mexico, representing a small-scale agro-system in a dryland. The oasis underwent a serious depopulation process that threatened its existence. Hence, the study aims to investigate the system's sustainability by identifying the drivers that have influenced the system and which drivers have led to a decline of this small-scale SES.

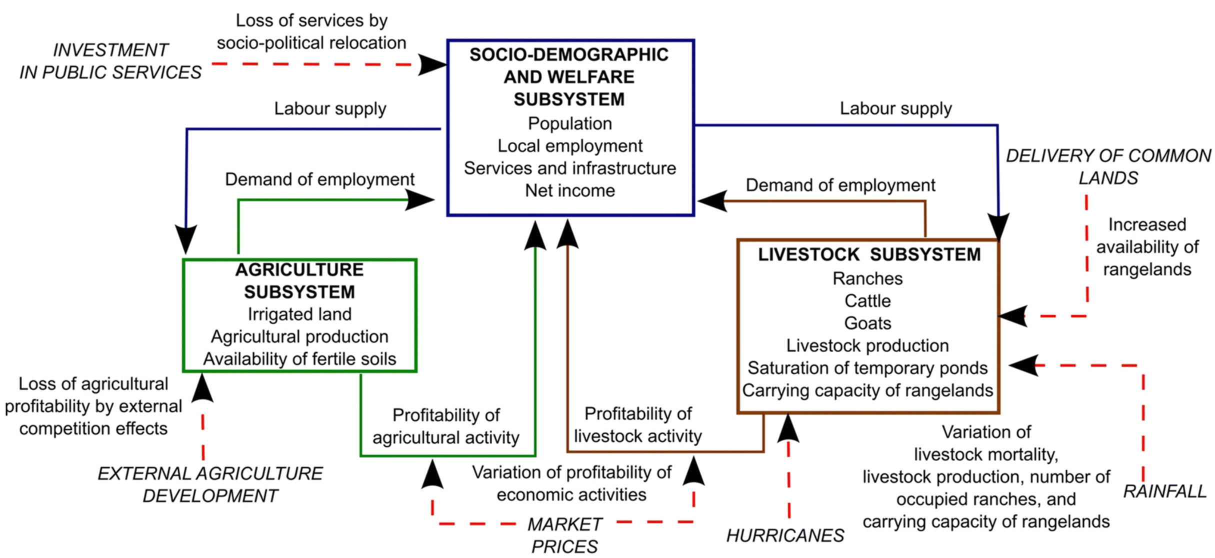

Figure 2 – Conceptual diagram of the social-ecological system of the oasis of Comondú. The external drivers are in italics and capital letters, and their effects on local dynamics are indicated with dashed lines. Image from Tenza et al. (2018).

The oasis of Comondú was conceptualised as an SES as shown in Figure 2. The SES is dominated by positive feedbacks between the socio-demographic and welfare system and the agriculture and livestock subsystem. The environmental limits to production activities in the agriculture and livestock system act as negative feedback, which control the growth dynamics. In addition, the SES is exposed to external drivers, such as market prices, hurricanes, and rainfall. Each of the subsystems contains variables and interactions within, for example, the sociodemographic subsystem contains population deaths and births, and migration. Whereas the agricultural subsystem contains variables such as cost, profit, wages, competition and their interaction with each other. The livestock subsystem contains different types of livestock, such as cows and cattle, and variables such as births, deaths, predation, and sales. For more details, see Tenza et al. (2018).

Water Harvesting. In an example from Liehr et al. (2017), the process of rainwater and floodwater harvesting is evaluated from a system perspective and the SES concept is applied to a case study of a small-scale food production system in Central Northern Namibia.

This study took a problem-oriented research approach and was conducted with the aim to address water challenges in the area. Two technologies for rainwater and floodwater management had already been developed. However, it had been unclear how to adapt and embed these technologies in the area, so that they could provide a complementary source of water, food, and income. The SES concept was applied to embed the idea of rain and flood water management into a broader context. The conceptual representation of the SES is shown in Figure 3.

Farmers are the main actors of the social system that interact with the ecological system. Food consumers, traders, and constructors also interact with the ecological system through their demand for food, income, and labour. The key components of the ecological system are water storage in the soil and primary plant production, which depend on various biophysical factors. The two systems are interlinked through a feedback loop in which the demand for food drives water and land management, which, in turn, influences the ecological system and generates agricultural products. Consequences of management interferences with water, land, and soil include changes in natural structures and processes. Unintended side effects of management could be, for example, the harmful effects of pesticides on human health, or reduced ground water recharge due to increased water retention. For more details on this case study, see Liehr et al. (2017).

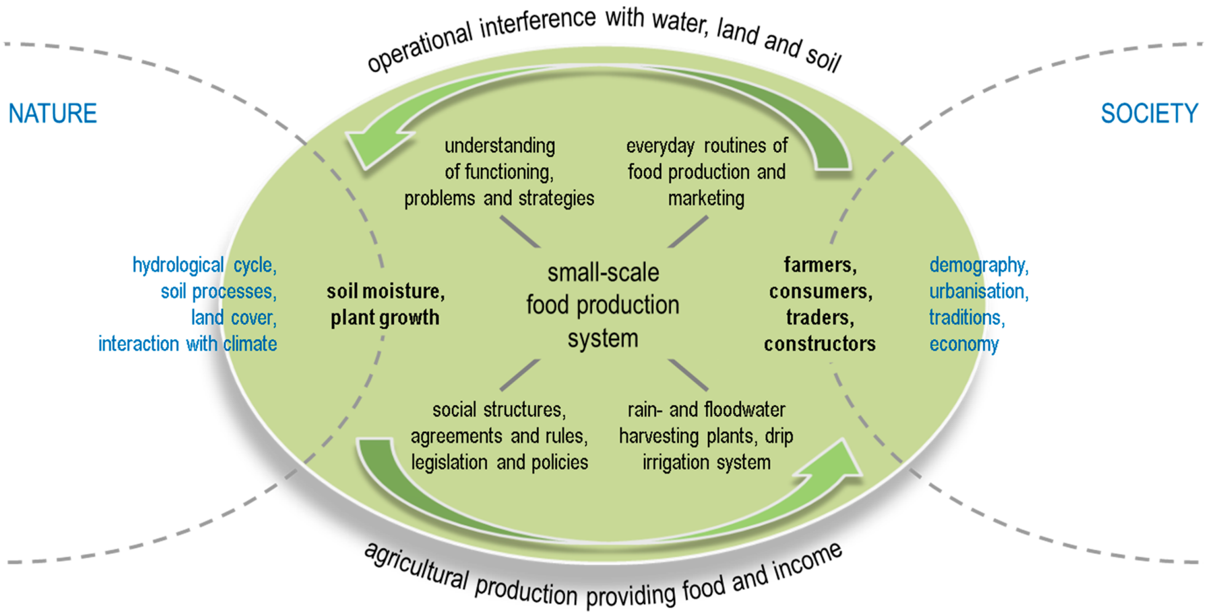

Figure 3 – Application of the concept of social-ecological systems (SES) to a case study of rainwater and floodwater harvesting as part of a small-scale food production system. Image from Liehr et al. (2017).

Fisheries. In a case study by Cenek and Franklin (2017), a Pacific salmon fishery in Alaska is investigated and conceptualised as an SES. The Alaska salmon fishery is a major social and economic driver in the area, which provides employment and subsistence, and also has a high cultural value for native Alaskans. The salmon is fished by various users, and active management is required to ensure the sustainability of the fishery.

The system was conceptualised as an SES to understand the interactions between the resource and the resource users, to identify the drivers that allow for enough salmon to escape, and to study the stability of the system. The SES approach allows for interaction between the different subsystems in the SES, and thus aims to capture the complexity of human behaviour and incorporate human uncertainty.

In the SES of the salmon fishery (see Figure 4), interaction occurs between the salmon (resource unit), fishermen (user), watersheds (resource system), and the fishery management (governance system). Interactions include, for example, the number of fish extracted, and when the governance system enforces regulations that will allow certain fishermen to fish, and others not. For more details, see Cenek and Franklin (2017).

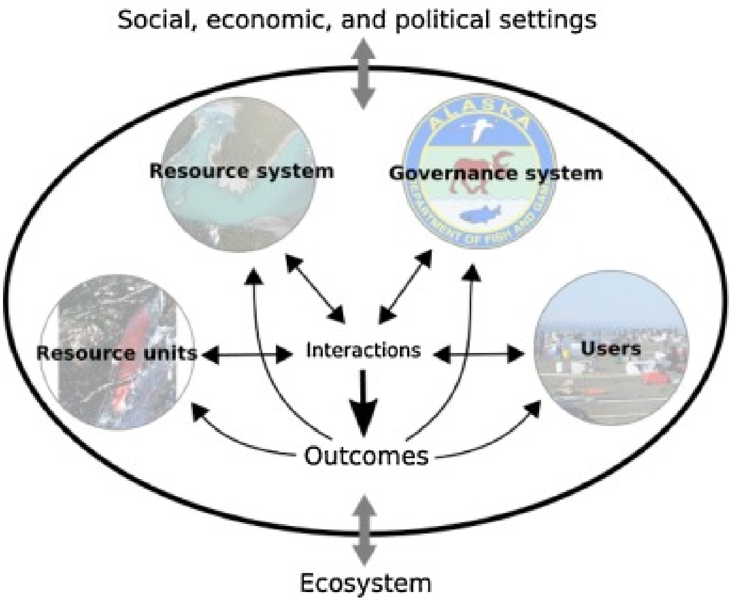

Figure 4 – Conceptual representation of the SES of the Alaskan salmon fishery. Image from Cenek and Franklin (2017).

2.2 Interdisciplinarity—Concept, Definition, and Practice

2.2.1 History of Disciplines

To understand the concept of interdisciplinarity, it is helpful to take a step back to the origin of disciplines. Since Aristotle, it was the philosopher's concern to divide, order, and classify the body of human knowledge, which was well connected to the need for teaching knowledge and for rational order, i.e. a controlled transition from one subject to the other. Hence, for the purpose of instruction, units of knowledge were generated and referred to as 'disciplines'—a teachable form of knowledge—derived from the Latin *discere*, meaning *learning* (Stichweh 1984).

Much later, around the 18th century, classifications of knowledge and encyclopaedic compilations were established in Europe because teaching areas of knowledge and sciences had become very diverse (Stichweh 1984). Disciplines were thought of as archives of knowledge deposits and unit divisions of knowledge (Stichweh 2001). Later in the 18th and 19th century, disciplines were described as production and communication systems, due to the early beginnings of specialisation. This was when scientists focused on small fields of science, and their specialised occupational roles were institutionalised by educational systems (Stichweh 2001). With specialisation came shared values and expertise among specialists, which formed the basis of specialist communities, and led to the emergence of scientific disciplines (synonymous with scientific community here). The emergence of scientific journals as the main form of communication demanded descriptions of scientific production processes, such as the method section, clear formulations of the hypotheses, and references to other scientists through citations (Stichweh 2001). Soon, research was understood as the 'search for novelties' and replaced the old notion of research as the preservation of knowledge. This transition led to the modern system of scientific disciplines, which is characterised by the establishment of disciplines in institutions (Stichweh 2001). It is also important to highlight that disciplines are dynamic and can expand and take up parts of other disciplines, with changing disciplinary boundaries. There is no hierarchy or centre, and all disciplines are considered equally important (Stichweh 2001).

2.2.2 What is a Discipline?

The classification and understanding of disciplines varied over time, depending on the institutionalisation of education and learning (Stichweh 2001). Also, the definition of a discipline varies among the different disciplines. However, the list below (based on Krishnan 2009) shows some of the more general criteria and characteristics that should be sufficient for the purpose of capturing the concept of a discipline:

- Particular object of research (can be shared with other disciplines at times)
- Body of accumulated specialist knowledge for the object of research, which is specific to that discipline and is not commonly shared with other disciplines
- Theories and concepts that can organise the specialist knowledge
- Specific terminology and technical language adjusted to the research object
- Specific research methods adjusted to the research requirements
- Must have an institutional manifestation, such as subjects taught at universities/colleges, respective academic departments, and professional associations

2.2.3 History and Developments of Interdisciplinarity

The modern term and phenomenon 'interdisciplinarity' did not emerge until the 20th century, but the basic ideas of unity of knowledge are much older. In ancient Greece, philosophers such as Plato had already talked about the undisciplined subject of philosophy as a 'unified science'. This initiated disputes about a lack of unity of science and the division of knowledge, which persisted throughout the centuries. Concerns about the overspecialisation and fragmentation of knowledge arose especially in the 16th through to the 19th century (Klein 1990a).

During the 20th century, discourse on interdisciplinary research increased, although the word *interdisciplinary* was first found in the literature of the social sciences and humanities in the mid-1920s (Frank 1988). Back then, it was the social sciences and general education that showed the most momentum for interdisciplinarity. Some colleges went through an era of general education reform that established programmes with the aim to move from a specialist to a generalist education. This was conducted through a curriculum that focused on a common set of values, including interdisciplinary objectives, such as solving modern problems by assembling disciplinary resources (Klein 1990a). The establishment of the Social Science Research Council (SSRC) in New York in the United States, promoted the propelled integration across disciplines. A member of the SSRC addressed the Council's future research objectives as follows: "*There is a certain limitation in the fact that we are an assembly of several disciplines, and in our official statements again it is expressed that we shall attempt to foster research which brings in more than one discipline.* [...] *There would be no other body, unless we assume the function ourselves, charged with the duty of considering where the best chances were for coordinated or interdisciplinary work.*" (Frank 1988).

Later, during the post-war period of the 1930s and 40s, it became apparent that many of the problems of the time, such as war, propaganda, housing, social welfare, and crime, were too large to be handled by one discipline alone, which encouraged integrative thinking. This spirit led scholars, and governmental and private agencies to acknowledge the importance of interdisciplinarity and applied social sciences. Social science scholars from institutions, such as the University of Chicago and Yale, attempted to stress forms of interdisciplinary research and interdisciplinary fellowship programmes .

By the mid-1950s, interdisciplinarity was a common concept in the social sciences and discussions emerged on practical consideration, such as how-to-do-it manuals and interdisciplinary methods and problems (Frank 1988). However, interdisciplinarity remained an ambiguous term through the 1940s and 1950s and even into the 1960s. Both concepts, the idea of grant unity, as well as the more limited integration of existing disciplinary methods and theories, were frequently applied (Klein 1990a). Only in the 1970s, was one of the first typologies of definitions produced by the Organisation of Economic Cooperation and Development (OECD), to describe and distinguish the term *interdisciplinary* and others, such as *transdisciplinary*, *multidisciplinary*, and *cross-disciplinary* (Frank 1988; Klein 1990a). The book, entitled *Interdisciplinarity: Problems of Teaching and Research at Universities*, was released in 1972 (Apostel et al. 1972) and marked a major milestone in the history or interdisciplinarity.

The era of the 1960s and 1970s was a time of reform with elevated awareness for, and in strong support of, interdisciplinarity through major funding. This led to the establishment of many new educational programmes of which some still remain today. The founding of the programmes was supported by funding agencies such as the Carnegie Foundation in the Americas, and the

OECD and the United Nations Educational, Social, and Cultural Organisation (UNESCO) in Europe. The OECD then released a new definition of interdisciplinarity after a survey of the relationships between the university and community in their member countries. This was followed by the OECD's conclusion for an increased demand of interdisciplinarity outside of universities to address more 'practical' problems of the complex and technological 'real' world, in contrast to the university approach of producing new knowledge with the aim of achieving unity of science (Klein 1990a).

Since the 1970s, a huge amount of literature has been produced on interdisciplinarity and discussions on the topics have increased across disciplinary, professional, and general published scholarship. These discussions are becoming both broader and deeper, and have shifted, changed, and diffused their focus, from educational programmes and ideas of unity, to designing and managing interdisciplinary teams and research projects. In conclusion, the modern concept of interdisciplinarity has been shaped by historical ideas to obtain unity and synthesis, the emergence of interdisciplinary research and educational programmes, and by interdisciplinary movements over time.

2.2.4 Defining Interdisciplinarity

The term 'interdisciplinarity' is often seen as confusing because it encompasses such a broad field and has been varyingly described as complex, heterogenous, dynamical, and contextual (Schmidt 2008). For some, interdisciplinarity is a form of nostalgia for a lost wholeness, whereas others see it as a form of evolution in the sciences, thus causing uncertainty over its definition. Additionally, unfamiliarity with interdisciplinarity among scholars and an interdisciplinary discourse that is widely diffused among general, professional, academic, and other literature has made interdisciplinarity a divisive term (Klein 1990a).

Many definitions of interdisciplinarity exist in the literature, but all point in the same direction (Van Rijnsoever and Hessels 2011). For example, the OECD provides a relatively wide definition, which refers to interdisciplinarity as any interaction ranging from the 'simple communication of ideas to the mutual integration of organising concepts, methodology, procedures, terminology, data and organisation of research and education' (Apostel et al. 1972, p. 25), whereas Rhoten and Pfirman (2007) understand interdisciplinarity as 'the integration or synthesis of two or more disparate disciplines, bodies of knowledge, or modes of thinking to produce a meaning, explanation, or product that is more extensive and powerful than its constituent parts'. Van Rijnsoever and Hessels (2011) focus on interdisciplinarity in relation to research collaboration and define it as 'the collaboration between scientists from different disciplines with the goal of producing new knowledge'. Interdisciplinary research (IDR) can therefore be thought of as a continuum of approaches rather than a uniform approach to research. However, in order to avoid ambiguity, the term *interdisciplinarity* is used and defined for the purpose of this study as follows:

Interdisciplinarity involves *'several unrelated academic disciplines in a way that forces them to cross subject boundaries to create new knowledge and theory and solve a common research goal'* (Tress et al. 2005a).

This means that the disciplines involved have contrasting research paradigms, e.g. qualitative vs. quantitative or analytical vs. interpretative approaches.

2.2.5 Drivers for Interdisciplinarity

Four primary motives and drivers for interdisciplinary research have been identified (National Academy of Sciences 2005):

- The inherent complexity of nature and society
- The drive to explore the interfaces of disciplines
- The need to solve societal problems
- The stimulus to produce revolutionary insights and generative technologies

One driver of interdisciplinary research is the inherent complexity of nature and society. For example, nature's complexity is apparent in some of the "grand challenge questions" of research like How did the universe originate? and What processes control climate? (National Academy of Sciences 2005). This driver also refers to the complexity of real-world problems that concern nature and society which are not easily solved and require crossing disciplinary boundaries, such as the challenges of sustainable resource use and eliminating world hunger (Repko 2008).

Interdisciplinarity is also driven by the desire to explore the problems and questions that lie at the interfaces of disciplines. Such investigations lead investigators beyond their own fields and can lead to discoveries or even the development of new fields. For example, Biochemistry is the result of such an interdisciplinary exploration, which has now departmental status at many universities (National Academy of Sciences 2005).

Societal problems, the third driver for interdisciplinarity, are certain kinds of problems that are of general public interest. These include problems such as food safety, access to education, terrorism, and immigration. These complex societal problems require expertise from multiple disciplines, and therefore, analysis and study of these problems requires an interdisciplinary approach (Repko 2008).

The last driver for interdisciplinarity is the desire to produce revolutionary insights and generative technologies. Revolutionary insights refer to those type of insights that transform how we learn, think, and produce new knowledge. Generative technologies are novel technologies that create applications of great value, and can also transform existing disciplines (Repko 2008). Examples of such generative technologies are the internet, GPS mapping, and the smartphone (National Academy of Sciences 2005).

2.2.6 Interdisciplinarity and the Disciplines

Interdisciplinary Critique of the Disciplines: The drivers of interdisciplinary research emphasise the value of interdisciplinary-based inquiries and the need to supplement disciplinary-based research. Yet, it also implies a critique of the disciplines and highlights weaknesses in the way disciplines operate. The interdisciplinary critique of the disciplines is discussed briefly, by touching on some of the weaknesses of disciplinary specialisation.

The first critique of the disciplines is that disciplinary specialisation hinders one to see the broader context, which can leave larger, more important issues, such as societal problems, unanswered (Repko 2008). Another critic argues that specialisation tends to produce tunnel vision and does not allow to capture the complexity of many of today's problems. However, many problems require an assessment from many different disciplinary perspectives to create a more comprehensive understanding. This is because even the most highly educated and trained specialists may be unaware of all the social, ethical, and biological dimensions of a certain problem or action (Repko 2008). The lack of appreciation by the disciplines for other disciplinary perspectives is also seen as a weakness, while another critique argues that some problems are neglected because the fall between disciplinary boundaries. Interdisciplinarity argues that creative breakthroughs occur more often when different disciplinary perspectives are brought together, compared to disciplinary work (Repko 2008). Finally, disciplines are critiqued for being products of a bygone age. Some argue that disciplines were formed during an earlier historical period and that their silo approach to learning and problem solving is no longer capable of providing understanding for contemporary issues *by itself* (Repko 2008).

Disciplinarity vs Interdisciplinarity: The interdisciplinary critique of the disciplines is often perceived as a rejection of the disciplines by interdisciplinarity, and has resulted in some tensions between specialists and interdisciplinarians. However, interdisciplinarity is itself rooted in the disciplines, which are, as such, foundational to the interdisciplinary approach. Interdisciplinarity aims to offer an alternative way of knowing to disciplinary specialisation. Yet, the disciplines still provide the necessary grounding to a particular problem (Repko 2008). As such, interdisciplinarity does not intend to supersede the traditional disciplines but rather complement them (National Academy of Sciences 2005). Disciplines offer rigid, and conservative methodological rigour, exactness, and control for error. Interdisciplinarity can offer dynamic, flexible, liberal, integrative ways for bridging knowledge and finding unity, all that a single discipline might not be able to be or do (Weingart and Stehr 2000). It is, therefore, important to keep and nurture the disciplines as the ultimate reference point, while embracing interdisciplinarity (Krishnan 2009).
Much more has been discussed on the role of disciplines and their relation to interdisciplinarity (see, e.g., Krishnan 2009; or Jacobs 2017), but an in-depth discussion on this topic is outside the scope of this study.

2.2.7 Interdisciplinarity compared to Other Modes of Research

Besides interdisciplinarity, other modes of research exist. Without aiming to provide a detailed description and discussion of these modes of research, they are briefly illustrated below and visualised in Figure 5. Generally, five different modes of research can be distinguished from each other: Disciplinary research, multidisciplinary research, participatory research, interdisciplinary research, and transdisciplinary research (Tress et al. 2005a). **Disciplinary**, also known as monodisciplinary research only has one specific goal within one of the currently recognised academic disciplines and recognises the artificial boundaries of that discipline. **Multidisciplinary** research involves several academic disciplines and has multiple, disciplinary goals in parallel, often with the purpose of comparison, but does not cross subject boundaries or aim for any form of integration. **Participatory** research involves academic researchers and non-academic participants aiming to solve a problem through knowledge exchange, but not with the aim of knowledge integration. **Interdisciplinary** approaches involve several unrelated academic disciplines in a way that forces them to cross subject boundaries to create new knowledge and theory and solve a common research goal. **Transdisciplinary** research combines an interdisciplinary with a participatory approach by integrating both participants from different academic disciplines and non-academic participants with a common goal to create new knowledge and theory through integration.

The main difference between these modes of research lies in the participants, academic and non-academic, and whether there is integration or not. Integration is only found in interdisciplinary and transdisciplinary research, which is why these are often referred to as 'integrative' approaches (Tress et al. 2005a).

2.2.8 Interdisciplinary Research in Practice

In practice, there is often a distinction between interdisciplinary research (IDR) and interdisciplinary education. Interdisciplinary education is often referred to as interdisciplinary studies (IDS) and can be practised in the form of interdisciplinary universities, undergraduate programmes, core curricula, and clustered courses, individual courses, independent studies, or as graduate and professional studies (Klein 1990a). However, the focus of this study is on IDR.

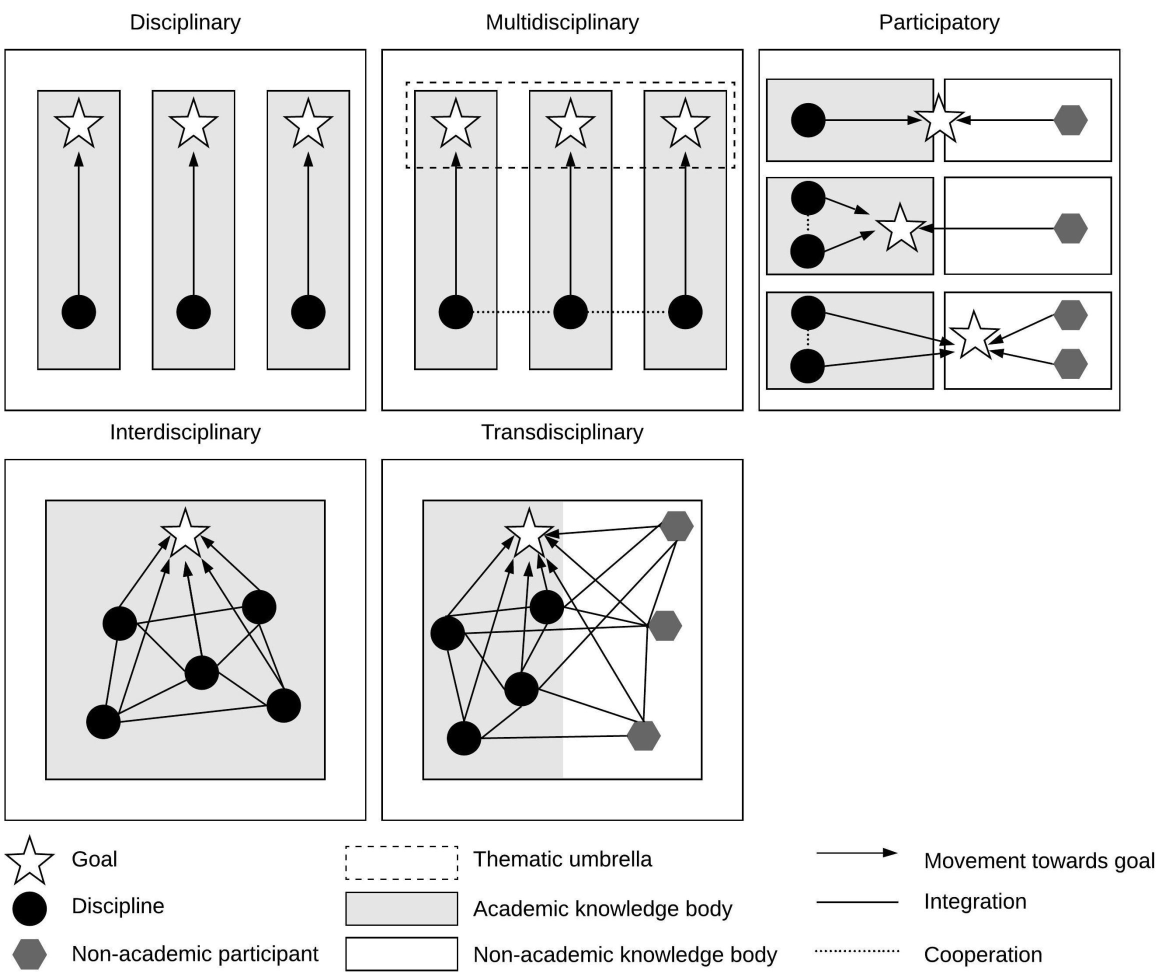

Figure 5 – Overview of research concepts. Image adapted from Tress et al. (2005b)[2].

Interdisciplinarity research practices exist in multiple forms, ranging from simple borrowing[1] to highly complex acts of knowledge integration and theoretical enrichment (Klein 1996). Interdisciplinarity in practice is, therefore, best understood as a variety of ways to cross, confront, and bridge prevailing single disciplines and approaches (Huutoniemi et al. 2010). Interdisciplinary research aspires to demonstrate the interfaces and frontiers of different disciplines to the researchers of those disciplines and to possibly even cross frontiers to develop new fields and disciplines. However, the motives for interdisciplinarity evolve from a variety of interests, and the form of practice will often depend on the interests that motivate the interdisciplinary path.

[2]Image adapted by permission from Springer Nature, *Clarifying Integrative Research Concepts in Landscape* Ecology by Tress, Tress and Fry, Copyright ©2018 by Copyright Clearance Center, Inc., 2005.

[1]The use of the tools, methods, concepts, and theories of one discipline in another is commonly known as 'borrowing' and 'cross-fertilisation' (Klein 1996). Sometimes a borrowing becomes so assimilated within a discipline that it is no longer perceived as foreign or borrowed. For example, electron microscopy originated within the physical discipline but has become a common tool within biological research (Weingart and Stehr 2000). See also the use of statistical methods by social scientists (Klein 1996).

Interdisciplinary research is also pluralistic in its modes of participation, in that it can be conducted in two different modes of participation: (1) in individual mode, in which a single investigator or researcher masters and integrates several fields; (2) in group mode, in which a group of investigators or researchers, wherein each has mastered one particular discipline, join together to work on a common problem through communication and collaboration (National Academy of Sciences 2005).

2.2.9 Examples of Interdisciplinary Projects: ClimeFish and SAF21

ClimeFish: The ClimeFish project is an EU-funded H2020 project (No 677039) financed under the societal challenges area of the Horizon 2020 funding programme of the EU, with a primary focus on research for innovation-related activities. The project addresses the societal challenge of food security under climate change by investigating the effects and challenges of climate change on fisheries and aquaculture. "The overall goal of ClimeFish is to help ensure that the increase in seafood production comes in areas and for species where there is a potential for sustainable growth, given the expected developments in climate, thus contributing to robust employment and sustainable development of rural and coastal communities."(ClimeFish 2016). To reach this goal, the ClimeFish project brings together a consortium of 21 institutes from 16 different countries, including non-academic stakeholders, which makes this not only an interdisciplinary project, but also a transdisciplinary one.

SAF21: The SAF21 project is an EU-funded H2020 Marie Skłodowska-Curie (MSC) European Training Network (ETN) (No 642080) with the primary focus on training a new generation of innovative PhD candidates. The project addresses the challenges of managing complex social-ecological systems by investigating fisheries systems from an interdisciplinary perspective. The overall goal of the project is to develop an integrated understanding of the fine mechanisms governing fishers' behaviour in relation to the regulative processes and the interplay and effects of such behaviour and processes on the ecological system. The aim is to use the knowledge from the project for better informed decision making and to develop innovative management strategies, to the benefit of decision makers, the fishing industry, and the environment. The project involves

10 PhD candidates that are based at seven different institutions and supported by an additional six partner organisations (SAF21 2015).

3 Methodology

The preliminary framework to guide and facilitate interdisciplinary SES research in practice was developed as a procedural framework, a framework that primarily provides sequences of steps or a set of planning guidelines (Cumming 2014). Procedural frameworks are often considered problem-oriented frameworks because they focus on applying theory, rather than developing or contributing to theory (Cumming 2014).

The framework development was based on an extensive literature review of interdisciplinary and SES research to answer each of the RQs (see Figure 6). An overview of the research process is briefly described here, and more details are provided below.

To address RQ1, design principles were developed and structured according to an ideal-typical interdisciplinary research process (see details below). For RQ2, the challenges to comply with the design principles and were identified, and for RQ3, the corresponding practical coping strategies, i.e. practical strategies that can be implemented to prevent or overcome practical challenges, were identified.

One of the main criticisms of many existing frameworks within the SES literature is the lack of comparison and incorporation of other existing frameworks (Cumming 2014). Therefore, a particular focus was put on the incorporation of existing frameworks from the literature during the development of the framework. As a final step, experiences and lessons-learned from two interdisciplinary EU projects ClimeFish (2016) and SAF21 (2015) were analysed and the coping strategies from within the projects were also included in the framework. The design principles, challenges, coping strategies, and existing frameworks were captured within the framework in a structured and coherent manner.

To address RQ4, three selected coping strategies of the framework were demonstrated through Papers 1–3 (Figure 6).

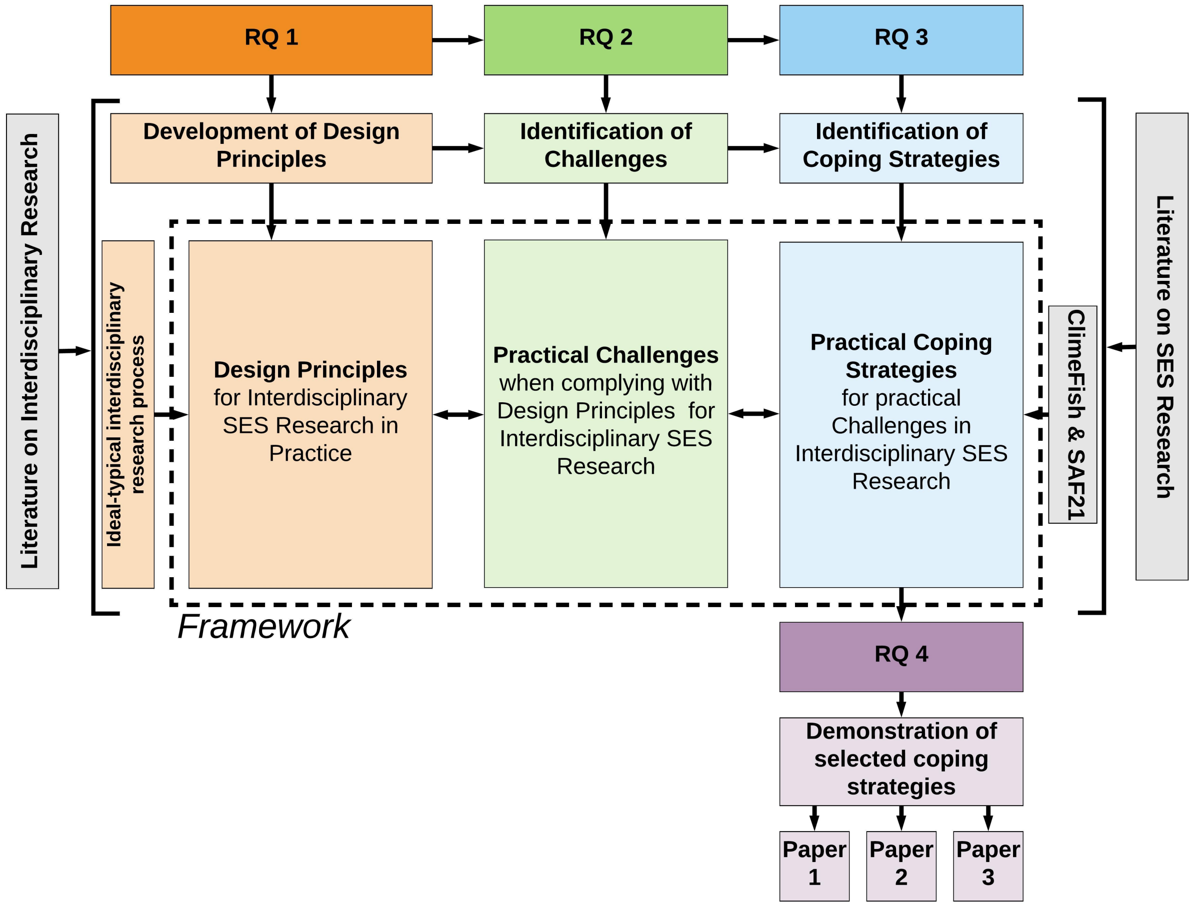

Figure 6 – Overview of the framework development in relation to the research questions (RQ). The literature on interdisciplinary research and on social-ecological system (SES) research was reviewed and synthesised to develop design principles for interdisciplinary SES research in practice, and to identify the practical challenges and coping strategies when complying with the design principles. Coping strategies identified within the EU projects ClimeFish and SAF21 were also added to the framework. Selected coping strategies were demonstrated through Papers 1–3.

Literature Review, Analysis and Synthesis. A literature review is an objective and thorough summary and analysis of relevant available research literature related to the topic being studied (Cronin et al. 2008). This methodology was chosen because literature reviews can be helpful to develop conceptual frameworks as well as to develop and update guidelines for practice (Cronin et al. 2008). The review process follows a number of steps (1–6, see also Figure 7).

(**1.**) Selection of a review topic. The topic selection was guided by the research questions, and therefore the two topics "interdisciplinary research in practice" and "SES research in practice" were chosen, which determined the main bodies of literature for the review: literature on interdisciplinary research; literature on SES research in practice; and any literature that addressed the two topics together. The focus was put on research practices, which are the 'sayings' or 'doings' by individuals or groups when conducting research.

(**2.**) The analytical reading process progresses from the general to the particular. This progress involves skim reading through a body of literature and then picking out the specific papers that are relevant to the research questions. The process can be repeated several times (Hart 1998). During the analytical reading process, the comprehensiveness and relevance of the literature needs to be considered (Cronin et al. 2008). Following the analytical reading process, particular focus was put on literature relevant to the research questions, which narrowed down the relevant literature to publications with a focus on *practice*, whereby only literature relevant for the development of the framework was considered. Only peer-reviewed literature was considered for this purpose.

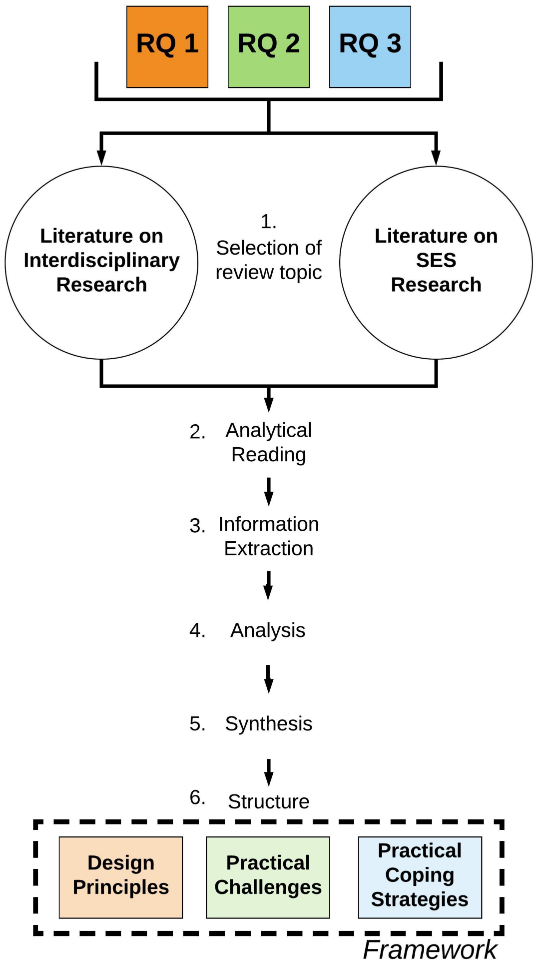

Figure 7 – Overview of the literature review process.

(**3.**) The relevant information was extracted from the literature.

(**4.**) During the analysis process, the researcher selects and differentiates between the information, to determine the organising principles between them and thereby identifying the main variables (Hart 1998). During the analysis, the extracted information from the interdisciplinary literature and the SES literature was examined and the main ideas and concepts were identified.

(**5.**) Synthesis is the process of integrating, combining, formulating, and reorganising the information derived from the analysis (Hart 1998). During the synthesis process, the analysed information from the two bodies of literature was integrated and combined to create new principles:

describing the process of interdisciplinary SES research in practice, thereby crossing the interface between interdisciplinary research literature and SES research literature.

(**6.**) The analysed and synthesised information was structured into the framework, based on the ideal-typical interdisciplinary research process.

This review method was used to develop the design principles for interdisciplinary SES research, to identify the practical challenges of this research process, and to identify the coping strategies to prevent and overcome the practical challenges of the interdisciplinary SES research process. These steps are explained in more detail below.

The **ideal-typical interdisciplinary research process** can be described through several steps (see Figure 8). These steps, based on Szostak (2013), are similar to what has been described by other authors (see e.g. Klein (1990b), Repko (2008), and Rutting et al. (2016)), and demonstrate what is generally considered important and commonly needed for an interdisciplinary research approach.

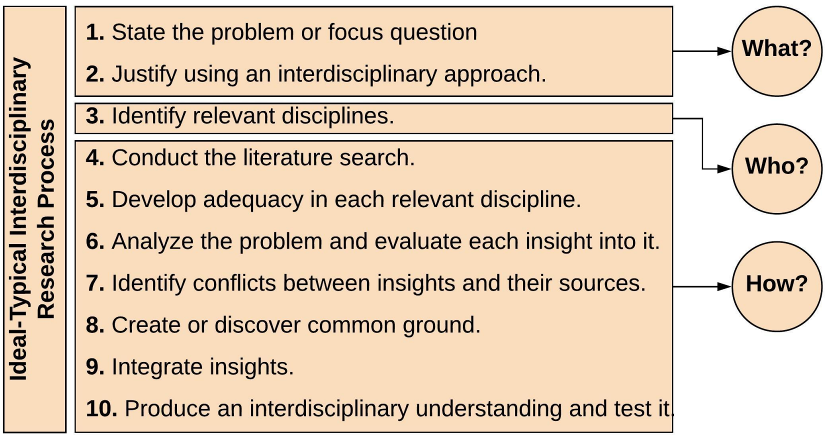

Figure 8 – The ideal typical interdisciplinary research process. The research steps are based on Szostak (2013), and were synthesised into three phases: '**What**' is the orientation phase for problem identification; '**Who**' is the preparation phase for identifying the disciplines and what scientists to include; '**How**' is the analysis and integration phase where new knowledge is produced.

The research steps were conceptualised into three phases: (1) '**What**' is the orientation phase for problem identification and framing; (2) '**Who**' is the preparation phase for identifying the necessary disciplines and building a collaborative team; and (3) '**How**' is referred to as the integration phase, but includes analysis, integration, and production of new knowledge and insights through collaborative research. The research steps were conceptualised into three phases to generalise the research process.

Different strands of literature—drawing on the literature of SES research (e.g., Binder et al. 2013; Cumming 2014), and on the literature of interdisciplinary research (e.g., Pischke et al. 2017; Repko 2008; National Academy of Sciences 2005) in theory and practice—were reviewed and synthesised into comprehensive and practice-oriented **design principles** for interdisciplinary SES research. The design principles were structured into the three different phases of the interdisciplinary research process (Figure 8).

In the next step, exemplary **challenges** and corresponding **coping strategies** of the design principles, and **existing frameworks** were identified through a review of the literature and empirical case studies of interdisciplinary or SES research.

The design principles, challenges, coping strategies and existing frameworks were structured and presented within the framework, which is described in the Results section 4.1.

In addition to the review process, the **experiences from the two EU-funded H2020 projects** ClimeFish (2016) and SAF21 (2015) were analysed. The project proposal and the overall project execution (e.g. in terms of scientific workflow, project coordination and management procedures), and personal experiences (e.g. from meetings and teamwork experiences) were analysed to identify any applied coping strategies. Coping strategies were identified by assessing the project's proposals and procedures, which were applied for scientific processes and team management. Any identified coping strategies were added to the framework. First-hand insights into both of these projects and their internal procedures were available because I was a PhD Candidate in SAF21 and I am employed as a researcher for ClimeFish at the time of writing this study.

In a final step, three coping strategies and three corresponding methodologies were selected to demonstrate these strategies. The Papers 1–3 demonstrate these strategies and methodologies. The methodologies are explained in detail within the individual papers.

4 Results

4.1 Framework to Guide and Facilitate Interdisciplinary Social-Ecological System Research in Practice

Framework Condition: Before applying the framework, a condition needs to be fulfilled: the study for which this framework will be used needs to qualify as SES research (see Glossary or Introduction). Only when this condition is fulfilled can the application of the framework be useful to guide and facilitate the planning and conduction of the study.

The framework developed in this preliminary study describes the design principles (A1–3, B1–3, C1–4), challenges, and coping strategies for conducting interdisciplinary SES research in practice, which are explained in detail below, and summarised in Table 4.1 at the end of the section.

A: Orientation phase—What?

- **A1**: *State the problem or research question.*

The research problem needs to be clearly defined within the social-ecological system context and trigger a scientific research question. This design principle can be challenged through a lack of guidance on research priorities and by difficulties to identify research gaps within an SES domain (Cumming 2014). In addition, if issues are not perceived as problematic due to a lack of problem awareness and recognition, a common problem definition can further be challenged (Lang et al. 2012). To overcome these barriers, firstly, a pre-assessment or pilot study can be conducted to raise problem awareness while assessing the status quo, e.g. through an overview of past research trends or a gap analysis. Research priorities can be set by identifying pressing societal challenges within an SES that need to be addressed (Brown et al. 2015), e.g. based on the United Nation's Sustainable Development Goals (United Nations 2015). In addition, all team members should be involved in the framing of the problem and definition of the research question to find common ground (Morse et al. 2007). A clear problem definition can be facilitated by using the framework for interdisciplinary problem framing by Clark et al. (2017), who offer the following guiding principles and questions: Clarify goals (value task): what are we trying to accomplish? (2) Map trends (history task): what has happened? (3) Identify conditioning factors (explanation task):

why has it happened? (4) Make projections (futuring task): what is likely to happen in the future? and (5) Develop and evaluate alternatives (practical task): what are we going to do about it?

- **A2**: *Consideration of theoretical elements for the study of SES.*

SES are inherently complex and therefore studying them requires the consideration of theoretical frameworks that can guide the conceptualisation of SES and an effective analytical focus (Cumming 2014). Yet, not one theoretical framework can provide sufficient theory for all feasible situations (McGinnis et al. 2012). Consequently, there has been a growing body of scientific theory on SES (Cumming 2011, p. 7) and many different frameworks have been developed to structure SES research (Ostrom 2009; Binder et al. 2013; Cumming 2014). These frameworks differ significantly in their goals, applicability, and conceptualisation of the SES, which hinders comparison of the frameworks and the diversity of results. In addition, researchers tend to develop new frameworks without fully explaining what its new elements are and how it relates to existing frameworks (Cumming 2014). The high diversity of frameworks, lack of overview, and uncertainty about strengths and weaknesses of the available frameworks, make it challenging to choose an appropriate framework for a particular research question (Binder et al. 2013).
To overcome these challenges, Binder et al. (2013) provide guiding questions for the selection of an appropriate framework as well as a comprehensive review of established frameworks one could possibly draw from. Additional reviews on existing frameworks should also be considered, like the one provided by Cumming (2014). The quality of these theoretical frameworks can then be assessed through the seven criteria for theoretical frameworks (Cumming 2014), to highlight strengths and weaknesses, and to evaluate whether they are suitable for the interdisciplinary SES study in question. These seven criteria can be summarised as follows (based on Cumming (2014)):

1. Social-ecological core: frameworks need to clearly link the social and the ecological system and be strong in both the social and the natural sciences.
2. Empirical support and translation modes: frameworks should be supported by rigorous empirical studies and should include translation modes that allow empirical observation to be connected to theory and vice versa.

3. Mechanisms: frameworks should be able to provide insights into causality and should offer explanations for the observed complex behaviours in real-world SES.
4. Spatio-temporal dynamics: frameworks should deal with the spatial nature and spatial variation of SES, as well as the nature of change through time.
5. Disciplinary context: frameworks should relate to previous frameworks and strive for synthesis between previous work, while highlighting their weaknesses and strengths.
6. Interdisciplinarity and transdisciplinarity: Frameworks should offer connections between, and cope with, complementary perspectives and different disciplines.
7. Direction: Frameworks should offer direction for the study of SES to advance our theoretical understanding of them.

- **A3**: *Justify and promote benefits of using an interdisciplinary approach.*

Interdisciplinary SES research requires an interdisciplinary approach. However, not every research question allows for an interdisciplinary inquiry. Similarly, some theoretical frameworks for the study of SES do not support the integration of different disciplines. Another challenge for an interdisciplinary approach may also be a lack of support by the researchers and research community. Researchers with negative perceptions and attitudes may not want to engage in interdisciplinary studies, and thereby also de-motivate others from doing so, or create a fear of failure. These attitudes and fears can hinder the creativity and innovation potential in researchers, and, as such, impede the interdisciplinary research process (Schleier and Carver 1993; West et al. 2009b; Rego et al. 2012; Darbellay et al. 2017).

To overcome these challenges, firstly, the formulated research question must be able to justify the interdisciplinary approach. The following criteria can be used to identify and justify if and why the research question and study requires an interdisciplinary approach (National Academy of Sciences 2005): (1) The problem or question is complex; (2) Important insights or theories of the problem are offered by two or more disciplines; (3) No single discipline has been able to address the problem comprehensively or resolve it; and (4) The problem is an unresolved societal need or challenge.

The underlying SES-theory should also be selected with care, to ensure that it allows for an integration and linkage of different disciplines, as already highlighted above (see guiding questions by Binder et al. 2013; and quality criteria by Cumming 2014).

The perceptions and attitudes of researchers towards interdisciplinarity can be assessed before starting the interdisciplinary project. An assessment can identify if and why researchers feel negatively about interdiscplinarity. These negative perceptions can then be targeted and addressed, to increase positive perceptions and thereby researchers' support. To gain the support of researchers for an interdisciplinary approach, it is important to foster optimism, positive thinking, and create a stimulating environment that enables team positivity and creative thinking. Optimism, positive thinking, and awareness of the importance and benefits of interdisciplinarity can be fostered by highlighting 'bright spots' (Cvitanovic and Hobday 2018). Bright spots are those instances in which interdisciplinary science and researchers have been positive and successful, and the benefits of interdisciplinarity are clearly shown. When people feel optimistic about their research endeavour, it increases their creativity and innovation potential, and has a positive effect on team work (Scott and Hofmeyer 2007; West et al. 2009a; Rego et al. 2012; Tang and Werner 2017).

B: Preparation phase—Who?

- **B1**: *Identify and select relevant disciplines.*

Disciplines that can substantially contribute to the problem and research question with their theories and insights should be selected. A common challenge is to identify relevant disciplines, weigh up their necessary contribution, and develop an understanding of the different disciplinary perspectives on the research topic. Relevant disciplines can easily become underrepresented during the research process if they have not been identified correctly or vice versa, where too many unnecessary disciplines are participating (Repko 2008). It can be very tempting to rely on an already existing network of research collaborators, the "usual suspects", the people who have previously been involved in research projects and who are generally interested in an interdisciplinary SES approach. However, selection of participating disciplines should be based on predefined expertise and expert selection criteria, informed by the framing of the problem. In addition, SES research requires that both the social and ecological system are considered, which means that both the natural and the social sciences should be involved in the SES research process (Cumming 2014).

To identify relevant disciplines in a structured manner that justifies their participation, the research question and SES theory can be 'mapped' with the potentially relevant disciplines (Repko 2008). This can be achieved through a research map, which explicitly states the purpose of the research, identifies what disciplines are potentially relevant to address that research, states the perspective of each discipline, and identifies assumptions of each discipline (Repko 2008, p.149). A competence matrix can be used to map the competences found in different disciplines to specific tasks within a project. This can help to identify overlap or lack of required disciplinary competences (ClimeFish 2016)[3].

- **B2**: *Identify and select relevant research team members.*

Members of interdisciplinary teams are often selected based on their disciplinary expertise. Yet, a common challenge when building an effective interdisciplinary research team can be to find personnel and team members with good interpersonal skills and who have shared goals (Halvorsen et al. 2016). A lack of interpersonal skills as well as conflicts in personality types among team members can strongly hinder interdisciplinary team work (Romero-Lankao et al. 2013; Pischke et al. 2017). Problems also occur when prejudices, reservations and resistances persist within disciplines when it comes to working with disciplines that are 'not your own' (Paterson et al. 2010).

One important aspect for any successful team is the selection of an interdisciplinary team leader. Leaders of interdisciplinary teams require a special skill set for them to be successful. They require high levels of intelligence, educational status, self-confidence, and sensitivity to the socio-emotional needs of the team members (Stokols et al. 2008), while they should also have a multi- or interdisciplinary expertise (Salazar and Lant 2018). Team leaders need to be assigned at the beginning of the project, so that they can delegate and help to get the team focused on preparation, maintaining cooperation, and providing a contact point for questions or problems during the project (Pischke et al. 2017). Team leaders should also encourage shared responsibility, individual and group accountability, flexibility, creativity, and patience among team members (Morse et al. 2007; Cheruvelil et al. 2014; Pischke et al. 2017). Strong leadership can create a strong identity with the group and a commitment of the team members to the group's aims and goals (Halvorsen et al. 2016). Leaders can also take the role of knowledge

[3] Any citation of SAF21 or ClimeFish in this section implies that the information was extracted from one of the projects.

brokers to support the knowledge integration process. Knowledge brokers should be experts in problem conceptualisation, rhetorically strong, and well-read in multiple disciplines (Arlinghaus et al. 2014).

It is important to employ the right mix of people when setting up an interdisciplinary research team (Arlinghaus et al. 2014). The researchers in the team should want to sit down together with researchers from other disciplines. The researchers should have an open mind and a broad interest, while it also makes it easier to step into other disciplines' concepts if they are widely-read (Paterson et al. 2010). Particularly important is also the ability to re-think one's own values or position when they are being challenged by colleagues from other disciplines. Developing such reflexivity will often require understanding on both the intellectual and personal level (Halvorsen et al. 2016).

Team members should be selected based on strong communication, interpersonal and teamworking skills, high social sensitivity and deep emotional engagement, besides their scientific and technical skills (Castán Broto et al. 2009; Halvorsen et al. 2016). An assessment of researchers culture through e.g. the Hofestede model of cultural dimensions (Hofstede 2011), could reveal additional insights into members' interpersonal strengths and weaknesses. Teams should also aim for high diversity in age, gender, race, and class amongst members to reach better performance (Halvorsen et al. 2016).

- **B3**: *Build and maintain a strong interdisciplinary research team.*

A successful interdisciplinary SES research project requires a strong interdisciplinary team from start to end. As such, establishing a team is just as important as maintaining a team by keeping all team members engaged and committed to the project. Challenges in managing and maintaining interdisciplinary teams can be caused through unequal research responsibilities among the involved disciplines (Lang et al. 2012), and asymmetries between senior and junior researchers that lead to conflicts (Pischke et al. 2017). Conflicts among team members can also be caused through personal conflicts, cultural differences, false expectations on what interdisciplinary work may entail, or arising frustrations among interdisciplinary researchers when lengthy time commitments are required to combine disciplinary data or write interdisciplinary papers (Pischke et al. 2017).

For interdisciplinary teams to be successful, they should aim to have ten essential key characteristics, including: leadership and management, effective communication, personal rewards, training and development, appropriate resources and procedures, appropriate mix of skills and individual characteristics, positive and enabling climate, clarity of a shared vision, quality and outcomes, and respect and understanding (Jacob 2015). For example, personal rewards could be small group gatherings with cake to celebrate the small successes. Training and development can be facilitated in research groups by hiring trainers and through active course participation (ClimeFish 2016; SAF21 2015); a positive and enabling climate can be promoted through support and encouragement by team leaders and colleagues; and quality and outcomes can be achieved through successful integration and documentation of the research.

Team members can be trained in cultural awareness, e.g. through the Hofstede culture compass[4], to better work in international environments with colleagues from different countries and cultures. Training in conflict management can also be provided to ensure that team members learn techniques and methods in how to reduce conflict potential or how to resolve arising issues. In case conflicts arise, these should be solved as close to the problem origin as possible and not involve more people than necessary (SAF21 2015; ClimeFish 2016), and researchers should consider to solve the conflict internally (National Committees for Research Ethics in Norway 2007, paragraph 21).

Team members can also be prepared and trained in advance of conducting interdisciplinary work to create realistic yet flexible expectations among the participants (Gardner et al. 2013). This could entail agreed guidelines for team members, which can facilitate planning and minimise misunderstandings, while also resolving timing and monetary problems (Pischke et al. 2017). Fostering respect and trust among researchers can additionally facilitate communication, and overcome time, logistics, and personal relationship barriers. Trust-building can be achieved by facilitating and designing interactive team-building experiences and exercises that have nothing to do with the research project (Pischke et al. 2017). Face-to-face meetings can also provide the opportunity to foster trust (Bridle et al. 2013), by providing the opportunity to discuss problems and disagreements (Huston 2012). Equally important is the immediate and conscious integration of social and natural scientists into the team to present their efforts as equally valuable (Halvorsen et al. 2016).

[4] https://www.hofstede-insights.com/cultural-survey-pre-paid/

C: Integration phase—How?

- **C1**: *Ensure clear communication.*

Clear communication is crucial for successful integration, as well as the overall execution of the research over the full project lifetime (Jacob 2015). Yet, finding a common vocabulary for communication across multiple disciplines can also create major challenges in interdisciplinary research (Strober 2006; Barlow et al. 2011; Romero-Lankao et al. 2013). Communication is often challenged due to the discrepancies in understanding of concepts and terminology among participants. Therefore, communication can be particularly challenging at the beginning of a project when new modes of communication still have to be developed, when explaining disciplinary concepts (Pischke et al. 2017), finding common ground for problem definitions, and setting up a research plan (Morse et al. 2007; Lang et al. 2012; Brown et al. 2015). Communicating the outcomes and results of the project to a wider audience in a coherent manner can be equally challenging (Morse et al. 2007). The more disparate the disciplines' traditions are from each other, the easier miscommunication occurs (Morse et al. 2007; Lang et al. 2012; Brown et al. 2015; Pischke et al. 2017).

To facilitate communication among researchers from different fields, project specific glossaries and ontologies could be developed early in the project or at the proposal stage. Open encounters also have a positive effect by fostering training in cross-disciplinary communication among participants (Bridle et al. 2013). During these encounters, individual researchers should be both, willing and able, to explain their science in simple words and concepts, while also being open to learn from each other. Feedback questions help to avoid 'disciplinary' misunderstandings.

Research team leaders can additionally facilitate team communication by applying leader communication strategies for which statements should be problem-focused, procedural, socioemotional, and action-oriented (Salazar and Lant 2018).

- **C2**: *Design and conduct interdisciplinary SES study.*

Thorough planning and design of an interdisciplinary SES study is essential to successfully navigate through the complexity inherent to conducting interdisciplinary SES research, on both a scientific, as well as an administrative and organisational level. Differing interdisciplinary practices of researchers can also lead to chaos and confusion, regarding research and publications protocols, treatments of subjects, data access and availability, roles, authorship or basic etiquette, due to traditions and disciplinary cultures (Bosch and Titus 2009; Pischke et al. 2017).

Interdisciplinary research can also be impeded by resources, most commonly time and money, because, often, more time and money is needed than would be necessary for a similar single disciplinary project (Morse et al. 2007; Pischke et al. 2017). Problematic is also that short-term funding is often not feasible for interdisciplinary projects that require long-term planning and execution.

To better manage the complexity of interdisciplinary SES project, an Interdisciplinary Research Management Framework can be applied in the organisational design of the project, which can help to manage work-flows and to set up functioning structures within the project team (König et al. 2013). This frameworks makes duties of researchers and project managers explicit and enables project set-up in a systematic way.

Also the scope, type and goal of the project is best to be set early and made explicit to all project participants. In particular, to explicitly plan and account for the scope, type and goal of interdisciplinarity, a typology for interdisciplinarity, such as the one by Huutoniemi et al. (2010) can be applied.

An iterative-loop can be incorporated into the project plan to evaluate and re-assess the quality and validity of the results. As such, the first loop of the research process will generate the results, which will then be evaluated. In a second loop, any issues or problems that have been identified with the results can be addressed. After the second loop, results are re-assessed and validated if their quality is satisfying. This loop process allows for an evaluation and for additional time requirements, that are often necessary in interdisciplinary work (ClimeFish 2016). In addition, planning and accounting for high resource needs is important, while also planning for a surplus in budget might be useful to cover unexpected costs in case problems or issues are encountered (Pischke et al. 2017; Bosch and Titus 2009).

- **C3**: *Integration.*

In interdisciplinary research, integration is perhaps among the biggest challenges (Strober 2006; Morse et al. 2007; Gardner et al. 2013; Romero-Lankao et al. 2013). Challenges of integration can occur on many levels, ranging from communicative, organisational, technical, to cognitive. In particular, integrating experimental design, fieldwork plans and data collection have been found challenging. Sharing and combining information across disciplines can create additional obstacles (Pischke et al. 2017). During integration processes, barriers can occur due to an attachment to one's own discipline, which creates difficulties when aligning research questions and focus across disciplines (Pischke et al. 2017). The lack of detailed plans from the beginning of a project, regarding how and what to integrate, can make the integration process messy and time-consuming (Morse et al. 2007; Barlow et al. 2011; Pischke et al. 2017).

The often difficult integration of social- and natural sciences in SES research can be facilitated by following well-defined processes that lead to effective execution and integration in interdisciplinary research practices. For example, the methodological framework developed by Tobi and Kampen (2018) provides guidance on the conceptual and theoretical design, operationalisation, execution, and integration of interdisciplinary research. The inclusion of a clear study design, data management plans and sampling designs facilitate interdisciplinary integration. In addition, researchers can be trained in methods that allow for an interdisciplinary process and integration in an SES context (SAF21 2015).

Integrative processes commonly contain many interdependencies between tasks, i.e. when one task needs to be fulfilled to address the next task. It can therefore be helpful to map these interdependencies, to highlight where the dependencies lie and with which team members. The interdependencies also represent risks that might hinder project completion. With an interdependency map, these risks can also be identified and risk mitigation strategies can be developed, e.g. what alternatives can be used in case task X cannot be fulfilled (ClimeFish 2016).

Regular and frequent meetings, preferably face-to-face, allow for a generative process that can go beyond parallel play and into integration. Frequent meetings also allow for researchers to germinate and refine their ideas, and to respond as the work evolves, while planning next steps in the research process (Huston 2012).

The connections between interdisciplinarity and creativity have also been explored with the aim to suggest strategies for interdisciplinary researchers. To appreciate interdisciplinary research as a creative thinking process, strategies such as mindfulness practice, meditation and physical exercise could additionally be considered because these practices have been found to enhance creativity (Darbellay et al. 2017). Serious games and live-action role playing can also be used to enhance creativity and stimulate discussions within teams (ClimeFish 2016; SAF21 2015).

- **C4**: *Documentation of interdisciplinary SES research and transferability of results.*

In interdisciplinary studies, the assessment of interdisciplinarity can be difficult if the integration process and outcome are not made transparent and explicit. The evaluation of the performance and quality of the results can also be hard to determine for external reviewers when novel and unfamiliar approaches have been applied. Yet, external evaluation often plays a crucial role for the success of a project and the dissemination of project outcomes, when facing (peer-)review and assessment of publications, grant proposals, and reports. In addition, the conceptualisation of the SES in question, and the theory underpinning the research, often lack reasoning for why a certain theory was chosen and whether it was based on existing theoretical frameworks. This hinders comparison and transferability of the results as such studies can only provide limited case-specific solutions.

To overcome these obstacles, first, a typology of interdisciplinarity (e.g. the typology by Huutoniemi et al. (2010)) can be applied to make the scope, type, and goal of interdisciplinarity explicit. The application of a typology can facilitate the documentation of interdisciplinary research and make the description of the integrative process comprehensible to outsiders. It, thereby, increases the transparency of the research and allows for an easier comparison to other interdisciplinary studies.

For the documentation of research performance and quality, the seven generic principles for interdisciplinary research evaluation by Klein (2008) provide a coherent framework that can be used as a guide. These principles include (1) variability of goals; (2) variability of criteria and indicators; (3) leveraging of integration; (4) interaction of social and cognitive factors in collaboration; (5) management, leadership, and coaching; (6) iteration in a comprehensive and transparent system; and (7) effectiveness and impact. Lyall et al. (2011) also provide practical quality criteria for interdisciplinary research proposals that can provide valuable insights when applying for research grants. These criteria include, for example, that the proposal should indicate the benefits for the disciplines, or the societal and business benefits, that the proposal should justify the interdisciplinary approach and the choice of disciplines. Following principles and quality criteria, such as the ones by Klein (2008) and Lyall et al. (2011), for the documentation of the research can facilitate the evaluation of the quality and performance of the research.

The conceptualisation of the SES and application of any existing theoretical frameworks should also be made explicit and contain clear reasoning for why a certain theory was chosen (see again Binder et al. (2013) from above). The gained knowledge can then be reintegrated into the literature and with similar studies. Therefore, a comparative study from which generalisable results can be derived and how the study builds on existing frameworks can already be considered when planning the research.

Finally, the practice of open science through open access data and publications and by making code and model simulations openly available increases the transparency of the research. Thus, it enables researchers, reviewers, and evaluators to access the data, re-run analysis and gain insights into the quality of the results and how they were generated. This also allows other researchers to use, replicate and adjust the analysis and to apply it to other case studies (ClimeFish 2016; SAF21 2015).

Table 1 – Design principles for an interdisciplinary SES research process and associated practical challenges with an outline of exemplary practical coping strategies. Sources contain references to challenges. Text in **bold** highlights coping strategies that have been demonstrated in practice through the Papers 1–3 (section 4.2). Text in *italic* highlights existing frameworks that have been incorporated into the coping strategies.

Design principles	Challenges	Description of Challenges	Exemplary Coping Strategies	Sources
A: Orientation phase—'What?'				
A1: State the problem or research question	Lack of guidance for future SES research; Lack of problem awareness	Difficulties to identify research gaps and research priorities in SES domain; lack of problem awareness; Difficulty finding common ground for problem definition	**Conduct pilot study** to build problem awareness; Gap analysis and **assessment of status quo**, mapping with societal challenges; apply *framework for interdisciplinary problem framing*	Morse et al. 2007; Lang et al. 2012; Cumming 2014; Brown et al. 2015; Clark et al. 2017
A2: Consideration of important theoretical elements for the study of SES	Difficulty choosing appropriate theoretical SES framework	Different existing theoretical frameworks and lack of overview; Theory context depended; Frameworks are not comparable	Follow guiding questions for selection of appropriate theoretical framework; Use existing reviews of SES frameworks; Apply criteria to assess theoretical frameworks	Binder et al. 2013; Cumming 2014
A3: Justify and promote benefits of using an interdisciplinary approach	SES theory does not integrate interdisciplinarity; Insufficient support for interdisciplinarity	Underlying SES-theory impedes interdisciplinary approach; Research question does not justify an interdisciplinary approach; Negative perceptions and lack of support for interdisciplinary approach	Apply criteria for identification and justification of an interdisciplinary research question; Select theoretical framework that allows interdisciplinarity; **Assess perceptions of interdisciplinarity**; **Build optimism**; Create awareness for need of interdisciplinarity	National Academy of Sciences 2005; Paterson et al. 2010; Binder et al. 2013; Cumming 2014

Table 1 – continued.

Design principles	Challenges	Description of Challenges	Exemplary Coping Strategies	Sources
B: Preparation phase—'Who?'				
B1: Identify and select relevant disciplines	Weigh disciplinary representation according to research question	Under- or over-representation of disciplines in the research process; Lack of understanding of disciplinary perspectives	Mapping of disciplines (expertise and interests) to SES-theory and research question; Application of competence matrix	Repko 2008; Lang et al. 2012
B2: Identify and select relevant research team members	Lack of team members with the right skill set; Lack of team leaders	Team members lack interpersonal skills and necessary expertise; negative perceptions, disrespect and prejudice towards other disciplines/members; Lack of leadership within the team	Assign skilled inter- and multidisciplinary team leaders and knowledge brokers early in the project; Choose team members with shared goals, and based on their attitudes, expertise and (inter-) personal qualifications	Stokols et al. 2008, Castán Broto et al. 2009; Paterson et al. 2010; Romero-Lankao et al. 2013; Arlinghaus et al. 2014,Halvorsen et al. 2016,Pischke et al. 2017; Salazar and Lant 2018
B3: Build and maintain a strong interdisciplinary team	Lack of trust, legitimacy and commitment; unbalanced team composition	Arising frustrations and conflicts between scientists; Project drop-outs; Conflict due to disciplinary, age, and gender differences; Unequal responsibilities	Pursue key characteristics for successful teams; Specialised training for team members; Solve conflicts close to the problem origin; Create realistic expectations; Team-building exercises and social activities	Schleier and Carver 1993,Stokols et al. 2008,West et al. 2009a,Lang et al. 2012; Jacob 2015; Pischke et al. 2017

Table 1 – continued.

Design principles	Challenges	Description of Challenges	Exemplary Coping Strategies	Sources
C: Integration phase—'How?'				
C1: Ensure clear Communication	Miscommunication	Misunderstandings; Different disciplinary languages; Discrepancy in understanding of concepts and terminology; Difficulty communicating interdisciplinary results	Develop project specific glossaries and ontologies; Open face-to-face encounters; Incorporate feedback questions; Follow good leader communication	Strober 2006; Morse et al. 2007; Barlow et al. 2011; Lang et al. 2012; Gardner et al. 2013; Romero-Lankao et al. 2013; Brown et al. 2015; Pischke et al. 2017; Salazar and Lant 2018
C2: Design and conduct interdisciplinary SES study	Complexity of project; Unstructured approach; Lack of resources	Conflicts over aims and goals; Different expectations among team members; time and money limitations	Follow *framework for interdisciplinary research methodology*; Identify scope, type and goal of interdisciplinarity early in the project; Apply *research management framework*; Incorporate iterative-loop to evaluate and assess quality of the results; Plan and account for high resource needs	Bosch and Titus 2009; Pischke et al. 2017, Tobi and Kampen 2018
C3: Integration	Lack of integration; Lack of clear project and integration management	Lack of research plan; Lack of integrative process; Misunderstandings of what to integrate and how; Unclear processes of who does what and when; Lack of creativity	Follow *framework for integration*; Training in methods that allow for integration; Map interdisciplinary interdependencies; Regular and frequent meetings; Promote and facilitate creative thinking processes	Morse et al. 2007; Barlow et al. 2011; Pischke et al. 2017

Table 1 – continued.

Design principles	**Challenges**	**Description of Challenges**	**Exemplary Coping Strategies**	**Sources**
C4: Documentation of interdisciplinary SES research and transferability of results	Lack of transparency; Difficulty to assess research quality and performance; Uncertainty of theoretical foundation; Lack of transferability	Integration difficult to identify; Difficulty to evaluate research performance and quality; Choice for theoretical framework unclear or not explicit; Generalisation and comparison of results not possible; Limited case-specific solutions	**Explicit documentation of scope, type and goal of interdisciplinarity**; Explicit and clear reasoning for the choice of theoretical framework underpinning the SES research; Reintegrate generated knowledge into the literature and with similar studies; Practice open science	Huutoniemi et al. 2010; Binder et al. 2013; Cumming 2014

4.2 Demonstration of Selected Coping Strategies

The three Papers 1–3 are demonstrations and practical examples for an application of selected coping strategies suggested in the framework. The papers provide a methodology that can be used to apply a coping strategy and demonstrate what the results may look like when applied to a specific research domain, which is explained in detail below and summarised in Table 2.

Demonstration of A1: Conduct Pilot study, Assessment of Status-quo. The coping strategy A1 is demonstrated in Paper 1 (*Using Machine Learning to Uncover Latent Research Topics in Fishery Models*). Paper 1 demonstrates a methodology to conduct a pilot study as a coping strategy for the design principle **A1**: "*State the problem or research question*". Challenges of this design principle include a lack of problem awareness, difficulties to identify research gaps and an overall lack of guidance for future SES research direction. Paper 1 applies a machine-learning method to conduct a topic analysis of fisheries modelling publications from 1990–2016. The results provide insights into the past and current research trends of the fisheries modelling domain. This analysis exemplifies a methodology that can be used to identify research topics, trends and gaps (for more details see the paper). The approach can serve as a coping strategy in two ways: (1) it can be applied as a **pilot study** that provides empirical evidence to scope the problem and to create problem awareness, e.g. to demonstrate that research trends do not align with research needs to address societal challenges and sustainable development goals; (2) it can be used to assess the **status-quo** within a domain, and to identify if and what topics are not addressed within a research domain. The results can be used to guide future research direction and to state the problem and research question.

Demonstration of A3: Assess Perceptions of Interdisciplinarity, Build Optimism. The coping strategy A3 is demonstrated in Paper 2 (*Interdisciplinary Optimism? Sentiment Analysis of Twitter Data*). Paper 2 demonstrates a methodology to assess perceptions of interdisciplinarity and how to build optimism as a coping strategy for the design principle **A3**: "*Justify using an interdisciplinary approach*". Negative perceptions of interdisciplinarity and lack of support for an interdisciplinary approach can challenge this design principle. Paper 2 identifies perceptions of interdisciplinarity and highlights optimistic opinions. The sentiment analysis of Paper 2 can be applied as a coping strategy in the following ways: (1) to assess whether there is support for interdisciplinarity on a larger scale, e.g. within a country or city, a wider research community, or within a university or faculty; (2) to identify the audience or cause of negative perceptions of interdisciplinarity in order to target particular negative audiences by creating specific incentives, or by solving the identified causes and problems; (3) to identify the audience and cause of positive perceptions, which can be used to highlight the 'bright spots' of interdisciplinarity to create more interdisciplinary optimism.

Demonstration of C4: Explicit Documentation of Scope, Type and Goal of Interdisciplinarity. The coping strategy C4 is demonstrated in Paper 3 (*An Interdisciplinary Insight into the Human Dimension in Fisheries Models*). Paper 3 demonstrates a methodology that can be applied for the explicit documentation of the scope, type and goal of interdisciplinarity as a coping strategy for the design principle **C4**: "*Documentation of interdisciplinary SES research and transferability of results*". Paper 3 identifies and assesses interdisciplinarity by applying a typology for the scope, type, and goal of interdisciplinarity to a diverse set of fisheries modelling publications. It shows how the application of a typology makes interdisciplinary work more comparable with other studies and therefore allows for an easier re-integration of case studies with the literature.

The method from Paper 3 can be applied as a coping strategies in two ways: (1) the typology can be applied before and during a project to *document* the interdisciplinary scope, type and goal of the research. This will make the interdisciplinary work more accessible, understandable, and transparent; (2) if the documentation of interdisciplinarity is lacking in e.g. a publication or grant proposal, the typology can be applied to *assess* interdisciplinarity. This can make other work more comparable to one's own study. However, proper documentation of interdisciplinarity should always be the primary goal. In particular, because Paper 3 also shows the large efforts required to identify and assess interdisciplinarity when there is a lack of documentation.

Table 2 – Overview of the methodologies and study objects that were used to demonstrate the coping strategies through the Papers 1–3.

Coping strategies	Methods	Study objects
A1: Conduct Pilot study; Assessment of Status-quo; (Paper 1)	- Information retrieval - Web-scraping - Machine-learning - Natural language processing	Fisheries; Models; Topics;
A3: Assess Perceptions of Interdisciplinarity; Build Optimism; (Paper 2)	- Information retrieval - Web-scraping - Opinion mining - Computational linguistics Natural language processing;	Interdisciplinarity; Sentiment; Discourse;
C4: Explicit Documentation of Scope, Type and Goal of Interdisciplinarity; (Paper 3)	- Typology of Interdisciplinarity	Fisheries; Models; Interdisciplinarity;

5 Discussion

5.1 Contribution to Science

The aim of this study is to develop a preliminary framework that can *guide* and *facilitate* interdisciplinary SES research in practice. To achieve that, the framework provides design principles, which can *guide* the research practice by helping researchers understand how to conduct this type of research. The practical challenges in the framework identify what impedes interdisciplinary SES research and the practical coping strategies identify how to prevent and overcome these challenges. Thereby, the challenges and coping strategies *facilitate* interdisciplinary SES research by making the research practice easier and by allowing researchers to gain in-depth insights into the application of the design principles.

The framework development took a pragmatic interdisciplinary approach in, and of, itself, and focused on research practice. Hence, it is difficult to assign the framework to a particular scientific domain, as the framework was not formulated to advance knowledge within one particular field. Instead, the framework is positioned at the interface of interdisciplinary research and social-ecological systems research, while the practical focus also places it into the field of research practices.

Research practices are commonly given through scientific principles that ensure integrity in the research process (National Academy of Sciences 1992). These scientific principles are traditionally very connected with the traditions of science and are mainly conveyed through discussions and informal education. This means that these principles exist primarily in unwritten form, which is why it has been suggested that they should be written down and made explicit (National Academy of Sciences 1992). The scientific principles also differ between disciplines and even within the same discipline, as they are shaped by the procedures of a discipline or a certain field of study (MacLeod 2018). This also explains why it is particularly difficult to conduct interdisciplinary research, since a general interdisciplinary research practice has not been developed as such, while the practices of other disciplines are difficult to access because they exist mainly in unwritten form. Nevertheless, it is possible for interdisciplinary research teams to collaboratively develop their own research practices through a learning-by-doing process (Carr et al. 2018). The literature suggests that real-world interdisciplinary collaborations are a valuable source to provide insights into what practical approaches for interdisciplinary SES research may look like (Redman et al. 2004). Therefore, the framework in this study followed an approach that tried to access the experiences of empirical case studies reported in the literature, as well as from two EU-funded projects to identify such 'hidden' interdisciplinary research practices. As such, the framework represents a novelty in research practices in general, and in the field of interdisciplinarity in particular, because it provides easy access to interdisciplinary research practices in a written and explicit form. The framework also combines the general (design principles) with the more specific (coping strategies) practices, which is an important trait of scientific principles for research practices (National Academy of Sciences 1992).

The framework also contributes to the literature on interdisciplinary research by providing a coherent overview of important research practices when conducting interdisciplinary work, which was not previously available to this extent. The literature on interdisciplinary research is large and discusses interdisciplinarity in many forms. For example, literature discusses experiences of interdisciplinary scientists (Gewin 2014; Enright and Facer 2016), how to organise, classify, and describe interdisciplinary research (Huutoniemi et al. 2010; Klein 2010; Siedlok and Hibbert 2014), how to conduct and foster interdisciplinary research (National Academy of Sciences 2005; Bruun et al. 2005), how to measure, evaluate and assess interdisciplinary research (Porter and Rafols 2009; Lyall et al. 2011; Wagner et al. 2011; Research Council UK and Digital Science 2016), and how to use it in education (Klein 2006; Davies and Devlin 2010). The many publications of case studies applying an interdisciplinary approach (see, e.g. Kuikka et al. 2011; Levontin et al. 2011; Clark et al. 2017) additionally contribute to this body of literature. Relevant information on interdisciplinary research practices and lessons learned can be found within all these parts of the literature, in addition to interdisciplinary research practices that have been described previously (Castán Broto et al. 2009; Carr et al. 2018; MacLeod 2018), but usually only on the basis of a single case study. Yet, because the literature is rather fragmented and dispersed, it is particularly challenging to draw connections between the different parts of the literature and distil them into a coherent overview on interdisciplinary research practices.

The framework compiles, combines, and integrates the parts of interdisciplinary literature relevant to research practice. It thereby connects these different fragmented branches of literature in a coherent manner, provides an easily accessible overview, and gives direct references to the particular branches of the literature for readers who wish to know more on a certain topic, including already existing frameworks (König et al. 2013; Clark et al. 2017; Tobi and Kampen 2018).

The framework contributes to the literature on SES research by compiling the different considerations that are important to the study of SES within the literature of SES case studies and theory. The framework also offers novel insights into the interdisciplinary components of SES research in practice, because this is the first time that the principles of SES research are explicitly presented in synthesis with the principles of interdisciplinary research. As such, the framework contributes to the science practice of SES research, rather than SES theory, yet is grounded in theoretical, practical, and empirical aspects of SES research. Hence, the framework contributes to the science of SES through its synthesis of different strands of fragmented SES literature, but also enriches the SES research practice through explicit integration of interdisciplinary research.

The papers demonstrate and operationalise three of the coping strategies in the framework through a practical application of three different methodologies into a research domain. This allows researchers gain insights into what methods can be applied for these particular coping strategies and what type of information the results of such an analysis can provide. Thereby, the papers contribute to: (1) knowledge on what method to use to apply the coping strategy; (2) knowledge on what the results of this method look like in a certain domain; (3) knowledge on what expertise is required to apply this coping strategy and method; and (4) a better understanding of the framework in general.

5.2 Using the Framework—Why, How, and by Whom?

The design principles reflect a generic interdisciplinary SES research process and should be understood as ideal-typical guidelines, rather than instructions for any given context. In addition, the order of the design principles is not strictly determined and depends on the particular research project; some steps of the process may be interdependent. For example, the research question will determine the design of the research project, which will ultimately define which disciplines should be involved.

The practical challenges are highlighted in the framework to increase awareness of these challenges and to allow researchers to put procedures in place to prevent them, or otherwise, overcome them. Depending on when and where the framework is applied, the coping strategies can be used for preventing or addressing challenges. If the framework is applied during the planning stage of a project, the coping strategies can be implemented as preventive measures. If the project is already ongoing and challenges arise during the project, the coping strategies can be applied to solve those challenges. Thus, practical coping strategies facilitate interdisciplinary SES research in practice.

The framework, including the demonstrations through Papers 1–3, can be used by different user groups and applied for different purposes, which are described below and summarised at the end of this section in Table 3.

Researchers. The primary target users of the framework are researchers. Researchers could use this framework during the **proposal writing** stage. Writing grant proposals and applying for funding are very important for interdisciplinary SES work as these types of projects commonly require large funds, often for longer periods (Pischke et al. 2017; ClimeFish 2016). Therefore, the framework could be used and applied during the thinking phase when drafting and designing projects and documenting these plans in a coherent manner and make the evaluation of the proposal easier for the external committee. The coping strategies specified in the framework could be particularly helpful for grant proposals. Calls for proposals now commonly require researchers to specify and describe any critical risks relating to the project implementation and are required to detail any risk mitigation measures[5]. The framework could be applied specifically for the risk section to identify potential practical risks (i.e. challenges) within the project, and could then also provide corresponding mitigation measures (i.e. coping strategies).

Researchers could then further apply the framework when **conducting their research**, in which the design principles could guide their practice, while coping strategies could facilitate the prevention of potential challenges or aid to overcome them if they arise. Papers 1–3 allow researchers to better assess whether any of these three coping strategies will be of value and

[5]See, e.g., section 3.2. in the template from the European Union for H2020 proposals here: https://ec.europa.eu/research/participants/data/ref/h2020/call_ptef/pt/2018-2020/h2020-call-pt-ria-ia-2018-20_en.pdf

whether the methodology and results of the papers are suitable to address or prevent their particular challenge. Researchers can also learn how to apply the coping strategy from the practical examples of the papers. Learning from examples is generally thought to be beneficial to the learning process (Lee and Hutchison 1998; Atkinson et al. 2000). The papers also make it easier to replicate coping strategies and their exemplary methodologies in a different domain.

The framework aims to facilitate research by making interdisciplinary SES research easier in practice, also with the goal in mind to help researchers to use their time more efficiently. Time is often a limiting factor in research, which often leaves researchers stressed and in haste when trying to finish their work within deadlines (Berg and Seeber 2016). Interdisciplinary approaches tend to take even more time when compared to monodisciplinary work (Pischke et al. 2017). For this reason, it is important to use research time well and efficiently. Yet, inadequate preparation for a research project can also easily lead to the wasting of time and thereby dissipate people's goodwill (Bell and Waters 2018). An application of the framework could help with better time management and planning, because it would both guide and facilitate the interdisciplinary SES research process. This means that, for example, researchers spend less time thinking about how to best plan an SES study and there will be less distraction from conflicts because of the prevention through the coping strategies. Hence, the application of the framework could minimise the time spent on challenges and frustrations, and could thereby enhance strategic thinking during research planning and design, while optimising research time.

The framework could further save time by supporting researchers in establishing a common research practice. Commonly, each discipline has its own established research practices, such as the format of meetings or the structure of papers. For interdisciplinary approaches, researchers first have to develop shared research practices, which also takes additional time and effort (Carr et al. 2018). The framework could facilitate this process by creating and providing a baseline for interdisciplinary SES research practice by providing research steps and strategies that can easily be understood and shared across disciplines. Facilitated research practice also creates a lower threshold for interested researchers to get involved and conduct interdisciplinary SES research, and could thus generate a higher uptake of the approach in general.

Consequently, the application of the framework, and the subsequent optimisation of time usage, could allow for the production of more interdisciplinary SES research within a shorter time, resulting in an overall increase of interdisciplinary SES research output. Integrative research approaches in general (Bruun et al. 2005; Darbellay 2015), and SES research in particular (Österblom et al. 2011; Jerneck et al. 2011), are thought to have high potential for discoveries and innovations supporting sustainability and conservation initiatives. Thereby, an increased SES research output could lead to increased innovation potential and an overall better understanding of SES, which could ultimately help to address many of today's societal challenges, such as climate change, food security, and biodiversity loss (United Nations 2015).

The framework also provides insights into practical skills that may be required from research (e.g. interpersonal skills, team-working skills, etc) to conduct the research. This information could be used by researchers to foster their career development by actively trying to develop these skills through learning-by-doing, or by engaging in targeted training activities to acquire them.

Through the papers, researchers can identify what expertise is required to apply these coping strategies. For example, Paper 1 and Paper 2 both make use of machine-learning techniques. This means that an application of these coping strategies using the methods of Paper 1 and Paper 2 will likely require computer scientists. Having prior knowledge of the skills and expertise requirements for coping strategies allows researchers to plan for these needs in advance, e.g. by inviting in necessary team members.

Transdisciplinary SES Researchers and Practitioners. Transdisciplinary approaches are of great importance in SES research, because they allow the inclusion of stakeholders and practitioners when addressing societal challenges (Guimarães et al. 2018; Haider et al. 2018), and ensure that the 'produced scientific solutions' are of value to the stakeholders (ClimeFish 2016). Notably, researchers working with transdisciplinary SES approaches may also find the framework valuable. According to Liehr et al. (2017), the ideal transdisciplinary research process first involves interdisciplinary integration, which is then followed by transdisciplinary integration. Hence, interdisciplinary integration is an integral part of transdisciplinary practices. Even when researchers have a lot of experience with participatory research, they might lack deeper insights into the interdisciplinary research process. For example, an approach developed by Lang et al.

(2012) provides guidance and advice for transdisciplinary research. Yet, the focus lies mainly on the participatory aspects of the science, and less on the interdisciplinary aspects. In this case, the framework could complement the suggestions by Lang et al. (2012) and provide additional guidance.

Funding bodies and organisations. Funding bodies and organisations, who provide grants for interdisciplinary SES research, are also potential users of the framework, and could apply it in two ways: (i) Funders could recommend that applicants follow the framework when **documenting and describing their research proposal** to ensure that the research process is well designed and that practical challenges are accounted for. This could be particularly relevant for call texts, in which funding is provided to address societal challenges[6], because such calls are likely to include interdisciplinary SES research to some degree (but not always). (ii) Funders could use the framework for the **evaluation process** of grant proposals for interdisciplinary SES research, to assess the quality of the proposed research.

Evaluators and Reviewers. Another potential user of the framework are evaluators and reviewers. The design principles of the framework could be used to **evaluate** grant proposals to check whether an interdisciplinary SES research project is well planned and designed, and if the required coping strategies have been accounted for.

Reviewers could use the framework to evaluate the quality of a study, for example, during peer-review of a publication. The framework could facilitate an evaluation by highlighting the aspects that are important for documentation and that need to be made explicit in interdisciplinary SES research. The criteria for the evaluation of interdisciplinary work by Lyall et al. (2011), which were incorporated into the framework, could help and guide evaluators and reviewers to fairly judge and assess an interdisciplinary SES grant proposal or publication.

Education. The framework could also be used for educational purposes by educators and teachers, but would have to be modified to fit the purpose. For example, the framework could be applied to **teaching** interdisciplinary research practices in higher education or to support

[6] See, e.g., https://ec.europa.eu/programmes/horizon2020/en/h2020-section/societal-challenges.

interdisciplinary courses and programme development. Study programmes that involve more than one discipline are increasing and require necessary interdisciplinary underpinnings (Jacob 2015). Yet, it often remains unclear in interdisciplinary education who, and how, to educate (Hall and Weaver 2001). These answers could be provided (at least in parts) by the framework, e.g. by highlighting necessary **skills** that training could be used for and how to integrate courses. Teaching interdisciplinary research practices to researchers could also increase interdisciplinary interaction, e.g. in doctoral programmes (Carr et al. 2018). As such, the framework could help to overcome the challenges of trying to train the next generation of interdisciplinary scientists (Lyall and Meagher 2012). However, detailed considerations of interdisciplinary education and training are beyond the scope of this study and the framework.

Research domains. Besides an application by different user groups, the framework could also be applied into other research domains that require an interdisciplinary approach. The framework could be adjusted by replacing the design principles and coping strategies concerning SES research with the specific requirements and considerations of the research domain in question. Possible application domains that are inherently interdisciplinary and could benefit from the framework include ethical and responsible research in artificial intelligence (Greene et al. 2019), serious games research (Wilkinson and Matthews 2016), or urban development (Vicenzotti et al. 2016).

Table 3 – Overview of the different potential user groups of the framework and suggestions for applications with an outline of potential benefits. ID = interdisciplinary, SES = social-ecological system.

Users	**Application**	**Benefits**
Primary users and applications		
Researchers	Grant proposals for ID SES research	Facilitates planning and drafting of the project outline; Easier identification of practical risks and mitigation strategies;
	ID SES Research	Guides and facilitates research practice; Optimises project preparation, planning, and research time; Minimises challenges and frustrations;
Researchers and Practitioners	Transdisciplinary SES Research	Optimise integration within transdisciplinary approach;
Funding bodies	Grant proposal templates	Ensures explicit documentation of ID SES research process;
Evaluators	Grant proposal evaluation	Highlights important aspects that need to be considered in ID SES projects; Guides evaluation through explicit criteria;
Reviewers	Peer-review	Facilitates evaluation of quality of a study
Potential users and applications where modifications of the framework are likely required		
Teachers and Educators	Teaching	Facilitates teaching about ID practices; Teaching and training in (interpersonal) skills necessary for ID SES research
	Course development	Facilitates integration during ID course development;
Researchers	ID research domain	Facilitates ID research practice;
	Career development	Highlights skills and training needs;

5.3 Limitations

The framework developed in this study has several limitations:

- Due to limited resources and time restraints, it was not possible to involve relevant user groups in the development process of the framework. The lack of co-creation and involvement of relevant users is a limitation in the methodology of the framework's development. Therefore, this study only serves as a preliminary assessment and a first step towards guiding and facilitating interdisciplinary SES research in practice.

- The framework could not be applied in practice. Hence, whether the design principles can effectively guide interdisciplinary research remains untested. The effectiveness of the coping strategies to prevent and overcome practical challenges with regard to the design principles is also unclear. Yet, many of the coping strategies were identified within empirical case studies, such as Climefish and SAF21. This means that these strategies have already been applied and shown to be of some value, at least in the context of these projects.

- The framework synthesises different strands of literature from interdisciplinary and SES research, but does not claim completeness for the design principles nor provides a complete list of practical challenges or coping strategies. Therefore, some design principles may be lacking, while others might need more detailed consideration. Also, it is likely that there are more practical challenges and coping strategies in the literature that could be added to the framework, but have not been identified at this stage.

- One of the main challenges when working in an interdisciplinary context is integration itself and how to integrate. Integration can be done in many ways, which is why there is not one generic way of doing it and there cannot be a standard solution for how to implement integration (Bruun et al. 2005). Hence, the design principle C3: *Integration* cannot guide integration itself but can only provide ways that can facilitate integration. This is a limitation of the framework.

- Only three of the coping strategies could be demonstrated through the papers with a specific methodology. Hence, the remaining coping strategies lack an example of methodology that could be used for these particular strategies; they also lack examples of an application into a research domain through a paper. The papers were chosen based on available expertise. Therefore, the selection of the coping strategies and the methodologies for the papers were limited by the available expertise.

5.4 Future Work

Future work to overcome some of the current limitations, and to further develop and improve the framework could include the following:

- The methodology for the framework could be expanded to further develop and validate this preliminary framework through co-creation and the involvement of relevant users. Potential users could apply and test the framework, de-construct it, and re-construct it with possible adjustments and changes, to ensure that it can fit their needs and be used as a practical tool.

- The framework could be tested and validated entirely through an application to a real-world research project, both during the grant proposal stage as well as during the project lifetime. This would allow to identify if and which of the suggested design principles and coping strategies are helpful and those that may need adjustment and improvement.

- Scientific output is produced in large amounts and faster than ever. Therefore, it is likely that the framework will have to be updated with current literature to include recent developments and findings within interdisciplinary and SES research.

- Specific methods and research examples (e.g. papers) should be provided for all the coping strategy (not only three) to further operationalise the framework. Practically, this could be done by adding a column to the framework with suggestions for methodologies that could be applied for each coping strategy. The methods should then be demonstrated in practice, e.g. through publications that have used this approach (as was done with Papers 1–3), or by conducting additional research (e.g. in the form of papers) with additional team members and added expertise. Then, interested researchers would already have a concrete method that they could turn to, or even a study that they could replicate and utilise within their own research project for the application of the coping strategies.

- The framework could be expanded to transdisciplinarity and participatory approaches in SES research, for example, by integrating and building on the work by Lang et al. (2012) on transdisciplinary research principles, and by Newton and Elliott (2016) on how to identify and select relevant stakeholder groups.

6 Conclusions

SES research is important for understanding and addressing some of today's complex problems and societal challenges. Yet, practical barriers often hinder SES research when trying to study SES effectively in an interdisciplinary manner. Therefore, practical guidance on how to conduct such an approach and how to overcome practical barriers is required.

This study has developed a preliminary framework to guide and facilitate interdisciplinary SES research in practice. The framework presents practical design principles for the SES research practice, highlights challenges when applying these practices, and provides practical coping strategies to prevent or overcome these practical challenges.

The review approach of the study highlights how there are many practical lessons to be learned for interdisciplinary SES research from the already existing case studies, projects, and researchers' experiences, which were synthesised in the framework. This synthesis allows for the experiences from individual studies and researchers from different fields to guide and contribute to the practice of SES research. Besides practical guidance, the framework also provides a first overview of key aspects of interdisciplinary SES research in practice, which makes it easier for inexperienced researchers to familiarise themselves with the concepts and practices of both interdisciplinary and SES research.

Selected coping strategies of the framework are demonstrated by providing practical examples of methodologies that could be used to apply these strategies in practice. The framework could be used for different purposes and by different user groups. Researchers and other users are encouraged to apply the framework to explore its benefits, validity, and possibly deconstruct, expand, adjust, or diversify it according to their needs and experiences.

The application of the framework could have many potential benefits, including easier SES research practice, increased SES research uptake, optimised research time, and, perhaps, an increase in SES research studies and output. This could advance interdisciplinary SES research as a field, and ultimately lead to a better understanding of SES in general, and a better understanding of how to address some of today's societal challenges, in particular.

7 Self-Assessment

7.1 Interdisciplinary Communication & Documentation

The study aims to follow the recommendations for communication and documentation that were established in the framework of this study. Therefore, a **glossary** is presented (see page viii) to establish a common set of terms with a clearly defined meaning, and to facilitate interdisciplinary communication. The practice of **open science** is pursued for transparency, replicability, and easier understanding of the approaches developed in the study. Therefore, the code from Paper 1 is available on GitHub[7]. Paper 1 is also published as open access, while the other papers have been submitted to full open-access journals with the intention of also making the data and code available upon publication. The interdisciplinarity in this study is made explicit through **documentation of interdisciplinarity** based on a typology, described below.

Interdisciplinarity in this Study. This study follows an interdisciplinary approach. For the purpose of the framework development, the focus was on empirical interdisciplinarity, which describes research that integrates different kinds of empirical data (Huutoniemi et al. 2010). This approach was applied by extracting and integrating empirical evidence from the literature and from two EU-funded projects to investigate the relationships between interdisciplinarity and SES research in practice.

Papers 1–3 follow the path of methodological interdisciplinarity, whereas 'methods from different fields are combined in order to test a hypothesis, answer a research question, and/or develop a theory' (Bruun et al. 2005, p.84). The term 'method' can refer to both a concrete method or a more general research strategy (Klein 2010).

A taxonomic analysis of interdisciplinarity in relation to this study is provided in the form of a typology. The typology and indicators used to assess interdisciplinarity in this study are based on Huutoniemi et al. 2010 (see Table 4).

Data science was largely involved in this study, which is already an interdisciplinary field on its own (O'Neil and Schutt 2014), combining scientific methods from mathematics, statistics, information

[7] https://github.com/shaheen-syed

science, and computer science, and requiring domain expertise as well as communication and visualisation skills (Hayashi 1998; O'Neil and Schutt 2014). Additional methods were drawn from the fields of medical science (systematic literature review) and social sciences (coding, content analysis, enumeration), and both quantitative and qualitative approaches were applied.

Table 4 – Taxonomic analysis of interdisciplinarity in this study. Typology and indicators according to Huutoniemi et al. 2010. FW=framework, refers to framework developed in this study; SES=social-ecological system

Typology	Indicator	Example
Scope of Interdisciplinarity - conceptual and cultural distance between the participating research fields)	**narrow** - participating fields are conceptually close to each other	Paper 1 (computer science & fisheries science); Paper 2 (computer science & computational linguistics)
	broad - conceptually diverse fields that cross the boundaries of broad intellectual areas	Paper 3 (fisheries science & social science); FW (interdisciplinarity & SES); This study as a whole
Type of Interdisciplinarity - categories of interdisciplinary interaction differ from each other, such as data or knowledge from different research fields being brought together	**empirical** - different kinds of empirical data are synthesised in a novel, integrated manner	FW
	methodological - different methodological approaches are combined in a novel, integrated manner	Papers 1, 2, 3; This study as a whole
Type of Goals - different interdisciplinary research goals	**epistemological** - intent to increase the knowledge about the research object	Papers 1, 2, 3
	mixed orientation - combination of both kinds of orientation: epistemological and instrumental	FW; This study as a whole

7.2 Personal Reflections

At the beginning of this research, I stood as a biologist. However, this interdisciplinary study required me to study a diverse field of disciplines and domains, including social-ecological systems, interdisciplinary studies, research practices, and fisheries science. In addition, the methodological approach required additional efforts to gain knowledge and understanding in the field of computer science and qualitative methods. It was challenging at times to navigate the different disciplinary theories and practices, especially those of disciplines furthest away from my own, such as the social sciences and humanities. As such, it was also not my intent to dwell on the depths of social science theories and concepts. Nevertheless, this interdisciplinary path has certainly widened my scientific horizons as well as my understanding of other domains, disciplines, and methodologies.

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Paper 1

Using Machine Learning to Uncover Latent Research Topics in Fishery Models.

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Using Machine Learning to Uncover Latent Research Topics in Fishery Models

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ABSTRACT

Modeling has become the most commonly used method in fisheries science, with numerous types of models and approaches available today. The large variety of models and the overwhelming amount of scientific literature published yearly can make it difficult to effectively access and use the output of fisheries modeling publications. In particular, the underlying topic of an article cannot always be detected using keyword searches. As a consequence, identifying the developments and trends within fisheries modeling research can be challenging and time-consuming. This paper utilizes a machine learning algorithm to uncover hidden topics and subtopics from peer-reviewed fisheries modeling publications and identifies temporal trends using 22,236 full-text articles extracted from 13 top-tier fisheries journals from 1990 to 2016. Two modeling topics were discovered: estimation models (a topic that contains the idea of catch, effort, and abundance estimation) and stock assessment models (a topic on the assessment of the current state of a fishery and future projections of fish stock responses and management effects). The underlying modeling subtopics show a change in the research focus of modeling publications over the last 26 years.

KEYWORDS

Topic models; latent Dirichlet allocation; fisheries science; fisheries models; research trends

1. Introduction

Global research efforts have increased significantly in recent years (Oecd, 2008), as has publication output within fisheries science (Aksnes and Browman, 2016). This growth has been partly driven by growing concerns about the state of fish stocks and the need to provide information for policy and decision makers globally. Since each fish stock is typically unique, and experimental approaches cannot be used to predict their response to fishing, it follows that the modeling and simulation of fisheries play a major role in providing management advice; these are among the most frequently used methods in fisheries science (Jarić et al., 2012). Models offer a feasible approach to the approximation of trends and processes, and they advance the understanding of fisheries and ecosystem dynamics (Angelini and Moloney, 2007) while guiding data collection and illuminating core uncertainties (Epstein, 2008). For this reason, and in contrast to common perceptions, a multitude of fisheries models is available besides standard stock assessment models, and these models take on many different shapes and forms depending on their method and purpose. Such models may include individual-based models to investigate fleet behavior (Bastardie et al., 2014); Bayesian belief networks to better understand stakeholder viewpoints and perceptions (Haapasaari et al., 2012); or conceptual models to analyze fisheries from a socio-ecological complex adaptive system perspective (Ostrom, 2009; Partelow, 2015).

The frequent use of models and their wide range of applications, in combination with the growing global collections of scholarly literature, have led to an ever-increasing number of publications on the various types of models and approaches. As a result, scientists are suddenly faced with millions of publications, overwhelming their capacity to effectively use these collections and to keep track of new research (Larsen and von Ins, 2010). Online collections can be browsed and explored using keyword searches, through which publications can be collected manually; however, in addition to being time-consuming, the size and growth of the body of research often has the effect of limiting the possibility of identifying all the relevant literature. Another problem is that the underlying topic of an article is not readily available in most collections. Thus, the topic of an article – that is, the idea underlying the article, which may be shared with similar articles – cannot always be detected using

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keyword searches (Srivastava and Sahami, 2009). Given such challenges, an assessment of the field of fisheries models could reveal overlooked research topics, identify important changes in research directions (i.e., trends), assess the diversity of topics in publication outlets, and ultimately help in identifying new and emerging modeling topics. Furthermore, an improved understanding of fisheries modeling approaches could help researchers to more easily synthesize historical and current research developments.

The developments and trends in fisheries science and fishery models are usually assessed through reviews (e.g., Bjørndal et al., 2004; Prellezo et al., 2012) and bibliometric studies (Jarić et al., 2012; Aksnes and Browman, 2016). These types of studies have several limitations, such as taking into account only a limited number of publications (e.g., only 61 publications, Gerl et al., 2016); a limited time period (e.g., from 2000 to 2009, Jarić et al., 2012); a limited scope or very specialized focus (e.g., stock assessment methods, Cadrin and Dickey-Collas, 2015; bio-economic models, Prellezo et al., 2012; models of an ecosystem approach to fisheries, Plagányi, 2007; and models of the Celtic Sea, Minto and Lordan, 2014). Other limitations include proxies for full text such as titles (Jarić et al., 2012) and abstracts (Aksnes and Browman, 2016), and proxies for research topics such as one word per topic (Jarić et al., 2012; Aksnes and Browman, 2016). Most importantly, previous attempts to identify trends in fisheries and fisheries modeling are based on top-down approaches, in which research topics are predefined by the researcher (Debortoli et al., 2016), such as region, species, habitat, or study area. Such approaches are prone to human subjectivity; researchers may end up with different results (Urquhart, 2001), or the mapping of text features to categories may not be explicitly known (Quinn et al., 2010).

This study aims to overcome the limitations of previous approaches by applying a bottom-up approach in which research topics automatically emerge from the statistical properties of the documents. In doing so, the topics are automatically uncovered without prior human labeling, categorization, or predefined classification of publications, and they are thus not biased by researchers' top-down subjective choices. For this purpose, a probabilistic topic model algorithm called latent Dirichlet allocation (LDA) (Blei et al., 2003), which belongs to the field of unsupervized machine learning algorithms, was used to reveal research topics within the field of fisheries models that are published in peer-reviewed journals and have a strong focus on fisheries. Topic model algorithms can automatically uncover hidden or latent thematic structures (i.e., topics) from large collections of documents. The unsupervized nature of LDA allows documents to "speak" for themselves, and topics emerge without human intervention. They have proven to be very useful in automatically identifying and interpreting scientific themes in relation to the journal's existing themes or categories (Griffiths and Steyvers, 2004).

By utilizing unsupervized machine learning, this study aims to provide comprehensive information on topical trends within fisheries modeling research for fisheries scientists and stakeholders. In particular, this study analyzes 22,236 full-text scientific publications published within the period from 1990 to 2016 in 13 top-tier fisheries journals. Thus, a unique dataset for the field of fisheries models was created, and topics in fisheries modeling and their underlying subtopics were identified to determine historical and current research interests. In addition, the species, areas, and methods occurring within the identified topics were assessed.

2. Methods

2.1. Latent Dirichlet allocation

The LDA model is a generative probabilistic topic model that represents documents (i.e., fisheries publications) as discrete distributions over K latent topics; each topic is subsequently represented as a discrete distribution over all the words (i.e., vocabulary) used. The words with high probability within the same topic are frequently co-occurring words, which can be seen as clusters or constellations of words that are often used to describe an underlying topic or theme (DiMaggio et al., 2013). In this way, LDA captures the heterogeneity of research ideas or topics within publications. The topics and their relative proportions within documents are hidden (i.e., latent) variables that LDA infers from the observable variables – that is, the words within the documents. The generative process behind LDA involves an imaginary random process, through which documents are created based on probabilistic sampling rules. The topics and their proportions are subsequently inferred from these generated documents by applying statistical inference techniques, such as variational and sampling-based algorithms (Blei and Jordan, 2006; Teh et al., 2006; Hoffman et al., 2010; Wang et al., 2011). LDA extends other popular topic model algorithms such as Latent Semantic Indexing (LSI) (Deerwester et al., 1990) and probabilistic Latent Semantic Indexing (pLSI) (Hofmann, 1999) while also overcoming their limitations. An explanation of LDA's generative process can be found in Appendix 1.

The LDA model makes two assumptions when analyzing and uncovering latent topics from documents. First, documents are represented as "bags of words" (i.e., unordered lists of words) in which the word order is neglected. Although this is an unrealistic assumption, it is reasonable if the aim is to uncover semantic structures from text (Blei and Lafferty, 2006; Blei, 2012). Consider a thought experiment where one imagines shuffling all the words in a document. Even when shuffled, one might find words such as "population," "size," "virtual," "minimum," and "recruitment" and expect that the document deals with aspects of population dynamics. One of the core underlying principles of LDA is based on word co-occurrences, and a small number of co-occurring words is sufficient to resolve problems of ambiguity. Second, LDA assumes that the order in which documents are analyzed is unimportant (i.e., document exchangeability is assumed); however, at the end of the analysis, all documents are analyzed. As a result, LDA is unable to explicitly capture the evolution of topics over decades or centuries of work. This would require a more complicated and computationally expensive dynamic topic model (Blei and Lafferty, 2006), which is currently not feasible given the large dataset; however, this is a potential approach for future work. Document exchangeability is a limitation in the case of topics whose presentation in the literature has dramatically changed (e.g., in terms of the terminology used to describe the topic), but it still captures the phenomenon by which current literature builds upon previous literature. Nonetheless, the assumption of document exchangeability is especially problematic when analysing topics that span 50–100 years of research.

2.2. Topic interpretation

The topics emerge from the statistical properties of the documents and the statistical assumptions behind LDA. The topics are represented as discrete distributions over all the words, in which the top words (e.g., top 15) for each topic – that is, the words with the highest probability and those that more frequently co-occur together – provide insights into the semantic meaning of the topic. Topics are thus a reference to these probability distributions over words to exploit text-oriented intuitions. No epistemological claims are made beyond this representation. Furthermore, by no means is the topic distribution over words limited to these top 15 words; in fact, every word occurs in every topic, but with different probabilities. The topics are used to uncover the themes prevailing the documents, as well as the extent to which such themes are present in each document. In doing so, the main ideas of a publication can be extracted and used to track how they have developed over time. Note that the underlying topics and to what extent the document exhibits these topics are not known in advance. These details are the output of the LDA analysis and emerge automatically from the statistical properties of the documents and the assumptions behind LDA.

2.3. Creating the dataset

This paper aims to identify latent fisheries modeling topics from scientific research articles published in peer-reviewed journals specializing in fisheries. In this manner, the selection of publications was restricted exclusively to fisheries journals; therefore, it follows that some subjective choices were made to achieve this. All journals included in this analysis contain the term "fishery" or "fisheries" in their title and have an impact factor of 1.0 or higher. Additionally, the journal *The ICES Journal of Marine Science* was included, because it is part of the International Council for the Exploration of the Seas (ICES), which channels science-based advice to decision makers for sustainable fisheries, and fisheries models are an important focus of this journal. A total of 13 fisheries journals were included in the study (see Table 1). A time frame of 26 years, from 1990 to 2016, was chosen to allow for enough variation within publication trends. Due to difficulties with journal subscription rights and the fact that some journals started after 1990 (e.g., *Fish and Fisheries* was first published in 2000), coverage was incomplete for the complete time range of 26 years for a few journals. Documents that did not constitute a type of research article (e.g., book reviews, forewords, errata, conference reports, comments, policy notes, corrigenda, and letters) were discarded. In total, 22,236 full-text research articles from 13 top-tier fisheries journals were downloaded using automated download scripts, as well as by utilizing the available application programming interfaces (APIs) offered by the publishers. The use of full-text articles, in contrast to only using abstracts, has shown to increase topic quality and provide a more detailed overview of the latent topics permeating a document collection (Syed and Spruit, 2017). Table 1 provides an overview of the complete dataset utilized in this study.

The selection of fisheries journals and underlying fisheries publications comes with some limitations. First, some of the highly influential and most cited papers on fisheries models are published in high-impact journals such as *Nature, Science*, and *PNAS*. Although highly influential, such publications would constitute only a small number of our sample and would only marginally or even negligibly contribute to the overall number of 22,236 publications downloaded from fisheries journals for this study. Two other reasons exist to exclude such generic journals. The first reason is that including all publications published in such outlets would drastically

Table 1. Overview of the dataset (i.e., corpus): years represent the years for which documents (i.e., articles) are downloaded; IF, the journal's impact factor according to ISI Journal Citation Reports 2016; *N*, the number of documents; *N/T*, the percentage of journal articles in relation to the total number of articles; $\overline{W}$, the mean number of words within each document; Std. W, the estimated standard deviation of words within each document; and $\overline{V}$, the mean vocabulary size (number of unique words) within each document. The total number of documents is 22,236.

Journal	Years	IF	*N*	*N/T*	$\overline{W}$	Std.W	$\overline{V}$
Canadian Journal of Fisheries and Aquatic Sciences	1996–2016	2.44	4427	19.9%	4075.5	1305.5	1266.7
Fish and Fisheries	2000–2016	8.26	419	1.9%	5892.9	2801.4	1757.4
Fisheries	1997–2016	2.43	477	2.1%	3409.9	1633.2	1312.3
Fisheries Management and Ecology	1994–2016	1.51	1001	4.5%	2692.2	1135.7	955.5
Fisheries Oceanography	1997–2016	2.73	752	3.4%	3866.7	1353.8	1187.8
Fisheries Research	1995–2016	2.23	3610	16.2%	3204.4	1326.3	1064.4
Fishery Bulletin	1990–2016	1.51	1441	6.5%	3356.3	2037.0	1074.4
ICES Journal of Marine Science	1990–2016	2.63	3903	17.6%	3379.8	1378.7	1118.9
Marine and Coastal Fisheries	2009–2016	1.44	274	1.2%	4473.7	1363.8	1368.0
North American Journal of Fisheries Management	1997–2016	1.01	2517	11.3%	3288.9	1420.9	1036.6
Reviews in Fish Biology and Fisheries	1991–2016	3.22	659	3.0%	5799.8	3994.4	1750.1
Reviews in Fisheries Science & Aquaculture	1997–2016	2.03	375	1.7%	6185.6	6020.2	1737.3
Transactions of the American Fisheries Society	1997–2016	1.47	2381	10.7%	3887.8	1382.4	1202.7
		Total	22,236				

increase the number of uncovered topics, as fisheries make up a small portion of the publications in *Nature, Science* and *PNAS*. While one might be able to use keyword searches and include only those publications that match fisheries-related terms, this brings up the second reason to exclude such journals: publication filtering is based on the subjective choice of relevant keywords and is limited in terms of how publications are indexed and subsequently can be retrieved (e.g., title, abstract, or full text) from these journals. Through the inclusion of publications from only fisheries journals, such subjective choices and associated limitations are avoided.

The second limitation concerns the exclusion of non-fisheries-specialized journals in which fisheries-modeling-related publication might appear. Such journals focus on, but not limited to, the field of marine science (e.g., *Marine Policy* and *Advances in Marine Biology*), the field of coastal areas or zones (e.g., *Coastal Management* and *Ocean and Coastal Management*), the field of toxicology (e.g., *Environmental Toxicology and Pharmacology* and *Aquatic Toxicology*), and the field of modeling (e.g. *Environmental Modelling & Software* and *Ecological Modelling*), in addition to a number of other journals, such as *Developmental Dynamics, Bulletin of the American Meteorological Society, Environmental Science and Technology, Philosophical Transactions of the Royal Society, Environmental Health Perspectives, BioScience, Journal of Fish Biology*, and *Progress in Oceanography*. Some publications related to fisheries modeling approaches are published in these outlets, which is a potential limitation of this study. Again, filtering for fisheries modeling publications in these journals would be biased by the subjective choice of keywords and limitations due to indexing and retrieval functionalities. Consequently, publications with a focus on the novelty in modeling approaches, which are commonly published in specialized modeling journals such as *Ecological Modeling*, were not assessed in this study. On the other hand, the modeling publications captured within the fisheries journals included in this study can potentially address other topics besides fisheries, such as climate change or habitat loss, which are likely to be included in the analysis of modeling publications.

The third limitation relates to the focus on peer-reviewed journals only. As a result, fisheries modeling research that appears in grey literature was excluded. As grey literature is not indexed in the same way as peer-reviewed studies, selecting only relevant grey literature would, again, introduce bias due to human subjectivity in the search and retrieval.

2.4. Preprocessing the dataset

Several important preprocessing steps were required to transform the documents into appropriate bag-of-word representations. First, each document was converted from PDF format into a plain-text representation. Image-based PDFs, mainly old documents from the 1990s, were converted using the Tesseract optical character recognition (OCR) library. Second, documents were tokenized, which involved creating individual words (e.g., from paragraphs and sentences); meanwhile, numbers, single characters, punctuation marks, and words with only a single occurrence were removed, since they bear no topical meaning. Additionally, words that occurred in $\geq$90% of the documents were discarded due to their lack of distinctive topical significance (see Appendix 2). Boilerplate content, such as title pages, article metadata, footnotes, margin notes and so on, was also removed. The reference list of each article was maintained so as to allow for referenced titles and names of authors to be part of the word distributions of topics. An advantage of this approach is that author names can be part of specific topics, but they can simultaneously introduce bias when the referenced articles have no direct link to the underlying topics. A standard English stop word list ($n = 153$) was used to remove words that serve only syntactical and grammatical purposes, such as *the, and, were*, and *is*. Finally, other than grouping lowercase and uppercase words, no normalization method was applied, such as stemming or lemmatization, to reduce the inflectional and derivational forms of words to a common base form (e.g., *fishing* and *fishery* to *fish*). Normalization reduces the interpretability of topics at later stages, as stemming algorithms can be overly aggressive and may result in unrecognizable words when interpreting topics. Stemming might also lead to another problem, as it cannot be deduced whether a stemmed word comes from a verb or a noun (Evangelopoulos et al., 2012). For these reasons, and considering that the interpretability of the topics at a later stage was considered to be highly significant, an extensive normalization phase was omitted.

2.5. Creating LDA models

The LDA models were created with the Python library Gensim (Rehurek and Sojka, 2010). The number of topics to be uncovered (i.e., K parameter) varied from 1 to 50, thus creating 50 different LDA models. The hyper-parameters for the LDA models, which affect the sparsity of the topics created and their relative proportions, were set to be symmetrical. Technically, since LDA is a Bayesian probabilistic model, the symmetrical hyper-parameters encode prior knowledge that a priori assign equal probabilities to topics within documents, and words within topics. The quality of each topic was calculated using a topic coherence measure to find the optimal value for K (analogous to finding the right number of clusters, e.g., K-nearest neighbors). A coherence measure calculates the degree of similarity between a topic's top N words. This provides a quantitative approach for assessing the interpretability of topics from a human perspective. As such, coherence measures aim to find coherent topics – a topic with top words *apple, pear*, and *banana* is more coherent than *apple, pear*, and *car* – rather than topics that are merely artefacts of the statistical assumptions behind LDA. The C_V coherence measure was adopted, since it has shown the highest accuracy of all available coherence measures (Röder et al., 2015). An elbow method was employed to find the K value with the best performing topic coherence score. A detailed description of the C_V coherence measure can be found in Appendix 3.

2.6. Identifying subtopics

For each modeling topic identified, a zoom-in was employed with the aim of uncovering underlying subtopics within each of the general modeling topics by applying an approach similar to that described above. These subtopics provide a more detailed deconstruction of the respective general modeling topics. A zoom-in is performed on a subset of the data consisting of documents that have the general modeling topic as the dominant topic. The dominant topic is defined as the topic with the highest relative proportion – that is, the topic that exceeds all other topic proportions within a document. Since documents are modeled as mixtures of topics, the dominant topic represents the primary topic of a document.

2.7. Labeling the topics

The LDA model outputs the uncovered topics as probability distributions over all the words used; when sorted, the top 15 words are used to label the topic semantically. Representing the words as probabilistic topics has the distinct advantage that each topic is now individually interpretable (Griffiths et al., 2007), compared to a purely spatial representation like the topic model of latent semantic analysis (Deerwester et al., 1990). As stated before, the distributions of words, and specifically the words with the highest probability within each topic, are used to describe an underlying theme; however, such themes are latent, and a semantic label that best captures those words needs to be attached. For example, a topic with the top 5 words *apple, banana, cherry, pear*, and *mango* describes the underlying theme of fruits and can be labeled as such.

To provide a semantically meaningful and logical interpretation of these probability distributions, a fisheries domain expert manually labeled the topics by close inspection of the top 15 high-probability words, together with an inspection of the document titles and content. Furthermore, to improve the labeling of the topics, the topics were visualized in a two-dimensional area by computing the distance between topics (Chuang et al., 2005) and applying multi-dimensional scaling (Sievert and Shirley, 2014). This two-dimensional topic representation aided in identifying similarities between topics and thus similarities between topic labels.

2.8 Calculating subtopical modeling trends

To gain insight into the subtopical temporal dynamics of the modeling subtopics, document topic proportions were aggregated into a composite topic-year proportion.

Such composite values provide insights into the prevalence of a modeling subtopic within a certain year, given all the publications within that year. It furthermore enables the analysis of changing topic proportions over the course of 26 years, as proportions increase or decrease for each subtopic and for each year. Additionally, to obtain insight into increasing and decreasing topical trends, a one-dimensional least square polynomial was fitted for different time intervals. The time intervals chosen were 1990–1995, 1995–2000, 2000–2005, 2005–2010, and 2010–2016, so as to allow for historical comparison. The polynomial coefficient is used as a proxy for the trend and defines the slope of the composite topic-year proportions for a range of years. Coefficients are multiplied by the number of years within each time interval to obtain the change measured in percentage points. Positive values indicate increasing or "hot" topics, and negative values indicate decreasing or "cold" topics. Color coding is used to represent the hot (i.e., red) and cold (i.e., blue) topical trends.

(1) ESTIMATION MODELS

word	prob.
MODEL	.015
ESTIMATES	.014
CATCH	.012
SURVEY	.008
SAMPLING	.008
ESTIMATED	.008
MODELS	.007
ESTIMATE	.007
DISTRIBUTION	.007
ABUNDANCE	.006
MEAN	.006
EFFORT	.006
SAMPLE	.005
METHOD	.005
SIZE	.005

(2) STOCK ASSESSMENT MODELS

word	prob.
MODEL	.024
STOCK	.014
MORTALITY	.014
POPULATION	.012
RECRUITMENT	.011
MODELS	.010
BIOMASS	.007
YEAR	.007
RATE	.007
MANAGEMENT	.007
PARAMETERS	.006
ASSESSMENT	.006
FISHERIES	.006
ESTIMATES	.006
FISHING	.005

Figure 1. The two uncovered fisheries modeling topics (i.e., estimation models and stock assessment models) from the dataset containing 22,236 fisheries publications (1990–2016; 13 journals). The figure displays the topic label (top) and the top 15 high-probability words.

3. Results and discussion

3.1. General modeling topics

The optimal LDA model for the complete corpus (N = 22,236 documents) uncovered 31 general fisheries topics. The calculated coherence scores to obtain the optimal number of topics, referred to as the K parameter, can be found in Appendix 3. Among these general fisheries topics, two topics deal with the aspects of fisheries modeling. The publications dealing with these two modeling topics account for 12% ($N = 2761$ documents) of the total number of publications. The remaining 29 topics, which relate to other aspects of fisheries research, are listed in Appendix 4. A bibliometric analysis of trends in fisheries science found a higher proportion of publications employing models – around 30%, as estimated from publication titles and abstracts from a dataset containing 695 fisheries-related publications (Jarić et al., 2012). Several reasons can be offered to explain why these two percentages differ, such as the used time range and the selected journals; most importantly, the present paper identifies publications which predominantly deal with fisheries modeling aspects, in contrast to publications in which a modeling method is employed.

Figure 1 shows the top 15 words and their probabilities for the two modeling topics. The first modeling topic concerns catch-effort and abundance estimation methods and is, therefore, given the short name estimation models. It contains the words "catch," "survey," "sampling," "effort," and "sample" among its top 15 words. These words reflect the collection of both fisheries-independent data, which are usually gathered through survey and sampling methods, and fisheries-dependent data (e.g., collected through logbooks), which commonly provide information on catch and effort. These and other obtained data feed into models in order to estimate intermediate parameters such as natural mortality rate or catchability (Hoggarth et al., 2006); this is a phase of research reflected in estimation models through the words "model," "estimates," "estimated," and "estimate." These types of models might also be called retrospective models, since they interpret the past based on collected data.

The second modeling topic concerns modeling approaches for the assessment of the current state of a fishery and future projections and is assigned the short name "stock assessment models." It contains the words "stock," "mortality," "biomass," "rate," and "estimate," which reflect the most commonly used indicators (i.e., fish catch, stock biomass, stock size, and fishing mortality; Hoggarth et al., 2006) to measure the status of the fishery and the state of the stock (Le Gallic, 2002). These indicators link to reference points, which give quantitative meaning to the goals and objectives set for a fishery (Jennings, 2005). Reference points are usually estimated through models that use stock and recruitment data, which is reflected in the words "stock," "population," "recruitment," "management," "parameters," and "estimates" in stock assessment models. Together, indicators and reference points play a crucial role in fisheries management and can be used to give quantitative meanings to the objectives of a fishery (Hoggarth et al., 2006).

The distinction between these two topics shows how they are treated separately in fisheries research

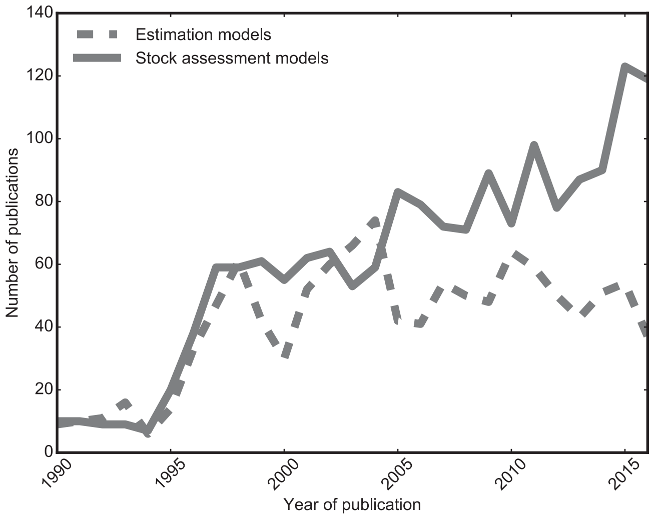

Figure 2. The number of publications per year for publications related to the topic estimation model and stock assessment model.

publications, whereas in practice (i.e., in fisheries stock assessments for management), these two topics are connected and combined into one model but reflect the different phases of the model development (Hoggarth et al., 2006). The distribution of publication frequencies for both general modeling topics is shown in Figure 2, which highlights the increased research interest in stock assessments models compared to estimation models. Additionally, the top five publications with the highest topic prevalence for each of the two modeling topics, indicating to what extent the content of a publication relates to the modeling topic, are shown in Table 2.

Interestingly, only the topics of estimation models and stock assessment models were uncovered (both of which focus on the ecological dimension of fisheries), whereas topics on economic and social fisheries aspects were not found within the modeling publications. This finding might be a result of the selection of journals used in this study. Most of the included fisheries journals declare a multi-disciplinary or interdisciplinary scope, while some specifically include socioeconomic considerations and the human dimension as subjects of interest. Therefore, at least one social or economic modeling topic could be expected to be identified by the LDA model. Another reason for the absence of other modeling topics may be that fisheries are still perceived as a natural science. The ICES only recently established the Strategic Initiative on the Human Dimension (SIHD) "to support the integration of social and economic science into ICES work" (ICES, 2017), and the majority of the ICES workgroups still lack social science input (ICES, 2016). As a result, social scientists and economists may pursue publication of their models not in a journal related to fisheries, but rather in a journal related to their respective disciplines or having a broader scope, such as *Ecology and Society, Marine Resource Economics* or *Marine Policy*. Merit issues could also contribute to the topic bias. Different scientific disciplines receive publication merits for different journals, which is more often dependent on the index of a journal (e.g., Science Citation Index (SCI), Social Science Citation Index (SSCI), or International Scientific Index (ISI)) than on its impact factor. As a result, non-biological and non-ecological disciplines are less likely to use top-tier fisheries journals as publication outlets. This might, in turn, lead to low visibility of non-ecological models among fisheries stakeholders, because many fisheries journals such as *Fish and Fisheries* and *Fisheries Research* intend to reach fisheries managers, administrators, policy makers, and legislators.

Table 2. Publication title, year, and topic prevalence (in percentages) for the five publications with the highest topic prevalence for each general modeling topic.

Modeling Topic	Title	Year	Prevalence
Estimation models	- Trawl survey based abundance estimation using datasets with unusually large catches.	1999	95.69%
	- Covariances in multiplicative estimates.	1999	94.35%
	- Use of simulation–extrapolation estimation in catch–effort analyses.	1999	93.90%
	- Reducing bias and filling in spatial gaps in fishery dependent catch per unit effort data by geostatistical prediction I methodology and simulation.	2014	92.23%
	- Confidence intervals for trawlable abundance from stratified-random bottom trawl surveys.	2011	90.48%
Stock assessment models	- The structure of complex biological reference points and the theory of replacement.	2009	99.37%
	- Analytical models for fishery reference points.	1998	98.50%
	- Implications of life-history invariants for biological reference points used in fishery management.	2003	98.14%
	- The estimation and robustness of FMSY and alternative fishing mortality reference points associated with high long-term yield.	2012	97.33%
	- Age-specific natural mortality rates in stock assessments: size-based vs. density-dependent.	2014	94.87%

(1) CATCH AND ABUNDANCE

word	prob.
MODELS	.013
CATCH	.011
ABUNDANCE	.008
SPECIES	.007
YEAR	.006
DEPTH	.006
EFFECTS	.005
CPUE	.005
VARIABLES	.005
SPATIAL	.004
LONGLINE	.004
LINEAR	.004
ENVIRONMENTAL	.004
EFFECT	.004
RATES	.004

(2) MORTALITY RATE (TAGS)

word	prob.
TAG	.016
MORTALITY	.014
RATES	.013
TAGGING	.013
RATE	.012
TAGS	.009
TAGGED	.009
MOVEMENT	.008
REPORTING	.006
MODELS	.006
YEAR	.006
FISHING	.006
RELEASE	.006
PARAMETERS	.005
FISHERY	.005

(3) ABUNDANCE (SURVEYS)

word	prob.
SPATIAL	.015
SURVEY	.011
ABUNDANCE	.009
DENSITY	.009
AREA	.009
ACOUSTIC	.007
VARIANCE	.007
SURVEYS	.006
SAMPLING	.006
DISTANCE	.005
BIOMASS	.005
RANDOM	.005
ESTIMATION	.004
SEA	.004
KM	.004

(4) RECREATIONAL FISHERIES

word	prob.
CATCH	.023
EFFORT	.015
FISHING	.012
SAMPLING	.012
SURVEY	.010
ANGLERS	.008
HARVEST	.007
SURVEYS	.007
RATE	.007
ANGLER	.007
FISHERY	.006
RECREATIONAL	.006
DAY	.005
VARIANCE	.005
LAKE	.005

(5) PARAMETERS AND ESTIMATORS

word	prob.
ERROR	.011
ABUNDANCE	.010
YEAR	.009
STOCK	.007
VARIANCE	.007
CATCH	.007
POPULATION	.006
MODELS	.006
INDEX	.006
YEARS	.005
ERRORS	.005
BIAS	.005
INDICES	.005
SAMPLE	.004
REGRESSION	.004

(6) SAMPLING

word	prob.
SAMPLING	.011
FISHING	.010
SPECIES	.010
FISHERY	.009
BYCATCH	.008
CATCH	.008
TRIP	.006
TRIPS	.006
OBSERVER	.006
VESSELS	.006
EFFORT	.005
SHRIMP	.005
LANDINGS	.005
VESSEL	.004
COMMERCIAL	.004

(7) ABUNDANCE (SAMPLING)

word	prob.
SAMPLING	.009
ABUNDANCE	.008
POPULATION	.007
BAYESIAN	.007
POSTERIOR	.007
PROBABILITY	.006
SPECIES	.006
CATCHABILITY	.006
MODELS	.006
CAPTURE	.006
DENSITY	.006
PRIOR	.005
SITES	.004
PARAMETERS	.004
ELECTROFISHING	.004

(8) FISH DISTRIBUTION

word	prob.
CATCH	.015
FISHING	.014
EFFORT	.013
FISHERY	.013
CPUE	.011
AREA	.011
COD	.011
ABUNDANCE	.010
CATCHABILITY	.009
BIOMASS	.008
STOCK	.006
AREAS	.006
SEASON	.006
CRAB	.006
RATES	.006

(9) SPAWNING

word	prob.
SPAWNING	.017
EGG	.014
EGGS	.012
PRODUCTION	.008
DAY	.007
STAGE	.007
BIOMASS	.006
LARVAE	.006
SAMPLING	.005
MORTALITY	.005
DAILY	.005
SAMPLES	.005
LARVAL	.005
TEMPERATURE	.004
FEMALES	.004

(10) NET SELECTIVITY

word	prob.
SELECTIVITY	.026
MESH	.013
LENGTH	.012
NET	.010
GILLNET	.009
SELECTION	.009
CATCH	.008
GEAR	.008
CURVE	.008
NETS	.007
CURVES	.007
GILL	.006
PARAMETERS	.006
MM	.006
RELATIVE	.006

(11) VESSELS AND FLEET

word	prob.
FISHING	.026
CATCH	.016
VESSEL	.012
EFFORT	.010
VESSELS	.010
FISHERY	.008
FLEET	.006
SPECIES	.006
CPUE	.006
POWER	.005
AREA	.004
YEAR	.004
MODELS	.004
RATE	.004
INFORMATION	.003

(12) TRAWL SURVEYS

word	prob.
SURVEY	.021
TRAWL	.019
SAMPLING	.013
SPECIES	.011
SURVEYS	.008
BOTTOM	.007
SAMPLE	.006
TOW	.006
LENGTH	.006
EFFICIENCY	.005
DESIGN	.005
AREA	.005
CATCH	.005
DENSITY	.005
TOWS	.005

(13) LENGTH AND GROWTH

word	prob.
LENGTH	.015
GROWTH	.014
PARAMETERS	.010
SAMPLE	.008
PARAMETER	.006
SAMPLES	.006
LIKELIHOOD	.006
ERROR	.005
MODELS	.005
STOCK	.005
FUNCTION	.005
DISTRIBUTIONS	.004
ESTIMATION	.004
STANDARD	.004
SET	.003

(14) SALMON

word	prob.
SALMON	.016
RIVER	.009
COUNTS	.007
SAMPLING	.007
ABUNDANCE	.007
RUN	.006
SURVEY	.005
SPAWNING	.004
POPULATION	.004
YEARS	.004
CHINOOK	.004
COUNT	.004
SAMPLE	.004
STREAM	.004
ESTIMATOR	.004

Figure 3. The 14 uncovered subtopics from the documents ($N = 1124$) exhibiting the topic estimation models as the dominant topic. The figure displays the subtopic label (top) and the top 15 high-probability words.

3.2. Subtopics within estimation models

The zoom-in (i.e., the process of uncovering subtopics from general topics) on the general topic of estimation models ($N = 1124$ documents) identified 14 subtopics (see Appendix 3). Figure 3 provides an overview of the 14 estimation model subtopics, the top 15 words of the topics with their probabilities, and the manually attached label that best captures the semantics of the top words. Furthermore, a two-dimensional topic representation can be found in the topic similarity map in Figure 4A, showing the topic similarity with respect to the distribution of the words. The trends (i.e., the change in overall topic proportion, in percentage points) and prevalence (i.e., the size of the overall topic proportion as a percentage) are presented in Figure 5A.

Most of the uncovered subtopics can be grouped. The principal group consists of the five subtopics focusing on the biological aspects of fisheries (i.e., catch and abundance, mortality rate (tags), fish distribution, spawning, and length and growth). This highlights the importance and scientific focus of the biological dimension in fisheries research. Catch and abundance shows the biggest overall increase over time (+15.46%) and had the largest proportion (14.84%) within the last six years (Figure 5A). Most of the other biological subtopics show very little variation over time, and some

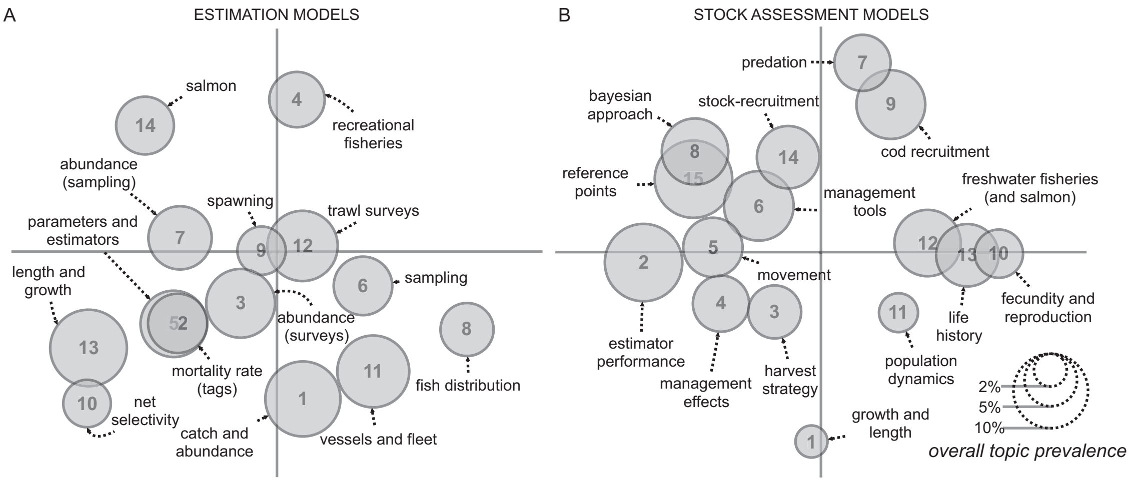

Figure 4. Topic similarity map that shows a two-dimensional representation (via multi-dimensional scaling). **A**: 14 estimation model subtopics. **B**: 15 stock assessment model subtopics. The distance between the nodes represents the topic similarity with respect to the distributions of the words (i.e., nodes closer together have more related word probabilities). The surface of the nodes represents the prevalence of the topic within the corpus.

only make a small contribution in terms of proportion (e.g., spawning), with only 3.82% overall topic proportion (Figure 5A). Length and growth showed the highest overall decrease over time (−14.04%), indicating a diminishing scientific interest. The subtopic of length and growth remained relatively high in terms of topic proportion, with an average of 9.13% between 2010 and 2016, possibly because growth is an important parameter for stock assessments (Lorenzen, 2016; Maunder et al., 2016) and is also most frequently discussed in fisheries, as shown by a previous trend analysis

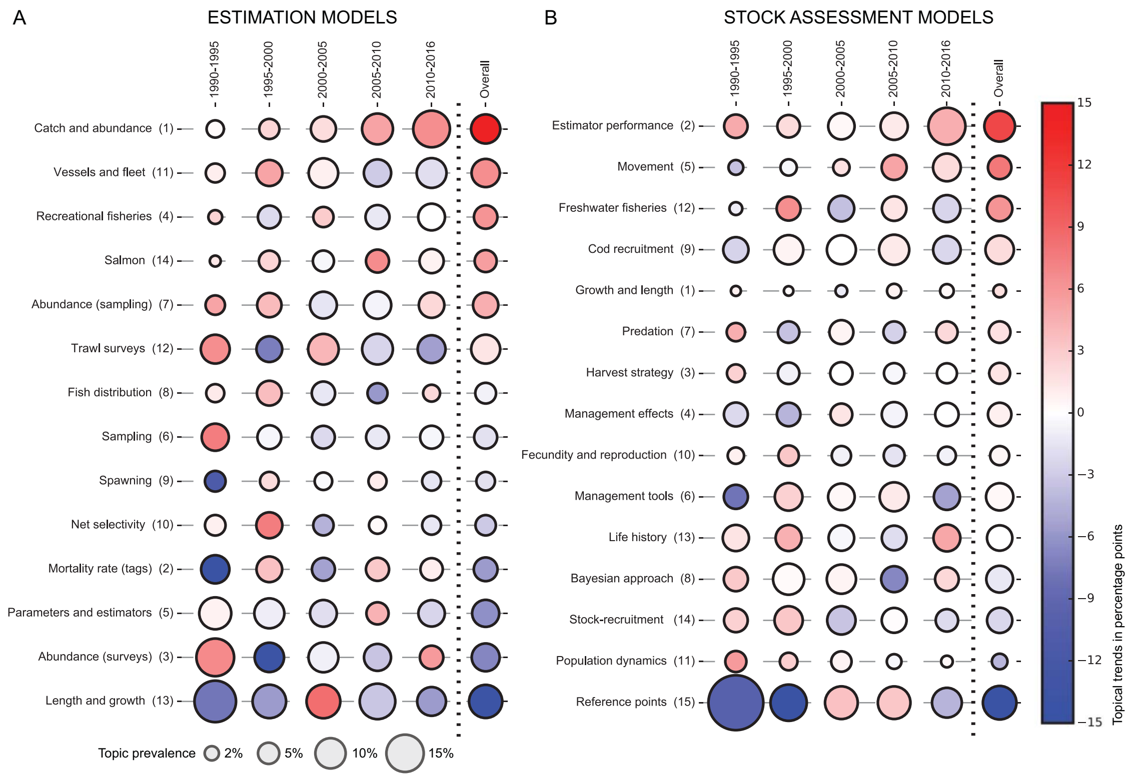

Figure 5. Trends in changing topic proportions for different time intervals for all subtopics. The left-hand side (**A**) displays the 14 uncovered estimation model subtopics. The surface of the node represents the topic prevalence within a certain time range and indicates how present a topic was within all the published material of that time frame. The colors indicate the trend in topic proportion (i.e., change in percentage points) and indicate whether a topic increased in popularity (hot topic) or decreased in popularity (cold topic) within that time frame. The right-hand side (**B**) displays the information for the 15 uncovered stock assessment model subtopics.

(Jarić et al., 2012). The subtopic of parameters and estimators relates more to the technical aspects of estimation modeling, but appears to be similar to the biological subtopic of mortality rate, as apparent from the similarity map (Figure 4A). Vessel and fleet showed a large topic proportion (between 8% and 10%) over the last 16 years (Figure 5A). Both the topic of vessel and fleet and that of net selectivity likely relate to biological considerations, but they could also hint at a slightly more economic perspective on industry (fleet) and gear-related matters; however, additional words such as "firm," "prices," or "market" would have to be present to confirm this hypothesis further. The four subtopics of abundance (survey), sampling, abundance (sampling), and trawl survey focus on survey and sampling, which are essential methods for gathering data and information on fisheries. In particular, information on catch and stock abundance is required by almost all stock assessment models (Hoggarth et al., 2006). These four subtopics account for a combined overall topic prevalence of 30.73%, indicating their importance to fisheries research. The subtopic of recreational fisheries refers to a type of fishery that differs in the estimation process compared to commercial fisheries, as it often employs surveys on anglers. This type of estimation process may refer not only to marine but also to freshwater fisheries. Recreational fisheries underwent an increase in topic proportion from 2.11% in the 1990–1995 period to 7.90% in the 2010–2016 period, indicating the growing importance of recreational fisheries assessments in fisheries science. The increased importance of recreational fishing on the commercial fish stocks (Griffiths and Fay, 2015) is in line with the observed trend in this study. Apart from recreational fisheries, no other types of fisheries (e.g., small-scale, artisanal, or commercial fisheries) were identified by the topic model. The distance of recreational fisheries from the other subtopics in the similarity map may explain this, as authors writing about recreational fisheries use distinctive words that are different from the discourse on other types of fisheries. Another possible explanation may be that there are more studies on recreational fisheries than on other types of fisheries. Salmon is the only topic that focuses on one particular species. The similarity map shows how the topic of salmon differs within the words used, indicating the particularity and specialized research niche of the topic (Figure 4A). Salmon showed a positive trend (+5.61%) over the study period; however, this result is in conflict with previous research that showed a diminishing research interest in the species (Jarić et al., 2012). This could be due to the increasing effort within aquaculture and the growing economic importance of the species over the period (FAO, 2016) that separates this study from that of Jarić, Cvijanović, Knežević-Jarić, and Lenhardt (2012).

Within the top 15 words of the subtopics, important subjects such as species and names/methods can be identified. Three subtopics contain species names (i.e., "shrimp" in sampling, "cod" and "crab" in fish distribution, and "salmon" and "chinook" in salmon). Methods mentioned within the subtopics of estimation models are "regression" in parameters and estimators and "Bayesian" in abundance (sampling). Parameters for fish stock assessments can be estimated through the least square method, represented in the form of regression analysis; however, maximum likelihood methods are now preferred, as they allow for a better specification in the form of errors in the models. Bayesian methods are commonly used to incorporate uncertainty into management advice, but this could also involve other methods such as maximum likelihood, bootstrapping, or Monte-Carlo modeling (Hoggarth et al., 2006). The two methods "regression" and "Bayesian" do not reflect the current diversity of modeling methods, nor necessarily the most conventional models used in fisheries assessments today, but they seem to have a strong association with the two topics of parameters and estimators and abundance (sampling). Note that references to names of species and methods highlight the importance and relation of such words within a specific topic – technically, they co-occur more frequently to describe the latent topic – but are by no means mutually exclusive (i.e., methods and species can occur in different subtopics simultaneously). They provide information from a topical perspective (i.e., a high-level decomposition of the document into clusters of co-occurring words), but fail to address on what basis such species and methods are linked within a specific topic.

3.3. Subtopics within stock assessment models

The zoom-in on the topic of stock assessment models ($N = 1637$ documents) revealed 15 subtopics (see Appendix 3 for the calculated topic coherence scores). Figure 6 provides an overview of the 15 subtopics, the top 15 words with their probabilities, and the label attached to each topic. The topic similarity for these subtopics can be found in Figure 4B. The subtopic trends and prevalence are displayed in Figure 5B.

Most of the subtopics of stock assessment models evolve around biological aspects and processes (i.e., growth and length, movement, predation, cod recruitment, fecundity and reproduction, population dynamics, life history, and stock recruitment). The majority of these subtopics show a slight increase over the study period (Figure 5B); together, these subtopics have an overall topic proportion of 42.91%, which shows their consistent importance within fisheries science and fisheries management (Hilborn and Walters, 1992). Within the biological subtopics, predation stands out as the only subtopic that refers to "interaction," "multi-species," and the "ecosystem." The subtopic of predation increased by 4.67% during the period from 1990 to 1995

(1) GROWTH AND LENGTH

word	prob.
GROWTH	.017
MM	.007
ABALONE	.006
LENGTH	.006
HARVEST	.005
PARAMETER	.004
ABUNDANCE	.004
BASS	.004
MEAN	.004
INDIVIDUAL	.004
LAKE	.003
MAXIMUM	.003
ENHANCEMENT	.003
RELEASE	.003
STUDY	.003

(2) ESTIMATOR PERFORMANCE

word	prob.
SELECTIVITY	.011
BIOMASS	.010
RECRUITMENT	.010
CATCH	.010
ERROR	.007
ESTIMATION	.006
RELATIVE	.006
BIAS	.006
PERFORMANCE	.005
FISHING	.005
PUNT	.005
TRUE	.005
SURVEY	.005
SIMULATION	.005
ASSESSMENTS	.005

(3) HARVEST STRATEGY

word	prob.
FISHING	.008
CATCH	.007
CRAB	.007
BIOMASS	.006
SHARK	.006
LOBSTER	.006
RECRUITMENT	.004
MEAN	.004
SHARKS	.004
FLOUNDER	.004
ABUNDANCE	.004
GROWTH	.003
MATURE	.003
RATES	.003
MALE	.003

(4) MANAGEMENT EFFECTS

word	prob.
FISHING	.013
CATCH	.011
LENGTH	.010
EFFORT	.006
LANDINGS	.004
GULF	.004
CATCHES	.004
SOUTH	.004
YIELD	.003
BIOMASS	.003
STUDY	.003
REFERENCE	.003
ESTIMATE	.003
STOCKS	.003
EXPLOITATION	.003

(5) MOVEMENT

word	prob.
SPATIAL	.008
TUNA	.007
MOVEMENT	.006
FISHING	.006
TAGGING	.006
RATES	.006
DISTRIBUTION	.005
ABUNDANCE	.005
TAG	.005
INFORMATION	.004
AREA	.004
SURVEY	.004
ATLANTIC	.004
CATCH	.004
ASSUMED	.003

(6) MANAGEMENT TOOLS

word	prob.
FISHING	.017
EFFORT	.011
HARVEST	.011
CATCH	.008
YIELD	.008
AREA	.007
AREAS	.006
BIOMASS	.006
OPTIMAL	.005
TARGET	.005
CONTROL	.004
POLICY	.004
RECRUITMENT	.004
LEVEL	.004
LEVELS	.004

(7) PREDATION

word	prob.
BIOMASS	.015
PREDATION	.014
PREY	.012
ECOSYSTEM	.010
FISHING	.009
PREDATOR	.008
FOOD	.007
TROPHIC	.006
MULTISPECIES	.006
PREDATORS	.006
COMMUNITY	.006
CONSUMPTION	.006
ABUNDANCE	.005
INTERACTIONS	.004
SEA	.004

(8) BAYESIAN APPROACH

word	prob.
PARAMETER	.008
DISTRIBUTION	.008
BAYESIAN	.007
PRIOR	.007
POSTERIOR	.007
UNCERTAINTY	.007
SERIES	.006
ERROR	.005
PROBABILITY	.005
PROCESS	.005
DISTRIBUTIONS	.005
FUNCTION	.005
LIKELIHOOD	.004
INFORMATION	.004
EXAMPLE	.004

(9) COD RECRUITMENT

word	prob.
COD	.022
RECRUITMENT	.013
SEA	.010
FISHING	.007
NORTH	.006
STOCKS	.006
SPAWNING	.006
ATLANTIC	.005
HERRING	.005
ENVIRONMENTAL	.005
SSB	.004
TEMPERATURE	.004
CHANGES	.004
BALTIC	.004
POPULATIONS	.004

(10) FECUNDITY AND REPRODUCTION

word	prob.
SPAWNING	.018
EGG	.015
REPRODUCTIVE	.014
FECUNDITY	.014
SURVIVAL	.013
LIFE	.009
EGGS	.008
LARVAL	.008
PRODUCTION	.008
RECRUITMENT	.008
STAGE	.007
POTENTIAL	.006
LARVAE	.006
MATURITY	.006
EFFECTS	.006

(11) POPULATION DYNAMICS

word	prob.
GROWTH	.013
SHRIMP	.012
RECRUITMENT	.009
BAY	.006
OYSTER	.006
SEA	.005
FISHING	.005
ABUNDANCE	.004
TEMPERATURE	.004
SQUID	.004
MM	.004
POPULATIONS	.004
BIOMASS	.004
RATES	.003
ANIMALS	.003

(12) FRESHWATER FISHERIES (AND SALMON)

word	prob.
LAKE	.012
SALMON	.011
RIVER	.011
POPULATIONS	.009
SURVIVAL	.009
RATES	.007
TROUT	.007
HABITAT	.006
ABUNDANCE	.005
DENSITY	.005
HARVEST	.005
LAKES	.004
ADULT	.004
CHINOOK	.003
RECRUITMENT	.003

(13) LIFE HISTORY

word	prob.
GROWTH	.041
LENGTH	.015
LIFE	.008
INDIVIDUALS	.006
HISTORY	.006
RATES	.005
MEAN	.005
MATURATION	.005
INDIVIDUAL	.005
BERTALANFFY	.004
BODY	.004
POPULATIONS	.004
CM	.004
ECOLOGY	.004
MATURITY	.004

(14) STOCK-RECRUITMENT

word	prob.
RECRUITMENT	.016
PACIFIC	.010
STOCKS	.008
ENVIRONMENTAL	.008
SALMON	.008
ABUNDANCE	.006
SARDINE	.006
ANCHOVY	.005
SERIES	.005
SPAWNING	.005
BIOMASS	.005
CLIMATE	.004
VARIABILITY	.004
RICKER	.004
MEAN	.004

(15) REFERENCE POINTS

word	prob.
FISHING	.011
BIOMASS	.010
REFERENCE	.008
CATCH	.008
STOCKS	.007
RECRUITMENT	.007
POINTS	.006
YIELD	.006
MSY	.005
SSB	.005
PRODUCTION	.004
EFFORT	.004
SEA	.003
FMSY	.003
MAXIMUM	.003

Figure 6. The 15 uncovered subtopics from the documents ($N = 1637$) exhibiting the topic stock assessment models as the dominant topic. The figure displays the subtopic label (top) and the top 15 high-probability words.

(Figure 5B), which reflects the increased scientific awareness of predator–prey interaction and model implications in the early 1990s (e.g., Yodzis, 1994). The topic proportion of predation shows a positive trend, as it rose from 3.75% in the period of 1990–1995 to 5.07% in the period of 2010–2016; this might indicate the increased attention of the scientific community to an ecosystem approach to fisheries and the implementation of multi-species and ecosystem considerations within stock assessments, modeling frameworks, and management advice (Maynou, 2014; Möllmann et al., 2014; Gaichas et al*i*, 2017). The four subtopics of harvest strategy, management effects, management tools and reference points all concern management measures and effects, but they mainly address biological components such as "recruitment," "abundance," and "biomass." Reference points shows the strongest overall negative trend of all subtopics (−26.55%), indicating that the popularity of this topic among fisheries scientists has decreased over the years. Nevertheless, the topic of reference points still makes up a relatively large proportion, 9.82% (Figure 5B); this is the second largest proportion in the period of 2010–2016 after estimator performance, which has a 15.19% topic proportion within the same period. This highlights the continuity of research on reference points from the 1990s to the present day (Caddy and Mahon, 1995; Caddy, 2004; Froese et al., 2017). The subtopic of estimator performance shows the highest increase (+11.11%) within the overall study period (i.e., 1990–2016) and makes up a large proportion within the last six years of the time frame, from 2010 to 2016 (15.19%); this finding could be related to the increased overall importance of models in fisheries science (Jarić et al., 2012). The subtopic of freshwater fisheries shows an overall positive trend (+6.28%), even though freshwater fisheries habitats have been found to be less studied than marine fisheries (Jarić et al., 2012). The topic proportion of freshwater fisheries rose over the study period, from 1.82% in 1990–2000 to 8.08% in 2010–2016 (Figure 5B). The importance of freshwater fisheries in areas such as Africa and India may explain the increase in research efforts within this field (FAO, 2016).

From the top 15 words (Figure 6), related subjects were identified, such as regions, species, and names/methods. The two marine regions mentioned are "Atlantic" and "Pacific," possibly because these are some of the world's major fishing areas (FAO, 2016). The various species names found within the top 15 words, such as "cod," "herring," and "anchovy," cover many of the commercially important species in marine capture production (FAO, 2016). These results stand in stark contrast to a bibliometric study on trends in fisheries science, which found virtually no research on many commercially important species (Aksnes and Browman, 2016); however, these results were based on word frequencies in publication titles and abstracts, which may not mention the species of concern. This finding highlights the strength of the full-text LDA analysis. Other mentioned species, such as "abalone," "lobster," and "shark," may have high probabilities for occurrence in the subtopics because they represent species of great economic value and also are often a focus of conservation efforts (Turpie et al., 2003; Simpfendorfer and Dulvy, 2017).

Several names within the words of the subtopics refer to a method named after a scientist, e.g., "Bayesian," "Bertalanffy," "Ricker," and "Punt," which could be a direct consequence of the inclusion of the reference list in the analysis. The subtopic of Bayesian approach indicates the importance of this methodology in fishery science and for fisheries models. A Bayesian approach can be used for stock assessments and decision analysis and resembles an improved way of fitting models to data and decision-making (Hoggarth et al., 2006). The scientists von Bertalanffy and Ricker both made substantial contributions to fisheries science – von Bertalanffy in metabolism and growth (von Bertalanffy, 1957) and Ricker in the computation and interpretation of computational statistics of fish populations (Ricker, 1975). Their methods are still applied today in the form of growth models (Allen, 1966; Piner et al., 2016) and in stock-recruitment models (Baker et al., 2014). The author Punt has not developed any particular method that takes his name; however, his name may occur within the top 15 words due to his significant contribution to research and his publications on estimator performance and data standardization, as well as his many citations by other scientists within the field. Although Punt is, relatively speaking, a newcomer compared to some of the early influential researchers in the field (e.g., Hjort, Beverton, and Holt), the occurrence of his name is perhaps a result of the timeframe examined, or it may indicate that the names of senior scientists and methods have become somewhat common knowledge and are therefore not always explicitly stated or cited.

4. Conclusions

The aim of this paper was to uncover fisheries modeling topics from 22,236 scientific publications from 13 peer-reviewed fisheries journals. Additionally, subtopics from general modeling topics were uncovered to provide insights into their developments and trends over the last 26 years. Overall, two main fisheries modeling topics were identified: estimation models and stock assessment models. This study demonstrates that research in the field of fisheries modeling shows a shift of scientific focus in topics and subtopics over the last 26 years. Stock assessment models are outperforming estimation models, and their underlying subtopics have moved from length and growth to catch and abundance, and from reference points to estimator performance over the last 26 years. Economically important species and areas show a high presence within the modeling subtopics.

Both general modeling topics focus primarily on the biological aspects of fisheries; however, since this study was limited to publications in 13 fisheries journals, other topics in fisheries modeling (e.g., with a focus on social, management or economic aspects of fisheries) may well exist in publications of other journals. Possible disciplinary merit issues and the remaining understanding of fisheries as a natural science discipline might further limit fisheries journals to models with an ecological focus, despite their multi-disciplinary scope.

In conclusion, this novel machine learning approach revealed interesting insights into the topical trends of a large dataset of models published in fisheries journals. This approach enables researchers to identify research topics and shifts in research focus, and it provides a bigger picture that captures the main ideas prevailing scientific publications.

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Appendix 1

Generative Process of LDA

The generative process of LDA is described below:

1. For each topic
   a. Draw a distribution over all the words, $\beta_K \sim \mathrm{Dir}(\eta)$
2. For each document
   a. Draw a distribution over topics $\theta_d \sim \mathrm{Dir}(\alpha)$ (per-document topic proportion)
   b. For each word in the document
      i. Draw a topic $z_{d,n}$ from θ_d (per-word topic assignment)
      ii. Draw a word $w_{d,n}$ from that topic

Each topic is a multi-nomial distribution over all the words and arises from a Dirichlet distribution β_k $\mathrm{Dir}(\eta)$. Additionally, each document is represented as a distribution over the topics and arises from a Dirichlet distribution $\theta_\mathrm{d} \sim \mathrm{Dir}(\alpha)$. The Dirichlet parameter η defines the smoothing of the words within topics, and α defines the smoothing of the topics within documents. The per-word topic assignment $z_{d,n}$ is the topic drawn from the per-document topic proportions (Step 2a) for the n-th word in the d-th document. The joint distribution of the observed words w_D and the hidden variables β_K (topics), θ_D (document topic proportions), and z_D (word topic assignments) becomes:

$$p\ (\beta_K, \theta_D, z_D, w_D) = \prod_{k=1}^{K} p(\beta_K \mid \eta) \prod_{d=1}^{D} p(\theta_d \mid \alpha) \prod_{n=1}^{N} p(z_{d,n} \mid \theta_d)\, p\big(w_{d,n} \mid z_{d,n}, \beta_{d,k}\big) \tag{1}$$

The per-word topic assignment $z_{d,n}$ depends on the per-document topic proportion θ_d it draws a topic for each word from the previously drawn per-document topic proportion. As a result, the generative process creates documents that contain multiple topics in varying proportions. The drawn word $w_{d,n}$ depends on the per-word topic assignment $z_{d,n}$ (it draws a word from the previously drawn topic) and all the topics β_K (the probability of $w_{d,n}$ (row) is retrieved from $z_{d,n}$ (column) within the $K \times V$ topic matrix).

Equation 1 shows the joint probability of all the hidden and observed variables and the encoded statistical assumptions underlying LDA. The process now is to infer the hidden variables from the observed variables in order to obtain the topics and topic proportions per document. The inference is based on the conditional probability of the hidden variables given the observed words, also known as the posterior distribution (see Equation 2). Moreover, this inference can be viewed as a reversal of the generative process, and it tries to identify the structure likely to have generated the data.

$$p(\beta_K, \theta_D, z_D \mid w_D) = \frac{p(\beta_K, \theta_D, z_D, w_D)}{p(\ w_D)} \tag{2}$$

Unfortunately, the posterior is intractable to compute (Blei et al., 2003) due to the denominator. The marginal probability $p(w_D)$ is the sum of the joint distribution over all instances of the hidden structure and is exponentially large (Blei, 2012). The computational problem now is to estimate the posterior distribution using statistical inference techniques. Several methods exist, such as variational and sampling-based algorithms, for achieving a sufficiently close approximation of the true posterior (Blei and Jordan, 2006; Teh et al., 2006; Hoffman et al., 2010; Wang et al., 2011). Variational methods place a family of probability distributions onto the latent structure and aim to find the distribution closest to the true posterior, measured with, for example, Kullback–Leibler (KL) divergence. Sampling-based inference is a repeated sampling process, generally using one variable at a time while fixing the other variables, until the process converges; the sample values will have the same distribution as if they came from the true posterior. An example of sampling-based inference is the Gibbs sampler (Griffiths and Steyvers, 2004), a Markov chain Monte Carlo (MCMC) algorithm. It is important to note that both variational and sampling-based approaches provide similarly accurate results (Asuncion et al., 2012).

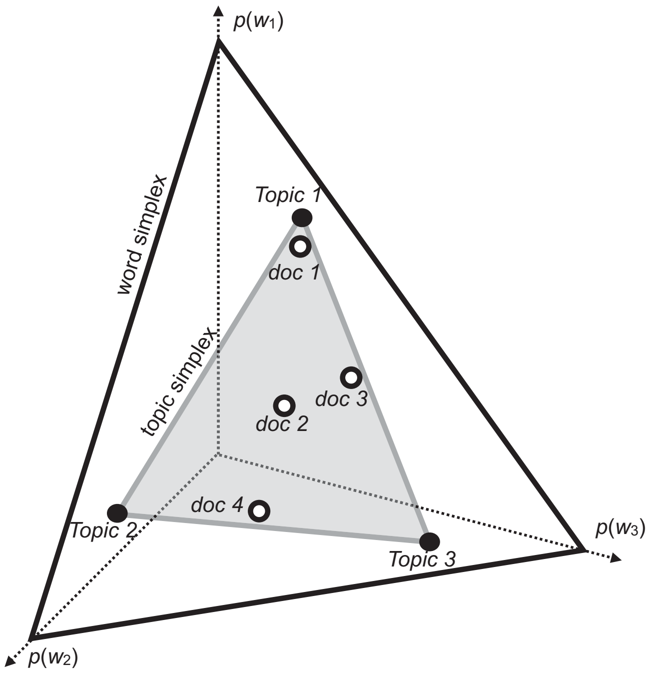

Figure 7. Geometric interpretation of LDA, showing a (V-1)-dimensional word simplex with $V = \{w1, w2, w3\}$, in which every point on the simplex represents a discrete distribution of word probabilities. A point closer to one of the corners indicates that more probability mass is placed on that word. Similarly, within the word simplex a topic simplex can be found, in which a topic represents some probability distribution over all the words (three words in this example). The documents, represented as distributions over topics, are placed within the (K-1)-dimensional topic simplex. As such, each document is represented as a discrete probability distribution over K topics, which in this example is three.

Figure 7 displays a simplified geometric interpretation of LDA. The vocabulary V contains just three words (w_1, w_2, w_3) and is represented as a (V-1)-dimensional word simplex. In reality, the word simplex contains many dimensions, as the vocabulary can easily contain thousands of words. The word simplex relates to all the probability distribution of words. Similarly, Figure 7 illustrates how the topics, modeled as distributions of the vocabulary, are positioned within the word simplex. The example shows three topics T, represented as a (T-1)-dimensional topic simplex. The documents, modeled as distributions over the topics, are points on the topic simplex. For example, Document 1 deals almost entirely with Topic 1; Document 2 exhibits all three topics in equal proportions; and Document 3 has equal proportions of Topics 1 and 3 but none of Topic 2. Note that this only holds if the topic simplex is defined by a uniform Dirichlet distribution that assigns equal probability mass to all topics. The shapes of the Dirichlet distributions within the word simplex and topic simplex are given by η and α, respectively.

Appendix 2

See Table 3

Table 3. The words that occurred in ≥90% of the documents and that are thus eliminated from the study. Words that occur in almost every document have no significant topical distinctiveness, and including them would cause these words to dominate every topic. *N* is the number of publications.

Dataset	*N*	Words
Overall	22,236	of, and, for, to, the, in, with, is, from, as, this, that, on, are, at, be, an, or, not, was, have, these, were, which, also, between, been, than, all, other, it, more, has, their, but, two, used, research, however, only, can, one, both, each, most, data, when, study, using, such, into, some, number, they, during, where, analysis, there, time, different, high, fish
Estimation models	1124	with, from, as, is, in, of, and, this, for, be, the, to, are, an, at, on, each, not, that, used, or, which, data, was, between, all, also, than, these, more, were, can, two, using, it, number, have, methods, when, but, where, been, fish, both, one, other, however, fisheries, only, if, analysis, their, has, based, because, estimated, such, estimates, different, estimate, use, research, total, some, there, same, size, over, distribution, mean, values, time, then, most, would, into, large, they, new, small, model, could, similar, given, within, study, three, first, those, method
Assessment models	1637	from, an, as, is, in, on, of, and, this, that, for, the, to, be, are, with, not, at, or, have, which, used, it, than, between, also, can, when, these, more, fish, all, where, but, was, however, has, fisheries, other, data, been, two, using, model, research, only, were, such, population, one, each, if, analysis, both, based, values, time, their, some, most, because, different, stock, would, models, there, number, over, management, given, marine, year, size, parameters, into, years, use, methods, first, value, dynamics, mortality, they, assessment, new, biological, then, same, rate, could, estimates, estimated, high, natural, fishery, similar, available, approach, those, should, large, total, its, will, we, species

Appendix 3

Calculating Model Quality

C_V uses four stages to arrive at an overall topic score: (1) segmentation of the topic's top N words into pairs; (2) probability calculations of individual words or pairs of words; (3) calculation of a confirmation measure that captures the agreement of pairs; and finally (4) aggregation of individual confirmation measures into an overall topic coherence score.

(1) The first step is to segment the data into word subsets to calculate the degree of support between two subsets. C_V segments each word in W with every other word in W, where W is the set of a topic's top 15 words. This segmentation creates pairs, S, where the left subset is $W' \in W$ and the right subset is $W^* \in W$. All pairs are formally defined as $S = \{(W', W^*) \mid W' = \{w_i\}; w_i \in W; W^* = W\}$. For example, if W = {salmon, catch, tag}, then one pair might be $S_i = (W', W^*)$ as W' = {salmon} and W^* = {salmon, catch, tag}.

(2) The probabilities of single words $p(w_i)$ and the joint probability of two words $p(w_i, w_j)$ can be estimated using Boolean document calculation – that is, the number of documents in which w_i or (w_i, w_j) occurs divided by the total number of documents. A Boolean document, however, ignores the frequencies and distances of words. C_v incorporates a Boolean sliding window in which a new virtual document is created for each window of size $s = 110$ (Röder et al., 2015) when sliding over the document, with one word token per step. For example, a document d_1 with w words results in the virtual documents $d'_1 = \{w_1, \ldots, w_{110}\}$, $d'_2 = \{w_2, \ldots, w_{111}\}$, etc. In contrast to a Boolean document, a Boolean sliding window tries to capture word token proximity to some degree.

(3) For every $S_i = (W', W^*)$ a confirmation measure ϕ is calculated that indicates how strongly W^* supports W' and this confirmation measure is based on the similarity of W' and W^* in relation to all the words in W. To calculate this similarity, W' and W^* are represented as context vectors (Aletras and Stevenson, 2013) as a means to capture the semantic support for all the words in W. These vectors are denoted by $\vec{v}(W')$ and $\vec{v}(W^*)$ and are created by pairing them to all words in W, as exemplified in Equation 3:

$$\vec{v}(W') = \left\{ \sum_{w_i \in W'} \mathrm{NPMI}(w_i, w_j)^{\gamma} \right\}_{j=1,\ldots,|W|} \quad (3)$$

Given the running example of W = {salmon, catch, tag}, this can be demonstrated with the pair $S_i = (W', W^*)$ as W' = {salmon} and W^* = {salmon, catch, tag}. One of these context vectors is $\vec{v}(W') = \vec{v}(salmon)$, now represented as $\vec{v}_{\text{salmon}}$ = {NPMI (salmon, salmon)$^{\gamma}$, NPMI (salmon, catch)$^{\gamma}$, NPMI (salmon, tag)$^{\gamma}$}.

The coherence between the individual words w_i and w_j is calculated using normalized pointwise mutual information (NPMI), as expressed in Equation 4. In

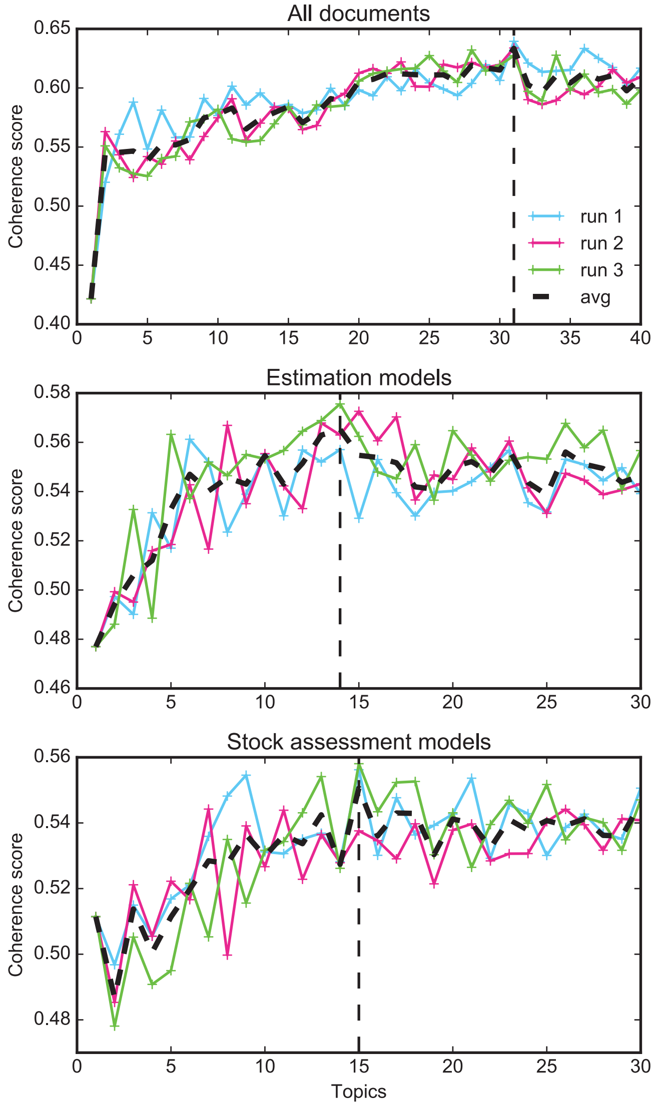

Figure 8. Calculated coherence scores (y-axis) for the number of topics (x-axis) (i.e., K parameter) for three different runs. The average coherence score is calculated by averaging the scores over all three runs for the same K parameter. The figures represent the following: A: all documents (N = 22,236); B: documents that exhibit the topic estimation models as the dominant topic (N = 1124); C: documents that exhibit the topic stock assessment models as the dominant topic (N = 1637).

contrast to pointwise mutual information (PMI), NPMI shows a higher correlation with human topic ranking data (Bouma, 2009). Additionally, $\varepsilon = 10^{-12}$ (Stevens et al., 2012) is used to account for logarithms of zero, and γ is used to place more weight on higher NPMI values.

$$\mathrm{NPMI}\left(w_i, w_j\right)^{\gamma} = \left(\frac{\log \frac{P\left(w_i, w_j\right) + \varepsilon}{P(w_i) \cdot P\left(w_j\right)}}{-\log\left(P\left(w_i, w_j\right) + \varepsilon\right)}\right)^{\gamma} \quad (4)$$

Within a pair $S_i = (W', W^*)$, utilizing all context vectors $\vec{v}\left(W'\right)$, denoted here as $\vec{u}$, and utilizing all context vectors $\vec{v}(W^*)$, denoted here as $\vec{w}$, the cosine vector similarity ϕ_{S_i} is calculated in order to obtain the confirmation measure of the pair $S_i = (W', W^*)$. The cosine vector similarity is expressed in Equation 5.

$$\phi_{S_i}\left(\vec{u}, \vec{w}\right) = \frac{\sum_{i=1}^{|W|} u_i \cdot w_i}{\|\vec{u}\|_2 \cdot \|\vec{w}\|_2} \quad (5)$$

(4) Finally, the arithmetic mean of all confirmation measures is taken to obtain the overall coherence score of a topic.

The calculated topic coherence scores can be found in Figure 8.

Appendix 4

See Table 4.

Table 4. The top 15 words (i.e., the words with highest probability) for each of the 31 uncovered general fisheries topics. Topics in bold (i.e., 4 and 9) are the identified modeling topics used in the analysis of this paper, with 4 being the topic estimation models and 9 being the stock assessment models.

Topic	Top 15 words
1	crab, crabs, lobster, eel, eels, size, traps, mm, lobsters, trap, american, anguilla, blue, females, fishery
2	salmon, hatchery, chinook, river, wild, atlantic, survival, coho, sockeye, juvenile, oncorhynchus, fisheries, smolts, pacific, steelhead
3	river, species, sampling, electrofishing, colorado, fishes, chub, capture, population, suckers, sucker, abundance, reach, sites, site
4	**model, estimates, catch, survey, sampling, estimated, models, estimate, distribution, abundance, mean, effort, sample, method, size**
5	genetic, populations, population, river, loci, samples, among, structure, individuals, microsatellite, within, stock, alleles, diversity, sample
6	prey, larvae, growth, larval, food, predation, size, feeding, diet, juvenile, zooplankton, abundance, mm, predator, rates
7	red, reef, gulf, species, snapper, florida, marine, mexico, reefs, fishes, shrimp, coral, habitat, artificial, drum
8	atlantic, bay, striped, tuna, bass, flounder, estuary, north, marine, new, river, carolina, chesapeake, estuaries, estuarine
9	**model, stock, mortality, population, recruitment, models, biomass, year, rate, management, parameters, assessment, fisheries, estimates, fishing**
10	species, variables, environmental, sites, lakes, assemblages, community, water, assemblage, richness, communities, diversity, index, models, spatial
11	cod, sea, atlantic, north, species, herring, size, cm, trawl, length, stock, area, mesh, baltic, fishing
12	fisheries, management, fishing, fishery, catch, economic, marine, effort, fishers, species, recreational, information, anglers, use, new
13	habitat, water, flow, use, depth, river, velocity, substrate, channel, areas, sites, site, area, movement, spawning
14	spawning, females, eggs, egg, males, female, reproductive, male, fecundity, sex, maturity, mature, stage, size, development
15	species, sharks, bycatch, shark, catch, longline, fishery, fisheries, fishing, gear, hooks, caught, hook, cm, atlantic
16	mortality, tag, tagged, tags, tagging, release, survival, released, movement, rates, fisheries, studies, capture, effects, transmitters
17	lake, lakes, perch, michigan, yellow, walleye, great, fisheries, northern, walleyes, mean, ontario, journal, consumption, population
18	growth, length, mm, size, otoliths, body, ages, otolith, cm, mean, years, first, weight, differences, lengths
19	temperature, water, growth, effects, swimming, treatment, energy, levels, temperatures, experiment, activity, body, effect, experiments, experimental
20	sea, squid, mediterranean, distribution, area, anchovy, species, waters, larvae, sardine, marine, spawning, shelf, temperature, mackerel
21	bass, largemouth, reservoir, river, species, lake, catfish, smallmouth, fisheries, shad, water, management, reservoirs, white, black
22	species, fishes, freshwater, carp, new, native, river, water, aquaculture, crayfish, populations, introduced, conservation, tilapia, many
23	species, dna, genetic, gene, mtdna, samples, molecular, mitochondrial, sequence, haplotypes, infection, atlantic, identification, disease, sequences
24	acoustic, depth, vertical, water, bottom, surface, ts, distribution, speed, range, target, density, measurements, night, behaviour
25	otolith, otoliths, sr, marine, river, ratios, samples, water, differences, juvenile, chemistry, isotope, freshwater, values, campana
26	fishing, marine, species, fisheries, areas, sea, area, fishery, catch, australia, effort, total, south, effects, coastal
27	river, sturgeon, dam, chinook, columbia, lower, passage, migration, salmon, downstream, steelhead, upstream, juvenile, spawning, dams
28	trout, brook, rainbow, brown, lake, sea, fry, lamprey, river, stocking, lampreys, salvelinus, arctic, streams, stocked
29	water, concentrations, phytoplankton, production, concentration, samples, nutrient, sediment, carbon, total, food, values, biomass, organic, levels
30	stream, trout, streams, creek, habitat, cutthroat, sites, reaches, river, effects, brook, temperature, watershed, abundance, aquatic
31	sea, pacific, marine, species, climate, ocean, north, alaska, rockfish, change, ecosystem, changes, abundance, temperature, california

Paper 2

Interdisciplinary Optimism? Sentiment Analysis of Twitter Data.

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Interdisciplinary Optimism? Sentiment Analysis of Twitter Data

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Interdisciplinary research can face many challenges, from institutional and cultural, to practical ones, while it has also been reported as a "career risk" and even as "career suicide" for researchers pursuing such an education and approach. Yet, the propagation of the challenges and risks can easily lead to a feeling of anxiety and disempowerment in researchers, which we think is counterproductive to improving interdisciplinarity in practice. Therefore, in the search of 'bright spots', which are examples where people have had positive experiences with interdisciplinarity, this study assesses the perceptions of researchers on interdisciplinarity on the social media platform Twitter. The results of this study show researchers' many positive experiences and successes of interdisciplinarity, and as such document examples of bright spots. These bright spots can give reason for optimistic thinking, which can potentially have many benefits for researchers' well-being, creativity, and innovation, and may also inspire and empower researchers to strive for and pursue interdisciplinarity in the future.

1. Introduction

Interdisciplinarity involves activities that integrate more than one discipline with the aim to create new knowledge or solve a common problem. The interdisciplinary approach has gained popularity in science, education, and policy over the last years and it is often advocated for solving today's complex problems and societal issues, such as climate change, biodiversity loss, food and water security, and public health issues [1,2]. It is hoped that interdisciplinary research will help solve these problems and help create innovative solutions through coordinated approaches. Such coordinated approaches combine knowledge and enable a coalescence at the interfaces and frontiers of the different scientific disciplines. This bridging of disciplinary boundaries facilitates development and innovation [3]. However, successfully crossing and integrating diverse fields and disciplines is not an easy endeavor.

Interdisciplinarity can face many challenges, from institutional [4] and cultural [5] to practical challenges [6,7]. Interdisciplinary work has also been reported to have lower funding success [8], can be challenging to publish [9], and interdisciplinary journals are commonly perceived as less prestige compared to single-disciplinary ones [10]. As a result, young scholars following an interdisciplinary career-path now fear to "risk their careers", or even to "commit career suicide" [11,12]. Others have perceived their interdisciplinary experience as if they did not belong to a discipline, a research community, or a research group. They had to live without the comfort of expertise, while having to fight for identity, recognition, and legitimacy within their work environment and among their peers [13]. In part because their background was too diverse or too broad to belong to a single discipline or to be considered an 'expert'. Many of these negative experiences and challenges have been, and continue to be, reported in the literature.

We claim that the continued propagation of challenges is counterproductive to improving interdisciplinarity in practice. For example, negative wording as in "less funding success", and "career suicide" can easily create anxiety in (early career) scientists and lead to a feeling of disempowerment. While the study of such challenges and shortcomings is an important step when trying to improve interdisciplinary research in the future, we argue that we also need to study the 'bright spots' in order to harvest the full potential of interdisciplinarity. These bright spots are examples where people have had positive experiences with interdisciplinarity and success stories of interdisciplinary research (IDR)—despite its challenges and barriers. We believe that the documentation of such bright spots and success can propagate optimism (understood here as the generalized expectancy that one will experience good outcomes [14]), which can further unlock creativity and innovation in interdisciplinary individuals and teams.

Previous research has shown that the social media platform Twitter is generally used to broadcast thoughts and opinions [15]. Within academia, Twitter is also used to acquire and share real-time information, and to develop connections with others [16]. Previous research, furthermore, shows that Twitter plays a significant role in the discovery of scholarly information and cross-disciplinary knowledge spreading. Therefore, the aim of this study is to assess the perceptions of academics (also referred to as researchers or scientists) on interdisciplinarity on a larger scale, in the pursuit of such bright spots within people's experiences shared on Twitter with the ambition to create interdisciplinary optimism.

2. Material and Methods

(a) Defining the different modes of research

The terms *interdisciplinary*, *transdisciplinary*, and *multidisciplinary* all describe different modes of research that include a range of participants with a degree of disciplinary interaction. While many definitions already exist in the literature (and most point in a similar direction), sometimes the meaning of the terms can be unclear, especially if they are used interchangeably. For the purpose of this paper, the different research concepts are conceptually visualized in Fig. 1 and understood and defined as follows [17]:

- **Interdisciplinarity** refers to the integration of several unrelated academic disciplines that forces actors to cross boundaries with the goal to create integrated knowledge and theory;
- **Transdisciplinarity** involves the same process as in interdisciplinarity, but includes non-academic participants;

- **Multidisciplinarity** involves multiple disciplines researching a common theme in parallel, but without integration or the crossing of subject boundaries.

The two research concepts, interdisciplinary and transdisciplinarity, were included in this study because they can both be considered interdisciplinary due to their integrative nature. The concept of multidisciplinarity lacks the integrative process according to the above definition, a view further supported by other literature [18]. However, not all literature makes that clear distinction and as a result, multidisciplinarity has been described as a mode of research that allows for the integration of knowledge [19]. In addition, multidisciplinarity is often included in research addressing interdisciplinary activities and impact [8,20,21]. Therefore, the research concept of multidisciplinarity was also included in this study for the assessment of sentiment towards interdisciplinarity. In this study, the three concepts, interdisciplinary, transdisciplinary, and multidisciplinary, will be referred to as *modes of research* and *integrative research approaches*.

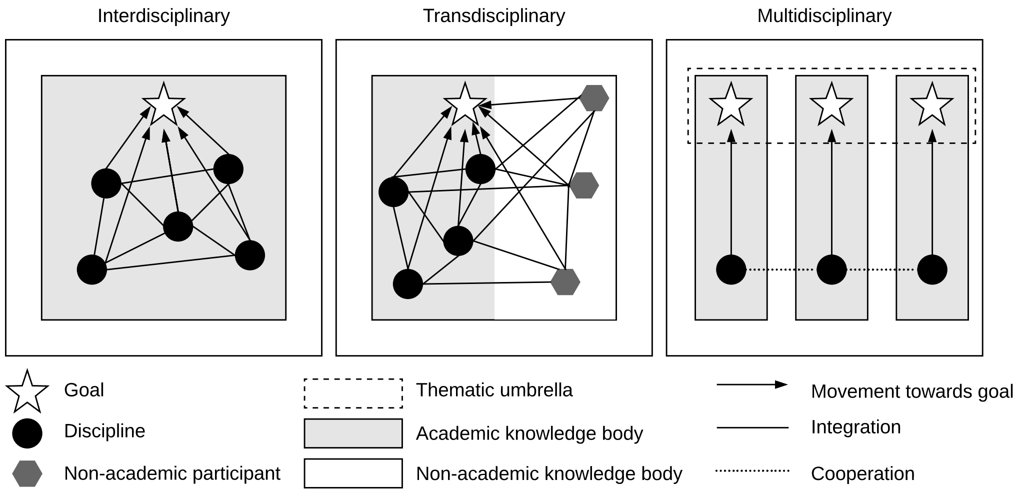

Figure 1: Overview of the three modes of research. Modified from [22].

(b) Dataset

The dataset of publicly available tweets related to the three modes of research was obtained by utilizing the Twitter Search API. The Twitter Search API returns tweet data, such as the tweet text (i.e., content) and ID, that matches a specified search query. We used the Python library *Tweepy*[1] to access the search API and query the tweets, which conveniently respects the Twitter rate limit of 900 tweets per 15 minute window. The used query strings for the three modes of research are listed in Table 1. The Twitter API automatically returns all hyphenated variants of the search words, such as inter-disciplinarity and inter-disciplinary, eliminating the need to include such variations within the search queries. Since the Twitter API only returns tweet data not older than 7 days, we collected tweets from week 32 (2017) up to week 33 (2018), a time frame of 53 weeks. During data collection, Twitter rolled out their expanded 280 character limit—previously 140 characters—which resulted in a dataset with 140 and 280 character limit tweets. It is important to note that the Twitter API is not an exhaustive source of tweets, as not all tweets are indexed or available via the search interface. The full dataset of all collected tweets is made available in the electronic supplementary material S1 Data.

[1]http://www.tweepy.org/

Table 1: Overview of search queries used to retrieve tweets related to the three modes of research.

Mode of research	Twitter search query
Interdisciplinary	'Interdisciplinary OR #Interdisciplinary OR Interdisciplinarity OR #Interdisciplinarity'
Transdisciplinary	'Transdisciplinary OR #Transdisciplinary OR Transdisciplinarity OR #Transdisciplinarity'
Multidisciplinary	'Multidisciplinary OR #Multidisciplinary OR Multidisciplinarity OR #Multidisciplinarity'

(c) Audience of the Dataset

Within this study, our aim is the make inferences regarding tweet sentiments associated with an academic or research domain. To identify tweets originating from a research domain setting, we filtered the dataset of all publicly available tweets for tweets from individuals who identify themselves as scientists (including all variations thereof, such as researchers or academics). To enable this, we used an adaptation of the systematic approach to identifying scientists on Twitter proposed by [23]. Our filtering process essentially aimed to match occupational classifications to the description field associated with the user account of the tweet. The description field is an optional field of maximum 160 characters where the user can describe herself, colloquially known as the user's bio.

We utilized the list of 322 scientific occupations (e.g., biologist, computer scientist, political anthropologist) compiled by [23]. This list was constructed by selecting the scientific occupations from: (i) the 2010 Standard Occupational Classification[2] (SOC) system released by the Bureau of Labor Statistics, United States Department of Labor; (ii) Wikipedia's list of scientific occupations[3]; and (iii) the authors choice of adding generic occupations such as 'scientist' and 'researcher'.

We furthermore augmented the list of 322 occupations by obtaining all the synsets (i.e., synonyms that share a common meaning) for each occupation from an on-line lexical reference system called WordNet [24]. Including the synsets and excluding duplicate entries resulted in a total list of 430 occupations related to a scientific or academic profession (see electronic supplementary material, Data S2). We then used regular expressions to match occupations with the user description field. This filtering approach identifies, for example, tweets from a user describing himself as 'senior lecturer in human geography at university of Liverpool' as valid for inclusion, and a description of a user describing herself as 'costume design & visual arts' as valid for exclusion. A random sample of 5,000 tweets were manually examined to assess the inclusion and exclusion criteria, and adjustments were made to the regular expressions to enhance the filtering process (for instance to capture American vs British spelling). We furthermore excluded tweets that contained no description text. On the one hand, the exclusion of tweets with no description text might negatively affect the recall of relevant tweets. On the other hand, it positively affects the precision. In other words, we might not be able to include all the tweets from an academic or research setting (i.e. lower recall), but we can be more sure that the included tweets are all from the correct audience (i.e., higher precision).

(d) Preprocessing Tweets

Tweeting, the process of publishing a tweet, proceeds in the form of free text, often in combination with special characters, symbols, emoticons, and emoji. This, in combination with a character limit, make tweeters creative and concise in their writing, favoring brevity over readability to convey their message—even more so with the 140 characters limit. Thus tweet data is highly

[2]http://www.bls.gov/soc/
[3]http://en.wikipedia.org/wiki/Scientist#By_field

idiosyncratic and several preprocessing steps were necessary (described below) to make the dataset suitable for sentiment analysis.

Retweets and duplicate tweets We removed retweets, identified by the string 'RT' preceding the tweet, as they essentially are duplicates of the initial or first tweet. Additionally, duplicate tweets that were identical in their content were also excluded.

Non-English tweets We focused our analysis on English tweets only and excluded all non-English tweets according to the 'lang' attribute provided by the Twitter API.

User tags and URLs For the purpose of sentiment analysis, the user tags (i.e., mentioning of other Twitter user accounts by using @) and URLs (i.e., a link to a specific website) convey no specific sentiment and were therefore replaced with a suitable placeholder (e.g. `USER`, `URL`). As a result, the presence and frequency of user tags and URLs were retained and normalized.

Hashtags Hashtags are an important element of Twitter and can be used to facilitate a search while simultaneously convey opinions or sentiments. For example, the hashtag #love reveals a positive sentiment or feeling, and tweets using the hashtag are all indexed by #love. Twitter allows users to create their own hashtags and poses no restrictions in appending the hashtag symbol (i.e., #) in front of any given text. Following the example of the #love hashtag, we preprocessed hashtags by removing the hash sign, essentially making #love equal to the word *love*.

Contractions and repeating characters Contractions, such as *don't* and *can't*, are a common phenomenon in the English spoken language and, generally, less common in formal written text. For tweets, contractions can be found in abundance and are an accepted means of communication. Contractions were preprocessed by splitting them into their full two-word expressions, such as *do not* and *can not*. In doing so, we normalized contractions with their "decontracted" counterparts. Another phenomenon occurring in tweets is the use of repeating characters, such as *I loveeeee it*, often used for added emphasis. Words that have repeated characters are limited to a maximum of two consecutive characters. For example, the word *loveee* and *loveeee* are normalized to *lovee*. In doing so, we maintained some degree of emphasis.

Lemmatization and uppercase words For grammatical reasons, different word forms or derivationally related words can have a similar meaning and, ideally, we would want such terms to be grouped together. For example, the words *like*, *likes*, and *liked* all have similar semantic meaning and should, ideally, be normalized. Stemming and lemmatization are two NLP techniques to reduce inflectional and derivational forms of words to a common base form. Stemming heuristically cuts off derivational affixes to achieve some kind of normalization, albeit crude in most cases. We applied lemmatization, a more sophisticated normalization method that uses a vocabulary and morphological analysis to reduce words to their base form, called lemma. It is best described by its most basic example, normalizing the verbs *am*, *are*, *is* to *be*, although such terms are not important for the purpose of sentiment analysis. Additionally, uppercase and lowercase words were grouped as well.

Emoticons and Emojis Emoticons are textual portrayals of a writer's mood or facial expressions, such as :-) and :-D (i.e., smiley face). For sentiment analysis, they are crucial in determining the sentiment of a tweet and should be retained within the analysis. Emoticons that convey a positive sentiment, such as :-), :-], or ;), were replaced with the positive placeholder word `EM_POS`; in essence, grouping variations of positive emoticons with a common word. Emoticons conveying a negative sentiment, such as :-(, :c, or :-c, were replaced by the negative placeholder word `EM_NEG`. A total of 47 different variations of positive and negative emoticons were replaced. A similar approach was performed with emojis that resemble a facial expression and convey a positive or negative sentiment. Emojis are graphical symbols that can represent an idea, concept or mood expression, such as the graphical icon of a happy face. A total of 40 emojis with positive and negative facial expressions were replaced by the placeholder word `EM_POS` and `EM_NEG`, respectively. Replacing and grouping the positive and negative emoticons and emojis will result in the sentiment classification algorithm learning an appropriate weight factor for the corresponding sentiment class. For example, tweets that have been labeled as conveying a negative sentiment (by a human annotator for instance) and predominantly containing negative emoticons (e.g., :-(), can result in the classification algorithm assigning a higher probability or weight to the negative sentiment class for such emoticons. Note that this only holds when the neutral and positively labeled tweets do not predominantly contain negative emoticons; otherwise their is no discriminatory power behind them (see also Section (e)).

Numbers, punctuation, and slang Numbers and punctuation symbols were removed, as they typically convey no specific sentiment. Numbers that were used to replace characters or syllables of words were retained, such in the case of *see you l8er*. We chose not to convert slang and abbreviations to their full word expressions, such as *brb* for *be right back* or *ICYMI* for *in case you missed it*. The machine learning model, described later, would correctly handle most common uses of slang, with the condition that they are part of the training data. As a result, slang that is indicative of a specific sentiment class (e.g. positive or negative) would be assigned appropriate weights or probabilities during model creation.

Input features Each tweet was tokenized, the process of obtaining individual words from sentences. Furthermore, we represented tweets as count vectors with and without inverse document frequency (IDF) weighting [25]. Different variations of tokenization were explored, such as 1-word (unigram), 2-word (bigrams), 3-word (trigrams), and 4-word (n-gram) combinations. Bi-grams are especially important to capture negation of words combinations, such as *not good* or *not great*, that would not be captured when using 1-word (unigram) features alone.

(e) Creating the Machine Learning Classifier

This paper employs a supervised machine learning approach to predict positive, neutral, and negative sentiments from the tweets related to the three modes of research. Supervised machine learning essentially learns a sentiment classification model, called a classifier, from labeled tweet data, that is, tweets that have been labeled as positive, neutral, and negative by human annotators. With the use of labeled data, the machine learning classifier learns that certain words convey, for example, positive sentiments when they more frequently occur in positively labeled tweets. The word *happy*, generally speaking, is used to convey a positive sentiment or feeling and tweets containing the word might be assigned a higher probability for the positive sentiment class. This is a somewhat basic and straightforward example but the classifier learns to assign every word—technically called a feature—a probability for each of the three sentiment classes. The tweet is thus a combination of features with corresponding probabilities and, ultimately, the classifier assigns the tweet a probability for the positive, neutral, and negative class. The class with the highest probability is the inferred sentiment class. In essence, a supervised machine learning classifier is built or trained from labeled data and is applied to unlabeled data to predict or infer their label.

Several online repositories are available that contain human annotated tweet data. We combined several of such online repositories that serve as input data, called training data, to create or train the machine learning classifier. A total of seven different repositories were used which contained a total of 71,239 labeled tweets, with 22,081 positive, 31,423 neutral, and 17,735 negative tweets. Table 2 shows an overview of the datasets used to train the classifier, together with the frequency of tweets for the three sentiment classes, the domain or subject of the tweets, the number of human annotators used to label the tweets, and a selection of research studies that have used the dataset. We provide descriptions of the seven datasets in the electronic supplementary material, Text S1. Note that the Twitter terms of service do not permit direct distribution of tweet

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content and so the tweet IDs (references to the original tweets) with their respective sentiment labels are often made available without the original tweet text and associated meta-data. As a result, we used the Twitter API to retrieve the full tweet content, the tweet text and meta-data, by searching for the tweet ID. Some tweets appeared not to be available from the Twitter API and this, in some cases, resulted in the training datasets having fewer tweets than originally included in the published datasets.

Table 2: Overview of training datasets. For a full description of the datasets, see the electronic supplementary material Text S1

Dataset	Positive	Neutral	Negative	Total	Domain	Annotators	Study
Sanders	424	1,996	475	2,895	Apple, Google, Microsoft, Twitter	1	[26–28]
OMD	704	-	1,192	1,896	#tweetdebate, #current,#debate08	3-7	[29–31]
Stanford Test	182	139	177	498	consumer products, companies, and people	1	[32–34]
HCR	537	337	886	1,760	#hcr	1	[31]
SemEval-2016	3,918	2,736	1,208	7,889	100 different topics	5	[35]
SS	1,252	1,952	861	4,066	major events	1	[36,37]
CLARIN-13	15,064	24,263	12,936	52,263	1% public available tweets	1-9	[38,39]
Total	22,081	31,423	17,735	71,239			

(f) Machine Learning Model Selection

The labeled training datasets serve as input for building the machine learning classifier (i.e., learning a model to classify tweets into positive, neutral, and negative sentiments). The tweets with their corresponding sentiment label enable the classifier to extract features that best predict the sentiment of a tweet. Typically, with supervised machine learning, one would need sufficient data for each sentiment class to make good predictions on new tweets. We obtained a training dataset containing 71,239 labeled tweets, which can be considered a sufficiently large dataset for sentiment analysis.

Several (supervised) machine learning algorithms are suitable for the purpose of creating a sentiment classifier from labeled tweet data. Unfortunately, no consensus exists on what classification algorithm to use since different studies have different datasets, perform different pre-processing steps, use different features, have incompatible performance measures, or simply have different use cases. Thus, adopting one strategy that worked for a particular use case might not work for another. The current state-of-the-art for sentiment analysis typically use algorithms based on neural networks [40,41]—also referred to as deep learning models—as can be seen from top-ranking teams during the SemEval 2017 competition [42]. The downsides of such winning entries are complexity, computational cost, and the fact that they are highly tuned and optimized to achieve a high score on the task's performance measure. Besides neural network models, more traditional machine learning classifiers have also shown high accuracy and performance on sentiment classification tasks. They include Support Vector Machines (SVM) [43–45], logistic regression [26,45], Naive and Multinomial Naive Bayes [26,31,44,46], and Conditional Random

Fields (CRF) [42]. Less complex neural networks, such as the Multi-layer Perceptron, have also been explored [46].

The aim of this paper is not to exhaustively explore the full suite of algorithms available but to use one that accurately predicts sentiments from tweets with reasonable complexity and computational time. Though complexity and computational time are hard to define concretely [47], we limit complexity to the basic machine learning and ensemble classification algorithms found in the Python library *Scikit-Learn* [48]. Additionally, we included a basic neural network, thus excluding very deep models and convolutional or sequence models. In terms of computational time, all selected models could be trained in reasonable amount of time (10-30 minutes of wall clock time per model) on an Apple MacBook Pro with i7 Processor and 16GB of internal memory. For example, the support vector machine with Gaussian kernel was not explored since it was too time consuming to train a single model. A total of seven different supervised machine learning algorithms were considered: (1) Support Vector Machine (SVM) Linear Kernel; (2) Logistic Regression; (3) Multinomial Naive Bayes; (4) Bernoulli Naive Bayes; (5) Decision Trees; (6) ADA boost; and (7) the Multi-Layer Perceptron.

The dataset of 71,239 labeled tweets was partitioned into two parts. The first part, called the training set, contained 80% randomly selected tweets used to train and validate the seven different algorithms. The second part, a random sample of 20% of the data called the test set, was used to test the performance of the algorithms on tweet data that was not used during training. All seven different algorithms were applied to the training set with 10-fold cross validation, which is a standard approach in machine learning [38]. During 10-fold cross-validation, the training set is partitioned into 10 parts, called folds, and training is done on 9 folds with the remaining fold used to test the performance of the algorithm. This process is repeated 10 times, essentially creating 10 different classification models in which each model is tested against the remaining fold. Partitioning the data into folds is done on a stratified random basis, preserving the percentages of samples for each sentiment class. Additionally, we used a standard grid-search approach to establish the optimal performing parameter values for each of the seven algorithms. Since algorithms are parameterized and regularized by a set of parameters or hyper-parameters, finding the best performing values of these parameters can be obtained by trying out different combinations of values, called a grid-search. Other approaches, such as a random grid-search or Bayesian optimization [49] can also be considered, but were not employed in this study. The grid-search approach was combined with the 10-fold cross validation method. For example, a grid search that tries out four different values for two separate parameters, combined with 10-fold cross validation for a single algorithm results in 4 x 4 x 10 = 160 different sentiment classification models. The different hyper-parameters and their parameter values that were explored are listed in Table 3. The model that achieves the highest performance score (described in Section (h)) is validated against the test set (i.e., remaining 20% of the data) to assess the performance of the model and its parameters on hold-out data; a way to measure the model's generalizability to unseen data.

(g) Suitability Training Data

It is important that the training data from which we train the supervised machine learning classifier can appropriately infer sentiment classes for the (unseen) tweets containing the three modes of research. By drawing on 71,239 training tweets (described in Table 2), we captured a wide array of sentiment expressions. However, specific sentiment indicators associated with the three modes of research can be absent from the training data, making accurate classification a challenging task. To mitigate this risk, we manually labeled a random subset of the tweets related to the three modes of research. A total of 1,000 tweets, stratified by mode of research, were labeled positive, negative or neutral. To have a common understanding of what a positive, negative or neutral tweets constitutes, we utilized the sentiment description text provide by Amazon Mechanical Turk's documentation for setting up a sentiment annotation project[4]. Amazon

[4]https://docs.aws.amazon.com/AWSMechTurk/latest/RequesterUI/Create-Sentiment-Project.html

Table 3: Overview of explored hyper-parameter values when performing a cross-validated grid search to obtain the machine learning classification model with best classification performance (F1-score). The value 'x' indicates that the hyper-parameter was used to explore different variations of the algorithm. Not all hyper-parameters are possible for all explored models, these are indicated by the absence of an 'x'. A full description of the hyper-parameters can be found in the Scikit-learn documentation at https://scikit-learn.org/stable/documentation.html

Hyper-parameter	Value Range	SVM	Logisitic Regression	Multinomial NB	Bernoulli NB	Descision Trees	ADA Boost	ML-Perceptron
n-grams	1–4	x	x	x	x	x	x	x
min-df	0,5,10,15	x	x	x	x	x	x	x
max-df	1.0, 0.95, 0.90	x	x	x	x	x	x	x
IDF	Yes, No	x	x	x	x	x	x	x
sublinear-TF	Yes, No	x	x	x	x	x	x	x
C (penalty term)	0.001, 0.01, 0.5, 0.1, 1, 5, 10, 15, 20, 100	x	x					
fit prior	Yes, No			x	x			
alpha	0.001, 0.01, 0.5, 0.1, 1, 5, 10, 15, 20, 100			x	x			
splitter	best, random					x		
criterion	gini, entropy					x		
max features	auto, sqrt, log2, None					x		
num. estimators	100,200,300,400,500						x	
algorithm	SAMME, SAMME.R						x	
neural architectures	(100,50,20),(200, 100, 100),(300, 50, 50, 50),(50, 40, 30, 10),(20, 30, 50, 50),(70, 50, 40, 30)							x
Cross-validation	10-Fold	x	x	x	x	x	x	x
	Total Models (x1000)	19.2	19.2	38.4	38.4	30.7	19.2	11.5

Mechanical Turk is typically used as a crowd sourcing platform to annotate tweets for their sentiments [29,50,51]. Positive tweets embodied a happy, excited or satisfied emotion; negative tweets embodied an angry, upsetting, or negative emotion; and neutral tweets did not embody much negative nor positive emotion. The 1,000 labeled tweets containing interdisciplinarity, multidisciplinarity, and transdisciplinarity content were added to training data to build the classification model. Additionally, we utilized Laplace smoothing—for the algorithms that allow smoothing—to mitigate some risk of misclassification related to absence of sample features in the training data [52]. Additionally, the preprocessing steps described in Section (d) were similarly applied on the training tweets and target tweets so that the learned features of the training data can be applied onto the target tweets.

(h) Calculating Classification Performance

Typically for classification purposes, the performance of a model is assessed by the number of correctly predicted tweet sentiments in relation to incorrectly predicted tweet sentiments. We can discern three evaluation metrics when classifying tweets into positive, neutral, and negative sentiments: (1) precision, (2) recall, and (3) F1. Precision measures how many of the tweets predicted to belong to a certain sentiment (e.g. positive) are actually positive. Precision, thus, measures how precise the predictions are. Recall measures how many of the e.g. positive tweets are captured by all of the predicted positive tweets. Recall can be seen as a metric to evaluate if the classification model is able to identify all the positive tweets from the complete dataset. There is a trade-off between optimizing recall and optimizing precision and a summarized measure between the two is captured by the F1 score, a harmonic mean of precision and recall. We equally care about precision and recall and thus optimize these to achieve a high F1 score, which is an appropriate performance metric when having imbalanced classes (i.e., classes that are not represented equally). The model with the highest F1 score was ultimately used to predict tweet sentiments for the three modes of research (i.e., interdisciplinary, transdisciplinary, and multidisciplinary tweets).

Additionally, after utilizing the best performing classification algorithm on the target tweets (i.e., tweets related to the three modes of research), we created a random stratified dataset of 1,000 target tweets (in addition to the 1,000 manually labeled tweets reported in section (g)), stratified by mode of research and the inferred sentiment label. This dataset was manually labeled for the true sentiment class, and the performance of the classification algorithm was measured against it. In doing so, the classification performance on the target tweets could be measured. We report the precision, recall, and F1 measure as previously described.

(i) Inspecting Tweets

For the analysis of the content of the tweets (to understand what people felt positive, neutral or negative about), a random set of tweets (n=2,000 or less, depending on the number of tweets classified into a specific sentiment) for each sentiment class and for each mode of research was manually examined for the content and context by one examiner. Additionally, word clouds were constructed to summarize each class and each mode of research (9 word clouds) for the most dominant words (here dominant measured by frequency). Each word cloud contained all the available tweets for that sentiment class and mode of research.

3. Results

(a) Classifier Performance

Table 4 shows the evaluation metrics (i.e., precision, recall, F1) for the seven different classifiers that were applied to the training (80%) and test (20%) partitions of the labeled tweet data. Ideally, the performance results between the training and test data should be similar; an indication that the model is not overfitting. A model that overfits the training data performs, generally, worse on the test data as it is unable to generalize to new unseen data. The results within the test set columns, and specifically, the reported F1 metric show that the SVM classifier performs best. As such, we applied the SVM algorithm, created from 80% of the labeled tweets (see Table 2 for an overview) to infer sentiment labels from the tweets related to the three modes of research. The hyper-parameter values that resulted in the classification model with best classification performance are listed in Table 5. The classification performance on the target tweets, thus the tweets related to the three modes of research, are shown in Table 6. The SVM classifier achieves an F1 score of 0.83 on the target tweets.

Table 4: Sentiment classification precision, recall and F1 for the six different classifiers. The Training set constitutes 80% of all labeled tweet data used to train the classification models. The remaining 20%, the Test set, is used to measure how well the classifiers performs on new unseen tweets.

	Training Set	**Test Set**		
Algorithm	**F1**	**Precision**	**Recall**	**F1**
SVM	0.66	0.67	0.67	**0.67**
Logisitic Regression	0.66	0.66	0.66	0.66
Multinomial NB	0.64	0.65	0.65	0.65
Bernoulli NB	0.63	0.64	0.64	0.64
Descision Trees	0.55	0.56	0.56	0.56
ADA Boos	0.62	0.64	0.64	0.63
ML-Perceptron	0.59	0.60	0.60	0.60

Table 5: Hyper-parameter values that resulted in highest F1 score for the seven explored classification algorithms.

Hyper-parameter	**SVM**	**Logisitic Regression**	**Multinomial NB**	**Bernoulli NB**	**Descision Trees**	**ADA Boost**	**ML-Perceptron**
n-grams	1–4	1–4	1–3	1–2	1–4	1–4	1–3
min-df	0	0	5	5	5	5	5
max-df	1	1	1	1	1	1	1
IDF	no	no	n	yes	no	no	no
sublinear-TF	yes	yes	yes	yes	yes	yes	yes
C	0.5	10					
fit-prior			yes	no			
alpha			0.1	1			
splitter					random		
criterion					gini		
max-features					None		
n-estimator						400	
algorithm						SAMME.R	
neural architecture							200,100,100

Table 6: Performance of the selected SVM Classifier on the target tweets.

Algorithm	**Dataset**	**Precision**	**Recall**	**F1**
SVM	1,000 int/mult/trans-disciplinary tweets	0.84	0.83	0.83

(b) Sentiment Analysis

The largest set of data, over 47,000 tweets, was collected for the interdisciplinary mode of research, followed by multidisciplinary, and transdisciplinary with the least tweets (Figure 2). All three modes of research contained more positive than negative tweets. Interdisciplinary tweets contained the largest percentage of positive tweets with almost half of the tweets being positive (45%), while the transdisciplinary and multidisciplinary modes of research contained less than 20% positive tweets.

The percentage of negative tweets was relatively low, with similar percentages between two and three percent amongst all the different modes of research. Neutral was the most common sentiment in all three modes, including more than 50% of the interdisciplinary tweets, and around 80% of the transdisciplinary and multidisciplinary tweets (Figure 2).

The full dataset, including all assigned sentiment labels is made available in the supplementary material in Data S2.

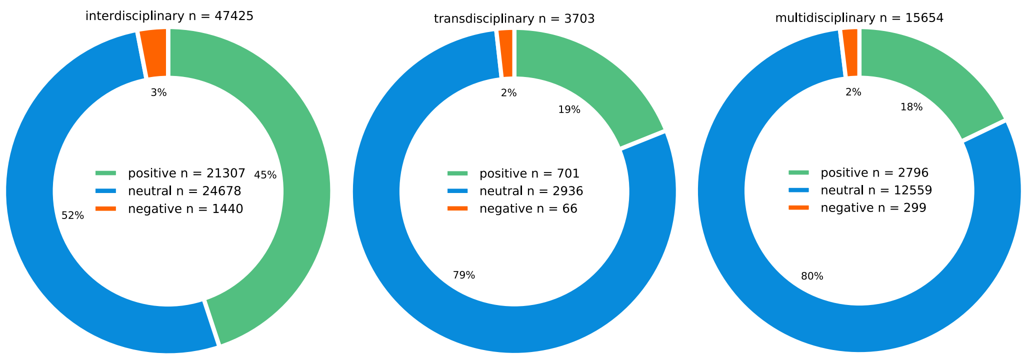


Figure 2: Frequency of tweets by sentiment for the three modes of research.

The different modes of research showed a high number of unique user names, which refers to the number of individual user accounts that tweeted within our dataset (Table 7). The ratio for the number of tweets per unique user is between one or 1.6 for all research modes and sentiments, which shows that the number of unique user IDs is close to the number of tweets posted (i.e. between one and 1.6 tweets per user). Within all three modes of research, neutral tweets showed the highest ratio, and negative tweets the lowest ratio.

Table 7: Number of unique user names for each mode of research and sentiment class and the ratio for the number of tweets per unique user.

Mode of research	Sentiment	Unique users	Ratio
Interdisciplinary	Negative	1,259	1.13
	Neutral	15,466	1.58
	Postive	15,022	1.41
Transdisciplinary	Negative	56	1.18
	Neutral	1,967	1.49
	Postive	584	1.20
Multidisciplinary	Negative	275	1.08
	Neutral	8,741	1.43
	Postive	2,445	1.14

The absolute number of tweets per week changed slightly over the course of the study period for both interdisciplinary and multidisciplinary tweets (Figure 3). The interdisciplinary tweets show that almost half of the tweets had a positive sentiment at times. Transdisciplinary tweets showed the highest fluctuation in numbers over time. All three modes of research show a drop in the number of tweets around week 52 in 2017 during what is typically called the winter holidays for everyone on the Northern hemisphere. The number of tweets also drops around week 23 in 2018 because tweets were not collected for 3 days due to server downtime. The sentiment and the proportions of positive, neutral and negative tweets stayed relatively proportional to each other over the study period.

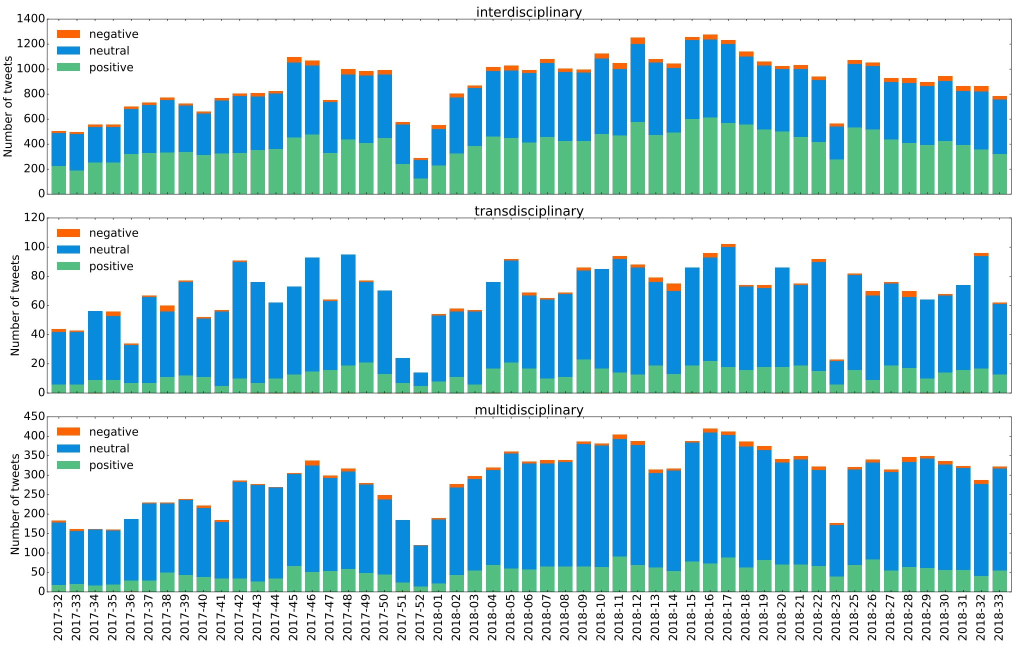


Figure 3: Sentiment over time

The manual inspection of the 2,000 randomly selected tweets provided detailed insights into the content of the tweets, and the reasons for a particular sentiment. Word clouds for each mode of research and sentiment summarize the most frequently used terms in each tweet class (Figure 4).

Negative tweets. Several of the negative tweets within all three modes of research contained explicit language. Negative tweets had a higher frequency in the use of user tags (@), compared to the use of URLs and emojis, but show similar results for each of the three modes of research (Figure 5). Negativity is associated with the multi, inter- or trans-disciplinarity itself, where researchers explicitly state that they do not enjoy the approach. Additionally, tweets reflect the hardship that is associated with integrative research in practice and being an integrative scholar. Additionally, negativity is expressed by criticizing the people or the system that discourages integrated research approaches, rather than the mode of research.

Negative interdisciplinary tweets most often discuss challenges of interdisciplinary research (IDR), such as rejections by peer-review (Figure 6a), a lack of integration, communication problems across disciplines, and difficulties to secure funding. Also criticism to the existing institutional system of disciplinary departments was mentioned. The need for more IDR was repeatedly mentioned, while the lack of acknowledgment and respect for IDR was also a re-occurring topic.

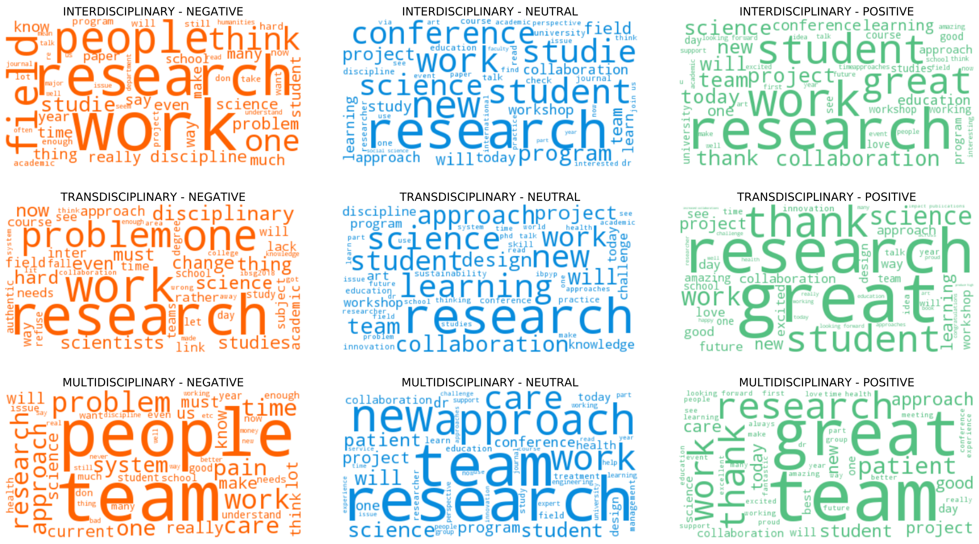


Figure 4: Word cloud displaying the most frequent words per sentiment class for the three modes of research.

There were only very few *negative transdisciplinary* tweets (n=66). However, the tweets related mostly to challenges within transdisciplinary work, being a transdisciplinary scholar, and funding concerns (Figure 6b).

Negative multidisciplinary tweets often related to the challenges and problems in health care, patient care, and treatment. Also education and teaching were a re-occurring theme, in which the lack of multidisciplinary perspectives and teaching approaches was criticized. Challenges in publishing were also mentioned.

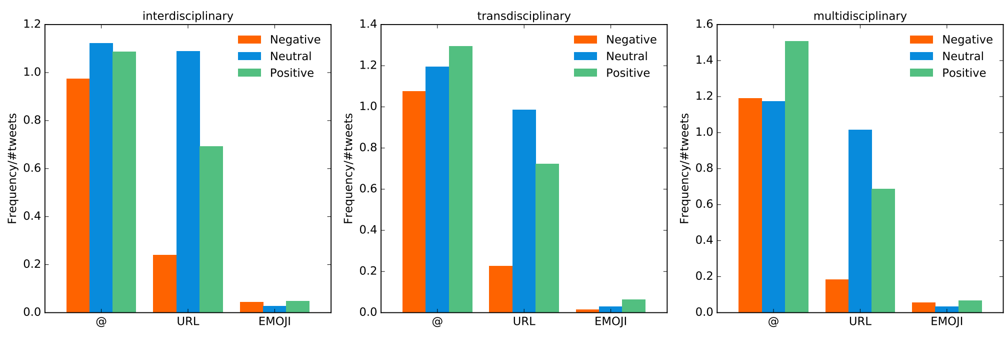
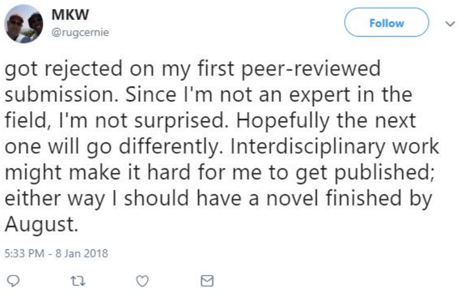
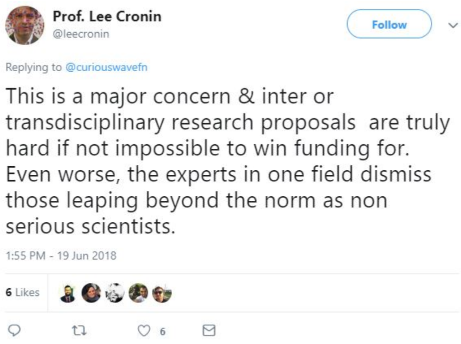


Figure 5: Relative counts of user tags (@), URLs, and emojis within the tweets of the three modes of research

Neutral tweets. The neutral tweets are mostly informative and many of them share and advertise publications, websites, or job announcements. The informative character of the neutral tweets is also apparent in the high frequency of URLs in the tweets (Figure 5). *Neutral interdisciplinary* tweets frequently share URLs referring to job postings, PhD positions, open calls for applications, news, blog posts, pod-casts, discussions, or researchers announcing a

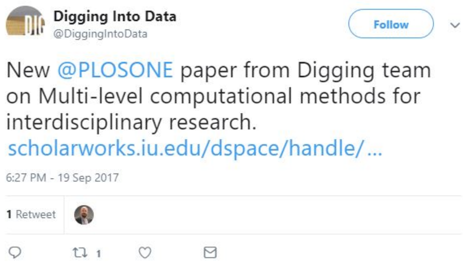


(a) negative



(b) negative

(c) neutral



(d) neutral

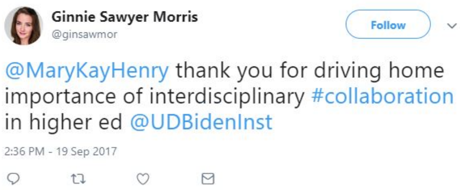
Figure 6: Examples of negative and neutral tweets.

paper publication (Figure 6c and 6d). A similar pattern is visible in the *neutral transdisciplinary* tweets, with many URLs referring to informative topics such as job posting, articles, and news publications. Similar results can also be found within the *neutral multidisciplinarity* tweets, which mainly refer to websites, news, events, articles, paper publications, and job postings.

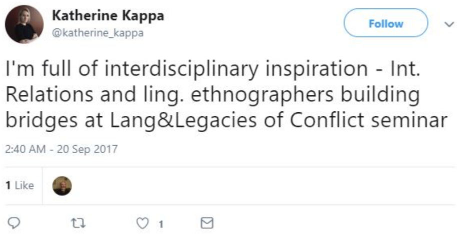
Positive tweets. The content of the positive tweets within all three modes of research showed enthusiasm and excitement by complimenting and praising different studies, lectures, approaches, and discussions. In addition, all three modes of research contained a high usage of the user tag (at least one per tweet). Emoji's were less frequently used, but appeared to be slightly more used compared to the neutral and negative tweets (Figure 5).

Many of the *positive interdisciplinary* tweets were positive about conferences, seminars, symposia, and workshops, in which researchers felt excited about it and thought that these events were interesting and useful. In particular, researchers were positive about meeting like-minded researchers and listening to inspiring talks, discussions and thoughts during conferences, seminars, and workshops. Researchers described their participation in such events as inspiring, exciting, and they felt lucky to have participated. In many of the tweets, researchers also described having fun learning, enjoyed listening to others, and appreciated critical interdisciplinary discussions. In many tweets, researchers were also thankful to the organizers and participants of these events.

The tweets also expressed positivity towards research communities, teams and collaboration (Figure 7a). Researchers were happy and excited about effective, successful, and inspiring team work, collaboration, and cooperation in integrative research projects and studies. Collaboration was also enjoyed during paper writing, seminars and workshops. Many expressed appreciation



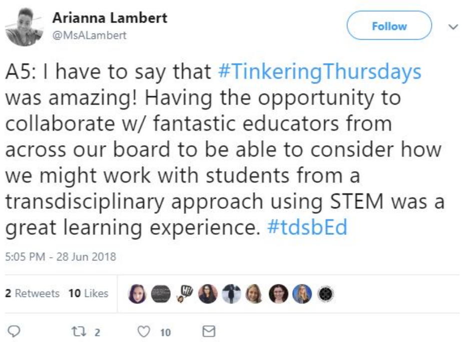
(a) importance of collaboration



(b) inspiring seminar

(c) funding acquisition

(d) work appraisal



(e) collaboration and education

(f) appreciation

(g) excitement

(h) value of collaboration

Figure 7: Examples of positive tweets referring to all three modes of research (interdisciplinary 7a–7d, transdisciplinary 7e–7g, and multidisciplinary 7h).

for cooperation and collaboration, and described how interdisciplinary collaboration can have an added value to advance research and understanding. The term 'Bridge building between disciplines' was often mentioned as a goal to strive for. Many of the positive tweets reported overall positive experiences, feelings, or praised interdisciplinary work and results (Figure 7b and 7d).

Researchers expressed their appreciation, the value and importance of integrative work, and were often in support of integrative research, as from their perspective, it can provide important solutions and promising results in different fields. For example, the fields of neuroscience, cancer research, political science, fisheries science, engineering, gender studies, cognitive science, computer science, and archaeology were mentioned. Researchers also expressed their explicit support for a certain interdisciplinary approach, conveyed their excitement about a study, and highlighted how they believe that a certain approach can address a particular challenge or solve a certain complex problem. Many described interdisciplinary work as impactful, excellent, creative and innovative, with potential for new discoveries. Others highlighted the strengths of integrative approaches, and how integrative research could potentially benefit sustainability and human well-being, such as patient care and mental health.

Tweets about a successful acquisition of funding and research grants for interdisciplinary research by individuals, teams, and research groups were also shared several times (Figure 7c). Some tweets showed excitement about having an interdiciplinary job, getting a new job within an interdisciplinary field, or the successful completion of an interdisciplinary PhD. Many described their work and research as fun and rewarding, feeling proud for their achievements and accomplishments. Researchers also appraised interdisciplinary universities and the value and importance of interdisciplinary education and training, and the benefits thereof. For example, researchers described the benefits of newly learned abilities and skills through interdisciplinary work, the interdisciplinary training that functioned as an eye-opener towards other fields, and how an interdisciplinary perspective can provide additional food-for-thought. Interdisciplinary training was also described as a way for researchers to open up alternative career paths.

Researchers also commonly shared their excitement and happiness about the successful publication of an interdisciplinary paper, a book, a book chapter, a news article, or blog post about interdisciplinary research or experiences. Some were also joyful about sharing news over the recognition of their interdisciplinary research and teaching through awards and prices.

Positive transdisciplinary tweets express positive sentiment about very similar topics found in interdisciplinary tweets, such as publication and funding successes, positive experiences from conferences and discussion, and the value of transdisciplinary teaching and education (Figure 7e). Also, positive experiences from the involvement into transdisciplinary research projects were shared and highlighted the value and importance of the work (Figure 7f and 7g).

Many of the *positive multidisciplinary* tweets referred to healthcare and medical topics (Figure 7h). Other topics included, similarly to inter- and transdisciplinary tweets, good experiences from teams and team work, positive conference experiences, a general positive attitude and excitement towards multidisciplinary work and success stories, such as winning an award.

Key Successes and Positive Experiences. In summary, the positive tweets demonstrate a number of key successes, and document positive experiences for the three modes of research. Key successes included:

- Attaining advanced skills
- Successful publications (papers, books, etc.)
- Acquisition of funding and research grants
- Production of creative, innovative, and impactful research
- Improved research practice and research results through effective and successful team work, collaboration, and cooperation
- Research results provide useful solutions and can be of value to science and society

- Recognition of scientific work through awards and prizes

Descriptions of positive inter-, trans-, and multidisciplinary experiences can be summarized as follows:

- Conferences, seminars, and workshops provide valuable insights and inspiring talks
- Meetings with other inter-, trans- and multidisciplinary scholars provide thought-provoking and inspiring discussions
- Work and research is fun, exciting, and rewarding
- Training and learning opportunities are interesting and valuable

4. Discussion

We used a sentiment analysis to explore the opinions of researchers towards different modes of research (including inter-, trans-, and multidisciplinarity) communicated via the social media platform Twitter. Twitter provides an immense resource of text-based data covering a very large group of people [53], with an average of 328 million active monthly users who broadcast their thoughts and opinion as tweets [15]. As such, Twitter offers an abundance of easily-accessible data which has resulted in the rise and development of machine learning techniques that enabled a sentiment analysis of tweets [54]. To date, sentiment analysis on Twitter data has been conducted across a variety of disciplines and topics, ranging from computer science to environmental and medical sciences [55–59]. In addition, Twitter data has also been used to e.g. save lives during earth quakes, while organizations such as the United Nations collaborate with Twitter to achieve the sustainable development goals[5]. For example to monitor outbreaks of diseases [60]. Hence, it is increasingly being recognized that tweets can provide valuable information and insights into peoples' lives, health, and opinions.

In our study, over 70,000 tweets were collected for the different modes of research over the time span of 53 weeks. The large number of unique users (Table 7) producing a large amount of tweets (Figure 2) demonstrate that there is an active scientific community that is interested in the discourse of integrative research concepts. Proportionally, interdisciplinarity appears to be the most popular research concept with the largest number of collected tweets, which could be related to the general interdisciplinary research 'break out' over the last couple of years [61].

Negative tweets. The negative tweets highlight the challenges of integrative research that people have experienced. It is often the integrative nature of these approaches that gives rise to challenges for the researchers involved, because disciplinary boundaries have to be crossed, which can introduce institutional and cultural issues [4,5]. The detection of negative opinions within the inter- and trans-disciplinary tweets was therefore foreseen. In contrast, multidisciplinary tweets, reflecting a non-integrative research concept, were expected to have less negative tweets because multidisciplinarity is often perceived as being 'easier'. Interestingly, this hypothesis could not be confirmed in this study nor in a similar study by [62].

However, only very few of the tweets were classified as negative (2–3%), which stands in contrast to the larger literature where often the challenges and difficulties of integrative research are propagated and discussed [4,5,7,8]. Therefor, this study highlights how a sentiment analysis can offer new insights into researchers' opinions, and has the ability to identify perspectives on a larger scale that contrast the common (negative) perception and experiences typically found in the literature. However, the articles and publications in the literature are usually published by selected individuals and do not necessarily reflect the opinion of the wider research community, whereas our study captured opinions of thousands of different individuals (Table 7). In addition, not all researchers may want to share their negative experiences with their friends and colleagues on Twitter, as it is often easier to share and disseminate one's successes rather than one's failures. Yet, from a scientific perspective, it may be perceived as more valuable to identify and analyze

[5]https://developer.twitter.com/en/developer-terms/more-on-restricted-use-cases

challenges within a research practice, with the aim to understand and overcome these challenges. However, human brains tend to have a tendency towards a negative bias [63], which means that people usually have a higher sensitivity to negative information. Despite the description of positive examples and experiences in the literature, e.g. [64,65], the negative ones might be more likely to be remembered by researchers.

Neutral tweets. The majority of tweets found in this study were neutral and mostly informative, which did not reflect any particular perception or sentiment. In these cases, Twitter is being accessed as a dissemination and advertising platform, rather than a way to express an opinion, since it is generally a cheap and easy way to spread information. This is not surprising, when considering that the Twitter platform is increasingly used as a source of real-time information from news channels, politics, business, science, and entertainment, but also the personal use by individuals and organizations lies at the core of Twitter's utility to express thoughts, share information and connect with friends [66].

Communication and dissemination is additionally facilitated by being able to tweet information with just a single click through the small 'Tweet button' displayed on the website to enable viewers to share the content on Twitter [67]. Also, the latest website plug-ins allow for new posts (e.g. blog posts) to be automatically shared on a user's Twitter account [68].

Typically, scholars, which are the population of this study, tweet rather neutral information, resources, and media [66] and this explains the high amount of neutral tweets with URLs found in this study (Figure 2 and 5). Twitter is also increasingly used as a teaching and communication platform by instructors [69], who have been found to have a higher credibility among students when their tweets are professional [70]. Such educational tweets most often express no sentiment but are of a neutral nature. There has also been a gradual shift within the scientific community towards increased communication and dissemination of research and scientific results. A possible explanation could be the increasing demands for dissemination by funding agencies such as the European Commission [71]. For researchers, the Internet has become a useful way to disseminate and promote events and publications because Twitter offers a quick and easy option to disseminate scientific results, to contribute to a discussion and increase visibility via hashtags [66]. The use of Twitter by researchers for these purposes is also apparent in our results.

Positive tweets. The positive tweets demonstrated experiences of success stories of the known challenges of interdisciplinarity, such as successful funding acquisitions, interdisciplinary publications, successful and positive team work experiences, and successful interdisciplinary projects (Figure 7). Thereby, demonstrating real-life examples of how also the positive opposite of what is commonly feared is possible and attainable within interidsciplinary research.

A large amount of the tweets were positive, in which users expressed positive experiences and perceptions. The high frequency of user tags (@) (Figure 5) implies discussions between people, projects and institutions, e.g. within a circle of friends, between co-workers, or in connection with a shared field of research or project. Participants from integrative projects are often found to have positive experiences based on the team work and collaboration with other participants [22,62], which is also indicated in our results (Figure 7a). The positive tweets are likely to originate from people who are actively involved in interdisciplinary projects themselves (Figure 7g), which is also the group of researchers that has been found to describe their work as positive most of the time [62].

We hypothesize that it is many of the younger generations of scientists within our dataset that perceive interdisciplinarity as mainly positive and beneficial, more intellectually interesting, and more practically important. This is due to the fact that younger researchers have been found to show higher rates of interdisciplinarity when compared to tenure track researchers and professor [12]. The perceptions of those early career researchers could possibly be dominating the positive discourse on Twitter due to the fact that 24 to 35 year olds make up the largest age group of Twitter users [72]. Women might also make up a larger proportion of the Twitter users sampled within this study because they have a higher preference for interdisciplinary work than men [73], and might therefore be among the researchers tweeting about it. Even though the integrative research path has been described as a career risks for early researchers, interdisciplinary PhD graduates have shown higher likelihood of academic employment and higher publication productivity [74]. These scholars are likely to share their enthusiasm and success through a positive attitude and discourse on integrative research. However, age and gender distributions were not investigated in this study and cannot be confirmed at this stage.

Reason for Optimism? Overall, our study revealed that researchers have mostly positive perceptions about multi-, inter-, and trandisciplinarity (Figure 2). This study also demonstrates many examples of positive experiences that were created through successful funding, accepted publications, interesting research outcomes, and effective teamwork and collaboration, besides other aspects. This highlights that there are indeed many of the 'good experiences' and 'bright spots' to be found within these research practices. It also shows the value of this Twitter analysis, as some of these experiences may not be shared to the same extent within the literature as such. For example, publications seldom cover success stories regarding the acquisition of funding for an interdisciplinary project or the experiences of conference participants. Hence, this Twitter sentiment analysis is able to capture and quantify interdisciplinary experiences from a different perspective.

We believe that the findings of this study demonstrate and document positive experiences and opinions, and as such, give reason for optimism within integrative research approaches. Hence, this study is a first step towards building interdisciplinary optimism. The continued documentation and propagation of such 'bright spots' and successes could further increase optimistic thinking about integrative research, which may have many potential benefits.

Optimism can increase people's psychological and physical well-being [14], and facilitate and increase creativity in individuals and teams [75]. Creativity is also closely linked and thought to play an important role in people's innovation capacity [76,77], which makes it a key aspect for integrative research approaches, which are often hoped to show high innovation potential. Positive thinking and optimism are also beneficial to team work—a crucial part of most integrative approaches—and can have positive effects on team level cooperation, collaboration, and overall team outcomes [78]. Hence, the findings of this study could potentially contribute to the future success of integrative research through their propagation of optimism.

We, therefore, believe that it is important to make these results visible to the wider research community through publication and dissemination, and that additional positive experiences as well as studies of bright spots should be shared and propagated. Thereby, interdisciplinary researchers are encouraged to follow this example and to participate in the interdisciplinary discourse and the study of bright spots to support integrative research practices in the future from an optimistic perspective.

(a) Limitations and future work

An inherent limitation of Twitter is that it is not representative of the whole population and our study could be expanded to compare and contrast our results with other communication media in the future. In addition, we provided only a snapshot in time and therefore, we would encourage the study of the long-term trends of public sentiment towards integrative research approaches, along with additional investigations on the distribution of age and gender among Twitter users. We included tweets exclusively in English because it is the most common language found on Twitter but this potentially excludes all non-English discourse on interdisciplinarity.

The detection of sarcasm and irony remains a difficult and challenging task, and is a limitation of this study. However, this limitation is somewhat mitigated by drawing on a large dataset of over 70,000 tweets. In addition, we assumed people to be truthful in their tweets. There is also a risk that the use of the words multidisciplinary, interdisciplinary, and transdisciplinary may not be based on a solid understanding of these terms. In addition, it is extremely difficult to assess whether a person has a correct understanding of the terms. However, by drawing on a large dataset, which was targeting tweets from scientists and researchers, this risk is reduced. Also, tweets in our dataset referred to definitions and the differences between the modes of research, which indicates that (at least some of) the researchers are familiar with the terminology and the different meanings of the three modes of research. In addition, we assume that there are tweets in which the content refers to the three different modes of research but does not mention the terms explicitly. These tweets were not capture in our dataset. Yet, such tweets are difficult to capture and require a manual analysis and context interpretation, which was not feasible within the bounds of this study.

Another limitation includes that 'transdisciplinary' can potentially have two different meanings, i.e. (i) the inclusion of non-academic participants in interdisciplinary research, and (ii) transcending disciplinary boundaries through the development of new methods from two or more scientific disciplines, which could potentially lead to a new discipline. However, based on the manual inspection of the content of tweets, it is assumed that transdisciplinarity is most commonly used with meaning (i) within the dataset.

The current state-of-the-art in sentiment analysis typically employs neural network models [42]. Specifically, the recurrent neural network model is better designed to handle sequence data, such as text, compared to, for instance, the Multi-layer Perceptron. Recurrent neural networks have the advantage of taking word order into account, and advanced implementations such as the LSTM model [41] achieve top ranking results in sentiment classification competitions. Additionally, tweet data is, increasingly, represented as word embeddings [79], a high dimensional vector representation of words, and have shown to boost performance of sentiment classification tasks [42,80]. However, such state-of-the-art methods and architectures come with a high degree of complexity and training these models can be challenging and time consuming. It would be an interesting approach to study in future research, although the purpose of this analysis was not to build top ranking sentiment classification systems. More importantly, the employed classifier, the support vector machine, achieves near to state-of-the-art results if properly parameterized [42,80], and would adequately provide a sense of sentiments for the three modes of research studied in this paper.

5. Conclusion

For the success of integrative research approaches, it is important to foster positive thinking and optimism through the study of 'bright spots'. Bright spots can help to harvest the full potential of integrative research and to enable a feeling of empowerment among researchers engaging in these approaches. This study identified such 'bright spots' by analyzing the sentiment of tweets on inter-, trans- and multidisciplinarity where researchers expressed dominantly positive opinions (excluding neutral tweets). Positive opinions were created through and based on positive experiences and successes within integrative research, such as accepted publications, the acquisition of funding and effective team work. As such, this study demonstrates and documents positive thinking within integrative research and gives reason for optimism. The continued study of bright spots and propagation of optimism can potentially have many benefits for integrative research, and maybe hopefully inspire and empower scientists to continue and strive for integrative research in the future.

6. Supplementary material

Data S1. Full dataset of all tweets that were collected and analyzed in this study. Contains tweet IDs for each modes of research and assigned sentiment labels.
Data S2. List of 430 occupations related to a scientific or academic profession.
Text S1. Description of the training datasets.

Data Accessibility. The dataset of all extracted tweets are made available in the supporting information (Data S1).

Authors' Contributions. C.T.W. and S.S. retrieved the data. S.S. processed the data and prepared the figures. S.S. analyzed the data. C.T.W. and S.S. designed the research, interpreted the results, wrote the manuscript and gave their final approval for publication.

Competing Interests. The authors declare no competing interests.

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Supplementary Text S1. Descriptions of the seven datasets used to train the sentiment classifier.

Sanders The Sanders dataset consists out of 5,513 hand classified tweets related to the topics Apple (@Apple), Google (#Google), Microsoft (#Microsoft), and Twitter (#Twitter). Tweets were classified as positive, neutral, negative, or irrelevant; the latter referring to non-English tweets which we discarded. The Sanders dataset has been used for boosting Twitter sentiment classification using different sentiment dimensions [1], combining automatically and hand-labeled twitter sentiment labels [2], and combining community detection and sentiment analysis [3]. The dataset is available from `http://www.sananalytics.com/lab/`.

Obama-McCain Debate (OMD) The Obama-McCain Debate (OMD) dataset contains 3,238 tweets collected in September 2008 during the United States presidential debates between Barack Obama and John McCain. The tweets were collected by querying the Twitter API for the hash tags #tweetdebate, #current, and #debate08 [4, 5]. A minimum of three independent annotators rated the tweets as positive, negative, mixed, or other. Mixed tweets captured both negative and positive components. Other tweets contained non-evaluative statements or questions. We only included the positive and negative tweets with at least two-thirds agreement between annotators ratings; mixed and other tweets were discarded. The OMD dataset has been used for sentiment classification by social relations [6], polarity classification [7], and sentiment classification utilizing semantic concept features [8]. The dataset is available from `https://bitbucket.org/speriosu/updown`.

Stanford Test The Stanford Test dataset contains 182 positive, 139 neutral, and 177 negative annotated tweets [9]. The tweets were labeled by a human annotator and were retrieved by querying the Twitter search API with randomly chosen queries related to consumer products, company names and people. The Stanford Training dataset, in contrast to the Stanford Test dataset, contains 1.6 million labeled tweets. However, the 1.6 million tweets were automatically labeled, thus without a human annotator, by looking at the presence of emoticons. For example, tweets that contained the positive emoticon :-) would be assigned a positive label, regardless of the remaining content of the tweet. Similarly, tweets that contained the negative emoticon :-(would be assigned a negative label. Such an approach is highly biased [10] and we choose not to include this dataset for the purpose of creating a sentiment classifier from labeled tweets. The Stanford Test dataset, although relatively small, has been used to analyze and represent the semantic content of a sentence for purposes of classification or generation [11], semantic smoothing to alleviate data sparseness problem for sentiment analysis [12], and sentiment detection of biased and noisy tweets [13]. The dataset is available from `http://www.sentiment140.com/`.

Health Care Reform (HCR) The Health Care Reform (HCR) dataset was created in 2010 – around the time the health care bill was signed in the United States – by extracting tweets with the hashtag #hcr [7]. The tweets were manually annotated by the authors by assigning the labels positive, negative, neutral, unsure, or irrelevant. The dataset was split into training, development and test data. We combined the three different datasets that contained a total of 537 positive, 337 neutral, and 886 negative tweets. The tweets labeled as irrelevant or unsure were not included. The HCR dataset was used to improve sentiment analysis by adding semantic features to tweets [8]. The dataset is available from `https://bitbucket.org/speriosu/updown`.

SemEval-2016 The Semantic Analysis in Twitter Task 2016 dataset, also known as SemEval-2016 Task 4, was created for various sentiment classification tasks. The tasks can be seen as challenges where teams can compete amongst a number of sub-tasks, such as classifying tweets into positive, negative and neutral sentiment, or estimating distributions of sentiment classes. Typically, teams with better classification accuracy or other performance measure rank higher. The dataset consist of training, development, and development-test data that combined consist of 3,918 positive, 2,736 neutral, and 1,208 negative tweets. The original dataset contained a total of 10,000 tweets – 100 tweets from 100 topics. Each tweet was labeled by 5 human annotators and only tweets for which 3 out of 5 annotators agreed on their sentiment label were considered. For a full description of the dataset and annotation process see [14]. The dataset is available from `http://alt.qcri.org/semeval2016/task4/`.

Sentiment Strength (SS) The Sentiment Strength (SS) dataset was used to detect the strength of sentiments expressed in social web texts, such as tweets, for the sentiment strength detection program SentiStrength [15]. The dataset was labeled by human annotators and each tweet was rated on a scale from 1 to 5 for both positive and negative sentiment, i.e. a dual positive-negative scale. For the purpose of this paper, we re-labeled the tweets into positive, negative and neutral tweets as follows. Tweets were considered positive if the positive score was at least 1.5 times larger than the negative score; a positive score of 4 and a negative score of 1 would result in a positive label. Tweets that have a negative score of 1.5 times larger than the positive score were considered negative. A similar score on the positive and negative scale would result in a neutral tweet, such when the positive score is 2 and the negative score 2. A similar re-labeling process was performed by [10]. A total of 1,252 positive, 1,952 neutral, and 861 negative tweets were used. SentiStrength has been used to quantify and statistically validate trading assets from social media data [16], and analyzing emotional expressions and social norms in online chat communities [17]. The dataset is available from `http://sentistrength.wlv.ac.uk/documentation/`

CLARIN 13-Languages The CLARIN 13-languages dataset contains a total of 1.6 million labeled tweets from 13 different languages, the largest sentiment corpus made publicly available [18]. We used the English subset of the dataset since we restricted our analysis to English tweets. Tweets were collected in September 2013 by using the Twitter Streaming API to obtain a random sample of 1% of all publicly available tweets. The tweets were manually annotated by assigning a positive, neutral, or negative label by a total of 9 annotators; some tweets were labeled by more than 1 annotator or twice by the same annotator. For tweets with multiple annotations, only those with two-third agreement were kept. The original English dataset contained around 90,000 labeled tweets. After recollection, a total of 15,064 positive, 24,263 neutral, and 12,936 negative tweets were obtained. The dataset is available from `http://hdl.handle.net/11356/1054`.

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Paper 3

An Interdisciplinary Insight into the Human Dimension in Fisheries Models. A Systematic Literature Review in a European Union Context.

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An Interdisciplinary Insight into the Human Dimension in Fisheries Models. A Systematic Literature Review in a European Union Context.

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Abstract

Fisheries are complex adaptive social-ecological systems (SES) that consist of interlinked human and ecosystems. Thus far, they have mainly been studied by the natural sciences. However, the understanding and sustainable management of fisheries will require an expansion of the study of the human element in order to reflect the SES perspective. Models are currently the most common method used to provide management advice in fisheries science, and these, in particular, will have to expand to include the human dimension in their assessment of fisheries. The human dimension is an umbrella term for the complex web of human processes within a social-ecological system and as such it is captured by disciplines from the social sciences and the humanities. Consequently, capturing and synthesizing the variety of disciplines involved in the human dimension, and integrating them into fisheries models, will require an interdisciplinary approach. This study therefore attempts to address the current shortcomings associated with the modelling of fisheries in the European Union and advise on how to include the human dimension and increase the interdisciplinarity of these models. We conclude that there is potential for the expansion of the human dimension in fisheries models. To reach this potential, consideration should be given to e.g. early involvement in model development of all relevant disciplines, and the formulation of operationalisable theories and data from the human dimension. We provide recommendations for interdisciplinary model development, communication, and documentation in support of sustainable fisheries management.

1 Introduction

Fisheries have been recognised as a social-ecological system (SES). As such, they consist of a coupling of a human system with a natural one (Ostrom, 2009). These two subsystems are connected and intertwined, and have a two-way feedback relationship, where a change in one of the subsystems can impact the other, and vice-versa (Berkes, 2011). Fisheries also have the characteristics of complex adaptive systems, such as non-linearity, uncertainty, and self-organisation (Leenhardt et al., 2015; Levin et al., 2012). Thus, fisheries can be understood as social-ecological complex adaptive systems (SECAS). Today, the SECAS perspective on fisheries has been acknowledged, yet fisheries are not always addressed as such (Syed, Borit, & Spruit, 2018).

The field of fisheries science has been traditionally dominated by natural scientists (Link, 2010). Their research efforts have focused mainly on topics relating to the natural subsystem (Syed et al., 2018). However, these efforts need to expand to include the human subsystem in order to ensure that fisheries science is addressing both elements of the social-ecological system, especially as a lack of consideration of the SES perspective in general, and the human subsystem in particular, has led, in some cases, to management and policy failures in the past (Freire & Garcia-Allut, 2000; Österblom et al., 2011). Thus, it is only through equal consideration of both subsystems that fisheries science can provide a SECAS perspective. In return, it is only through a SECAS perspective that the field can capture the complexity of fisheries appropriately, and contribute to effective sustainability, conservation, and management initiatives (Marshall et al., 2018; Rissman & Gillon, 2017; Starfield & Jarre, 2011).

Fisheries science uses modelling approaches to assess fisheries systems and to provide management advice. As such, models are the most commonly used method in this field (Jarić, Cvijanović, Knežević-Jarić, & Lenhardt, 2012). A common way to integrate various data and additional considerations on, for example, theory or indicators (Link, 2010, p. 89), models can provide an inspiring point of departure and a guiding principle for interdisciplinary (e.g. (Heemskerk, Wilson, & Pavao-Zuckerman, 2003)), and as such models have a high potntial to be used as an integrative research method in itself. Consequently, including considerations of the human subsystem into these models will provide a better assessment of fisheries as SECAS, while supporting their sustainable management. However, the human subsystem is not easily captured, as it is a broad and diverse field of study.

The umbrella term 'human dimension' in relation to fisheries has been used in order to refer to the diversity within the human subsystem and to highlight its importance (Charnley et al., 2017; OECD, 2007). The human dimension (HD) can be understood as a complex web of human processes that relate to natural resources (Spalding, Biedenweg, Hettinger, & Nelson, 2017) . It can be categorised into social phenomena, social processes, and individual attributes (Bennett et al., 2017). To study the HD, human dimension aspects (HDA) (i.e. smaller components within an HD category) are often analysed, such as compliance or trust. Due to the diversity of the human subsystem, the HD and its HDAs are addressed by many different disciplines, ranging across the social sciences and the humanities. This makes the HD a ***broad multi- and interdisciplinary concept*** that can be studied from various angles and at different scales, from global to local (Bennett et al., 2017; Spalding et al., 2017). Thus, interdisciplinary approaches are required to capture the full diversity of the HD.

However, models commonly use economic and environmental data, because these data are more easily available and accessible, e.g. *catch* and *effort*. Such data are commonly recorded during fishery-independent surveys or as fishery-dependent data for all (large-scale) fleets and markets in the European Union (EU), for example. Economic and environmental considerations are also commonly very prominent in frameworks for a comprehensive approach to fisheries management

(Stephenson et al., 2018). In comparison, consideration of the HD and the collection of HD data has been falling short in the EU compared to collection efforts associated with environmental and economic data and as such social data is often lacking or unavailable (Hatchard & Gray, 2014). Social information is also more difficult to collect as social issues range from individual to global concerns (Bennett et al., 2017), additionally hindering the quantification of HDAs (Hatchard & Gray, 2014; Symes & Phillipson, 2009). In cases where social science data has been provided, information is usually presented in the form of descriptive text, which is often neither read, nor integrated into fisheries assessments in a meaningful way (Hall-Arber, Pomeroy, & Conway, 2009).

In order to ensure that fisheries models can capture the HD and its diversity, multi- and interdisciplinary efforts are needed, with support from various disciplines. Through such efforts, the necessary support for the inclusion and incorporation of the broad concept of HD can be provided. However, it remains unclear to what extend the HD has been integrated into fisheries models and exactly how interdisciplinary the field of HD in fisheries models is at present, and into what areas it should be expanded.

Therefore, the aim of this study is to assess the presence of HD in fisheries models, and to evaluate interdisciplinarity within modelled HDAs. These objectives were translated into the following research questions: *How interdisciplinary is the field of the human dimension in fisheries modelling? Is there a gap between the HDAs that are modelled and those that could be modelled? Are HDAs included in fisheries models modelled in an interdisciplinary manner?*

2 Conceptual Framework

2.1 Interdisciplinarity

In this study, we understand interdisciplinarity as an attempt at mutual interaction between disciplinary components that involves crossing the boundaries of several academic disciplines with contrasting research paradigms in order to create new theories and knowledge (Tress, Tress, & Fry, 2005). Interdisciplinary activities and studies apply, synthesize, integrate, or transcend parts of two or more disciplines with a common goal (Chiu, Kwan, & Liou, 2013; Huutoniemi, Klein, Bruun, & Hukkinen, 2010; Tress et al., 2005). To make the distinction, multidisciplinarity involves several academic disciplines that have multiple parallel goals, often with the purpose of comparison, but does not cross subject boundaries or aim for any form of integration. Transdisciplinarity combines interdisciplinarity with a participatory approach by involving non-academic participants and knowledge bodies to create new knowledge and theory (Tress et al., 2005).

To assess interdisciplinarity within the field of the human dimension in fisheries models, we used the typology and indicators for interdisciplinarity developed by Huutoniemi et al. (Huutoniemi et al., 2010). This typology considers interdisciplinarity on three dimensions: 1. the scope of interdisciplinarity, i.e. what is being integrated; 2. the type of interdisciplinary interaction, i.e. how it is being done; and 3. the types of goals, i.e. why an interdisciplinary approach is being used.

The scope of interdisciplinarity refers to the conceptual and cultural distance between the participating disciplines or research fields. It is understood as *narrow* if the participating fields are conceptually close to each other (e.g. life sciences and biological sciences), whereas it is considered *broad* when the fields are conceptually diverse (e.g. law and engineering). The type of interdisciplinary interaction describes how interdisciplinarity is being carried out, and three different approaches can be distinguished: *empirical*, *methodological*, and *theoretical*. *Empirical* interdisciplinarity integrates different types of empirical data (e.g. qualitative and quantitative data). *Methodological* interdisciplinarity implies the integration of different methodological approaches. As we chose to explore only models as a fisheries research methodology, this dimension of interdisciplinarity has not been assessed in this study. *Theoretical* interdisciplinarity occurs when concepts, models, or theories from more than one field or discipline are synthesized in order to develop new theoretical tools (Huutoniemi et al., 2010). By considering only empirical and theoretical interdisciplinarity, we assumed that the HD should be fit into fisheries models and did not consider potential other methodological approaches that could be suitable for studying fisheries as SECAS and providing science advice to management.

The types of goals can be *epistemologically* oriented to increase knowledge, or *instrumentally* oriented to achieve an extra-academic goal or solve a societal problem. The types of goals can also have a *mixed* orientation when they have both, an epistemological and an instrumental orientation.

3 Methodology

In order to address our research questions, we employed a systematic literature review (SLR) approach that consisted of three consecutive steps: 1. relevant literature was collected and selected in a systematic, reproducible manner; 2. the selected literature was analyzed in a qualitative way through content analysis and hierarchical coding, which was followed by 3. the design of data visualizations. Subsequently, we applied a typology and indicators to assess interdisciplinarity within the data. All the applied methods are explained in detail in the following sections, followed by their limitations.

3.1 Literature collection and selection

In order to select a large enough sample of papers on fisheries models to study the practices being used to the model the human dimension, we decided to use a systematic approach. This provides transparency and replicability and makes the choice of the publications under review comprehensible by determining: 1. a set of keywords to be used as search terms in an unbiased academic search engine, and 2. clear inclusion and exclusion criteria by which the resulting literature will be evaluated. These steps are described in Sections 3.1.1 and 3.1.2.

This methodology is commonly referred to as a Systematic Literature Review (SLR) and is an effective approach for sampling the literature in a systematic and reproducible way. SLRs are commonly applied in fields such as medical science (e.g. Weitzen, Lapane, Toledano, Hume, & Mor, 2004) and software engineering (e.g. Kitchenham et al., 2009), and they are an emerging method in fields such as organisational studies (Maier et al. 2016), education (e.g. Hainey et al. 2016), and marine and coastal studies (e.g. Liquete et al. 2013).

3.1.1 Search terms

The search was conducted using the scientific search engine Scopus (www.scopus.com), where the search terms ‘fisheries’, ‘model*’, and ‘common fisheries policy’ were employed to select for peer-reviewed publications on fisheries models. All subject areas as identified by Scopus (i.e. life sciences, health sciences, physical sciences, social sciences, and humanities) and all possible publication years were selected. The precise search string used in Scopus can be found the Appendix S1. The search was conducted on 25/08/2015.

We used the term ‘fisheries’ in order to select for models with a system perspective, rather than select for models only considering the environmental components (e.g. fish), and therefore we did not use the search term ‘fish*’. To achieve a general perspective on the field of fisheries modelling, we chose not to limit this study to a particular modelling technique (e.g. Bayesian belief networks) or a particular model type (e.g. stock assessment). Thus, we sampled models created for a large variety of fisheries that are performing under similar managerial assumptions. Among the multitude of possible managerial assumptions, we chose the Common Fisheries Policy of the European Union (EU), a common set of rules that applies to all EU fishing fleets and EU fish stocks. This decision was driven mainly by the fact that the EU fisheries are among the most extensively studied in the world (Jarić et al., 2012), therefore presumably offering a large, but still manageable, sample for qualitative analysis. In addition, we considered the source to include a model if the respective item was referred to as a model by the authors of the publication, including qualitative/quantitative models, process/conceptual models, and frameworks.

3.1.2 Inclusion and exclusion criteria

The full text of all publications was downloaded, and the publication metadata was exported from Scopus, including authors, title, year, journal, and journal subject areas. All articles were screened for relevance to the study objectives and included or excluded based on the criteria listed in Table 1.

Throughout this process, we followed the guidelines for systematic reviews in conservation and environmental management (Pullin & Stewart, 2006), and the PRISMA reporting guidelines (Moher, Liberati, Tetzlaff, Altman, & Group, 2009). These guidelines ensure a thorough execution of the sampling and analysis of the literature while carrying out the SLR.

3.2 Content Analysis

The SLR process was followed by a qualitative analysis and synthesis through content analysis, which is a research methodology for making valid inferences from texts in a replicable manner (Krippendorff, 2013). This study followed a problem-driven approach to content analysis, which means that it was motivated by epistemic questions about currently inaccessible information that the text is assumed to be able to answer (Krippendorff, 2013). During our content analysis, coding categories and recording instructions were developed, and an analytical procedure was selected. These steps are explained in detail in Section 3.2.1.

3.2.1 Coding of the human dimension aspects

The content of the selected publications, i.e. the information relevant to the research questions of this study, was analysed through coding and the development of a category system. Coding is the process of categorising and organising information into a meaningful framework (Johnson, 2007) to empower and speed up systematic qualitative data analysis (Lofland, Snow, Anderson, & Lofland, 2006). The term coding refers to the process of reading the data and dividing it into meaningful analytical units, also known as segmenting the data. Once a meaningful unit has been identified, it is coded, which means that the unit is marked with a descriptive word or a category name. During coding, a master list is maintained in order to keep track of all previously coded units, so that codes can be reapplied to new data segments each time an appropriate unit or segment is discovered within the text (Johnson, 2007). We developed an indicative code, which means that it was created by the researcher whilst directly inspecting the data, in contrast to, for example, using a pre-existing set of codes that had been developed *a priori* to the analysis.

We coded the data according to a hierarchical category system. This enables organisation of the data into different levels or categories based on the idea that some themes are more general than others, and that codes are therefore related vertically (Johnson, 2007). We used the term 'function' to describe the categorical relationship between the codes. A functional relationship between two variables essentially means: *X is used for Y* (Johnson, 2007).

In the code developed for this study the main aspect modelled by a publication, or the main subject of the model, was coded as the first hierarchical unit representing the general theme and overall goal. The main aspect modelled was identified based on what the authors themselves stated in the title, the abstract, or the introduction to the article (e.g. "…we modelled the exploitation of a fishery…"). The theme identified as the overall goal or main aspect of the model was categorised into one of three dimensions: human/social, economic, or environmental, or a combination of these (see Section 3.2.2).

Studies whose main aspect was identified as the human dimension were analysed in depth via further hierarchical coding to determine through which variables they had been modelled. Two more descending hierarchies were introduced into the coding, which resulted in a three-level code hierarchy: Level 1—the main HDA; Level 2—variables that were used to model Level 1 and the functional relationship between them; Level 3—variables that were employed to model Level 2 and the functional relationship between them. In more mathematical terms, this can be described as follows:

$$HDA = \mathrm{F}\,(b, c)\,, \qquad \text{with } b = \mathrm{G}\,(d, e)$$

where HDA is the main HDA, (Level 1), which is modelled as a function F of the variables b and c, and where b is modelled as a function G of the variables d and e.

All these variables were coded in NVivo 11 (QSR International Pty Ltd, 2015). The codes, which are represented as nodes in NVivo, were assigned to hierarchical categories in order to distinguish between Level 1, Level 2, and Level 3 variables (Figure 1).

In addition, information on the modelling techniques and types e.g. Bayesian belief network, bioeconomic model, etc., were extracted from the publications and recorded in Microsoft Excel 2016.

3.2.2 Assigning the dimensions identified in the fisheries models to the human dimension aspects

The identified HDAs and other variables were assigned to the dimensions described previously (*human/social*, *economic*, and *environmental*) based on the indicators for sustainable development of marine capture fisheries developed by the Food and Agriculture Organization (FAO) of the United Nations (see Section 2.3. Table 3 in FAO Fishery Resources Division, 1999). We included the FAO's *governance* dimension in the *social* one and renamed the latter as the *human* dimension. The *economic* dimension was treated as a dimension in its own right, as the tradition of treating it separately in fisheries science seems to be very strong (Haapasaari, Kulmala, & Kuikka, 2012). We found the FAO framework appropriate given its global penetration level and authority in fisheries science, but we are aware that other categorizations and divisions of fisheries systems exist (A. Charles, 2000). The human dimension aspects were categorized into three topics as described by Bennett et al. (2017): *social phenomena*, *social processes*, and *individual attributes*.

3.2.3 Enumeration of the qualitative data

The qualitative coding analysis of the publications was followed by enumeration, which refers to the quantification of the qualitative data and coding results, for example, the number of HDAs and the human/social, economic, and environmental variables for each HDA were counted. The enumeration of the qualitative data was conducted using the software NVivo 11 (QSR International Pty Ltd, 2015) because computer-aided qualitative data analysis allows for the automated enumeration while enabling all data to be exported into other formats (e.g. csv, excel, etc.).

3.3 Visualizations of the human dimension aspects

The creation and use of displays (i.e. visualisations—the organised, compressed assembly of information that permits the drawing of conclusions and subsequent actions) is an important part of qualitative data analysis (Miles & Huberman, 1994). In order to be able to design relevant visualisations for this study, the qualitative data (i.e. the HDAs and their corresponding variables) were exported from NVivo 11 to Microsoft Excel 2016. They were transformed using Python into a data format (source-to-target) adequate for import into Gephi (Version 0.9.1), which is an open source visualisation tool for graph and network analysis (Bastian, Heymann, & Jacomy, 2009). This program allows for visual analytics and functions as a complementary tool to perform enumeration, to enable visual thinking, and to facilitate reasoning. In particular, Gephi was used for qualitative and quantitative visualisation of the hierarchy and the connections between the HDAs and the variables, as shown in Figure 1.

To give a qualitative representation of how the HDAs were modelled, the HDAs and variables were represented as nodes and the connections between them as edges, while the colour of each node was set according to the dimension that was assigned to the variable. The colours were assigned as follows: pink: human; blue: economic; green: environmental; white: other (e.g. time) or more than one dimension (e.g. sustainability). To include a quantitative representation of the results, the size of the nodes was set according to the publication count (i.e. the overall number of sources that featured this variable), which gives an impression of the relative importance of each. Each HDA in the study was treated separately, and a visual representation was created for each. The network algorithm used in Gephi was ForceAtlas2 (Jacomy, Venturini, Heymann, & Bastian, 2014).

3.4 Assessment of interdisciplinarity

Interdisciplinarity was assessed based on the typology and indicators described by Huutoniemi et al. (2010), as explained in Section 2. We assessed interdisciplinarity in the modelling of the human dimension in fisheries through: 1. indicators of the scope of interdisciplinarity (narrow or broad, i.e. what is being integrated), and we assessed interdisciplinarity within the modelled HDAs through 2. the types of interdisciplinary interaction (empirical or theoretical, i.e. how the integration is done). The former was determined by an inspection of the diversity of the journals in which the papers were published, and their subject areas, and as well as the diversity of the types of models. The latter was determined by inspecting the diversity of the HDAs found within the models (theoretical interdisciplinarity), and examining the diversity of the fisheries dimensions (human, economic, environmental) within the variables used to model the HDAs (empirical interdisciplinarity). It is important to emphasize that we assessed the interdisciplinarity of the sample as a whole (based on the aggregated empirical data we had collected), rather than looking at each individual model separately.

We did not asses the types of goals because this was not the primary purpose of our study.

3.5 Limitations of the applied methodology

One limitation of the SLR approach, as with any keyword-based study, is that the choice of keywords is prone to human subjectivity, and that relevant literature can be potentially excluded if the keywords are not present in the searchable fields, e.g. abstract, title, or keywords of the item. Also, the similar managerial assumptions introduced through the keyword search of "common fisheries policy" might not necessarily encourage the incorporation of the HD into fisheries models, and are as such a limitation of this study. Additionally, the number of publications reviewed is often much smaller than in, for example, computational approaches such as topic modelling (Syed & Weber, 2018).

Another limitation of the SLR approach is the exclusion of grey literature. Grey literature is not indexed in the same manner as scientific publications, and therefore cannot be sampled in the same way. On the other hand, grey literature does not undergo the same rigorous peer-review process as scientific journal publications, which gave us a good enough reason to exclude it and focus our interest on peer-reviewed scientific publications. We are aware that due to the limitations of this approach, relevant documents might have been excluded and are therefore absent from our sample. As such, our work reflects the academic contributions to the incorporation of HD into fisheries models, but not the fisheries science contributions as a whole (including modelling of stock assessments and advice) to this domain. However, since the aim of this study was to select a large sample of the literature in a transparent manner, rather than to identify all of the literature in the field, the methodological approach described above was considered sufficient.

Another limitation of the SLR approach is inherent to qualitative analysis and synthesis: it is an interpretative process, and the results can vary between human coders. Therefore, to ensure coding consistency, the coding was conducted by only one of the authors.

Interdisciplinarity is difficult to assess (Huutoniemi et al., 2010) and the approach applied here is therefore another limitation of this study. The measures used to assess interdisciplinarity (journal subject areas, model diversity, human dimension categories, and diversity of variables used to model the human dimension) are indicators and thus not direct measures of interdisciplinarity because they do not measure actual integration. This is due to the fact that the exact form and degree of integration in interdisciplinary research is often difficult to identify within a publication if it is not made explicit (e.g. whether the theories underlying the model were integrated and which theories they were). However, we assume interdisciplinarity (and not multidisciplinarity) because the HDAs are modelled in individual models and as such, various variables and data were integrated into the model to achieve the overall goal of modelling the HDA (instead of achieving multiple parallel goals).

4 Results and Discussion

4.1 How interdisciplinary is the field of modelling the human dimension?

The Scopus search generated a total of 211 publications, out of which 131 were excluded based on the inclusion and exclusion criteria in Table 1. This left 80 publications that were eligible for further qualitative analysis. Within these 80 publications, we identified 31 papers as modelling an HDA, based on our coding criteria of the content analysis (see Appendix S3 for a full list of these papers). These 31 articles had been published in 20 different journals, which were listed in eight different subject areas in Scopus (Table 2). While some of the subject areas can be considered relatively similar from a conceptual point of view (e.g. *environmental sciences* and *agricultural* and *biological sciences*), other subject areas were conceptually diverse and crossed the boundaries of broad intellectual areas (e.g. *social science* and *computer science*). At the same time, many of these journals were registered in more than one field (e.g. *Marine Policy* is listed in three fields, *Land Economics* is listed in two fields). This spread of journals and subject areas, together with the presence of the same journals in multiple fields, could indicate the potential for both narrow and broad interdisciplinarity in the modelling of the human dimension in fisheries. At the same time, it is interesting to note that, even though the models we analysed were about the human dimension, and one would expect these to be published mainly in journals in the field of social sciences, the most highly-represented subject field was environmental science, with social sciences being only half the size. This result is in line with the fact that fisheries science has been traditionally dominated by natural scientists (Link, 2010).

The journal with the highest frequency of appearance in the dataset was *Marine Policy*, accounting for almost one third of the articles on modelling an HDA in fisheries. This is not surprising, considering that the journal describes its contributions as a "*unique combination of analyses in the principal social science disciplines relevant to the formulation of marine policy*" (Elsevier, 2018), while the main topics published by this journal are fisheries management, conservation, fishing gear, and models (Syed et al., 2018).

A total of 36 different model types were identified within the publications, ranging from classic economics models (e.g. econometrics models) to theoretical frameworks (Table 3). As is the case for publication outlets and subject areas, this spread of model types could indicate the potential for both narrow and broad interdisciplinarity in the field being analysed. The application of various modelling approaches could be a potential first step towards an integration of the human dimension into fisheries assessments (Schlüter et al., 2012).

Almost one fifth of the publications included in this analysis used a bioeconomic model. The greater use of these models is likely related to their long-term use in fisheries, dating back to Gordon (1954) and Clark (1973). It might also indicate the interdisciplinary practice of borrowing methods and tools from across the disciplines in an effort to address the needs dictated by the specific problem at hand (Huutoniemi et al., 2010). It is also possible that the uptake of models more suitable for modelling the human dimension, e.g. agent-based models (Schlüter et al., 2012), and social network analysis (Scott, 2017), is rather slow.

4.2 Is there a gap between the human dimension aspects that are modelled and those that could be modelled?

A total of 20 different main HDAs (Table 4) were identified within the 31 publications. These aspects cover all three of the categories of topics relating to the human dimension described by Bennett et al. (2017), which could be taken as a sign of theoretical interdisciplinarity at the field level. However, the number of specific aspects that have been modelled is rather small compared with the wealth of HDAs that could be modelled. As stated in Syed et al. (2018), the human dimension in fisheries in particular, or in any similar social-ecological sytem in general, could be explored by addressing topics such as: "institutional aspects (enforcement and compliance, policy interactions etc.), social aspects (gender, religion/beliefs, welfare, social cohesion, social networks, education and learning, human agency, health, safety and security at sea, food security, perception, attitudes, social norms, compliance, mental models of various actors involved in fisheries etc.), economic aspects (poverty, innovation, distribution of benefits, spiritual, inspirational, and aesthetic services of fisheries etc.), political aspects (power structures, transparency etc.), and cultural aspects (traditional/local ecological knowledge, history, cultural dimensions, culinary choices, heritage, blue humanities, fisheries literacy etc.)". Note that this list is not exhaustive and the items are listed in random order.

Comparing this list with the results of this study, there appears to be a wide and obvious gap between the HDAs that are modelled and the ones that could be modelled. However, considering our sample size of 31 papers, this gap exists only within the context explored by this review and does not necessarily reflect the situation in the Common Fisheries Policy area.

A theory describes our understanding of the components and aspects of reality, and their interactions. Once developed, a theory guides modellers in their decisions regarding what elements, relationships, and processes to include into their models. It is therefore the case that a model itself and the generalizability of its results can be judged by the validity and quality of the theories incorporated (Raser, 1972). Moreover, when studying complex systems, a single theory taken in isolation is rarely sufficient (Orcutt, Greenberger, Korbel, & Rivlin, 1961). From this perspective, achieving theoretical interdisciplinarity is a pre-requisite for integrative theories and/or theories from more than one field, assuming that these theories are suitable for integration. The low amount of HDAs in our systematic literature review might indicate a shortage of adequate theories or data in the context of fisheries, as particularly data (or their lack) are often a limiting factor.

4.3 Are human dimension aspects modelled in an interdisciplinary manner?

The 20 Level 1 HDAs were modelled through a total of 43 different Level 2 variables and 137 different Level 3 variables (see Appendix S4 and S5.). All visual representations of the HAD are presented in Figure 3 and in Appendix S6. *Perception and views* has the most Level 2 variables. *Fish auctions* has the smallest number of Level 3 variables, with only three (Figure 3), whereas *socio-bio-economic consequences* has the largest number of Level 3 variables, with 37. *Fish auctions* also has the smallest number of variables overall, with a total of five across Level 2 and Level 3. Other HDAs with generally low numbers of Level 2 and Level 3 variables are *fisheries dependency* (n=6) and *decision making* (n=6). The majority of the HDAs have a total number of variables between 10 and 20. The HDA *socio-bio-economic consequences* has the largest number of variables overall, with a total of 41. This variety of Level 2 and Level 3 variables might indicate the existence of several theories around the same aspect of Level 1, something which contributes to theoretical interdisciplinarity of the field.

The number of aspects modelled and the variables assigned to each dimension are shown in Figure 2. A close inspection of this figure reveals that the proportion of each of the three fisheries dimensions changes with an increase in the depth of analysis. Thus, at Level 2, the count and usage of human dimension variables are higher, compared to the environmental variables. Whereas at Level 3, human dimension variables' usages is much lower compared to economic variables' usage. This diversification might indicate an empirical interdisciplinary nature to the modelling of the human dimension. However, it might also indicate a lack of suitable operationalisation of human dimension variables and, consequently, a lack of suitable data to use in modelling. At the same time, this highlights how the human dimension can be modelled through economic and environmental variables, and the entanglement of the dimensions.

Only one HDA, *governance,* was modelled entirely through human dimension variables on all levels. *Fish auctions* was the only HDA where all Level 2 and Level 3 factors were economic (Figure 3). The two HDAs *fishing strategy* and *institutional inertia* were modelled through Level 2 and Level 3 variables from only two different dimensions, whereas *fishing strategy* was modelled through factors from the *economic* and *environmental* dimensions, and *institutional inertia* was modelled through factors from the *economic* and *human* dimensions (see Appendix S6). Thirteen HDAs were modelled through Level 2 and Level 3 variables from three different dimensions (n=12) and five HDAs were modelled through Level 2 and Level 3 variables from all dimensions. These were: *socio-bio-economic consequences, compliance*, *evaluation of management plans*, *perception and views*, and *TAC setting process*.

Overall, variables from the *economic* dimension were used the most often (Figure 2); in particular, *cost* (n=13), *effort* (n=13), and *price* (n=12) were the most used *economic* variables in Level 3. The variables from the *human* dimension that were used most often in Level 3 were *demography* (n=4), *regulation* (n=4), and *employment* (n=3), whereas the most frequently used variables from the *environmental* dimension in Level 3 were *stock* (n=13), *area* (n=6), and *fishing mortality* (n=4). This study suggests that HDAs are mainly modelled through economic and partly through environmental variables, which represents the data typically available for fisheries assessments. Some of the social aspects, such as *governance*, might be very difficult (if not maybe impossible) to be expressed in numerical terms.

4.4 How to advance the interdisciplinarity of the field

As a first step to advance the interdisciplinarity of the field, we suggest a protocol based on Huutoniemi et al. (2010) that succinctly describes the elements necessary for assessing various interdisciplinary typologies, shown in Table 5. Such a protocol could guide scientists on how to take an interdisciplinary approach during model development and implementation. It is also paramount for the advancement of the field that human dimension models are reproducible. Many of the descriptions of models in published articles are incomplete, which makes it impossible to re-implement them or replicate their results (Railsback & Grimm, 2012). As we have ourselves encountered when carrying out this study, model descriptions are often “a wordy mixture of factual descriptions and lengthy justifications, explanations, and discussions of all kinds” (Railsback & Grimm, 2012). Therefore, we also suggest that this protocol is used as a documentation tool in order to help modellers to express the interdisciplinary characteristics of their models clearly. This would also aid model communication, in-depth model comprehension, model assessment, model replication, model comparison, theory building, and code generation (Müller et al., 2014).

Social issues are often complex and understanding these issues from a fisheries management perspective will require interdisciplinary efforts from the natural and social sciences, as well as the humanities (Urquhart, Acott, Symes, & Zhao, 2014). This assertion is backed by this empirical study, which brings evidence on how entangled the human dimension is when viewing fisheries as SECAS. Multi- and interdisciplinarity would entail the transfer of knowledge, tools, and methods from a multitude of disciplines into the field of fisheries science, making it possible to integrate various data inputs (e.g. quantitative and qualitative data). Existing methods, such as agent-based models, systems analysis, and social network analysis from domains ranging from political science to business organisation could be integrated into fisheries science and used to study societies, social interactions, and people’s behaviour in fisheries (Libre et al., 2015; Scott, 2017).

Through an expansion of current practices, a wider range of the HDAs could be considered in fisheries models to better reflect the diversity of the human dimension. This endeavour could be fostered further through the inclusion of scientists from the social sciences and the humanities right from the start of a project (Criddle, 2016). In this way, they can contribute to the formulation of the research questions that ought to be answered by a model, which could lead to a more diversified investigation of the human dimension.

The challenges of performing interdsiciplinary research are not new, as they have been alredy identified 20 years ago (see for example Volume 2, Issue 4, 1999 of the journal Ecosystems).Thus, in order to address the issues identified by the above analysis, it might be that fisheries science will require new types of experts, besides biologists, mathematicians, and statisticians: 1. scientists from the social sciences and the humanities; 2. scientists with interdisciplinary backgrounds who can address fisheries from a more holistic perspective and apply the concept of SECAS to multi- and interdisciplinary fisheries workgroups and research; and 3. modellers with the latest skillset who are trained to use tools that can reflect fisheries as SECAS, and include the human dimension in an interdisciplinary way. This would potentially lead to the rise and also the recognition of a new kind of natural resources expert: interdisciplinary individuals with the flexibility required to move between fields and explore various SECAS, e.g. sustainability science (Haider et al., 2018), conservation science, and complexity science.

Researchers putting aside their differences and finding better ways to communicate could support the practice of interdisciplinary science and disciplinary cross-fertilisation (Arlinghaus, Hunt, Post, & Allen, 2014), whilst the interdisciplinary development of conceptual models could support communication between social and natural scientists (Hall-Arber et al., 2009). Some things in the culture of science might have to change, e.g. arrogances and the way we speak to each other, but we also need to rethink our assumptions, values, and institutional structures (Degnbol et al., 2006). Researchers from cross-disciplinary research programs, as well as innovative graduate training programs, would have to become more involved. In addition, interdisciplinary career choices would have to be rewarded instead of generating a fear of risking one's career (Fischer et al., 2012; Rhoten & Parker, 2004).

Besides experts and scientists from different disciplines, the insight of stakeholders should also be taken into account. Stakeholders and practitioners, such as management authorities and non-governmental organisations, can contribute to the modelling process through co-creation (Santiago et al., 2015; Wood, Stillman, & Goss-Custard, 2015). Co-creation could highlight the importance of HD components and lead to assurances that managers and policy makers will take the behaviour of individuals and organisations into consideration within their fishing communities. As such, this would make models of the human dimension more relevant for management and decision making, while supporting local and global policies and goals, such as the EU's Common Fisheries Policy and the United Nations' Sustainable Development Goals (United Nations, 2015).

Furthermore, with this study we wish to stimulate the discussion on how best to model the human dimension of SECAS. As it currently stands, based on our empirical results, the human dimension is largely modelled through economic and environmental variables. One could argue that the field of human dimension modelling needs more operationalisable social theories and more data relevant to these theories. At the same time, using more easily available economic and environmental data is a more practical short-term approach. In contrast, some argue for extreme caution in modelling the human dimension, and social phenomena in general (ní Aodha & Edmonds, 2017). These decisions will likely be made on an individual level, but we hope that researchers from all fields can engage in these discussions and share their experiences as well as the reasons for the approaches they have taken and their lessons learned.

5 Conclusions

This study identifies a variety of HDAs that have been investigated in the context of fisheries models. There is broad potential for the expansion of the human dimension in fisheries models. This expansion is important in order to increase our understanding of fisheries systems in general, and to better reflect the interdisciplinarity of the field in order to support sustainable fisheries management.

In the support of modelling the human dimension in a SECAS context, interdisciplinary approaches are required. Such efforts need to focus on several aspects, including: acknowledging that exploring the human dimension requires interdisciplinarity; early involvement of all relevant disciplines and stakeholders in model development through co-creation; improved development and integration of tools for the modelling of HDAs; the formulation of operationalisable theories and the collection and inclusion of more data from the human dimension. To further improve and advance the interdisciplinarity of human dimension modelling in the long term, model transparency, documentation, and communication will be key. A model publication should be easy for the reader to understand and follow, and it should make the HDAs and levels of interdisciplinarity explicit. Clear model descriptions will enable interested readers and modellers to understand how interdisciplinarity and human dimension modelling was achieved, thus facilitating model uptake and re-use by scientists, managers, and policy makers.

6 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

7 Author Contributions

CW collected and analyzed the data. CW and MB interpreted the data. CW, MB, and MA wrote the manuscript.

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10 Supplementary Material

The Scopus search string (Appendix S1), the PRISMA flow diagram (Appendix S2), a table listing all publications included in analysis and synthesis phase (Appendix S3), a table for all Level 2 variables (Appendix S4), a table for all Level 3 variables (Appendix S5), and all remaining visualisations (Appendix S6) are available in the Supplementary Material.

1 Data Availability Statement

The list of publications analyzed in this study can be found in the Supplementary Material.

Table 1. Inclusion criteria used to select publications for the systematic literature review of modelling the human dimension in fisheries models.

Inclusion criteria	Why this criterion
Published in the English language.	English is by far the most common language for scientific publications in this field.
Study/research published in a scientific journal or conference paper.	Articles in scientific journals have undergone rigorous quality controls and conference proceedings are published more often and much more quickly than articles.
Refers to a fisheries model.[1]	Our study focuses on models pertaining to fisheries.
Refers to the Common Fisheries Policy.	Our study focuses on studies connected to this set of rules for managing European Union fishing fleets and for conserving European Union fish stocks.
Contains the words 'human dimension', 'social', or 'socio*' within the body of the full text.[2]	Our study focuses on articles connected to the human dimension of fisheries.
Models a human dimension aspect of fisheries.	Our study focuses on the human dimension.

[1]We considered it to be a model if it was referred to as 'model' by the authors of the publication.
[2]We included the words 'social' and 'socio*' because 'human dimension' is a relatively new term in fisheries and might not be included as such in older publications.

Table 2. The subject areas and corresponding journals identified in this study. Subject areas are labelled as indicated by Scopus. *Count* refers to the number of articles found in each subject area. *Journal (count)* refers to the journal title and the number of articles from our study found within that journal (shown in parentheses after the journal name). Numbers are only indicated if there was more than one article per journal. Note that several journals are included in more than one subject area.

Count	Subject Areas (as indicated by Scopus)	Journal (count)
21	Environmental Sciences	Ambio
		Ecological Modelling
		Fish and Fisheries
		Human Ecology
		ICES Journal of Marine Science (3)
		Journal of Institutional and Theoretical Economics
		Land Economics
		Marine Ecology Progress Series
		Marine Policy (9)
		Methods in Ecology and Evolution
		Ocean and Coastal Management
20	Agricultural and Biological Sciences	Canadian Journal of Fisheries and Aquatic Sciences
		Ecological Modelling
		Ecology and Society
		Fish and Fisheries
		Fisheries Management and Ecology
		Fisheries Research
		ICES Journal of Marine Science (3)
		Journal of Fish Biology
		Marine Ecology Progress Series
		Marine Policy (9)
		Methods in Ecology and Evolution
		Ocean and Coastal Management
14	Economics, Econometrics and Finance	Applied Economics

		Journal of Institutional and Theoretical Economics Land Economics Marine Policy (9) Panoeconomicus
12	Social Sciences	Ambio Human Ecology International Journal of the Commons Marine Policy (9)
5	Earth and Planetary Sciences	ICES Journal of Marine Science (2) Fish and Fisheries Ocean and Coastal Management Ecology and Society
1	Decision Sciences	International Transactions in Operational Research
1	Computer Science	International Transactions in Operational Research
1	Business, Management and Accounting	International Transactions in Operational Research

Table 3. Model types extracted from the publications in this study, sorted alphabetically. Counts of each model type are indicated in parentheses if there was more than one occurrence.

Model Types	
• 3-Dimensional Wellbeing Framework	• Individual-Based Model (IBM)
• Accessibility Analysis	• Linear Model
• Age-Structured Model	• Logistic/Ordered Regression Model (n=3)
• Allocation Management Model	• Management Evaluation Framework
• Bayesian Approach in Participatory Modelling	• Management Scenario Model
• Bayesian Belief Network (BBN) (n=3)	• Management Strategy Evaluation Model/Approach (MSE)
• Binary Logit Model	• Market-Orientated Value-Adding (MOVA) Management Model
• Bioeconomic Model (n=6)	• Multinomial Logit Model
• Conditional Logit Model (n=2)	• Press Perturbation Analysis
• Decision Making Model (Single-Species)	• Principal Agent Model
• Discrete Choice Random Utility Model (RUM) (n=2)	• Qualitative Model Analysis
• Dynamic State Variable Model (DSVM) (IBM)	• Socio-Bio-Economic Model
• Econometric Model	• Statistical Analysis
• Flow Chart	• Statistical Model
• Game Theoretical Model	• System Dynamics Model
• Generalised Additive Model (GAM)	• Theoretical (Framework) Model of Governance Architecture
• Generalised Linear Model (GLM)	• Theoretical Institutional Model (n=2)
• Gravity Model	• Theoretical Model of An Evaluation Framework for Fisheries Resource

Table 4. List of human dimension aspect (HDAs) identified within the publications, mapped against the general human dimension topics of study proposed by Bennett et al. (2017) . Count is the number of publications that model the HDA.

Human Dimension Category (Total count)	HDA (Level 1)	Count
Social phenomena (8)	Fisheries Dependency	1
	Governance	1
	Institutional Inertia	1
	Regulation	2
	Socio-Bio-Economic Consequences	3
Social processes (15)	Commitment	2
	Compliance	3
	Decision Making	1
	Effort Allocation	3
	Enforcement	2
	Evaluation of Management Plans	2
	Fish Auctions	1
	Total Allowable Catch Setting Process	1
Individual attributes (11)	Enter and Exit the Fishery	2
	Fishing Strategy	1
	Métier Selection	1
	Over-Quota Discarding	1
	Perception and Views	4
	Switching of Métiers	1
	Wellbeing	1

Table 5. An overview of the protocol for assessing the interdisciplinarity of models, based on Huutoniemi et al. (2010).

<table>
<tr><td rowspan="2">What</td><td rowspan="2">Scope of Interdisciplinarity</td><td colspan="2">Narrow</td><td colspan="2">Broad</td></tr>
<tr><td colspan="4">What disciplines and knowledge bodies were involved and integrated, e.g. what disciplines contributed to this model, what stakeholders added knowledge to the concept of the model etc.</td></tr>
<tr><td rowspan="2">How</td><td rowspan="2">Type of Interdisciplinarity</td><td>Empirical</td><td colspan="2">Methodological</td><td>Theoretical</td></tr>
<tr><td>Which types of data and data sources (knowledge bodies) were included (e.g. social, economic, environmental; qualitative data, quantitative data, academic data, non-academic data from stakeholders/local ecological knowledge etc.)?</td><td colspan="2">Which different modelling tools/methods were integrated? Is this a new integrative modelling method involving different stakeholders (e.g. participatory modelling)? How was integration achieved?</td><td>Which theories were used and integrated (e.g. which social theories were used?)?</td></tr>
<tr><td rowspan="2">Why</td><td rowspan="2">Goal of interdisciplinarity</td><td colspan="2">Epistemological</td><td colspan="2">Instrumental</td></tr>
<tr><td colspan="2">The production of new understanding and knowledge. (Why do we need this understanding? What is the new knowledge for?).</td><td colspan="2">To solve a problem or a societal challenge (What is the problem the model is trying to solve?)</td></tr>
</table>

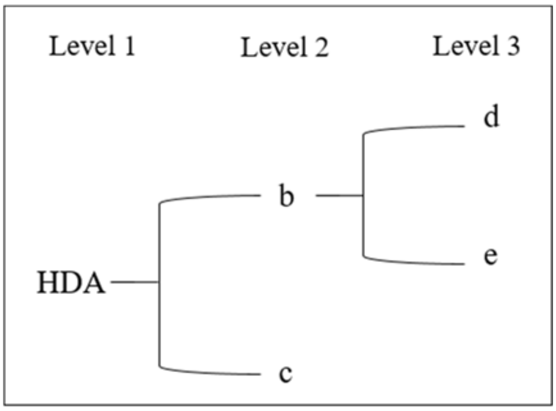

Figure 1: A conceptual display of the hierarchy of variables used to model the main Human Dimension Aspects (HDA) of the human dimension fisheries models. Level 1 represents the main HDA, and Levels 2 and 3 represent the variables (b,c and d,e) that were used in a functional relationship to model the HDA.

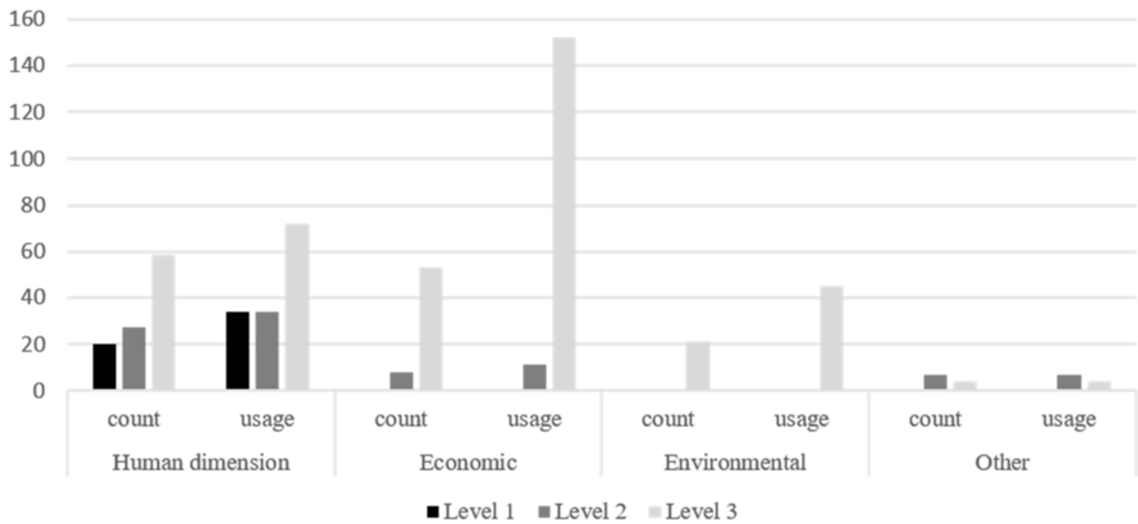

Figure 2. Occurrence and usage of Human Dimension Aspects (HDAs) for all three levels of variables. Count indicates the number of different aspects identified for each level and each dimension. Usage indicates the number of times that aspects/variables from each dimension were used. Other includes variables that could not be categorized within the three dimensions, human, economic, and environmental, such as time.

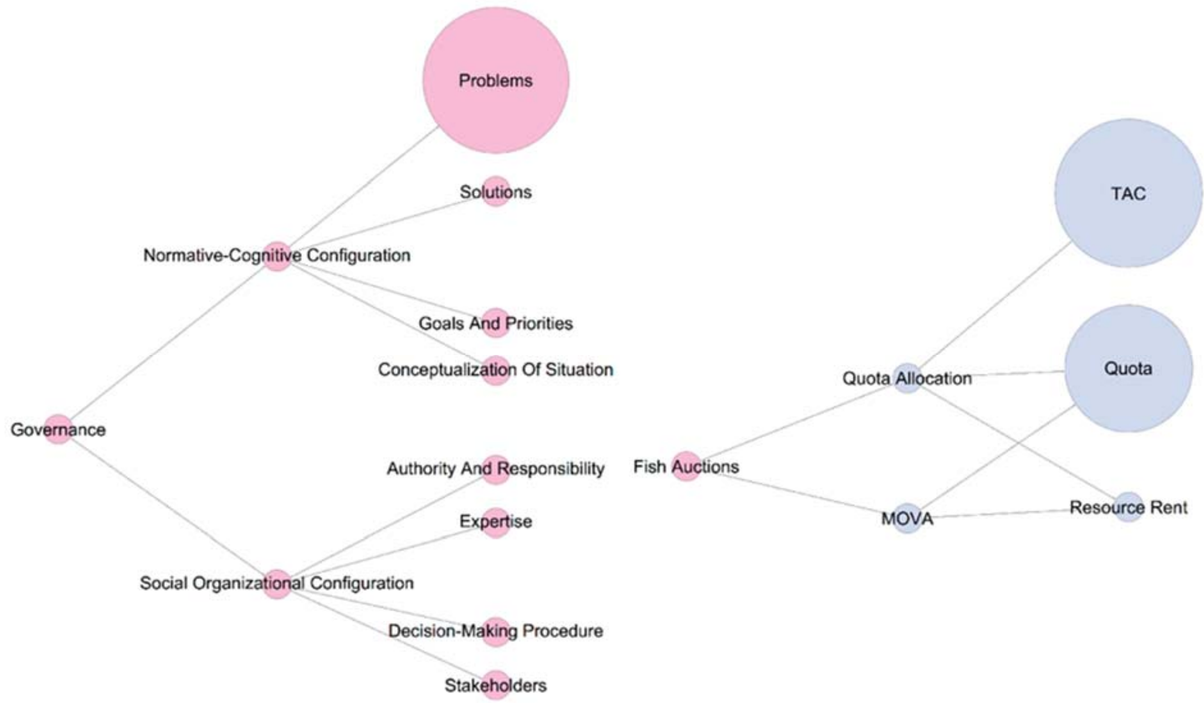

Figure 3. A visual representation of the Human Dimension Aspects (HDAs) governance (left) and fish auctions (right) and the Level 2 and Level 3 variables that were used to model these social aspects. The size of each node represents the relative importance of the variable (i.e. the number of publications using it) and the color indicates its dimension (pink: human; blue: economic; green: environmental; white: other/more than one dimension). The position of each node (left – middle – right) indicates its level (Level 1 – Level 2 – Level 3).

Supplementary Material

An Interdisciplinary Insight into the Human Dimension in Fisheries Models. A Systematic Literature Review in a European Union Context.

Charlotte Teresa Weber*, **Melania Borit, Michaela Aschan**

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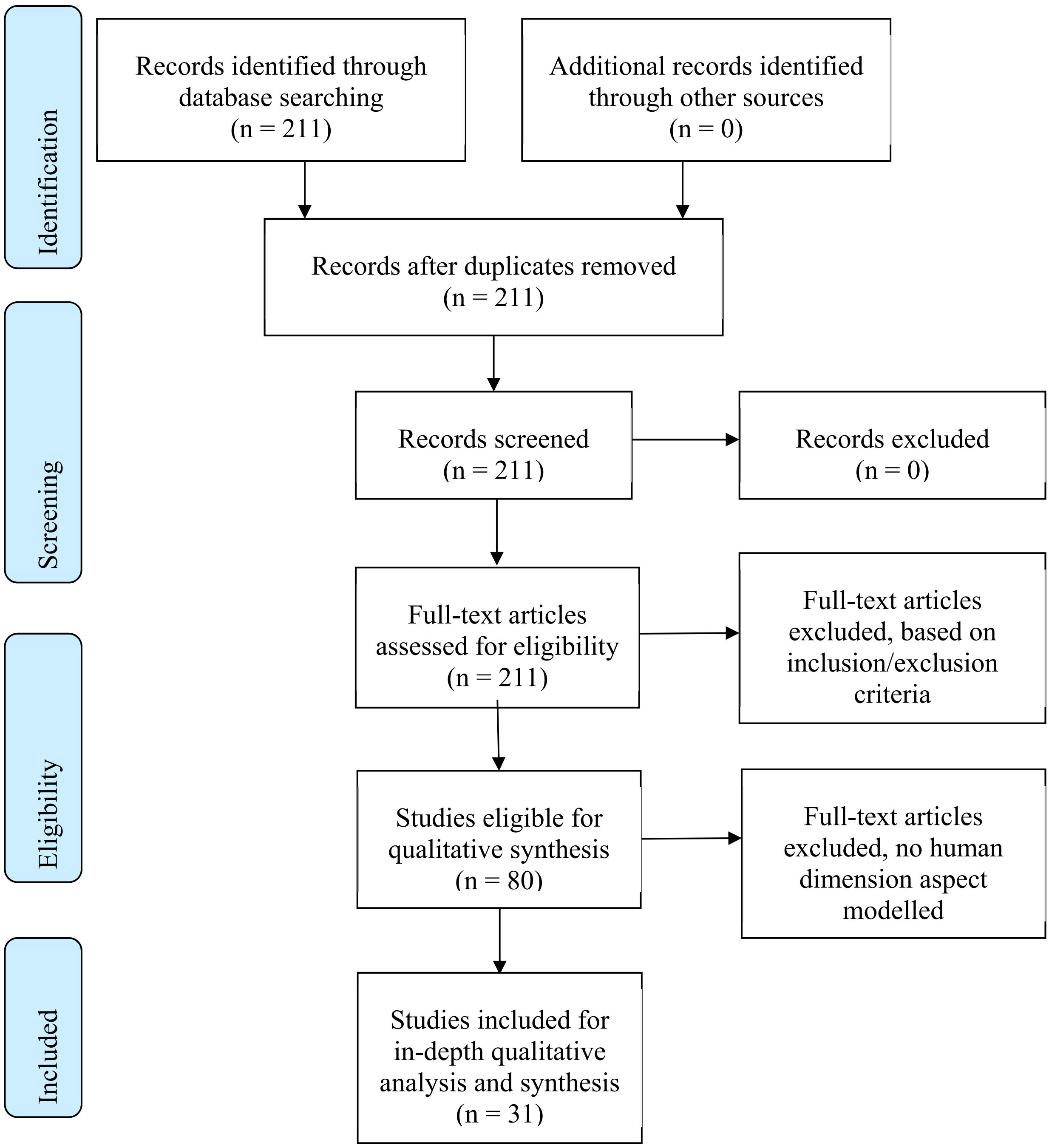
1 Appendix S1.

Scopus Search String:

(TITLE-ABS-KEY(fisheries) AND TITLE-ABS-KEY(model)AND ALL("Common Fisheries Policy")) AND (LIMIT-TO(LANGUAGE,"English")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"cp"))*

Appendix S2.

PRISMA Flow Diagram, adapted from (Moher et al., 2009), containing all steps and short explanations for the process of document exclusion during the process of selecting the publications suitable for analysis.



3 Appendix S3.

List of all publications included in the analysis and synthesis phase. In alphabetical order based on first author.

Authors	Title	Year	Journal
Aanesen, M; Armstrong, C	Stakeholder influence and optimal regulations: A common-agency analysis of ecosystem-based fisheries regulations	2013	Journal of Institutional and Theoretical
Aanesen, M; Armstrong, C W	The implications of environmental NGO involvement in fisheries management	2014	Land Economics
Amigo-Dobaño, Lucy; Dolores Garza-Gil, M.; Varela-Lafuente, Manuel	The perceptions of fisheries management options by Spain's Atlantic fishermen	2012	Marine Policy
Andersen, B S; Ulrich, C; Eigaard, O R; Christensen, A S	Short-term choice behaviour in a mixed fishery: Investigating métier selection in the Danish gillnet fishery	2012	ICES Journal of Marine Science
Astorkiza, K; del Valle, I	Changing the total allowable catch (TAC) decision-making framework: A central bank of fishes?	2013	Panoeconomicus
Bastardie, Francois; Nielsen, J Rasmus; Miethe, Tanja	DISPLACE: a dynamic, individual-based model for spatial fishing planning and effort displacement — integrating underlying fish population models	2014	Canadian Journal of Fisheries and Aquatic
Batsleer, J; Poos, J J; Marchal, P; Vermard, Y; Rijnsdorp, A D	Mixed fisheries management: Protecting the weakest link	2013	Marine Ecology Progress Series
Britton, E; Coulthard, S	Assessing the social wellbeing of Northern Ireland's fishing society using a three-dimensional approach	2013	Marine Policy
Burns, T R; Stöhr, C	Power, knowledge, and conflict in the shaping of commons governance. The case of EU Baltic fisheries	2011	International Journal of the Commons

Da Rocha, J M; Cerviño, S; Villasante, S	The Common Fisheries Policy: An enforcement problem	2012	Marine Policy
Da Rocha, J M; Villasante, S; González, R T	Credible enforcement policies under illegal fishing: Does individual transferable quotas induce to reduce the gap between approved and proposed allowable catches?	2013	Ambio
Gezelius, S S; Raakjær, J; Hegland, T J	Reform drivers and reform obstacles in natural resource management: The Northeast Atlantic fisheries from 1945 to the present	2010	Human Ecology
Haapasaari, P; Michielsens, C G J; Karjalainen, T P;	Management measures and fishers' commitment to sustainable exploitation: A case study of Atlantic salmon fisheries in the Baltic Sea	2007	ICES Journal of Marine Science
Haapasaari, P; Mäntyniemi, S; Kuikka, S	Baltic herring fisheries management: Stakeholder views to frame the problem	2012	Ecology and Society
Hatcher, A; Jaffry, S; Thebaud, O; Bennett, E	Normative and social influences affecting compliance with fishery regulations	2000	Land Economics
Jensen, C L; Aarset, B	Explaining noncompliance in the Norwegian coastal cod fishery: An application of the multinomial logit	2008	Applied Economics
Levontin, P; Kulmala, S; Haapasaari, P; Kuikka, S	Integration of biological, economic, and sociological knowledge by Bayesian belief networks: The interdisciplinary evaluation of potential management plans for Baltic salmon	2011	ICES Journal of Marine Science
Martins, J H; Camanho, A S; Oliveira, M M; Gaspar, M B	A system dynamics model to support the management of artisanal dredge fisheries in the south coast of Portugal	2015	International Transactions in
McCausland, W D; Mente, E; Pierce, G J; Theodossiou,	A simulation model of sustainability of coastal communities: Aquaculture, fishing, environment and labour markets	2006	Ecological Modelling
Miethe, T; Bastardie, F; von Dorrien, C; Nielsen, J R	Impact assessment of a fisheries closure with effort and landings spatial analyses: A case study in the Western Baltic Sea	2014	Fisheries Research

Natale, F; Carvalho, N; Harrop, M; Guillen, J;	Identifying fisheries dependent communities in EU coastal areas	2013	Marine Policy
Nielsen, K N; Holm, P	A brief catalogue of failures: Framing evaluation and learning in fisheries resource management	2007	Marine Policy
Parés, C; Dresdner, J; Salgado, H	Who should set the total allowable catch? Social preferences and legitimacy in fisheries management institutions	2015	Marine Policy
Pita, C; Pierce, G J; Theodossiou, I	Stakeholders' participation in the fisheries management decision-making process: Fishers' perceptions of participation	2010	Marine Policy
Pita, C; Theodossiou, I; Pierce, G J	The perceptions of Scottish inshore fishers about marine protected areas	2013	Marine Policy
Rätz, H J; Charef, A; Abella, A J; Colloca, F; Ligas, A;	A medium-term, stochastic forecast model to support sustainable, mixed fisheries management in the Mediterranean Seaa	2013	Journal of Fish Biology
Thorpe, R B; Le Quesne, W J F; Luxford, F; Collie, J S;	Evaluation and management implications of uncertainty in a multispecies size-structured model of population and community responses to fishing	2015	Methods in Ecology and Evolution
Tidd, A N	Effective fishing effort indicators and their application to spatial management of mixed demersal fisheries	2013	Fisheries Management and Ecology
Trenkel, V M; Rochet, M J; Rice, J C	A framework for evaluating management plans comprehensively	2015	Fish and Fisheries
Trondsen, T; Matthiasson, T; Young, J A	Towards a market-oriented management model for straddling fish stocks	2006	Marine Policy
Van Putten, I E; Quillérou, E; Guyader, O	How constrained? Entry into the French Atlantic fishery through second-hand vessel purchase	2012	Ocean and Coastal Management

4 Appendix S4.

Table of all Level 2 variables and their frequency (count).

Level 2	Count
Acceptance Of Management Regime	1
Attitudes On Regulatory Options	1
Central Bank-Like Of Fishery Resources	1
Change In TAC Level	1
Closed Areas	1
Commitment	1
Compliance	2
Components and Interrelationships Of Fishery	1
Conflicts	1
Diagnostics	1
DPSIR Indicators	1
Employment Opportunities	1
Fleet	1
Fleet Adaptation	1
Impact of Shocks to Aquaculture	1
Implementation Uncertainty	1
Interests	1
Intervention	1
ITQs	1
Management Decision	1
Management Measures	4
Management Option	2
Material Wellbeing	1
Motives For Non-Compliance	1
MOVA	1
Normative-Cognitive Configuration	1
Objectives	1
Objectives For Society	1
Participation In Decision-Making Processes	2

Policy Making	1
Preferences	2
Preferred Management Measures	1
Quota Allocation	1
Regulation	1
Relational Wellbeing	1
Social Organizational Configuration	1
Stock Dynamics	1
Subjective Wellbeing	1
Sustainability	1
TAC	1
Tactical Choices	1
Utility	4
Vessel Behavior	1

5 Appendix S5.

Table of all Level 3 variables and their frequency (count).

Level 3	Count
Accessibility	1
Administration Body	1
Aquaculture Escapes	1
Aquaculture Production	1
Area	6
Atmospheric Pressure	1
Authority And Responsibility	1
Believes	2
Biomass	2
Bureaucracy	1
Business Characteristics	2
Capacity	3
Capital	1
Catches	6
Closed Area Or Season	1
Compliance	2
Conceptualization Of Situation	1
Confidence In Management	1
Conservation Systems	1
Consulted	1
Cost	13
CPUE	1
Crew	1
Days At Sea	1
Decision Variables	1
Decision-Making Procedure	1
Decommissioning Grant	1
Demand	3

Demographics	4
Discards	2
Distance	1
Distribution System	1
Earnings	2
Economic Rent	2
Education	1
Effort	13
Employment	3
Existing Wealth	1
Experience	2
Expertise	1
Family Connections	1
Feed	1
Fine	3
Fish Abundance	1
Fishing Gear	1
Fishing Mortality	4
Fishing Operation Characteristics	1
Fishing Points	1
Fleet	2
Fuel	5
GDP	1
Go Out Fishing Or Stay In Port	1
Goals And Priorities	1
Government	1
Government Support	2
Harvest	2
Holistic View	1
Immigration Flows	1
Implementation	1
Income	2
Industry Support	1

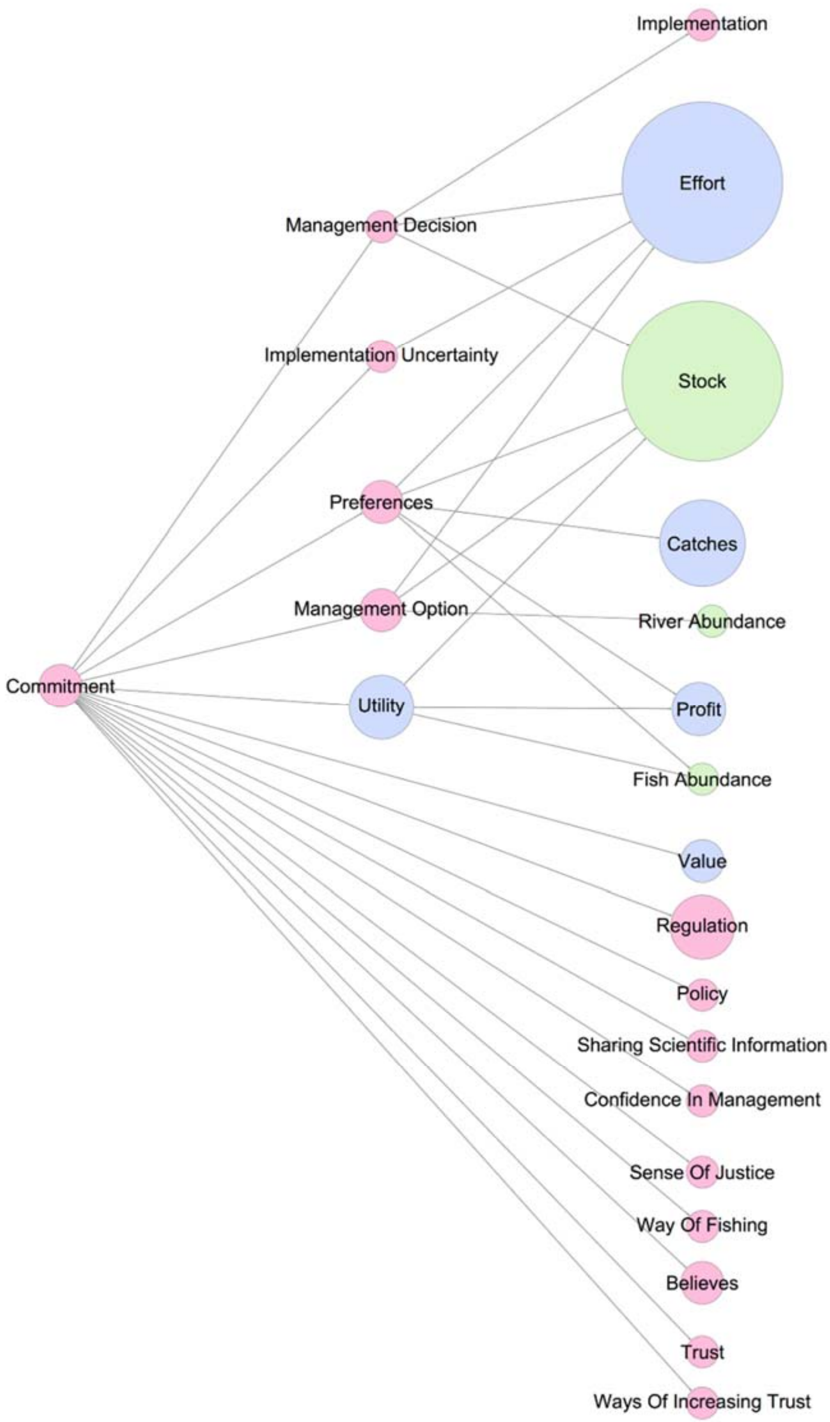
Info From Other Fishers	1
Informed	1
Involved	1
Labour	1
Landings	8
Legitimacy	1
Local Fishing Interests	1
Market Trader Network Structure And Dynamics	1
Material Resources	1
Metier	4
Monetary Return	1
Monitoring Programme	1
Moral Norm	1
Mortality Reduction	1
Multispecies	1
Natural Resources	1
Needs For A Good Life	1
Network Integration	1
Number Of Participants Or Fishers	1
Number Of Vessels	5
Others Are Cheating	1
Performance Indicators	1
Policy	1
Pollution	1
Ports, Harbours	1
Prices	12
Probability Of Being Caught	1
Probability Of Making A Choice	1
Problems	2
Production	1
Profit	3
Profitability	1
Quota	6

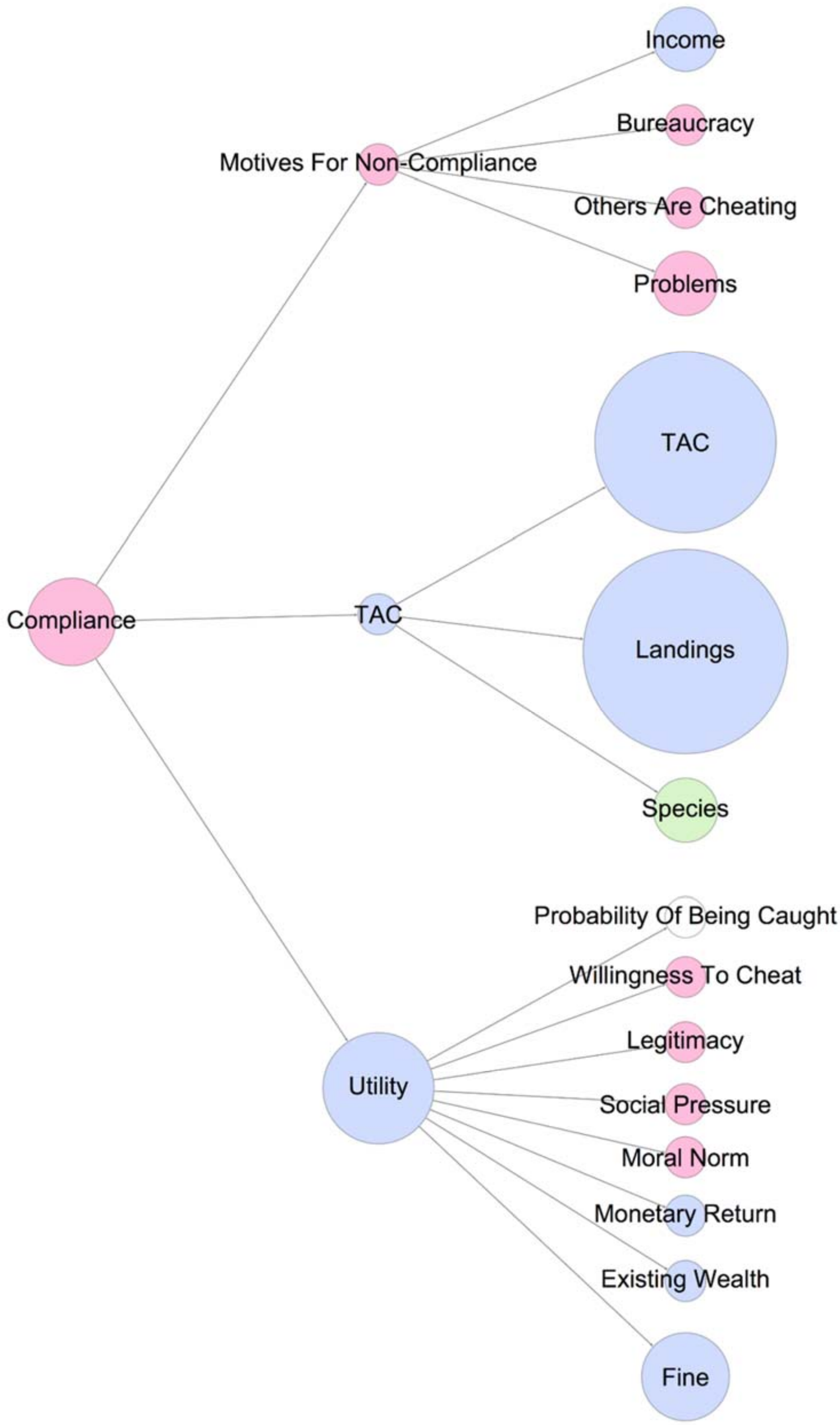
Regulation	4
Regulatory Preferences	1
Relationships Influencing Fishing	1
Resource Rent	1
Revenue	7
Risk	1
River Abundance	1
Rules	1
Sense Of Justice	1
Sharing Scientific Information	1
Social Preferences	1
Social Pressure	1
Social Resources	1
Solutions	1
Species	2
Spawning Stock Biomass	1
Stakeholders	1
State Of Nature	1
Stock	13
Strength Of Relationship Between Variables	1
Subsidies	1
Supply	1
TAC	7
TAE	1
Tax	3
Technological Parameters	1
Time	3
Trip	1
Trust	1
Uncertain Variables Of Fishery	1
Utility, Loss, Preference Variables	1
Value	2
Vessel	4

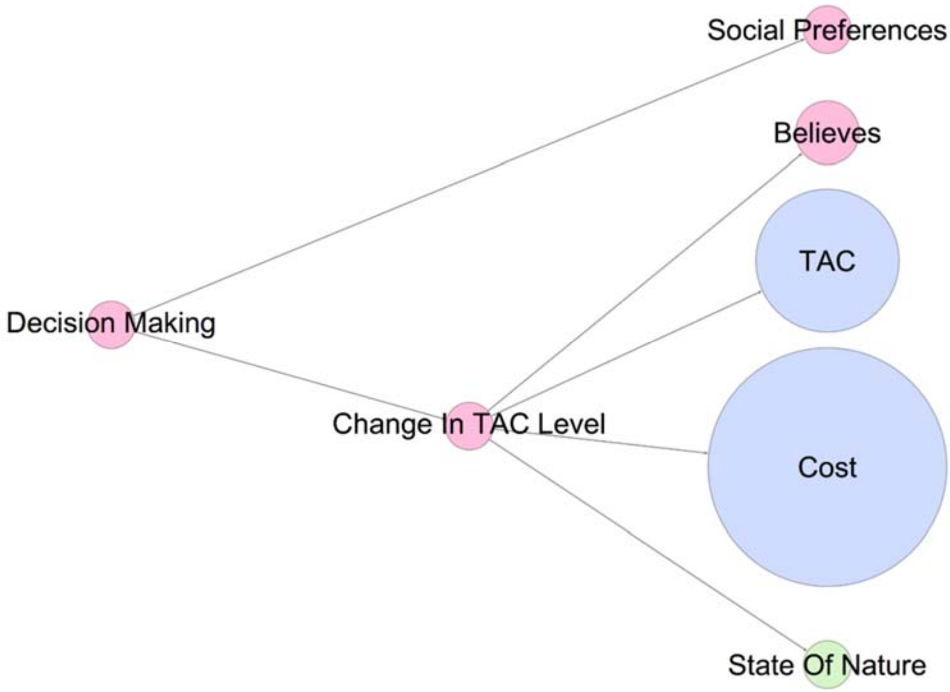
Veto Right	1
VPA	1
VPUE	1
Waste	1
Way Of Fishing	1
Ways Of Increasing Trust	1
Weather	1
Weight	2
Willingness To Cheat	1
Yield	3

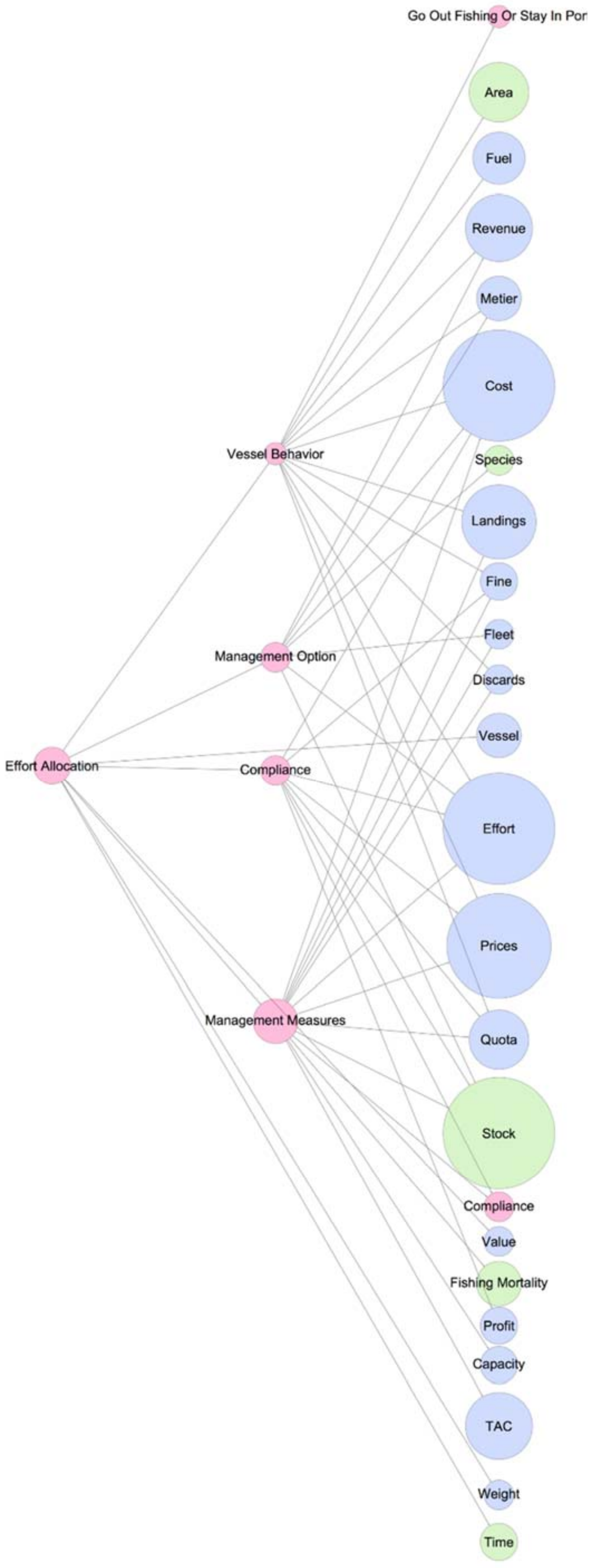
6 Appendix S6.

Individual visualizations of all human dimension aspects and their level 2 and level 3 variables. Human dimension aspects are listed in alphabetical order. The color of the node indicates the dimension it belongs to, with pink = human, blue = economic, green = environmental, and white = other / more than one dimension; Size of the node shows relative importance, i.e. the number of publications that used this node; hierarchy of the nodes is displayed by order from left to write, where nodes on the very left are level 1 human dimension aspects, nodes in the middle are level 2 variables, and nodes on the very right are level 3 variables.

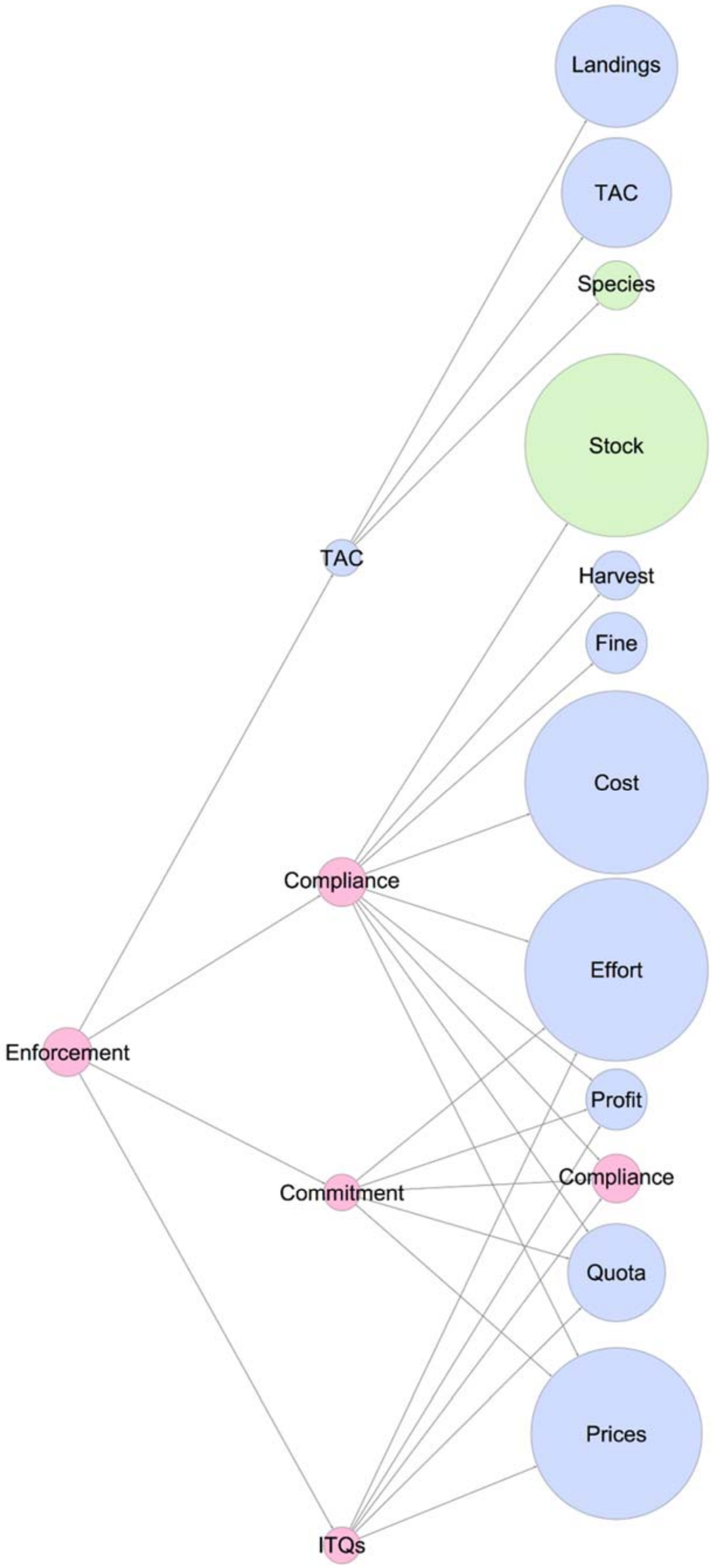

Implementation
Effort
Management Decision
Implementation Uncertainty
Stock
Preferences
Catches
Management Option
River Abundance
Commitment
Utility
Profit
Fish Abundance
Value
Regulation
Policy
Sharing Scientific Information
Confidence In Management
Sense Of Justice
Way Of Fishing
Believes
Trust
Ways Of Increasing Trust

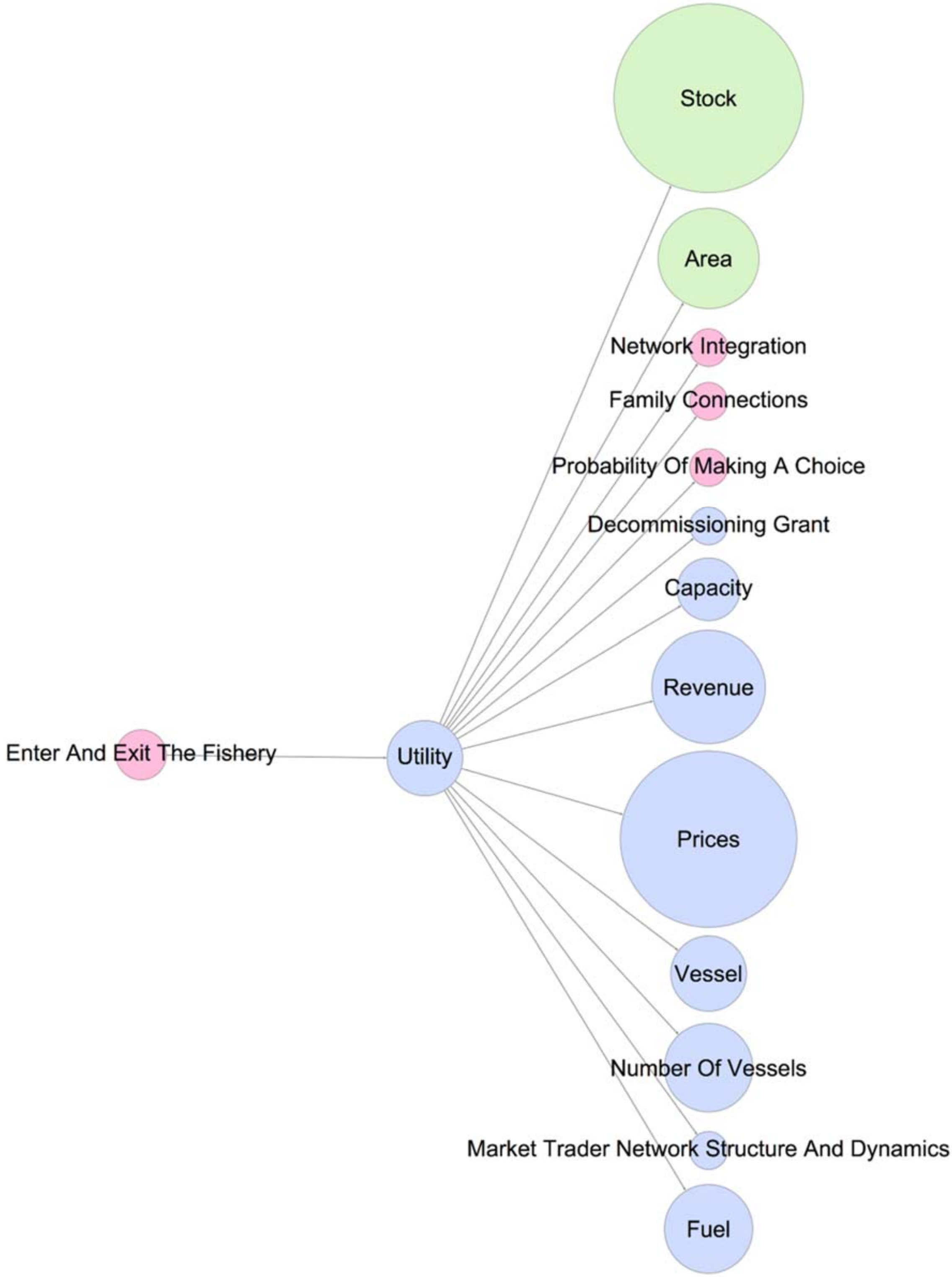

Income
Bureaucracy
Motives For Non-Compliance
Others Are Cheating
Problems
TAC
Compliance
TAC
Landings
Species
Probability Of Being Caught
Willingness To Cheat
Legitimacy
Utility
Social Pressure
Moral Norm
Monetary Return
Existing Wealth
Fine

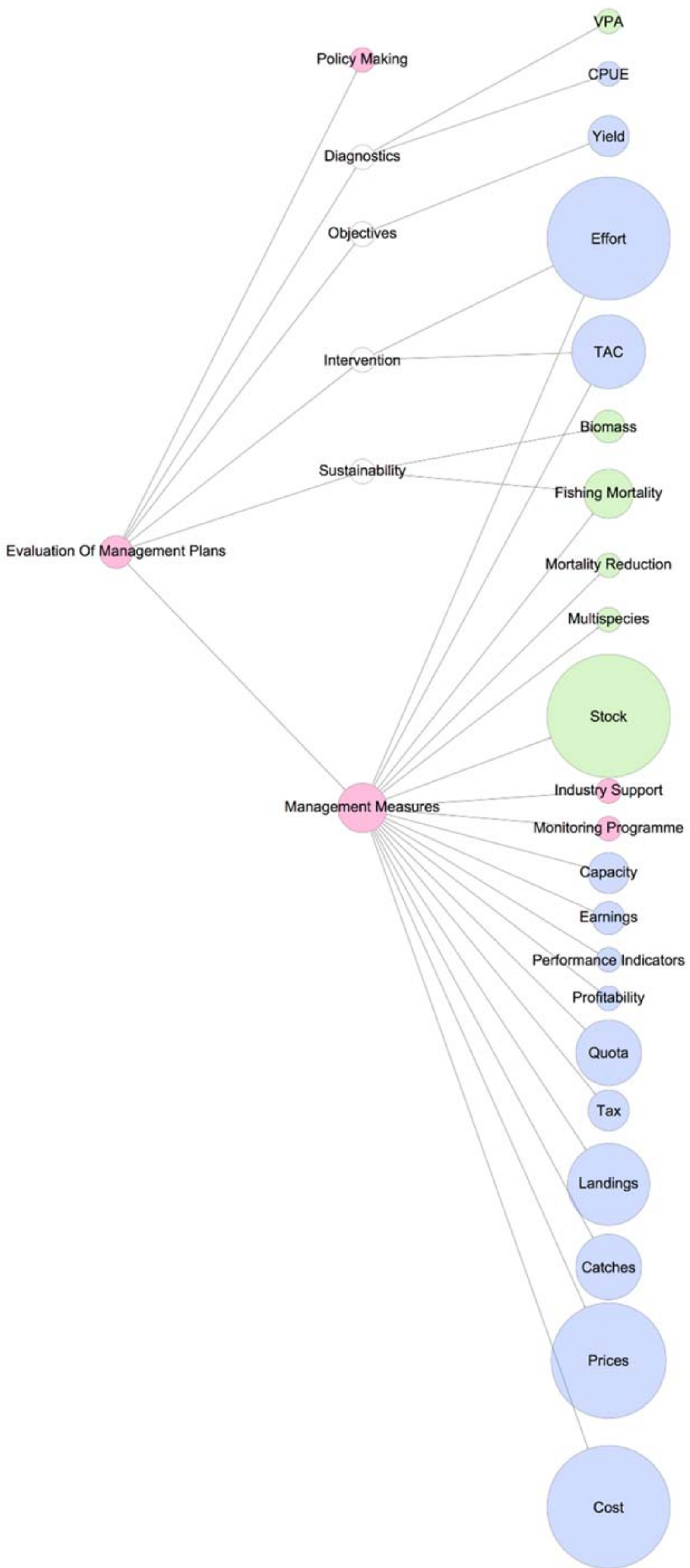

Social Preferences
Believes
TAC
Decision Making
Change In TAC Level
Cost
State Of Nature

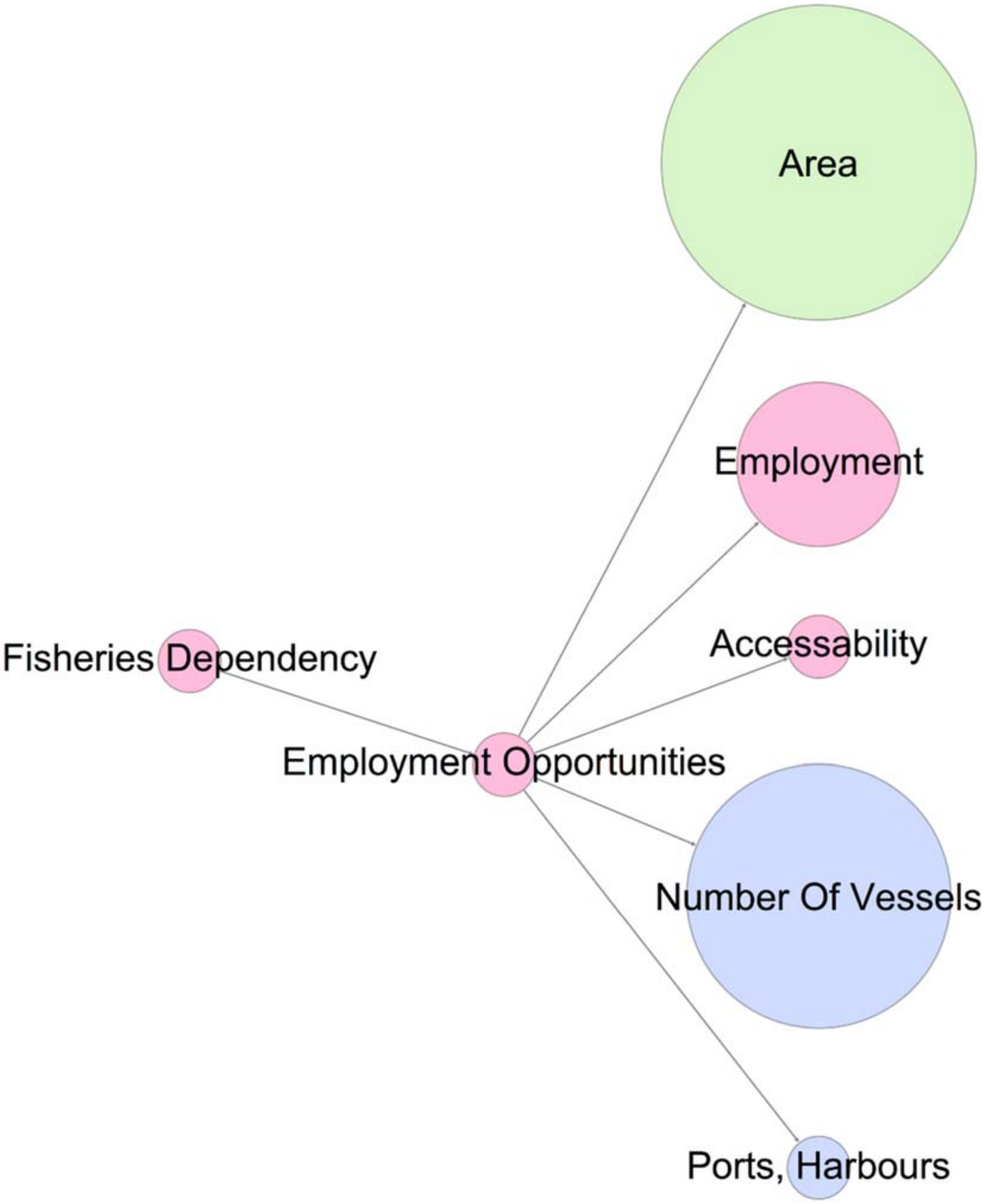


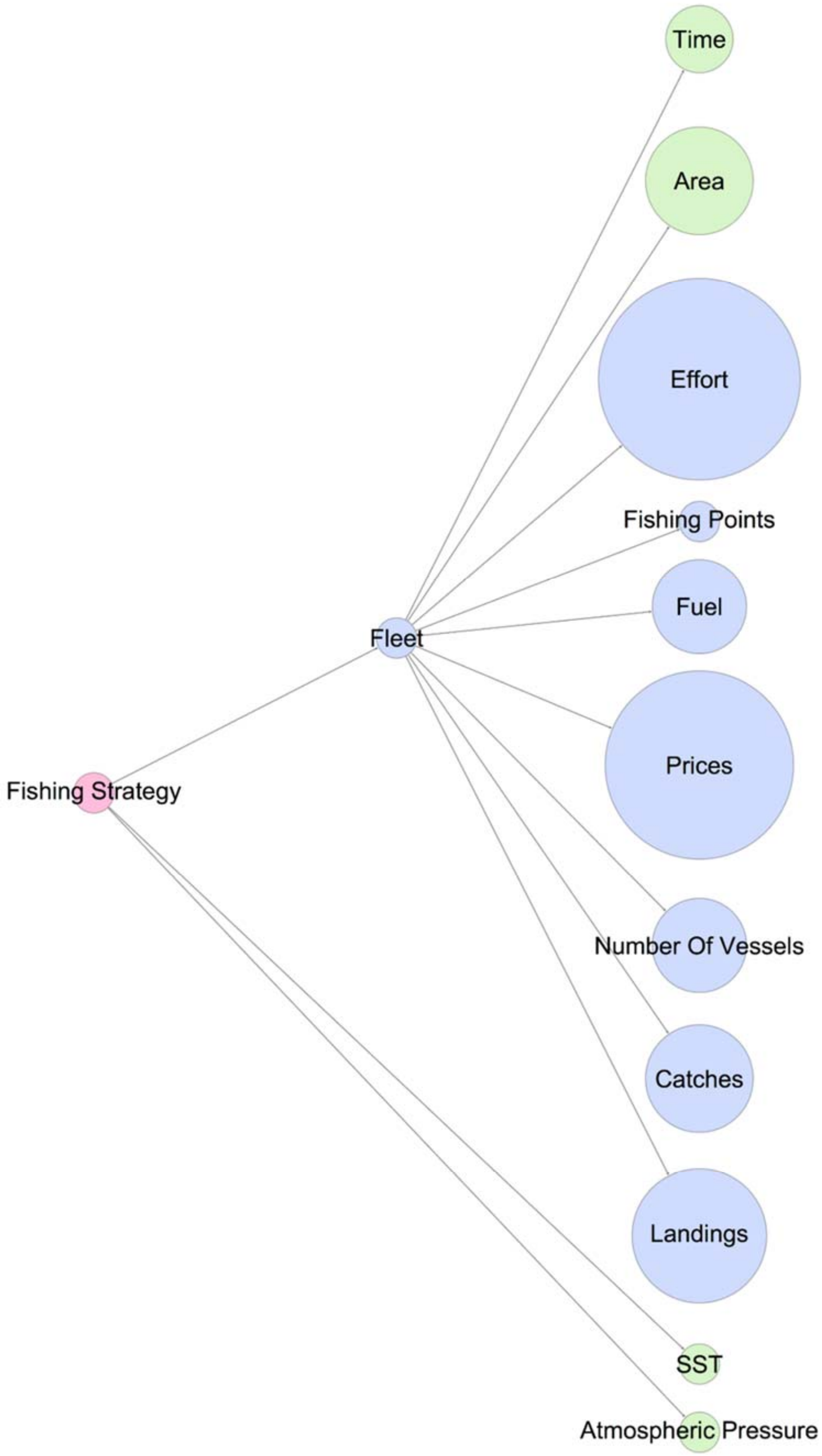
Go Out Fishing Or Stay In Por
Area
Fuel
Revenue
Metier
Cost
Vessel Behavior
Species
Landings
Fine
Fleet
Management Option
Discards
Vessel
Effort Allocation
Compliance
Effort
Prices
Management Measures
Quota
Stock
Compliance
Value
Fishing Mortality
Profit
Capacity
TAC
Weight
Time

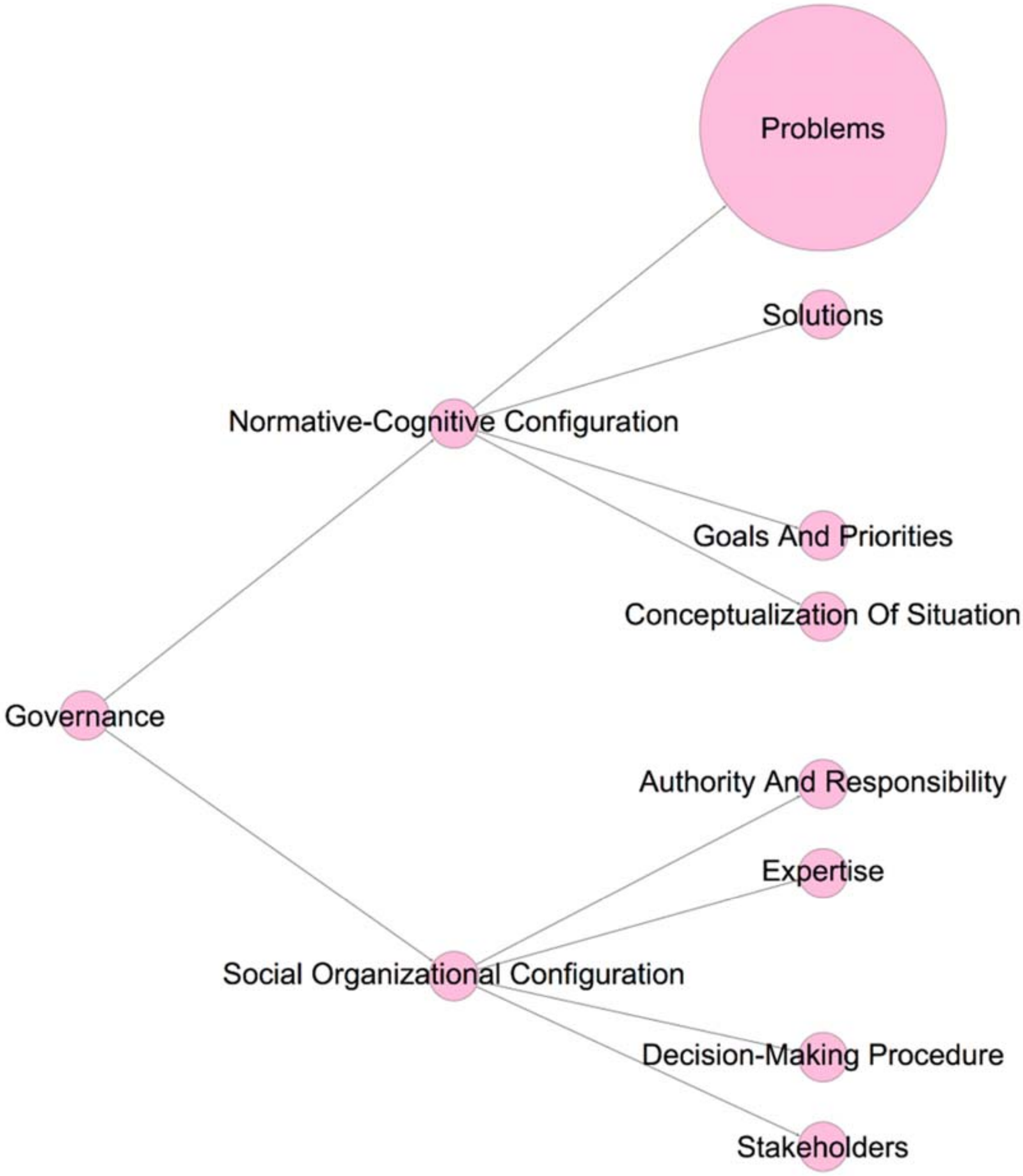

Landings
TAC
Species
Stock
TAC
Harvest
Fine
Cost
Compliance
Effort
Enforcement
Profit
Commitment
Compliance
Quota
Prices
ITQs

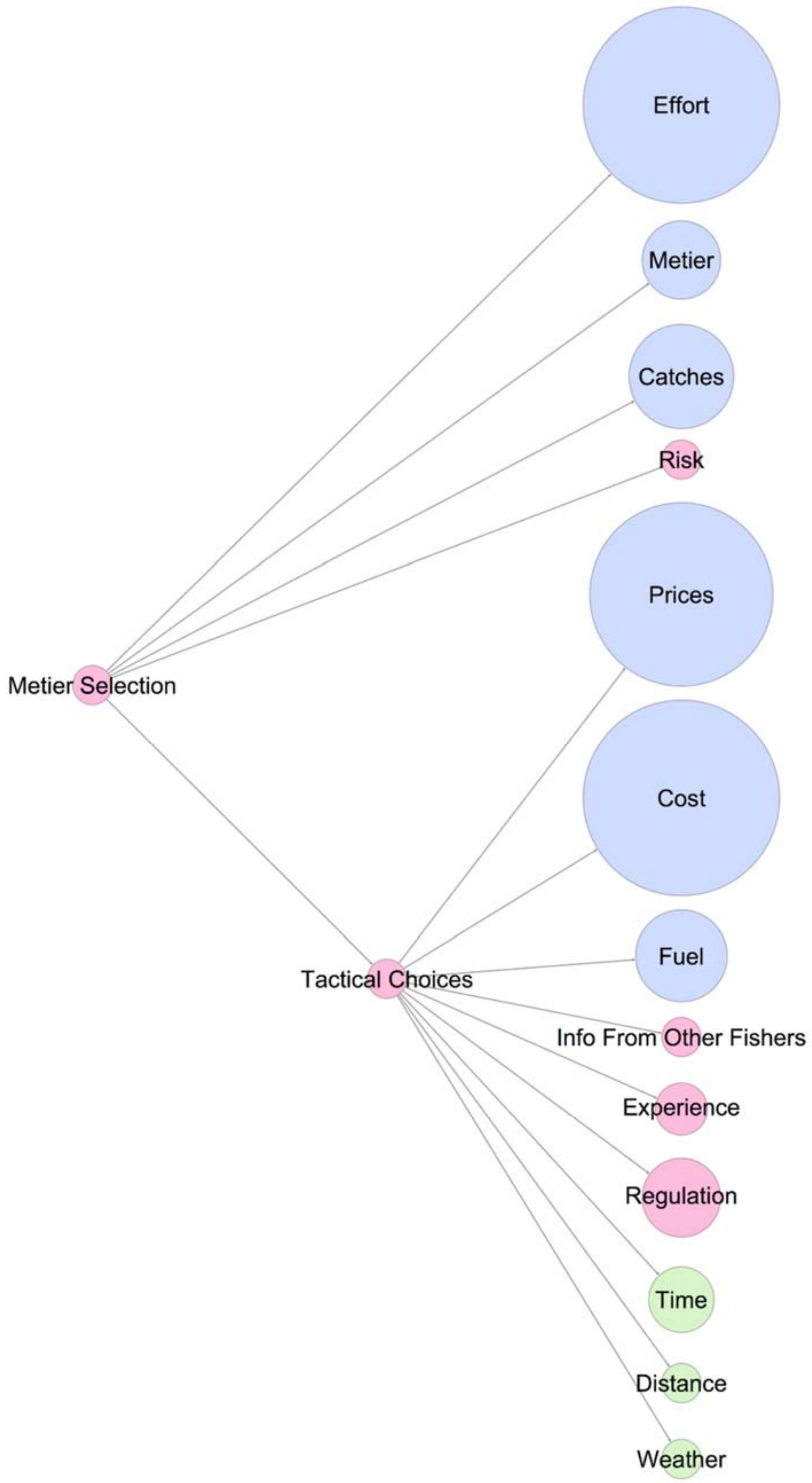

Stock
Area
Network Integration
Family Connections
Probability Of Making A Choice
Decommissioning Grant
Capacity
Revenue
Enter And Exit The Fishery
Utility
Prices
Vessel
Number Of Vessels
Market Trader Network Structure And Dynamics
Fuel

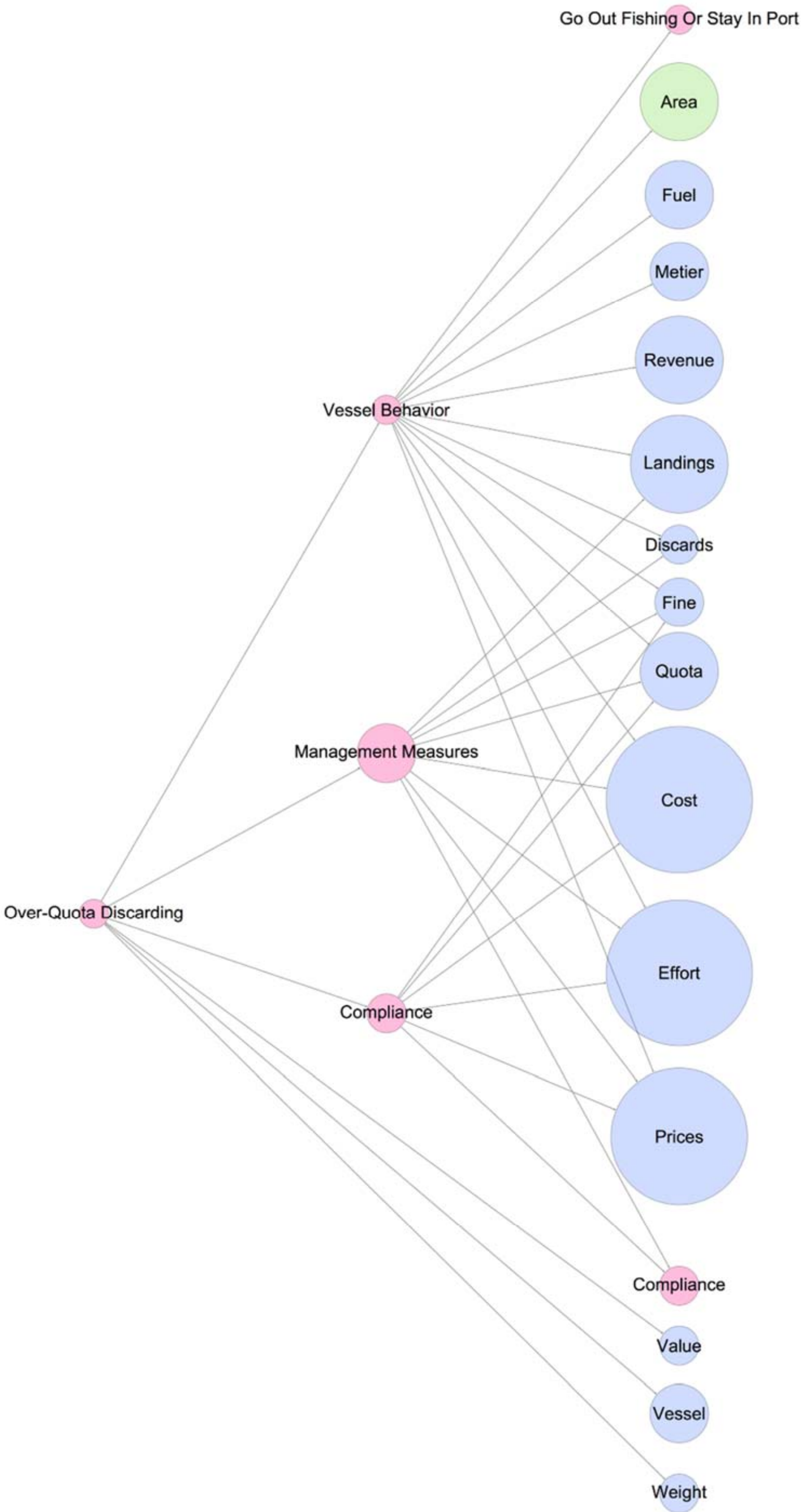

VPA
Policy Making
CPUE
Yield
Diagnostics
Objectives
Effort
Intervention
TAC
Biomass
Sustainability
Fishing Mortality
Evaluation Of Management Plans
Mortality Reduction
Multispecies
Stock
Industry Support
Management Measures
Monitoring Programme
Capacity
Earnings
Performance Indicators
Profitability
Quota
Tax
Landings
Catches
Prices
Cost

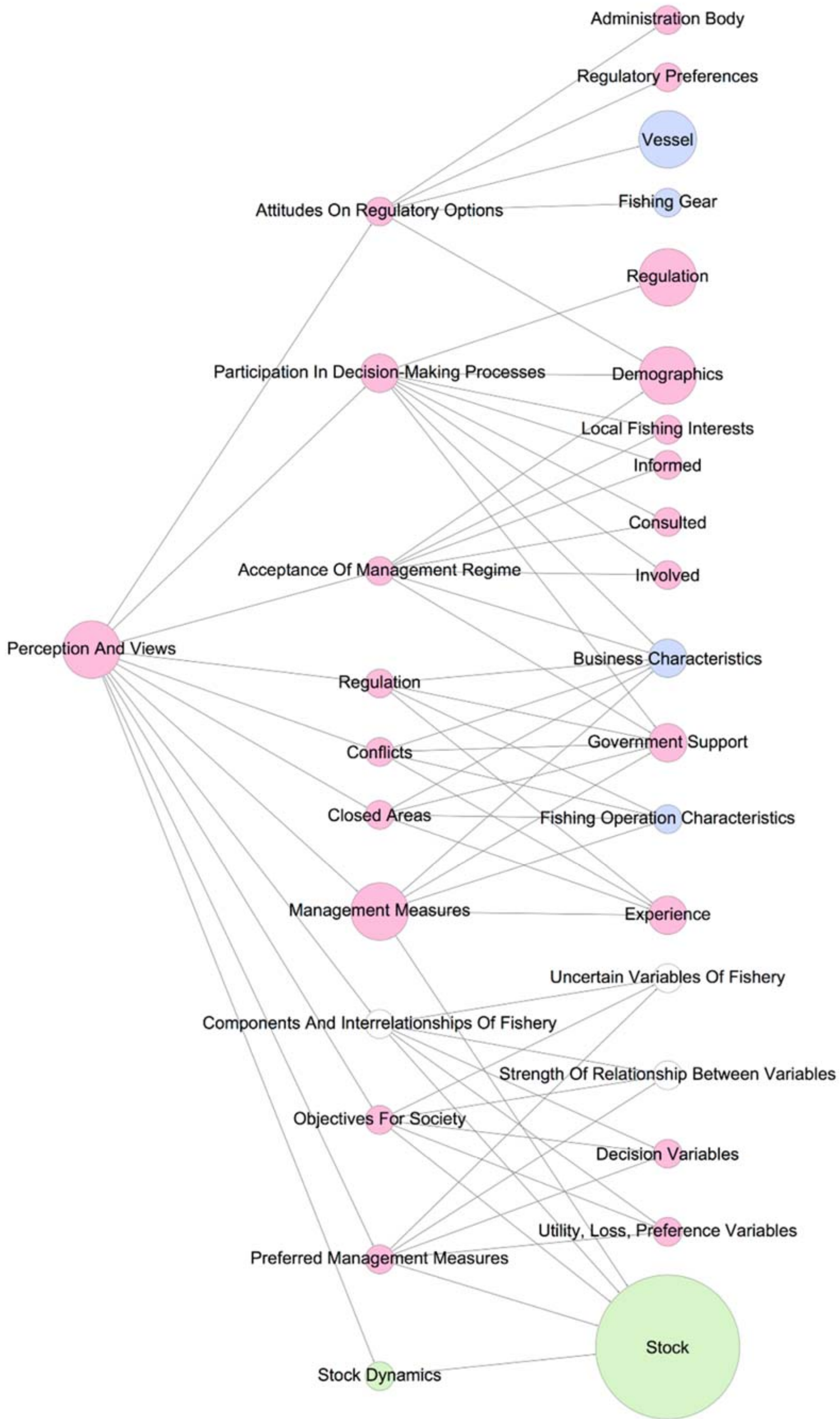

Area
Employment
Accessability
Fisheries Dependency
Employment Opportunities
Number Of Vessels
Ports, Harbours

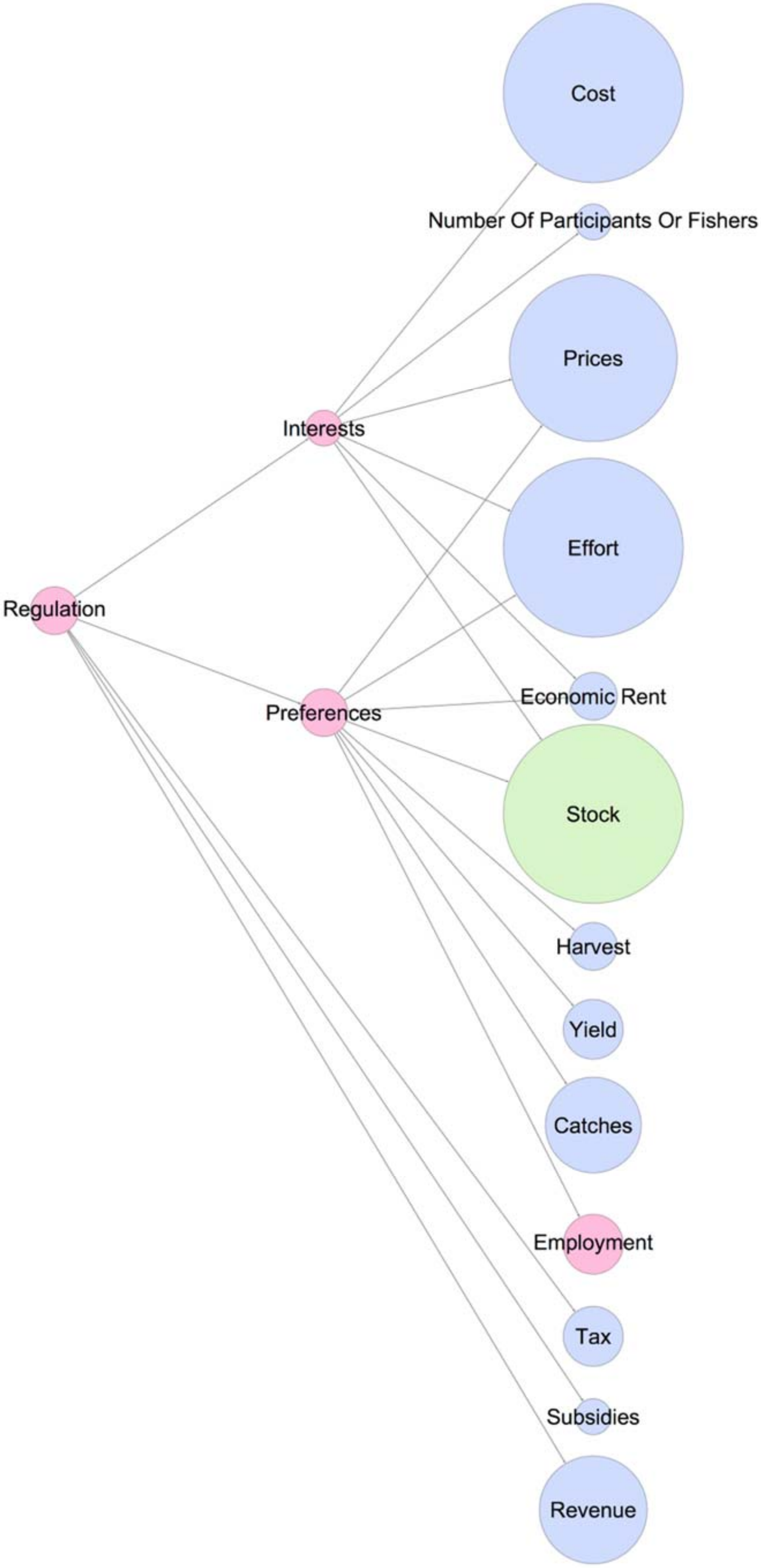

Time
Area
Effort
Fishing Points
Fuel
Fleet
Prices
Fishing Strategy
Number Of Vessels
Catches
Landings
SST
Atmospheric Pressure

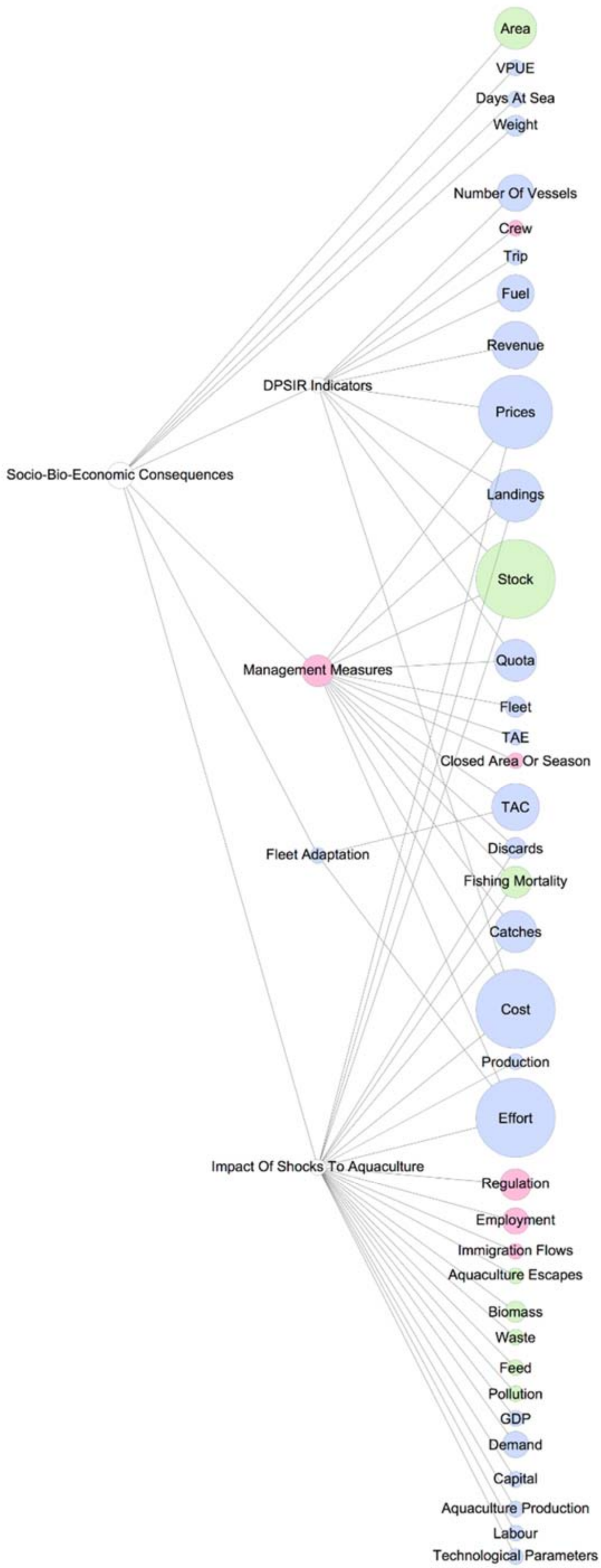

Problems
Solutions
Normative-Cognitive Configuration
Goals And Priorities
Conceptualization Of Situation
Governance
Authority And Responsibility
Expertise
Social Organizational Configuration
Decision-Making Procedure
Stakeholders

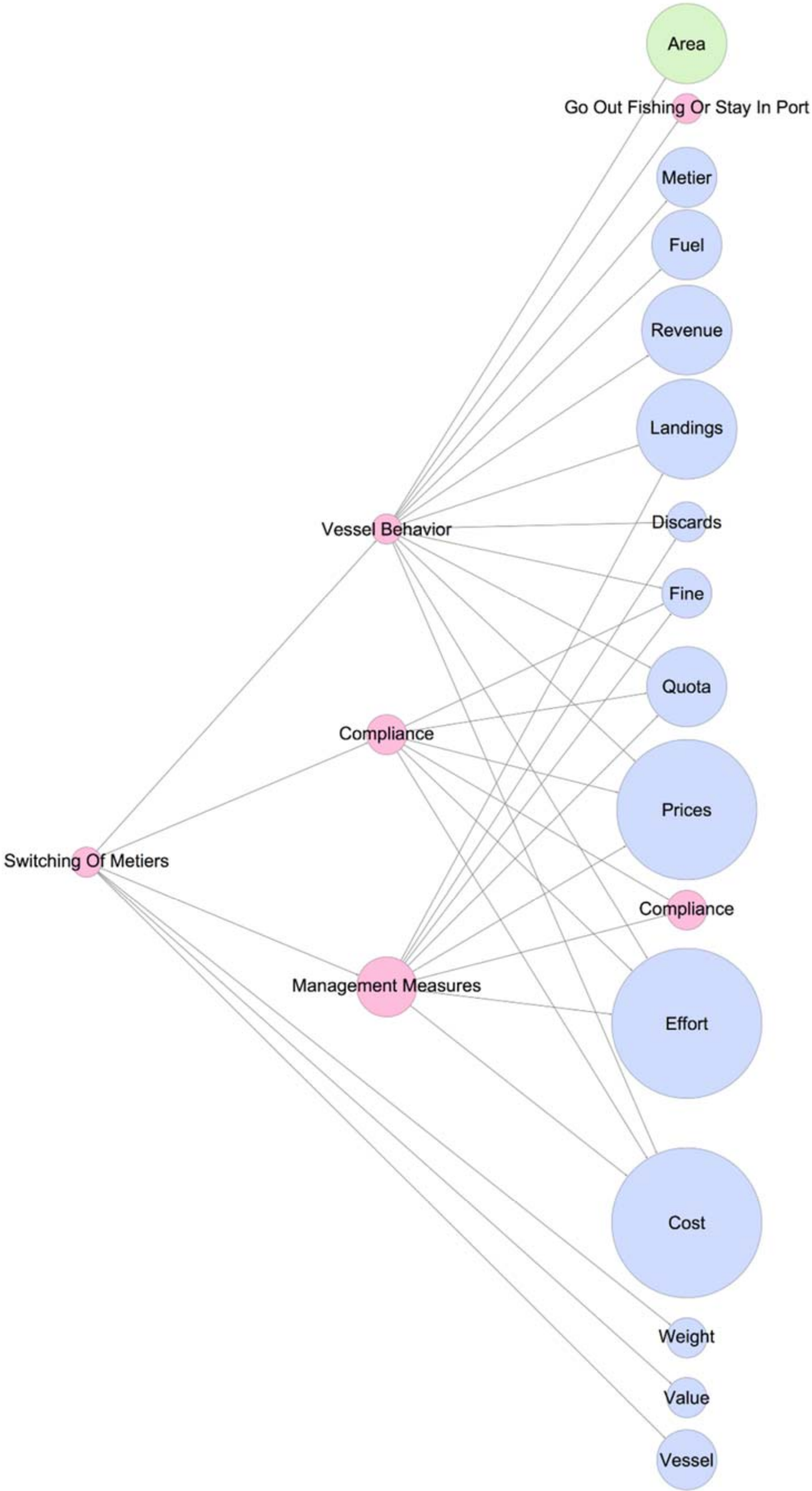

Effort
Metier
Catches
Risk
Prices
Metier Selection
Cost
Fuel
Tactical Choices
Info From Other Fishers
Experience
Regulation
Time
Distance
Weather

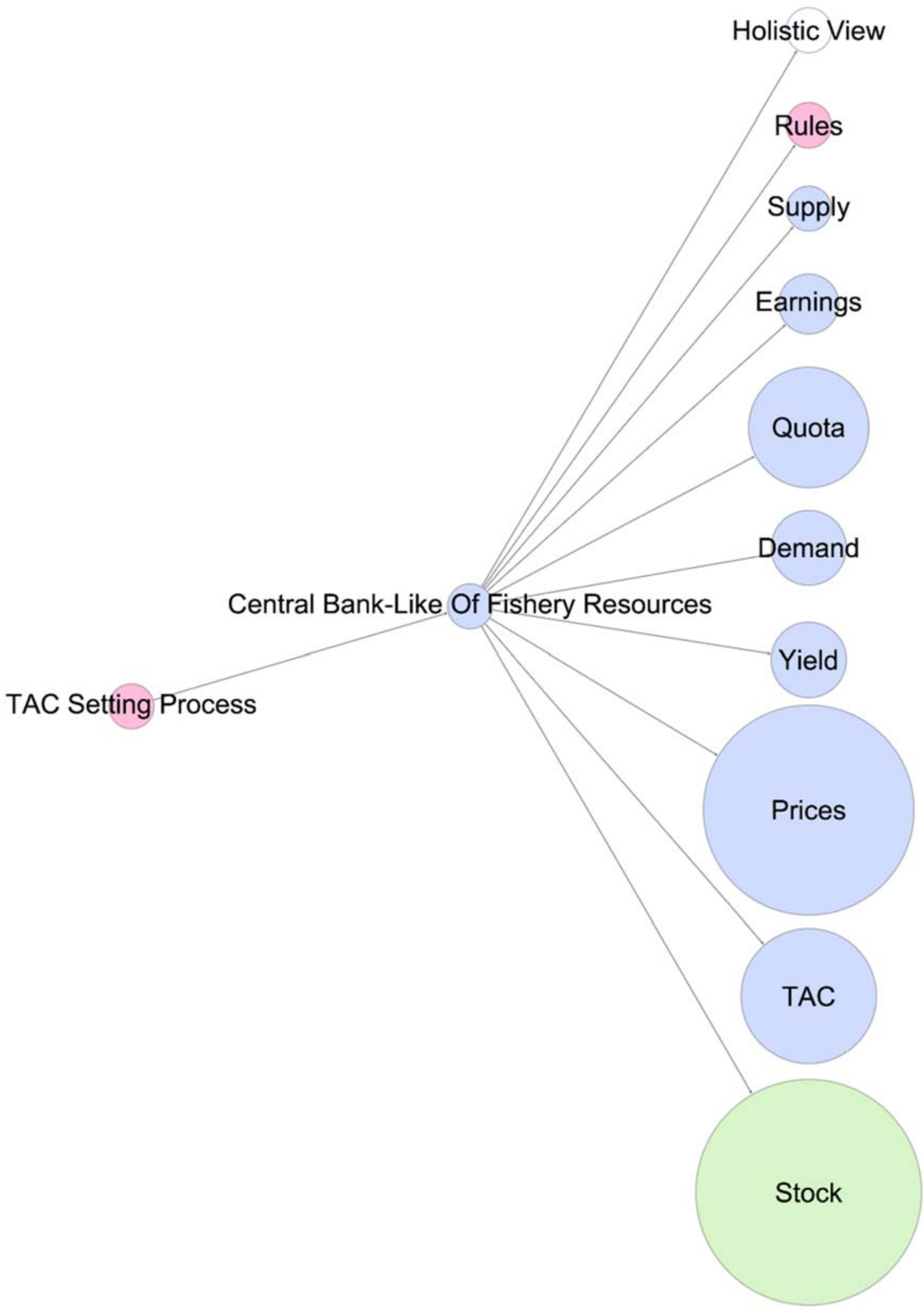

Go Out Fishing Or Stay In Port
Area
Fuel
Metier
Revenue
Vessel Behavior
Landings
Discards
Fine
Quota
Management Measures
Cost
Over-Quota Discarding
Effort
Compliance
Prices
Compliance
Value
Vessel
Weight

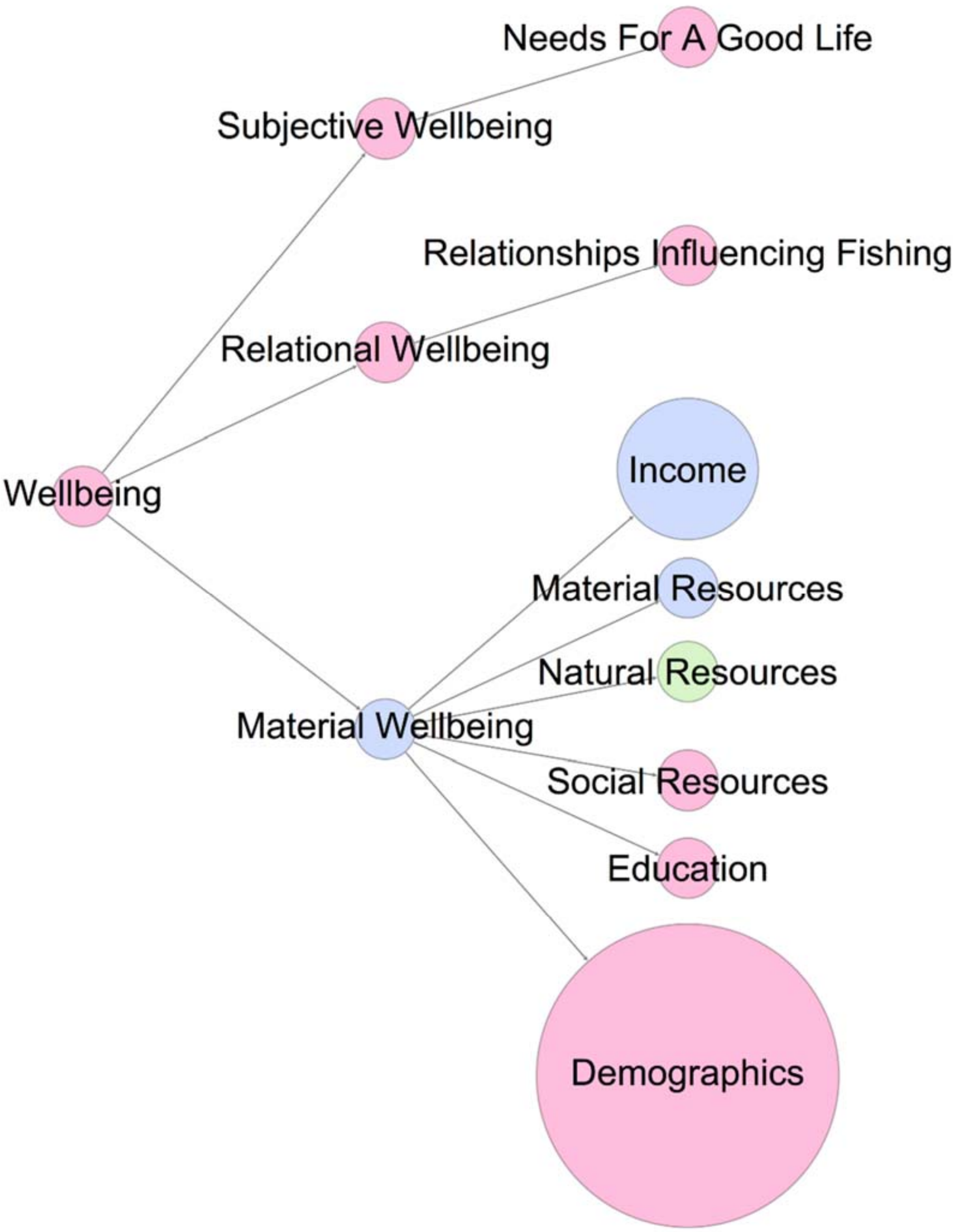

Administration Body
Regulatory Preferences
Vessel
Fishing Gear
Attitudes On Regulatory Options
Regulation
Participation In Decision-Making Processes
Demographics
Local Fishing Interests
Informed
Consulted
Acceptance Of Management Regime
Involved
Perception And Views
Business Characteristics
Regulation
Government Support
Conflicts
Closed Areas
Fishing Operation Characteristics
Management Measures
Experience
Uncertain Variables Of Fishery
Components And Interrelationships Of Fishery
Strength Of Relationship Between Variables
Objectives For Society
Decision Variables
Utility, Loss, Preference Variables
Preferred Management Measures
Stock
Stock Dynamics


Cost
Number Of Participants Or Fishers
Prices
Interests
Effort
Regulation
Economic Rent
Preferences
Stock
Harvest
Yield
Catches
Employment
Tax
Subsidies
Revenue


Area
VPUE
Days At Sea
Weight
Number Of Vessels
Crew
Trip
Fuel
Revenue
DPSIR Indicators
Prices
Socio-Bio-Economic Consequences
Landings
Stock
Quota
Management Measures
Fleet
TAE
Closed Area Or Season
TAC
Fleet Adaptation
Discards
Fishing Mortality
Catches
Cost
Production
Effort
Impact Of Shocks To Aquaculture
Regulation
Employment
Immigration Flows
Aquaculture Escapes
Biomass
Waste
Feed
Pollution
GDP
Demand
Capital
Aquaculture Production
Labour
Technological Parameters


Area
Go Out Fishing Or Stay In Port
Metier
Fuel
Revenue
Landings
Vessel Behavior
Discards
Fine
Quota
Compliance
Prices
Switching Of Metiers
Compliance
Management Measures
Effort
Cost
Weight
Value
Vessel


Holistic View
Rules
Supply
Earnings
Quota
Demand
Central Bank-Like Of Fishery Resources
Yield
TAC Setting Process
Prices
TAC
Stock


Needs For A Good Life
Subjective Wellbeing
Relationships Influencing Fishing
Relational Wellbeing
Wellbeing
Income
Material Resources
Natural Resources
Material Wellbeing
Social Resources
Education
Demographics