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Research

How the qualities of actor-issue interdependencies influence collaboration patterns

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ABSTRACT. Environmental governance is complex because it addresses challenges anchored in different sectors and concerns multiple interdependent issues. Managing those complex interdependencies through collaboration is vital for efficient long-term environmental governance. However, because interdependencies between environmental issues are challenging to unravel and vastly complex, it is challenging for actors to account for them when deciding with whom to collaborate. I use the concept of social-ecological networks to study interdependencies among actors and environmental issues and ask how the quality of actor-issue interdependencies influences collaboration patterns. Based on the actor-issue network, I account for interdependencies based on three distinct qualities of actor-issue paths, i.e., (i) length of actor-issue paths: how closely actors are connected by environmental issues, (ii) multiplexity of actor-issue paths: if actors have multiple parallel paths connecting them through environmental issues, and (iii) similarity of actor-issue paths: whether actors' environmental impact is similar to one of their potential collaboration partners. Using exponential random graph models and data on eight Swiss wetlands, a qualitative meta-regression analysis of the results reveals that the three qualities of actor-issue interdependencies influence collaboration patterns between actors. Whether the impact of actor-issue interdependencies on the probability of collaboration ties is positive or negative largely depends on the complexity of the governance situations. Only in situations with homogeneous case areas and under the absence of borders (low network exogenous governance complexity) as well as in the presence of many actors do the length, multiplexity, and similarity of actor-issue interdependencies have a clear, positive impact on the formation of collaboration ties. Although the comparative setting helps identify specific governance settings where the hypotheses are supported, it also reveals the importance of multi-case studies to compare contextual differences between cases.

Key Words: *collaboration; exponential random graph model (ERGM); natural resource governance; social-ecological networks (SEN); social-ecological systems (SES)*

INTRODUCTION

Collaboration among actors is seemingly imperative for the successful governance of environmental systems (Bodin and Crona 2009, Prell et al. 2009, Lubell 2013). Still, we have only a partial understanding of how actors decide to collaborate for the purpose of governing environmental systems. This research analyzes the impact of interdependent environmental issues on actor collaboration. In order to advance the body of knowledge pertaining to environmental issues influencing actor collaboration, I adopt a governance perspective of complex social-ecological systems (SESs).

The governance of SESs can be complex because of external conditions influencing the structure of SESs or based on different types of internal complexity of the SESs themselves. External conditions that influence the structure of SESs can be the fragmentation of the geographical or administrative settings. In itself, the governance of SESs can be complex because of the number of interdependent actors and environmental issues (Adkin et al. 2017, Brandenberger et al. 2022). The environmental issues and actors are interdependent because they can be influenced by activities of actors or other environmental issues. For example, water quality is an environmental issue affected by the operation of wastewater treatment plants. Because interdependencies between environmental issues are often vastly complex, it may be challenging for actors to understand their activities' full impact on specific environmental issues (Crona and Bodin 2006, Bergsten et al. 2019). Additionally, interdependencies between environmental issues are complex because they are not binary—either present or absent—but rather can have different qualities (Sayles et al. 2019, Jasny et al. 2021). For wastewater treatment plants it is, for example, not enough to state that they influence the water quality but it is important to specify that they potentially improve water quality.

For studying how the quality of interdependencies among environmental issues influences actors' choices of collaboration partners, I adopt a social-ecological network (SEN) perspective based on SES theory (Bodin and Tengö 2012, Bodin et al. 2019). The concept of SEN emerged more than a decade ago to describe and analyze SES using multilevel networks (Cumming et al. 2006, 2010, Janssen et al. 2006, Bodin and Tengö 2012). SEN studies often focus on collaboration among resource users and the resilience of interdependent SESs (Janssen et al. 2006, Bodin et al. 2014, Dakos et al. 2015, Guerrero et al. 2015). Although I generally refer to the literature on SEN, I characterize the network under study as an actor-issue network. This is as I apply the SEN logic not to ecological elements but rather to environmental issues and the ways in which actors collaborate to manage those interdependent environmental issues (Bergsten et al. 2019, Hedlund et al. 2020). Further, I use the term actor-issue paths to refer to interdependencies between the two levels of the actor-issue network and different qualities thereof. Conceptualizations of SENs using different concepts of nodes are common and can include social entities, such as institutions or practices, and ecological entities, such as resources, species, or environmental issues. Environmental issues are often used for SEN studies that operate on an intermediate level of aggregation where a clear

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definition of ecological nodes is difficult (Bodin et al. 2019). Further, I analyze how the impact of different qualities of actor-issue paths on collaboration ties in the SENs changes depending on the overall complexity of the governance setting.

With this research, I contribute to the SEN literature in two ways. First, I increase the understanding of the governance of environmental systems and the network paths between environmental issues by acknowledging these systems' inherent complexity. When the concept of SEN is applied to study ecological or environmental systems, the network ties are often binary and do not include any information about the quality of ties (Sayles et al. 2019, Vasudeva et al. 2020, Jasny et al. 2021). Accounting for the quality of dependencies can help explain why many environmental problems entail conflicts of interest (Herzog and Ingold 2019, Bodin et al. 2020). Although complex environmental and ecosystem networks are established in natural science fields, for example, to analyze cross-ecosystem fluxes in biology (Altermatt et al. 2020, Harvey et al. 2020), this is often not the case for networks used for analyzing and informing environmental governance decisions (Bodin et al. 2019).

Second, a more detailed perspective of the qualities of network paths between environmental issues is essential for understanding collaboration patterns. Within the field of SEN research, the concept of (social-ecological) fit is prevalent for explaining which collaboration patterns are beneficial for the governance of ecosystems (Guerrero et al. 2015, Treml et al. 2015, Sayles and Baggio 2017, Enqvist et al. 2020). The literature on fit claims that the alignment of collaboration patterns with the structure of the ecosystem enhances governance effectiveness (Ostrom 2007, Epstein et al. 2015, Widmer et al. 2019). By contrast, a poor fit can cause non-efficient resource use resulting in exhaustive or non-productive consumption. However, current discussions on fit often do not account for different qualities of network paths between environmental issues when assessing collaboration patterns among actors. This gap limits the power of the concept of fit because the achievement of fit depends not only on the existence but also on the quality of actor-issue paths. Although the quality of actor-issue paths is often not accounted for in studies on fit, the general importance of different qualities of network paths for the study of social-ecological systems using networks is recognized (Debortoli et al. 2018).

The methodological approach of this study combines qualitative expert interviews and quantitative survey data of eight Swiss wetlands with statistical modeling of networks using exponential random graph models (ERGMs). The ERGMs are then further compared using a qualitative meta-regression analysis that combines the results across the cases of wetland governance. Wetlands are among the ecosystems with the richest biodiversity in Europe and worldwide. However, 90% of the wetlands that existed in 1850 in Switzerland have disappeared because of intensive use and various demands of societal, political, and economic actors (Müller-Wenk et al. 2003, Verhoeven 2014). The research setting is based on eight separated yet comparable case study areas with around 500 actors active in the local governance across these wetlands. The cases differ in their level of governance complexity characterized by four conditions: (1) number of actors in actor network, (2) number of ties in issue network, (3) case area structure, and (4) existence of cantonal borders. The four conditions are used in a qualitative meta-regression analysis to compare how actors' ability to account for actor-issue paths influences the achievement of fit in different contexts. By using SEN in a comparative study setting, I additionally answer the call from the field of SEN studies to move beyond single case studies and provide an exciting opportunity to evaluate and compare SEN in a comparative setting across cases (Bodin et al. 2019, Sayles et al. 2019), contributing to a more general understanding of collaboration patterns in SEN.

THEORY

The governance of social-ecological systems (SESs)

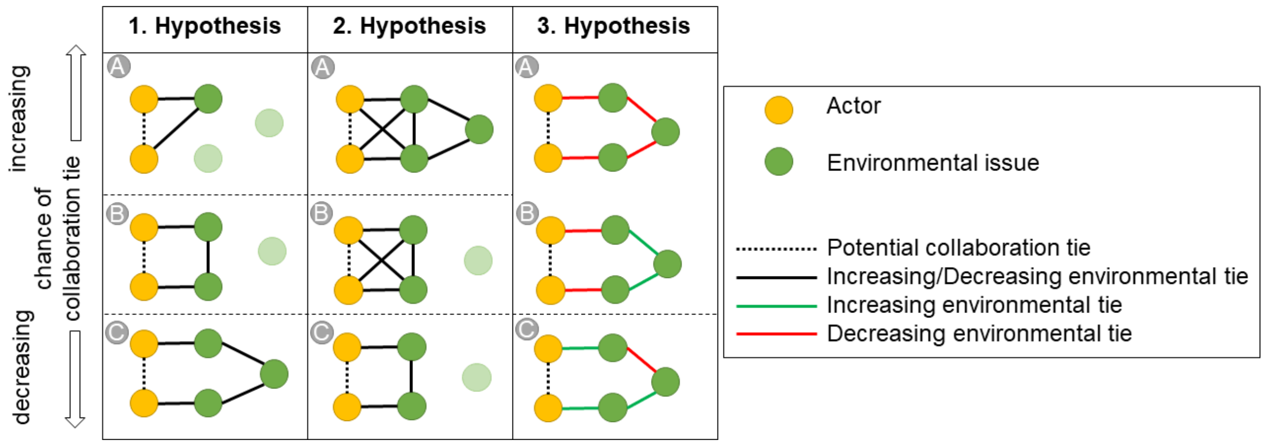
Previous research in ecosystem governance established the importance of governing ecological and social systems in an integrated manner (Berkes and Folke 1998, Ostrom 2007, Bodin and Crona 2009, Prell et al. 2009, Lubell 2013). The integration of social and ecological aspects is important because processes in SESs are often entangled within and across the levels of the SESs. Further, the governance of SESs does not take place in isolation but is influenced by exogenous governance complexities, given, e.g., by the geographical as well as the administrative setting. Consequently, ecosystem governance often faces the challenge of managing the high inherent complexity of intertwined social and ecological systems in relation to larger system dependencies (McGinnis and Ostrom 2014).

I build on the SES framework by Ostrom (2007) that holistically conceptualizes and analyzes governance structures of ecosystems (Gerber et al. 2009, Ostrom 2009, McGee and Jones 2019). The SES framework emphasizes the importance of aligned social and ecological systems to resolve policy issues and achieve sustainability of SESs (Ostrom 2009, Lubell et al. 2014, Epstein et al. 2015). To achieve an alignment of social and ecological systems and manage SES successfully, the importance of actor collaboration is often stressed in research building on the SES framework (Pittman and Armitage 2017, Ingold et al. 2018, Hedlund et al. 2020). I define collaboration here as an interaction between two actors to govern environmental issues. Although collaboration is generally assumed to be beneficial, it is also associated with certain costs (Hileman and Bodin 2019). The costs of collaboration ties are also a matter of interest in the ecology of games framework (EoG; Lubell et al. 2014, Berardo and Lubell 2019). The EoG analyzes how actors' capacities to collaborate are constrained by the availability of physical and cognitive resources, and how constraints on collaboration influence governance outcomes. In addition to interdependencies between actors, interdependencies between issues within the environmental/ecological systems are also relevant for understanding collaboration but tend to remain understudied (Bodin and Tengö 2012).

The role of social-ecological networks (SEN) for the governance of ecosystems

One approach to structure complex interdependencies within and across systems focuses on networks. In networks, social and ecological systems are both conceptualized based on nodes and ties. Networks play an increasingly important role in analyzing the governance of SES and exploring different forms of dependencies (e.g., collaboration) between actors (Robins et al. 2012, Dragicevic and Shogren 2017). However, the concept of networks is not limited to actor interactions (Janssen et al. 2006, Scott and Ulibarri 2019) but can equally include other forms of dependencies between any

Fig. 1. Illustration of simplified network motifs for the three hypotheses; different motifs that include more/less environmental issues are possible. Motifs with an A always have the greatest chance to cause a collaboration tie from all the motifs presented, and motifs with a C have the lowest chance of causing a collaboration tie. For the third hypothesis, motifs A and B have the same chance to cause a collaboration tie. For the first hypothesis, actors are more likely to collaborate in the triangle motif because the connecting actor-issue path is shorter. For the second hypothesis, the actors are more likely to collaborate in the top motif because the number of connecting actor-issue paths is higher. Finally, for the third hypothesis, actors are more likely to have a collaboration tie in motif A or B because they impact the state of an environmental issue in the same direction based on their actor-issue path, given by the multiplication of the increasing (+1)/ decreasing (-1).



units of analysis (Bentley et al. 2019). The concept of SEN has gained popularity for its combined analysis of social and ecological systems. The concept of SEN builds on two parallel network levels, the social and the ecological, with ties within and across those levels (Barnes et al. 2017). Because the SEN concept is still relatively new, only a few attempts exist to standardize the conceptualization of SENs (Bodin et al. 2019, Sayles et al. 2019, Felipe-Lucia et al. 2022). Research using SENs often focuses on analyzing the governance of ecosystems based on single case studies (Bodin et al. 2019, Sayles et al. 2019).

To analyze the governance of SESs using networks, the concept of fit gives particular emphasis to social-ecological paths illustrating interdependencies between the two network levels (Sayles and Baggio 2017, Widmer et al. 2019). The concept of social-ecological fit implies that the social systems should be aligned with the ecosystems (Ostrom 2007, Epstein et al. 2015, Widmer et al. 2019). The ecological and social network structures in SENs are aligned when actors managing dependent environmental issues collaborate. Different concepts of fit have emerged (Folke et al. 2007, Lebel et al. 2013, Bodin et al. 2014, Widmer et al. 2019) that can be categorized as ecological fit, social fit, and social-ecological system fit (Epstein et al. 2015). I refer to the latter when identifying structures in SENs that are potentially influencing the governance of SESs. The benefit of social-ecological fit is that it accounts for the full SES and not only one component of inextricably interlinked SESs as social fit and ecological fit concepts do (Moss 2003, Epstein et al. 2015). The challenge with social-ecological fit is, however, to properly conceptualize the complex interdependencies of SESs. In this paper, I use networks to conceptualize actor-issue interdependencies. Fit in those networks exists when the interdependencies represented by actor-issue paths are aligned with collaboration ties.

The importance of the quality of actor-issue paths for collaboration patterns

I define actor-issue paths as a combination of two or more ties that connect the social and ecological levels of SENs, in contrast to general network paths that connect any two nodes in a network. Using actor-issue paths, it is possible to characterize how actors are connected at the issue network level. When actor-issue paths connect two actors that collaborate, a network motif of fit is created where the management of environmental issues is aligned. However, unlike other scholars analyzing fit based on networks, I do not differentiate between different network motifs of fit, e.g., triangle vs. four-cycles (Lubell et al. 2014, Bodin et al. 2016), but rather focus on how different actor-issue paths contribute to network motifs of social-ecological fit. The three hypotheses that focus on different qualities of actor-issue paths and thus describe different situations of fit, are illustrated in Figure 1. The top row presents the configuration with the highest probability of observing a collaboration tie, and the further rows show additional configurations with lower expected probabilities for collaboration ties. Additional configurations that can be more or less complex are also taken into account in the analysis as such configurations potentially influence the probability of observing a collaboration tie. The three hypotheses illustrated in Figure 1 are assessed for a diversity of cases with different levels of governance complexity. I assume that the support of the hypotheses varies depending on the level of governance complexity, as governance complexity likely influences actors' perception of the qualities of actor-issue paths. The analysis of the relation between governance complexity and the three hypotheses has a hypotheses generating character in this article.

When the probability of a collaboration tie forming is assessed, this is often done based on the shortest network connection between two actors (Berardo and Scholz 2010, Moon et al. 2019). In the literature on fit, the path length plays a minor role because only very limited motifs of fit with only a small number of nodes are analyzed (Guerrero et al. 2015, Pittman and Armitage 2017, Enqvist et al. 2020). I include the path length connecting pairs of actors in the first hypothesis to analyze how proximity across actor-issue networks influences actors' decisions to collaborate. The assumption is that the shorter the actor-issue path connecting two actors, the stronger the connection between them, and the more likely actors are to collaborate. This assumption is based on the idea of bounded rationality, where actors make decisions based on a limited perception of the underlying problem (Simon 1991). The concept of bounded rationality serves to limit the cognitive load to a manageable level for everyday decisions. The cognitive load essentially addresses the amount of information that needs to be processed to make a decision (Renkl et al. 2009), in this case, with whom to collaborate. In complex governance settings reducing the cognitive load is essential, as actors only have limited resources they can invest in collaboration ties (Lubell et al. 2014, Hileman and Bodin 2019). Therefore, actors might focus on short actor-issue paths when choosing collaborators.

1. Hypothesis: Length of actor-issue paths: Actors are more likely to collaborate if the actor-issue path connecting them is shorter.

Furthermore, only one actor-issue path (that connects two actors based on their impact on a common issue) is usually included when the alignment of collaboration patterns with an ecosystem's ecological or environmental structure is analyzed (Epstein et al. 2015, Guerrero et al. 2015). This is in contrast to the frequent existence of multiple alternative paths in SENs. Multiple alternative paths are typical for complex networks (Widmer et al. 2019, Guimarães 2020). Therefore, the second path quality accounts for multiple parallel actor-issue paths connecting pairs of actors. The assumption is that the more alternative paths exist, the more likely it is that those actors are aware of each other (Huang 2014, Siciliano et al. 2021). Therefore, I assume that the multiplexity of actor-issue paths increases the chance of actors sharing a collaboration tie because those actors manage multiple common environmental issues together. Similarly, as with shorter path lengths, higher multiplexity also has the potential to increase the mutual awareness between actors (Dörner 1983, Renkl et al. 2009) and increase the probability that actors share a collaboration tie.

2. Hypothesis: Multiplexity of actor-issue paths: Actors are more likely to collaborate the more alternative actor-issue paths are connecting them.

Finally, actor-issue paths are often not neutral, i.e., simply describing an influence, but rather can be specified as having an increasing or decreasing effect on the state of dependent environmental issues. If two actors influence the state of an environmental issue in the same direction, increasing or decreasing the state of the issue, their management practices tend to be aligned. The alignment of management practices has the potential to facilitate collaboration between actors. This does not mean that actors should not collaborate when they influence environmental issues differently. However, differences in actors' influence on environmental issues are likely to increase the cost of establishing collaboration ties. Therefore, the third hypothesis assumes that actors are more likely to collaborate if they have a similar influence on the state of an environmental issue. Similarity of actors with respect to different characteristics is commonly used to explain why actors collaborate (Siciliano et al. 2021). Typical applications of similarity explaining actor collaboration are based on shared beliefs (Calanni et al. 2015) or occupational similarity (Cepić and Tonković 2020). Here I investigate actor similarity in terms of the direction in which they impact environmental issues (e.g., decreased/increased state of an environmental issue).

3. Hypothesis: Similarity of actor-issue paths: Actors are more likely to collaborate if they influence the state of an environmental issue in the same direction.

CASE, METHODS, AND DATA

Case description

In this paper, I study the governance of eight wetlands across Switzerland. Wetlands comprise various habitats that are characterized by high biodiversity. However, many wetlands are also located in areas that are economically utilized as farmland or for recreational purposes. Therefore, while the importance of wetlands to sustain rich biodiversity is recognized, the size and number of wetlands have continuously decreased to the point where they only make up 0.7% of Switzerland's area (Müller-Wenk et al. 2003, Verhoeven 2014). In the revised Water Protection Act, the poor condition of wetlands is recognized, as one-quarter of Swiss water bodies have been designated as being in need of active restoration measures (Werth et al. 2012). However, 10 years later, the restoration of the water bodies is proceeding slowly, and the status of most wetlands does still not satisfy the requirements of the law (Bonnard et al. 2020).

Although the water protection act is initiated and funded on the federal level, cantons and municipalities (the constituent states and sub-states of Switzerland) are responsible for its implementation. Thus, when analyzing the governance of wetlands in Switzerland, I primarily focus on actors on the regional and local levels, such as cantonal agencies and municipalities, as well as a diverse set of private actors (NGOs, associations, or private companies).

When I selected the cases of Switzerland's wetlands, I considered multiple criteria. First, only the wetlands that are listed in the inventory for alluvial wetlands of national importance were considered (Bundesamt für Umwelt 2014). The inventory of alluvial wetlands is managed by the federal office for the environment to improve the protection and maintenance of wetlands and ensures that all the areas identified for this article show characteristic features of Swiss wetlands. Second, the case selection covers different regions and cantonal administrations across Switzerland to account for geographical and socio-cultural diversity, including the German, French, and Italian-speaking regions. Also, while some cases are located within one canton's administration area, other cases cut across cantonal borders and are governed by multiple cantons. Third, wetlands were selected that represent goal conflicts between societal, economic, and ecological interests. Therefore, the focus is on river wetlands and wetlands along lakes, which are often located in densely populated areas. Finally, the wetlands' size was also a factor when deciding on the case selection of the wetlands. Small wetlands (< 0.6 km^2) were excluded from the study to avoid cases with only a few actors, as those would have complicated a meaningful statistical analysis.

However, purely geographic case boundaries cannot fully demonstrate the multiple dimensions of governance issues (Moss 2012). Therefore, I also account for socioeconomic aspects relevant to the management of wetlands (e.g., close by farming land or upstream hydropower plants) to include further surrounding areas that form one functional unit (for further details, see Appendix 1, Location of selected wetlands).

From the wetlands that fulfill all criteria, I selected eight cases across Switzerland that are included in the analysis of this paper (for detailed information on the data gathering approach, see Appendix 1, Data gathering). For each of the eight cases, I then chose key actors deeply involved in managing the respective wetlands representing the public and private sectors. In expert interviews with those key actors, I identified environmental issues and interdependencies between them using a conceptual mapping approach inspired by the Open Standards (OS) framework (Schwartz et al. 2012) (for examples of the data gathered in the expert interviews, see Appendix 2, Conceptual maps). Subsequently, I sent out a survey to 395 of the total number of 499 actors identified to be relevant. The number of contacted actors was lower because some actors present in multiple areas (mostly those active on the national level with no local presence in the wetlands) could not be contacted for all surveys. Of the actors that I contacted, 276 filled out the survey (response rate: 70%). The two most important survey questions for this paper were "Which of the activities below has your organization been involved in over the past three years in the [case area]?" and "Which of the organizations listed below have you regularly collaborated with in the past three years as part of your activities in the [case area]?" (For further details on survey structure and questions, see Appendix 3, Survey text).

For the analysis of the cases, collaboration ties are the dependent variable, and different qualities of actor-issue paths are the independent variables. The characterization of collaboration ties and different qualities of actor-issue paths is identical for all cases and dependent on the set of actors and the relevant environmental issues for each case. Where the cases differ is regarding their level of governance complexity. The level of governance complexity increases actors' cognitive load and influences their ability to account for the length, multiplexity, and similarity of actor-issue paths (Dörner 1983, Jones 2003, Widmer et al. 2019). Governance complexity has a hypotheses generating character for this paper because it potentially influences the actors' decision to collaborate based on actor-issue paths.

The governance complexity is characterized using four conditions (see Table 1): (1) Number of actors in actor network, (2) number of ties in issue network, (3) structure of case area, and (4) existence of cantonal borders. The conditions can be grouped based on their integration in the actor-issue network. The number of actors and ties between environmental issues are elements of the actor-issue network and, therefore, indicators of the endogenous network complexity. The case structure and presence of borders are not part of the actor-issue network but influence the network structure and, therefore, are measures for exogenous network complexity. The index for the case area structure includes the size of the case area as well as the number of separately protected wetlands within one case and is zero-centered. The condition of cantonal borders separates the cases into two categories: (i) cases that cut across cantonal borders, and (ii) cases located within one single canton. I use this differentiation as a measure representing the institutional fragmentation of the cases. A high index for the case area structure and the presence of cantonal borders indicates a high governance complexity and increases the cognitive load of actors.

Table 1. All cases, categorized based on the four conditions of governance complexity: (1) number of actors in actor network, (2) number of ties in issue network, (3) case area structure, and (4) existence of cantonal borders. The conditions are grouped into endogenous network conditions directly integrated into the actor-issue networks (the number of actors and environmental issue ties) and exogenous network conditions that influence the structure of the actor-issue networks (case structure and cantonal borders).

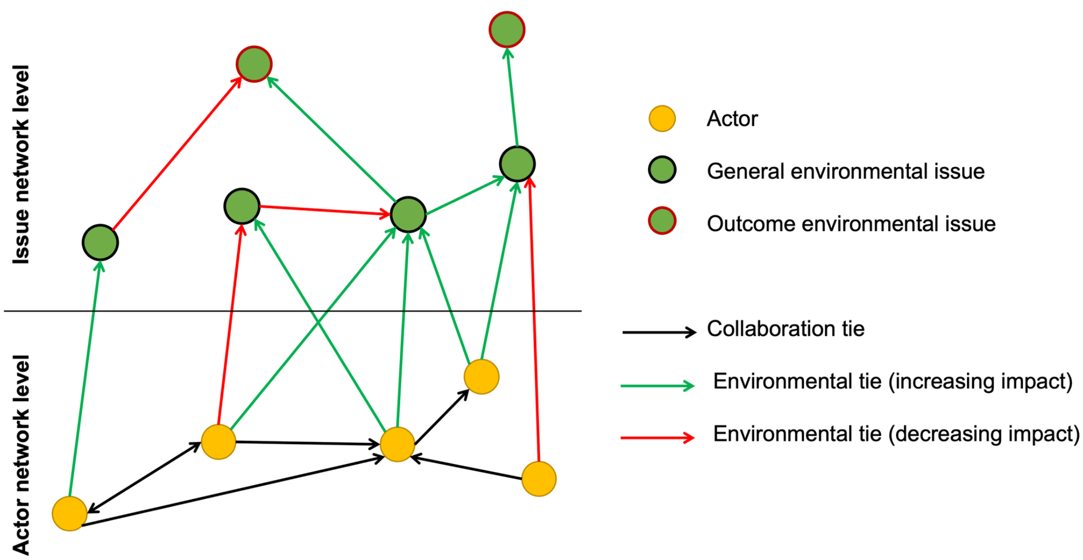
Cases	Network endogenous		Network exogenous	
	Number of actors in actor network	Number of ties in issue network	Case area structure	Existence of cantonal borders
Alte Aare	59	105	0.7	No
Bolle	74	80	-0.2	No
Sense	67	103	-0.1	Yes
Murtensee	59	92	-0.7	Yes
Reussebene	72	111	0.4	Yes
Untere Saane	61	85	-1.6	No
Rhone	44	74	-0.6	Yes
Neuchatel	63	70	2.2	Yes

Methods

The survey data of the wetlands was analyzed using ERGMs. I used ERGMs to test the three hypotheses individually for each of the cases' specific network structures. ERGMs build on the idea of analyzing networks by studying smaller structures that function as building blocks (Robins et al. 2007, Snijders 2011). They have their origin in spatial statistics, and were first introduced as Markov graph models but have been extended in various ways (Cranmer et al. 2017). At the tie-level, the interpretation of ERGM coefficients is similar to logistic regression models, indicating the ceteris paribus change in the likelihood of a tie given a change in a node or dyadic attribute. To estimate the models, ERGMs build on the Markov Chain Monte Carlo maximum likelihood estimation (MCMC MLE). I used the ERGM package (Handcock et al. 2019) in R (R Core Team 2020) to estimate the models for each case and hypothesis. All exogenous variables of the ERGM models were operationalized as either node-level or dyad-level covariates to explain the occurrence of collaboration ties (dependent variable).

To compare the ERGM results related to the hypotheses across cases and to recognize trends related to the four conditions of governance complexity, I used a qualitative meta-regression analysis. The qualitative meta-regression analysis helps compensate for the small sample size of the individual cases by pooling together the results across all cases. The qualitative meta-regression analysis is based on separate regressions for each case and each of the three hypotheses. The individual ERGM results used to calculate the regression lines are associated with different

Fig. 2. This illustration highlights the characteristic features of the actor-issue networks used for the analysis of this paper. The illustration is split into two dimensions: (1) The actor network with actors as nodes (yellow) and directed collaboration ties. (2) The issue network consists of environmental issues (green) and directed ties based on the impact of environmental issues. The environmental issues are split into general environmental issues (e.g., water quality) and outcome environmental issues (e.g., biodiversity). Both types of environmental issues are based on environmental interdependencies, but outcome environmental issues are aggregated stronger than general environmental issues and can not be directly influenced across network levels by actors. Ties between network levels exist when actors directly impact general environmental issues based on their environmental management activities. The color of the environmental ties illustrates if environmental issues or actors have an increasing (green)/decreasing (red) impact on the state of other environmental issues.



variances. As an indicator of the variances of the ERGM results, I used the associated p-values with smaller p-values indicating smaller variances of the results. The p-values are used as the weights (weight = |1 - p-value|) for the weighted least squares regressions. Consequently, results associated with a lower p-value have a stronger influence on the qualitative meta-regression analysis.

Conceptualization of the actor-issue network

To analyze the case data from the qualitative interviews and quantitative surveys using ERGMs, I conceptualized the data as actor-issue networks (for further details, see Appendix 1, Detailed conceptualization of the actor-issue networks). More specifically, the actor network level was conceptualized as the dependent network in the ERGMs. The issue network as well ties across network levels were included as dyad-level covariates, one for each hypothesis. Because the same actor-issue paths can be relevant for the operationalization of the dyad-level covariates for all three separate hypotheses, I calculated separate ERGMs for each of the three hypotheses (for further details, see Appendix 4, Aggregated covariance table for hypotheses). This was done in an effort to avoid interdependencies between the hypotheses and to distinguish between the effects of the hypotheses on collaboration ties in the actor-issue networks. The reason for possible interdependencies between the hypotheses was that the dyad-level covariates were all partially based on the same actor-issue paths but differed in how they were operationalized. The variables of path length and multiplexity, for example, both depended on the same shortest actor-issue path connecting an actor pair. The difference is that while the operationalization of the variable of path length only relies on the shortest actor-issue path connecting an actor pair, the operationalization of the variable path multiplexity also takes into account longer parallel paths connecting an actor pair.

The actor-issue network consisted of two interdependent network levels that characterize the interdependencies between actors, between issues, and between actors and issues (see Fig. 2). The nodes of the actor network were actors, and the directed ties represented a collaboration between those actors. The nodes in the issue network were environmental issues. Environmental issues were aggregated features of ecosystems (e.g., water quality or population of beavers) or issues that had an impact on them (e.g., amount of trash). Directed, increasing/decreasing ties between environmental issues existed if one could increase/decrease the state of another environmental issue. The "amount of trash," for example, decreases the "water quality" as the state of the environmental issues of "water quality" is worsened because of the higher "amount of trash." The issue network can also be described as a network of cause and effect relationships between multiple interdependent environmental issues. Finally, ties between the two network levels were also possible. Similar to ties between environmental issues, such ties that connect the two network levels were also directed and had either an increasing or decreasing impact. A tie between the two network levels existed if actors directly impacted the state of an environmental issue by executing their activities or if environmental issues influenced the execution of the activities of actors. A "park ranger" who was responsible for the cleaning of the area, for example, had a decreasing impact on the "amount of trash"; therefore, a decreasing tie from the "park ranger" to the issue "amount of trash" existed. Environmental issues were additionally grouped into two categories of nodes: (1) general environmental issues and (2) outcome environmental issues. The difference between the two categories of nodes is that outcome environmental issues represent more aggregated goals, and are not directly influenced by actors but only by incoming ties from general environmental issues. Outcome environmental issues allow assessing the similarity of actors' impact on the actor-issue network relevant for hypothesis three on a system level.

Operationalization of network variables

The first hypothesis was based on information on the length of the actor-issue paths (see Fig. 1). A triangle network motif of two actors and one environmental issue indicated a shorter actor-issue path than, for example, a square or hexagon motif with two actors and multiple environmental issues. The second hypothesis relied on information on the multiplexity of the actor-issue paths. The focus here was on the amount of parallel actor-issue paths between actors. The shortest of those actor-issue paths connecting two actors had the strongest weight; the longest actor-issue paths had the smallest weight for calculating the multiplexity index.

The operationalization of the third hypothesis was based on the increasing or decreasing impact of actors on the two outcome environmental issues: local biodiversity and recreational value. Both were selected because they were mentioned as most relevant in the expert interviews across all cases. Actors' influence on outcome environmental issues was based on actors' actor-issue paths. In this particular case, actor-issue paths were not used to directly assess the connection between a pair of actors (as in the operationalization of H1 and H2) but to assess the connections between an actor and outcome environmental issues. For example, the presence of a "ranger" responsible for the "maintenance of a wetland area" decreased the "amount of trash." Further, the "amount of thrash" decreased "habitat quality" and consequently also the "biodiversity." Therefore the presence of a "ranger" had overall a positive impact on the "biodiversity" based on the actor-issue path. Each actor had multiple such paths connecting them with outcome environmental issues. The aggregated impact of actors on outcome environmental issues based on their actor-issue paths was used to construct a similarity coefficient for each pair of actors using the Euclidean similarity metric (Liberti et al. 2014). Actors with a high similarity index had a similar, either positive or negative, effect on the biodiversity and recreational value of the wetlands, and were more likely to collaborate (for further details, including examples for the operationalization of all hypotheses, see Appendix 1, Detailed examples for the operationalization of the independent variables).

I also included several established explanatory factors for actor networks as control variables for the tie formation process (Bodin and Crona 2009, Prell et al. 2009). First, I controlled for the power of actors because actors perceived to be powerful were attractive collaboration partners (Fischer and Sciarini 2015). Second, I controlled for homophily among actors based on their type of organization (state actors, cantonal actors, municipal actors, NGOs and associations, and others) and their activity area (on the spatial level of cantons). Actors with the same organization type and activity area were more likely to collaborate because they shared organizational logic and were active within the same functional areas (Ingold 2011). Third, actors who did not respond to the survey were also included in the analysis. Therefore, controlling for the response of individual actors was needed as the information available to construct the actor-issue network was less complete for actors who did not respond to the survey. Non-response also had an impact on their ego network, which was sparser compared to other actors. Fourth, I adjusted for endogenous network processes (Handcock et al. 2019). Therefore, I included an edges term in the model, which was conceptually similar to an intercept in conventional regression models, establishing a baseline probability for a tie to occur in the network. Additionally, I controlled for triadic closure (the tendency of an actor pair with a common tie to also have a common partner in the network) by including ergm terms for edgewise and/or dyadwise shared partners (Hunter 2007).

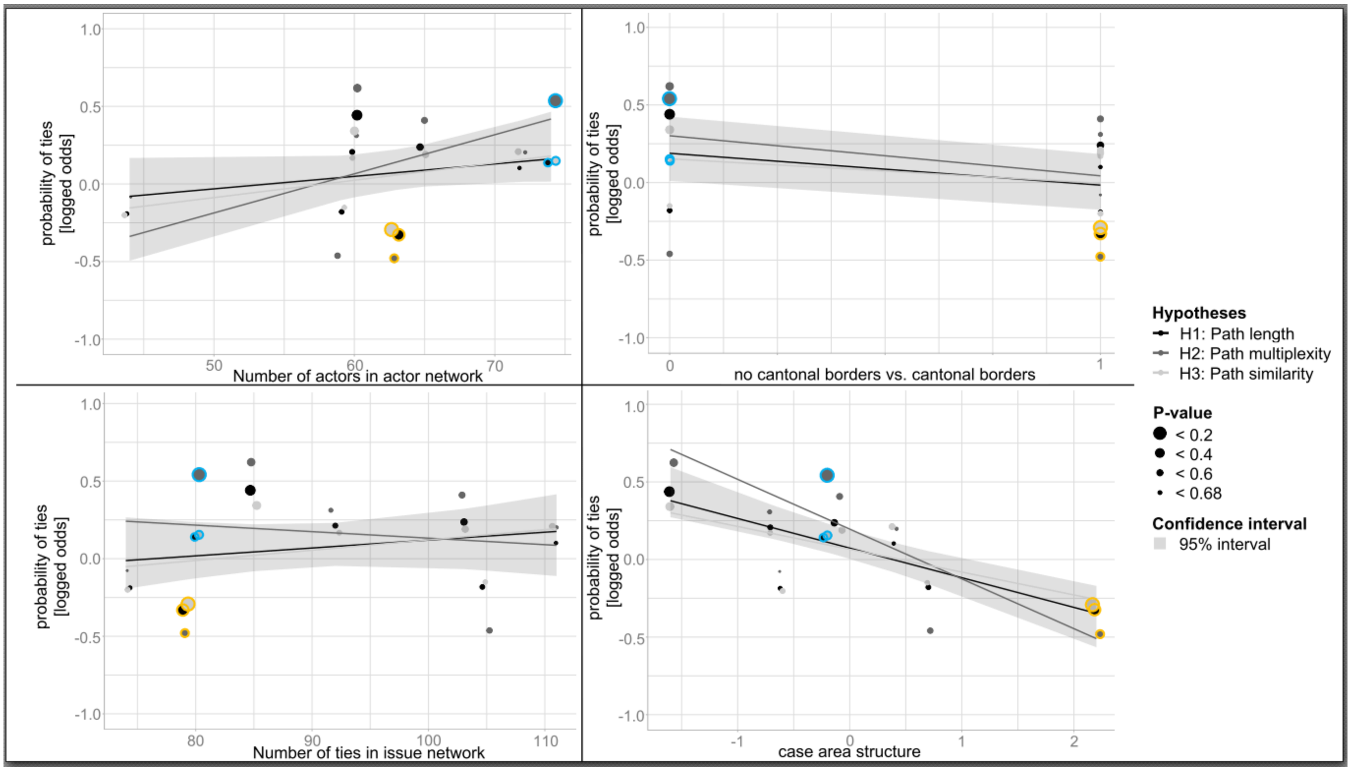
RESULTS

I calculated separate ERGMs for each case and each hypothesis. Based on the goodness of fit (GOF) statistics analysis, ERGMs of all cases provided a relatively good fit to the data given the limited sample size of the individual case studies (for result tables and GOF statistics as well as an additional discussion of limited sample size, see Appendix 4, ERGM results and GOF statistics). Two cases for which I had data are not included in the analysis because of poor GOF statistics (for result tables and GOF statistics, see Appendix 4, Additional ERGM results and GOF statistics not included in the analysis).

Overall, the results (see Table 2) indicated a certain effect for all three hypotheses. However, although only a positive effect of the variables of path length, multiplexity, and similarity on collaboration ties was hypothesized, the effect of the variables on collaboration ties ranged from positive to negative. Further, many of the results of the ERGMs were associated with relatively high levels of uncertainties because the sample sizes of the individual cases were relatively small (for further information on the influence of sample sizes on statistical tests, see Wasserstein et al. 2019, Foulley 2020). To overcome this uncertainty on the case level and to characterize the cases where the hypotheses are supported, I relied on a qualitative meta-regression analysis (see Figure 3). The qualitative meta-regression analysis pooled together the results across cases, which helped to compensate for the small sample size of the individual cases.

Trends for the influence of the three hypotheses of path length, multiplexity, and similarity on actor collaboration appear in the qualitative meta-regression analysis presented in Figure 3. The four scatter plots of the qualitative meta-regression analysis plot the logged odds of tie probability against the four conditions of governance complexity (number of actors, number of ties in issue network, case area structure, and existence of cantonal borders). An increase in the size of the dots symbolizes higher confidence in the results (lower p-value), and the regression lines represent the trends weighted based on the p-values for the three hypotheses

Fig. 3. Qualitative meta-regression analysis with the logged odds of the Exponential Random Graph Models (ERGM) for the three hypotheses (y-axis) plotted against the four indicators of governance complexity (x-axis): number of actors, ties in the issue network, the existence of cantonal borders, and structure of case area. The size of the dots indicates the p-value of the corresponding logged odds of the hypotheses, with the largest points having the lowest p-values. The slopes represent the linear regression lines weighted based on the p-values for all the logged odds for each separate hypothesis. The grey area represents the 95% confidence interval for the combined regression lines of the three hypotheses. Finally, the minor blue and yellow points refer to the cases of Neuchatel (yellow) and Bolle (blue) that are discussed in-depth in the Discussion section in order to highlight the importance of contextual differences between the cases.



across cases. Although the trends differ between the four conditions of governance complexity, they are mostly similar for all of the three hypotheses of actor-issue path length, multiplexity, and similarity.

The most robust trend for the influence of the independent variables—and in particular the variable of the multiplexity of actor-issue paths—on the probability of collaboration ties appeared for the exogenous condition of governance complexity related to the case area structure. For the case area structure, the influence of the three qualities of actor-issue paths was on average positive for homogenous cases and negative for more heterogeneous and complex cases. A similar but less accentuated trend appeared for the second exogenous complexity condition based on the existence of cantonal borders. Further, the regression lines slopes were positive for the endogenous condition of governance complexity based on the number of actors. Therefore, unlike for the exogenous conditions, the probability of path length, multiplexity, and similarity to cause a collaboration tie was on average higher in situations of high complexity. Finally, the number of ties in the issue network did not influence the relationship between any of the three independent variables and the probability of collaboration ties.

DISCUSSION

The results of the ERGMs presented in the qualitative meta-regression analysis show the importance of exogenous and endogenous governance complexity to identify general trends for the effect of the three independent variables on the probability of collaboration ties. The exogenous governance complexity, based on the case area structure and the existence of cantonal borders, has a negative effect on the independent variables' influence on the probability of collaboration ties. Therefore the hypotheses are, on average, only supported when the exogenous governance complexity is low. This might be explained because in cases with a low exogenous governance complexity, the cognitive load of actors to perceive actor-issue path qualities is also low (Jones 2003, Renkl et al. 2009). Therefore a low exogenous governance complexity increases the chance that actors account for actor-issue path qualities when deciding with whom to collaborate. However, other mechanisms also need to be in place as in cases of high exogenous governance complexity, the effect on the probability of path length even turns negative. The negative effect on collaboration ties is particularly distinct in cases with complex case area structures. One mechanism that might explain this negative effect is that in such cases, environmental issues can be tightly connected to actors based on the actor-issue path but at

Table 2. Exponential Random Graph Model (ERGM) results for the three hypotheses for each of the eight cases. The estimate values are the logged odds of the hypotheses on the probability of a collaboration tie. The estimates and p-value presented in the table are again illustrated in Figure 3. Full ERGM results, including all control variables, can be found in Appendix 4.

Case	Model	Estimate	Std error	p-value
Alte Aare	H1-path length	-0.18	0.24	0.45
Alte Aare	H2-path multiplexity	-0.46	0.50	0.36
Alte Aare	H3-path similarity	-0.15	0.21	0.48
Bolle	H1-path length	0.14	0.15	0.35
Bolle	H2-path multiplexity	0.54	0.27	0.05
Bolle	H3-path similarity	0.15	0.12	0.20
Sense	H1-path length	0.24	0.22	0.26
Sense	H2-path multiplexity	0.41	0.40	0.31
Sense	H3-path similarity	0.19	0.17	0.28
Murtensee	H1-path length	0.21	0.25	0.42
Murtensee	H2-path multiplexity	0.31	0.51	0.54
Murtensee	H3-path similarity	0.17	0.22	0.44
Reussebene	H1-path length	0.10	0.21	0.63
Reussebene	H2-path multiplexity	0.20	0.46	0.66
Reussebene	H3-path similarity	0.21	0.21	0.32
Untere Saane	H1-path length	0.44	0.24	0.07
Untere Saane	H2-path multiplexity	0.62	0.47	0.18
Untere Saane	H3-path similarity	0.34	0.24	0.15
Rhone	H1-path length	-0.19	0.32	0.54
Rhone	H2-path multiplexity	-0.08	0.49	0.87
Rhone	H3-path similarity	-0.20	0.25	0.42
Neuchatel	H1-path length	-0.33	0.20	0.09
Neuchatel	H2-path multiplexity	-0.48	0.39	0.21
Neuchatel	H3-path similarity	-0.29	0.14	0.05

the same time, those environmental issues are geographically distant from those actors. Actors might, therefore, not collaborate based on the quality of their actor-issue paths but based on their geographical proximity.

For the endogenous network complexity based on the number of actors, a positive trend can be recognized. This indicates that the more actors are present in the governance of wetlands, the more likely actor-issue paths positively influence the tie formation process. The positive slope of the regression line might be explained as actors using the quality of actor-issue paths as a coping strategy to reduce the cognitive load when selecting from a large set of actors, a few of which might be favorable to collaborate with (Dörner 1983, Renkl et al. 2009). The quality of actor-issue paths reduces the complexity as it provides additional criteria for actors to decide on a promising collaboration partner. The condition of endogenous governance complexity based on the number of ties in the issue network does not affect any of the three hypothesized relations. Very likely, the number of issue ties does not affect the shortest actor-issues paths that are the most important ones for the operationalization. The reason why there is hardly any effect of number on issues ties on the shortest path lengths is that already with fewer ties in the issue network the path lengths of connecting actor-issue paths are relatively short. A higher number of issue ties increases the number of longer parallel actor-issue paths. These longer actor-issue paths are, however, weighted less for the operationalization of the three hypotheses. Consequently, hardly any effect can be identified based on the complexity condition of the number of issue ties.

Case insights

To go beyond analyzing general trends across cases, I analyzed two of the cases in depth: one where the hypotheses were supported and another case where the results did not support the hypotheses. The two selected cases did not reflect the proportions of cases that support or reject the hypotheses but rather illustrated how different local governance situations influence the results.

The first case was a wetland system along the shore of the lake Neuchatel (see dots marked yellow in Fig. 3). Results for this case did not provide support for the hypotheses. The area of the case of Neuchatel is rather large and split across the administration areas of three cantons. The large size and the administrative heterogeneity of the area likely made it more difficult for actors to perceive the qualities of actor-issue paths. In such a situation, other factors explaining actor collaboration than the quality of actor-issue paths might be more important. For the case of Neuchatel, such mechanisms might relate to two distinct case characteristics. First, the case area's high complexity might favor collaboration based on geographical proximity instead of common environmental issues. Second, most actors have been active in the case area for quite some time, as the wetland has already been protected for multiple decades. Therefore, it might be easier for actors to rely on their personal contacts as they already know most potential collaboration partners and do not need to account for actor-issue path qualities when deciding whom to collaborate with. However, in the case of Neuchatel, instead of having no impact of the actor-issue path qualities on collaboration ties, we even see a negative impact on collaboration ties. This unexpected result might be due to two factors. First, actors might have problems in perceiving actor-issue path qualities because of the high exogenous governance complexity of this case. By contrast, in other cases with lower exogenous governance complexity, it is likely easier for actors to perceive the quality of actors-issue paths. Second, in cases with high exogenous governance complexity like the case of Neuchatel, alternative, more dominant mechanisms that correlate with actor-issue path qualities might influence the probability of actor collaboration.

The second case, which offers relative support for the three hypotheses, is the case of Bolle (see dots marked blue in Fig. 3), a river delta that includes the river mouths of the river Ticino and Verzasca into the Lago Maggiore. On one side, the wetlands in the Bolle are among the most popular tourism destinations in Switzerland and attract many visitors, but they are also surrounded by large industrial areas. As a consequence, several actors with different goals influence the governance of the wetland. The high number of actors makes it challenging for actors to recognize relevant collaboration partners. In such situations, the quality of actor-issue paths can help to identify relevant collaboration partners. Besides, the exogenous governance complexity of the Bolle is rather low as the case is quite homogenous and located in one single canton. This makes it easier for the actors to perceive qualities of relevant actor-issue paths. Together, the high number of actors and low exogenous governance complexity increase the chance that actors depend on the length, multiplexity, and similarity of actor-issue paths when deciding with whom to collaborate.

CONCLUSION

Analyzing the governance of eight Swiss wetlands based on a qualitative meta-regression analysis of the ERGM results, I can make three key statements on the influence of the quality of actor-issue paths on the probability of collaboration ties. (1) Overall, the three hypotheses have a meaningful effect, positive or negative, in most cases. If a positive effect can be identified and therefore, the hypotheses are supported depends however strongly on the characteristics of the individual cases. (2) In cases where the endogenous network complexity is high because of many involved actors, the qualities of the actor-issue paths have a positive influence on the formation of collaboration ties. Therefore, the qualities of the actor-issue paths can potentially help actors identify fitting collaboration partners. (3) When the exogenous network complexity is low, particularly because of a simple case area structure but also because of the absence of cantonal borders, actor-issue path qualities play an essential role in identifying collaboration partners. The second and third statements illustrate the importance of differentiating between network endogenous and exogenous governance complexity. Depending on the combination of endogenous and exogenous forms of complexity, the hypotheses— chance to be supported or rejected varies. The strongest support exists when actors can easily perceive actor-issue paths, and at the same time, strongly benefit from actor-issue paths in their decision process with whom to collaborate. Further, the three key statements illustrate that it is important to account for the context sensitivity of results of SEN studies based on a diverse set of multiple cases. A diverse set of cases is important as results are often not generally applicable but rather depend on multiple contextual factors. A direct consequence of this is that hypotheses are likely not to be supported by all cases. However, mixed support of the hypotheses is a sign that the cases are selected based on meaningful contextual differences across cases.

Overall, the results show that the quality of actor-issue paths have generally an influence on collaboration patterns in the actor network. However, there are no large differences between most of the three qualities of the actor-issue paths; the differences that exist largely depend on the governance complexity. This is in line with other research findings (e.g., Widmer et al. 2019), which also identified complexity as a factor that influences the tie formation process in actor networks. The reason for such influence of complexity is that in complex governance situations, actors can often not take all actor-issue paths into account (Crona and Bodin 2006, Bergsten et al. 2019). Here I additionally show the importance of distinguishing between different forms of complexity, network endogenous and exogenous complexity, when analyzing the influence of complexity on the formation process of collaboration ties. Similarly, Bergsten et al. (2014) have shown that not only the number of paths between issues (endogenous complexity) but also the existence of cross-sectoral issues (exogenous complexity) influence the capacity of actors to achieve fit. One reason for the differences between exogenous and endogenous complexity is that exogenous complexity increases the cognitive load of actors to perceive actor-issue path qualities. In contrast, actor-issue path qualities can help actors identify potential collaboration partners and, therefore, reduce the cognitive load in situations of high endogenous complexity.

Because the support for most of the hypotheses heavily depends on contextual factors influencing the governance complexity, the approach of this paper highlights the importance that SEN case studies are combined in comparative settings. Only then is it possible to meaningfully account for varying contextual factors in the analysis (Bodin et al. 2019, Sayles et al. 2019, Siciliano et al. 2021). Using single-case studies only, it would not be possible to identify trends across cases for different qualities of actor-issue paths. However, the comparative analysis of SENs in general and applying a qualitative meta-regression analysis to the ERGM results in particular also poses new challenges. First of all, the same ERGM-terms need to be applied to all models. But even if the same ERGM-terms are used, significant differences can exist because of the uneven distribution of input values to the ERGM terms. When I control for the activity area of actors, for example, the diversity is consistently higher for cases that cut across cantonal borders than for such located in one single canton. Further, there is a lack of robust measures for network comparisons tailored to SEN approaches (Bodin et al. 2019, Sayles et al. 2019). With this paper's approach of comparing different qualities of actor-issue paths across cases based on the concept of governance complexity, I take the first step toward advancing the comparative analysis of multiple SEN using the hypotheses-generating character of governance complexity in a qualitative meta-regression analysis.

By comparing the cases, I show that collaboration patterns in cases with high network endogenous and low exogenous governance complexity are, on average, better aligned with the issue network. Although the impact of complexity on the achievement of fit has been discussed in some articles (Bergsten et al. 2014, Epstein et al. 2015, Widmer et al. 2019), the impact of endogenous complexity based on the number of involved actors brings in a new perspective. While the level of fit generally increases when the actor-issue paths are easier to perceive, as is also shown in other literature on fit (Guerrero et al. 2015, Treml et al. 2015, Sayles and Baggio 2017, Enqvist et al. 2020), this is not necessarily true for cases with only a few involved actors. However, this behavior might not necessarily have a negative impact on the governance outcomes because in a situation of low endogenous complexity actors might be perfectly capable of identifying relevant actors for collaboration. Regardless, different qualities of actor-issue paths correlate with the probability of collaboration ties and therefore impact the achievement of fit. This is why I recommend including them in further analyses of fit, particularly in settings of low exogenous governance complexity. Furthermore, it would also be interesting to analyze how contextual factors influence the role of fit for deciding with whom to collaborate. Additionally, it would be worth looking more in depth at specific qualities of actor-issue paths and develop limits where actors stop perceiving actor-issue path qualities. Finally, whether the governance outcome benefits from a higher fit achieved in governance settings of lower complexity would also be an issue for future research.

It is also important to note that the results of this study are limited by several factors. First, the analysis is based on cases studies that are limited to Switzerland. Whether the results are transferable to other kinds of ecosystems and regions remains an open question. However, the underlying concept of fit has been applied in different contexts. Therefore, it can be assumed that the quality of actor-issue paths is generally also important for other cases. Second, the number of actors in the networks is rather low, which is likely to increase the uncertainties associated with the ERGM results (Wasserstein et al. 2019, Foulley 2020). This can be compensated for to some degree by the qualitative meta-regression analysis that combines the eight cases of wetland governance. However, to further reduce the uncertainties associated with the ERGM results, larger networks with more actors would be needed. This again would have consequences for the issue networks that would become more complicated to conceptualize in larger case areas. Third, in this research, I do not account for the evolution of networks over time, and it should be acknowledged that only the observation of networks over longer time periods allows advancing the understanding of how the quality of actor-issue ties and collaboration patterns among actors dynamically co-evolve. Fourth, even though the study compares different cases of wetland governance, a statistical analysis of the differences among the cases is not possible without strongly increasing the number of cases. Still, the value of this study lies in it contributing evidence to the growing set of SEN studies and showing that different qualities of actor-issue paths can influence collaboration patterns among actors, and should therefore be included in further analyses of fit.

Responses to this article can be read online at:
https://www.ecologyandsociety.org/issues/responses.php/13536

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Data Availability:

The data that support the findings of this study are available on request from the corresponding author, MH. None of the data are publicly available because they contain information that could compromise the privacy of research participants. The code that supports the findings of this study is in Appendix 5.

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Appendix 1

Further information on data gathering and data conceptualization

Location of selected wetlands

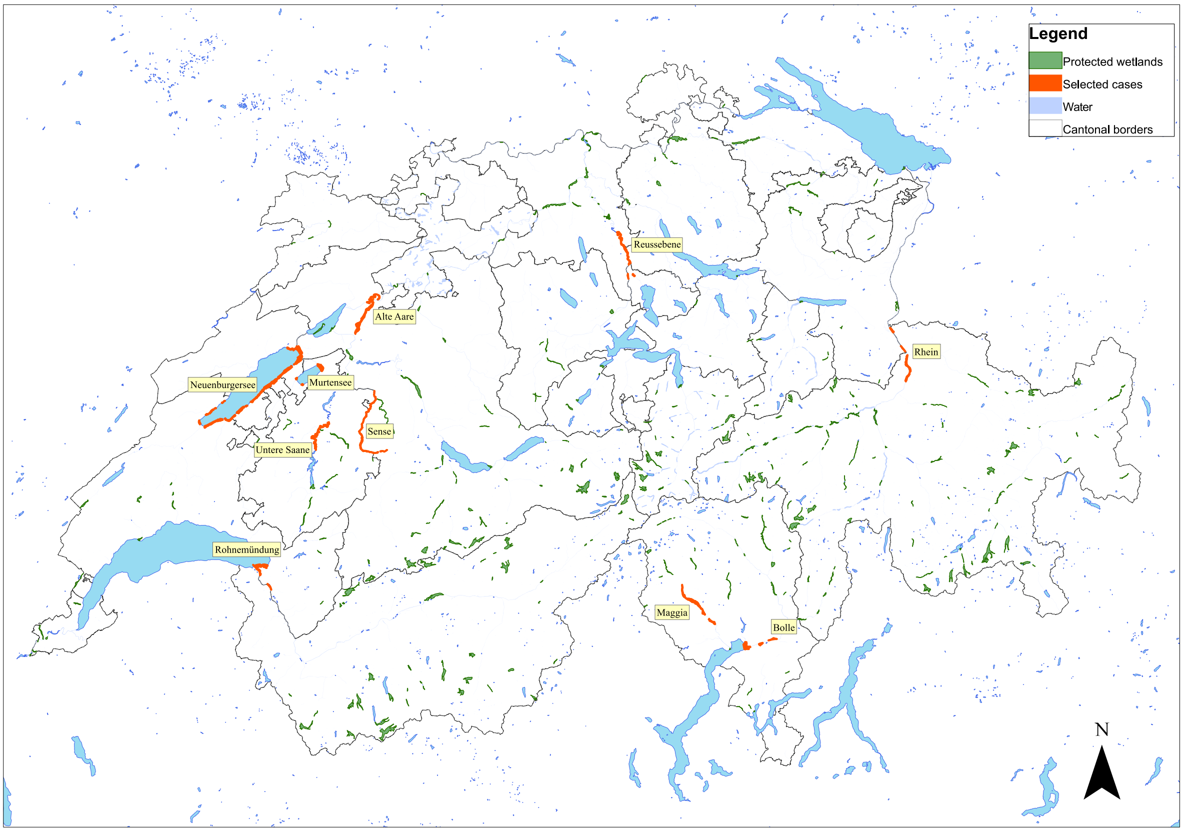


Figure 1: Map of Switzerland with the selected wetlands (red), including the two wetlands that are not part of the analysis of this paper.

Data gathering

Data gathering was conducted in three phases. The first phase aims to confirm the case areas and identify an initial set of relevant actors. Therefore, I conducted a desktop research that included documents, such as action plans, project reports, fact sheets, or monitoring reports. The initial set of actors is identified based on those documents using a combination of decisional, positional, and reputational approaches (Knoke, 1993). The second phase of the data gathering is based on semi-structured interviews with a limited number of key experts for each case. The data is used to develop a conceptual map (for further details on conceptual maps, see Appendix 2, Conceptual maps) for each case. To structure the interviews, I used the Open Standards (OS) framework that is normally applied to organize conservation projects (Schwartz et al. 2012). The case knowledge from the first two phases of data gathering is then in the third phase used to construct a survey (for further details on survey structure and questions, see Appendix 3, Survey text) that was sent out to all previously identified actors relevant to the governance of the wetlands. On average, 35 actors participated in each case in the survey, which accumulates to a total number of 276 actors and a response rate of 70 %. Additionally to the actors who participated in the survey also the other relevant actors of the case study areas are included in the further analysis. The missing information for actors that did not answer the survey questions is estimated using the R package mice (van Buuren and Groothuis-Oudshoorn 2011) to impute incomplete multivariate data by chained equations.

Detailed conceptualization of the actor-issue networks

The nodes at the actor network level are actors that are relevant for the governance of the wetlands. Actors are included if they are identified as active in the specific region and participated and/or are mentioned by other relevant actors. Actors that were determined to be relevant in the initial data gathering phase but did not participate in the survey nor were mentioned by any other actors are assumed to be irrelevant for the analysis and are therefore excluded. For an actor to have an outgoing tie to another actor, the actors need to specify that they collaborate in the survey. While collaboration is a reciprocal activity involving two actors, I choose to conceptualize collaboration based on directed ties. This is because often, actors do not agree on the perception of collaboration. Therefore, to capture these differences in perceived collaboration, I decided to conceptualize the collaboration ties to be directional.

To identify ties across network levels, I use environmental management activities (e.g., fishing, planning/realization of restoration projects, or farming) to connect actors to specific environmental issues. Environmental management activities as an intermediate step are needed because actors do not directly influence environmental issues but only do so through their environmental management activities. All actors needed to specify in the survey for which environmental management activities they are responsible for. Based on the conceptual maps from the expert interviews, I know what effect specific environmental management activities have on environmental issues. Finally, while the ties within the actor network level are value-neutral, the ties across the network level have either an increasing or decreasing impact on the state of environmental issues. For example, an actor responsible for the environmental management activity labeled "ranger" potentially reduces the amount of trash in the area. Therefore, the actor has a decreasing tie to the environmental issues of "amount of trash".

The nodes in the issue network are environmental issues, and ties between the environmental issues represent how issues can increase/decrease the state of another environmental issue. Habitat quality and trout population, for example, are connected because an increase in habitat quality leads to an increase in the trout population. The information about the ties and nodes comes from the interviews with the individual cases' experts. Similarly, as environmental issues can be increased/decreased by incoming ties from other environmental issues, environmental issues can also be increased/decreased by incoming ties from actors. It is important to mention that the state of the environmental issues can not be compared between different environmental issues, and the ties just describe a general increase/decrease but do not give any information about the actual state of the environmental issue.

Detailed examples for the operationalization of the independent variables

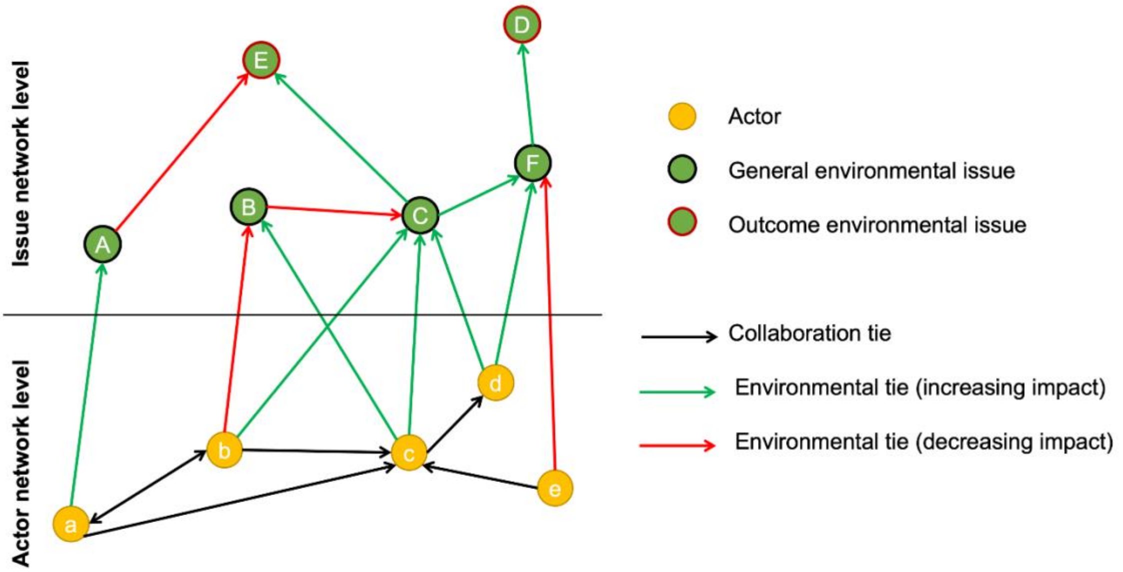


Figure 2: This illustration highlights the characteristic features of the actor-issue network used for the analysis. The illustration is split into two dimensions: 1) The actor network level with actors as nodes (yellow) and directed collaboration ties. 2) The issue network consists of environmental issues (green) and directed ties based on the impact of environmental issues. The environmental issues are split into general environmental issues (black border) and outcome environmental issues (red border). The color of the ties illustrates if environmental issues have an increasing or decreasing impact on the state of other nodes. Additionally, ties across the network levels exist when actors have a direct impact on environmental issues.

Following, I describe two examples for the calculation of the variables for the three hypotheses:

1. Hypothesis: The actor-issue path length of actor d and e [d-F-e] is two, and the actor-issue path length of actor c and e [c-C-F-e] is three. Since an actor-issue path length of one is not possible, all paths are subtracted by one. The corrected actor-issue path length of d and e is one and two for c and e. Therefore, based on the first hypothesis, I assume that actors d and e are more likely to collaborate since their connecting path is shorter.
2. Hypothesis: Two actor-issue paths exist that connect actor b and c [b-B-c / b-C-c]. Therefore those two actors have a multiplexity index of two. Also, actors, a and b, have two connecting paths [a-A-E-C-b / a-A-E-C-B-b]. But as the second path is longer than the first path and, therefore, does not represent the shortest connecting path between the actors a and b, the second path is weighted less. Therefore I assume that actors b and c are overall more likely to collaborate than actors a and b.
3. Hypothesis: The impact of actors on outcome environmental issues is calculated based on their increasing (+1) or decreasing (-1) impact on general environmental issues and dependent outcome environmental issues. First, the directionality of impact for each actor on outcome environmental issues is calculated separately based on the multiplicated value of increasing/decreasing ties. The impact of actor a and c on the outcome environmental issue E is for actor a: *1*-1 [a-A-E] = -1* and for actor c: *1*1 [c-C-E] = 1*. The impact of the actor b and d based on the outcome environmental

issues D is for actor b: *(-1*-1*1*1 [b-B-C-F-D] + 1*1*1 [b-C-F-D])/2 = 1* and for d: (*1*1 [d-F-D] + 1*1*1 [d-C-F-D])/2 = 1*. Based on the third hypothesis c and d are more likely to collaborate since they both have the same impact on the outcome environmental issue. In a second step, all those separate paths are then used to calculate a similarity index that combines all outcome environmental issues using the Euclidean similarity metric (Liberti et al. 2014).

$$p(q,p) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}$$

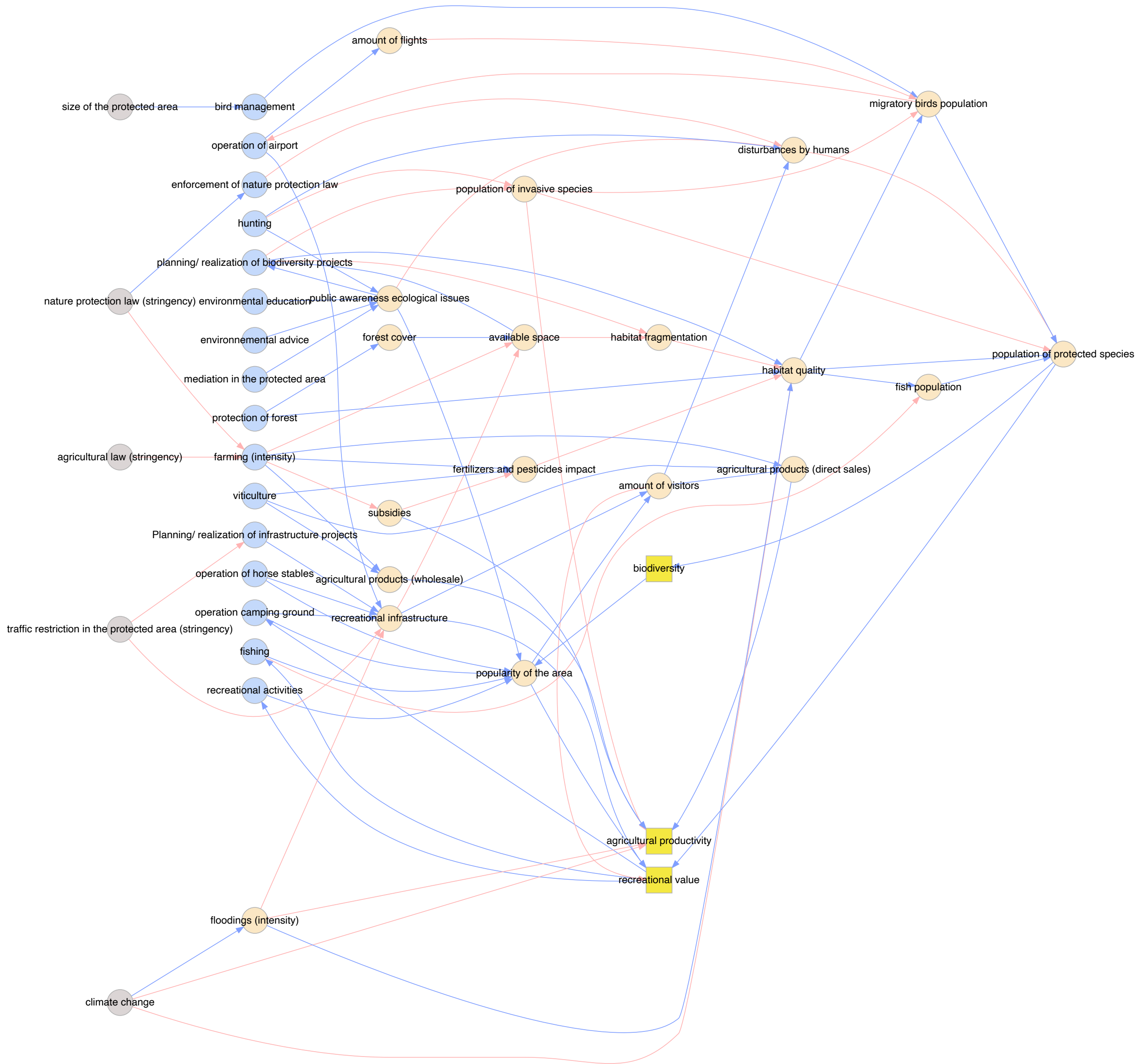
Appendix 2

Conceptual maps

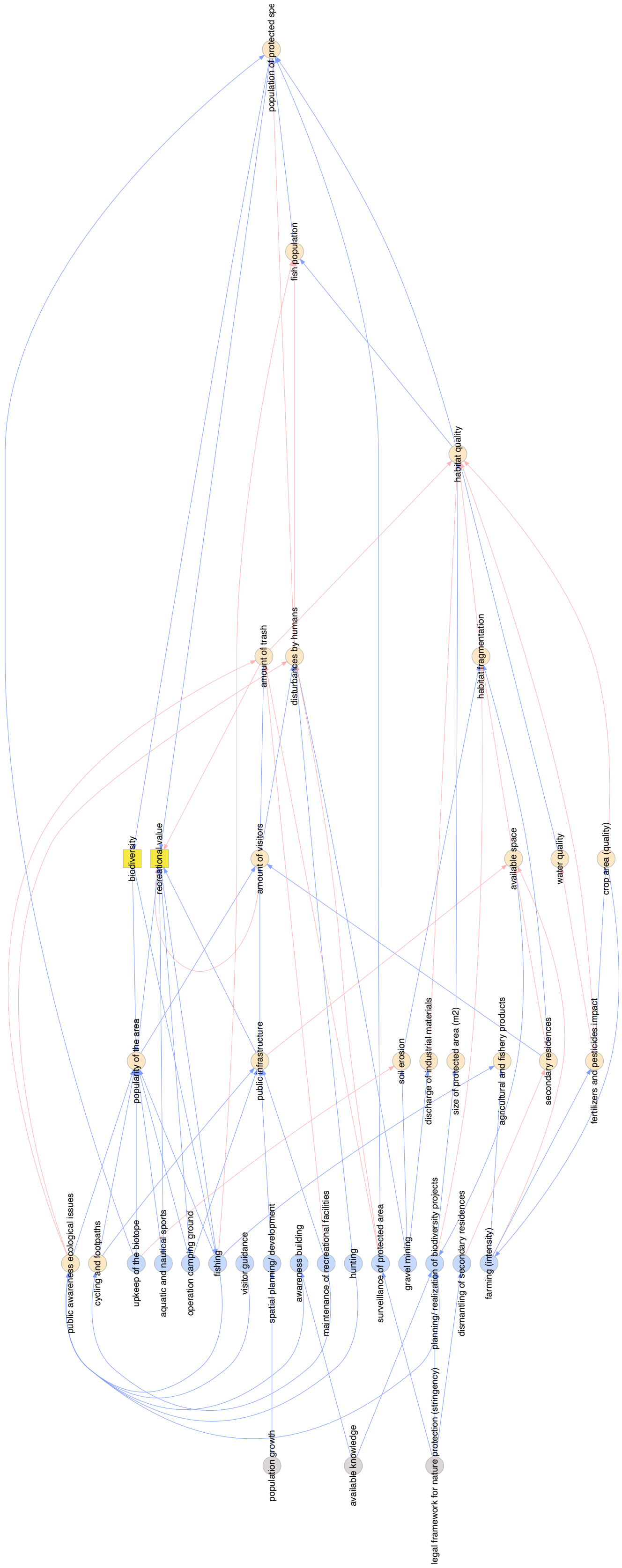
The colors of the nodes in the map represent 1) yellow: outcomes, 2) orange: factors, 3) blue: activities, and 4) grey: external factors. For this paper, factors and activities are combined to ecological issues, while external factors are not included in the analysis of this paper. The colors of the ties in the map stand for 1) blue: positive ties and 2) orange: negative ties.

Here only the conceptual maps of two exemplary cases are used – the same ones that are also in-depth analyzed in the discussion section of this paper.

Example of a conceptual map for the case of Bolle



Example of a conceptual map for the case of Neuchatel



Appendix 3

Survey text

Explanation
The survey was conducted in multiple cases using LimeSurvey. Using Limesurvey, the survey made use of multiple filtering steps that cannot be reproduced in an offline format of the survey. Therefore, instances that are variable within or across surveys are marked with square brackets containing basic information about the information content that was presented to the survey participants.

Floodplain management in the [case area]

Introduction Text
Research project
In floodplain areas, various interrelated problems come together in a limited area, ranging from biodiversity protection to visitor management and flood protection. In a research project funded by the Swiss National Science Foundation, Eawag, the water research institute of the ETH Domain, is investigating various floodplain areas in Switzerland. We are interested in how public authorities, civil society organizations, and also companies exchange and organize themselves around problems in floodplain areas. Our goal is to identify what constitutes successful floodplain management - and where there might be potential for improvement.

The [case area]
As part of this research project, we are also investigating floodplain management in the [case area]. Specifically, we are looking at the floodplain shown in dark red on the map below and other nearby wetlands and floodplains and their surrounding areas (shown in light red) [map of case area]. The organization for which you are active has been identified in our research as a relevant organization in at least one aspect of floodplain management in the [case area].

The Survey
Therefore, in order to get a as complete picture as possible of floodplain management in the [case area], we would like to ask you about your organization's activities in the [case area] through the following brief survey. In particular, we are interested in your collaboration with other organizations and your priorities regarding various possible goals in the [case area].

Completing the survey should take no more than 20 minutes on average. Your answers will be treated confidentially. Results of the surveys are published in anonymized form as standard and in non-anonymized form only after an explicit request for permission.
We would be very pleased about your participation. Please do not hesitate to contact us [contact information] if you have any questions or are interested in further information.

Kind regards and many thanks already in advance
The project team.

Your organization
We would like to ask you to complete this survey on behalf of the organization for which you work in the [case area]. In the following, the term organization can refer to public authorities (e.g., municipalities or cantonal offices), associations, NGOs, and private companies.

What is the name of the organization and organizational unit for which you are completing this survey?

By organizational unit we mean the smallest unit (e.g., department/section) within the organization for which you work.

Your name

[empty field]

Your activities in the [case area]
Which of the activities below has your organization been involved in over the past three years in the [case area]?

By activity, we mean both planning, decision-making, implementation, and evaluation of projects. [Please select the answers that apply:]

[List of activities]

Cooperation with other organizations
Which of the organizations listed below have you regularly collaborated with in the past three years as part of your activities in the [case area]?

Regular cooperation includes:

- in-depth exchange of information and expertise (more than once a year)
- joint planning, decision-making, implementation and evaluation of projects

[Please select the answers that apply:]

[List of actors.]

Which farms in the [case area] do you work with?

[empty field]

Are there other organizations you work with that are not on this list?

[empty field]

Below is a selection of other floodplain areas near the [case area]. Do you regularly work with organizations in these areas?

[Map of surroundings of case area]

[List of actors]

What are the main organizations you work with in the selected areas?

[empty field]

More about your cooperation with other organizations
Below you will find a list of organizations and activities that you have pre-selected. Please indicate those organizations with which you regularly collaborate in the respective activities.

Example [picture with example]: In this example, the organization regularly cooperates with organization A regarding visitor guidance. Regarding nature conservation, the filling organization regularly cooperates with organization B.

[List of relevant actors and activities]

Disagreements with other organizations

Subsequently, you will see your selected cooperation partners again. With which of them do you regularly have disagreements regarding procedures and goals in the activities you carry out?

Example [picture with example]: In this example, the organization regularly has discrepancies with organization B regarding visitor management. Regarding nature conservation, the filling organization regularly has discrepancies with organization B.

[List of relevant actors and activities]

Targets in the [case area]

Below are [Number of goals] possible goals for floodplain areas in the [case area]. How well do you think these goals are being achieved?

[List of destinations]

Which goals in the [case area] are particularly important for your organization?

All your answers must be different, and must be assigned.

Arrange the elements in the right list (highest rating at the top). The elements can be moved with the mouse. Double-click moves an element to the other list.

Are there other goals in the [case area] that are particularly important to your organization?

Influence of other organizations on the achievement of goals in the [case area].

You mentioned [goal] as the most important goal for floodplains in the [case area]. Which of the organizations below do you think are particularly important in achieving this goal?

Do you agree with the following statements?

My organization is sufficiently involved in decisions that affect the [case area].

[Disagree fully / Disagree by majority / Agree by majority / Agree full]

When decisions are made in the [case area], all stakeholders are involved on an equal level.

[Disagree fully / Disagree by majority / Agree by majority / Agree full]

Floodplain management in the [case area] is well positioned to deal with the challenges of the future.

[Disagree fully / Disagree by majority / Agree by majority / Agree full]

[List of additional questions regarding specific situations in the case area]

Forums

Has your organization participated in events at the following forums in the past three years?

[List of forums]

Has your organization participated in other events that address issues in the [case area]?

[empty field]

Questions and interest in the study results

May we contact you regarding any queries about the survey?

- Yes, by email:
- Yes, by phone:
- I'd rather not:

Do you want to be continuously informed about the results of this investigation?

- Yes
- Yes, only important results
- No
- No answer

Would you be interested in attending a workshop where the results of this research would be presented?

- Yes
- Under certain circumstances (see comment)
- No
- No answer

Appendix 4

Aggregated covariance table for the three hypotheses

Table 1: Covariance table for the three hypotheses separated based on the eight cases included in the analysis. Covariance between the dyad-level covariates of path length, multiplexity, and similarity exists as all of them are based on actor-issue paths connecting actor pairs. The values of the dyad-level covariates used to calculate the covariance table are all normalized on a scale from 0 to 1. Overall, the covariance table indicates a significant interdependence between the three dyad-level covariates of path length, multiplexity, and similarity. Consequently, the dyad-level covariates for the three hypotheses are modeled separately to single out the effect of each dyad-level covariate on collaboration ties.

	H1	**H2**	**H3**
Alte_Aare_H1	0.49	-0.4	-0.27
Alte_Aare_H2	-0.4	1.8	-0.35
Alte_Aare_H3	-0.27	-0.35	0.41
Reussebene_H1	0.19	-0.2	-0.09
Reussebene_H2	-0.2	0.89	-0.16
Reussebene_H3	-0.09	-0.16	0.18
Rhonemündung_H1	0.82	-0.23	-0.47
Rhonemündung_H2	-0.23	1.25	-0.42
Rhonemündung_H3	-0.47	-0.42	0.58
Sense_H1	0.55	-0.29	-0.32
Sense_H2	-0.29	1.45	-0.37
Sense_H3	-0.32	-0.37	0.44
Untere_Saane_H1	0.35	-0.29	-0.2
Untere_Saane_H2	-0.29	1.11	-0.21
Untere_Saane_H3	-0.2	-0.21	0.33
Murtensee_H1	0.43	-0.29	-0.23
Murtensee_H2	-0.29	1.68	-0.44
Murtensee_H3	-0.23	-0.44	0.41
Neuchatel _H1	0.37	-0.08	-0.23
Neuchatel _H2	-0.08	0.86	-0.24
Neuchatel _H3	-0.23	-0.24	0.26
Bolle_H1	0.2	-0.03	-0.13
Bolle_H2	-0.03	0.53	-0.2
Bolle_H3	-0.13	-0.2	0.19

ERGM results and GOF statistics

The result tables and GOF statistics of the ERGMs appear below. The two capital letters in the result tables of the ERGMs indicate the type of ERGM term:

- EC (edgecov): This term adds one statistic to the model, equal to the sum of the covariate values for each tie appearing in the network (Hunter et al. 2021).
- NM (nodematch): The number of ties whose incident nodes match the value of the nodal attribute (Hunter et al. 2021).
- NF (nodefactor): The number of times that nodes with a given level of a categorical nodal attribute appear within the tie set (Hunter et al. 2021).

A positive value for any of the terms indicates that this specific variable positively influences the probability of collaboration ties. For further information on ERGM terms and the interpretation of GOF statistics, see: www.statnet.org/Workshops/ergm_tutorial.html (Statnet Development Team).

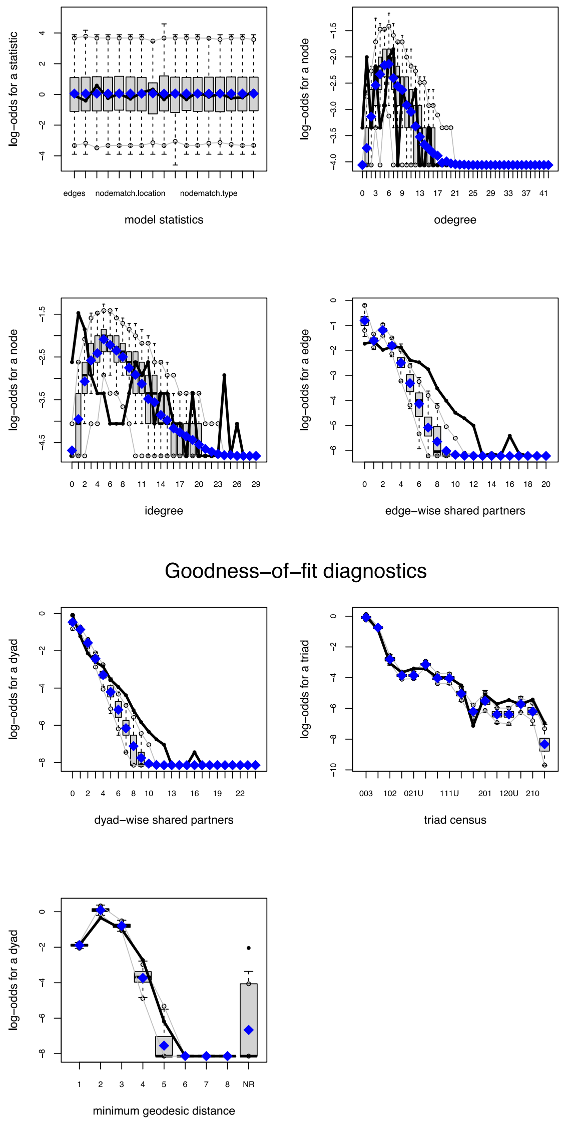
The terms relevant to the three hypotheses are EC.H1_length (length of actor-issue paths), EC. H2_multiplexity (multiplexity of actor-issue paths), and EC. H3_similarity (similarity of actor-issue paths) and are all based on the edgecov term. Additionally, the control variable of power is also built on the edgecov term. The control variable of power is based on a matrix with information if actor A perceives actor B to be powerful. The remaining control variables are based on nodematch and nodefactor terms. The control variable of location uses information on the activity area of actors. The activity area of actors is split up into the different cantons of Switzerland, including two additional categories (inter-cantonal and others) for actors that are active in more than one canton and actors that cannot be attributed to a specific physical location. The control variable actor type differentiates between five types of actors relevant to the management of the wetlands (state actors, cantonal actors, municipal actors, NGOs and associations, and other actors). Finally, the control variable of response accounts for how the actors were involved in the survey based on four categories (normal answer, normal no answer, add later answer, and add later no answer). The labels “normal” and “ad later” indicate if actors were included from the beginning on in the list of possible collaboration partners or if they were only added later based on the other participants’ feedback. Actors that were only added later are not listed in the default list of possible collaboration partners and therefore had to be added manually by the other survey participants. Further, the label “answer” indicates that an actor participated in the survey, while “no answer” indicates that an actor did not participate in the survey.

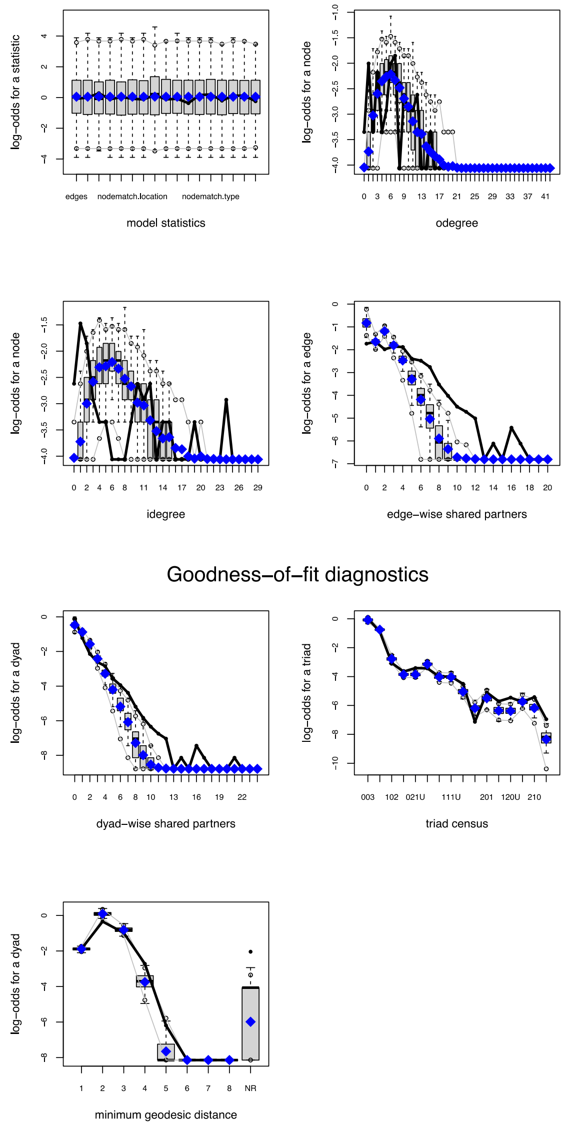
As the ERGMs are all based on small-n samples, p-values, standard errors as well as overall GOF statistics indicate relatively high uncertainties (Foulley, 2019, Wasserstein et al. 2019). However, given the presence of multiple comparable case studies in this article, the main conclusions rely on the qualitative meta-regression analysis that combines the results from the different case studies. The qualitative meta-regression analysis is weighted based on the p-values of the individual results and assesses whether differences across cases, based on the four conditions of governance complexity (number of actors in actor network, number of ties in issue network, case area structure, and cantonal borders), influence the impact of the variables of path length, multiplexity, and similarity on the probability of collaboration ties. In order to keep the individual ERGM results comparable across cases, no additional ERGM terms (e.g., weighted terms for edge-wise shared partner [gwesp]) are implemented, even though the model fit in general and the fit of the edge-wise and dyad-wise shared partner distributions, in particular, could be improved. Additional analyses including weighted terms for edge-wise and dyad-wise shared partners as well as additional case-specific terms on the dyad level (e.g., belief similarity) show that results remain robust.

Case Alte Aare, hypotheses 1 & 2

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-1.95	0.32	0	-6.07	0
mutual	0.78	0.18	0	4.35	0
esp1	-0.69	0.12	0	-5.76	0
EC.H1_length	-0.18	0.24	0	-0.76	0.45
EC.power	0.01	0.16	0	0.07	0.95
NM.location	0.12	0.12	0	0.94	0.35
NF.location.inter-cantonal	0.6	0.14	0	4.29	0
NF.location.other	0.88	0.45	0	1.94	0.05
NM.response	-0.06	0.11	0	-0.53	0.6
NF.response.add_later_no_answer	-0.43	0.25	0	-1.74	0.08
NF.response.normal_answer	0.71	0.15	0	4.72	0
NF.response.normal_no_answer	0.47	0.15	0	3.14	0
NM.type	-0.24	0.14	0	-1.75	0.08
NF.type.Federal_Office	-1.28	0.21	0	-6.22	0
NF.type.Municipality	-0.69	0.11	0	-6.13	0
NF.type.NGO_organization_association	-0.67	0.12	0	-5.66	0
NF.type.Other	-0.92	0.14	0	-6.73	0

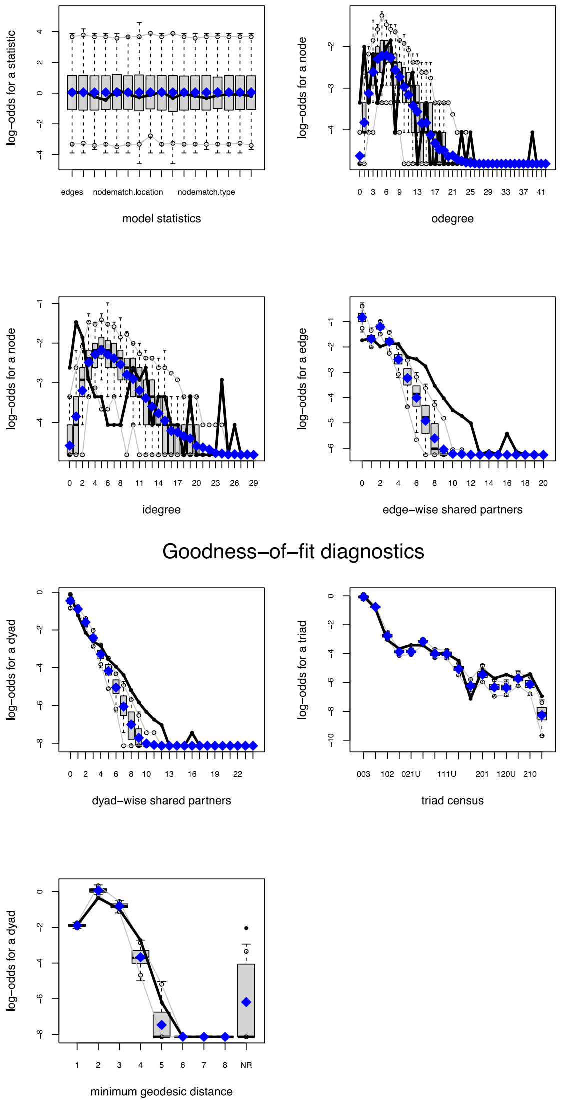
	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-1.91	0.32	0	-5.95	0
mutual	0.78	0.18	0	4.34	0
esp1	-0.7	0.12	0	-5.85	0
EC.H2_multiplexity	-0.46	0.5	0	-0.92	0.36
EC.power	0	0.16	0	0.01	0.99
NM.location	0.11	0.13	0	0.86	0.39
NF.location.inter-cantonal	0.59	0.14	0	4.25	0
NF.location.other	0.87	0.45	0	1.93	0.05
NM.response	-0.05	0.11	0	-0.47	0.64
NF.response.add_later_no_answer	-0.44	0.26	0	-1.73	0.08
NF.response.normal_answer	0.7	0.15	0	4.63	0
NF.response.normal_no_answer	0.46	0.15	0	3.1	0
NM.type	-0.23	0.14	0	-1.68	0.09
NF.type.Federal_Office	-1.28	0.21	0	-6.22	0
NF.type.Municipality	-0.7	0.11	0	-6.36	0
NF.type.NGO_organization_association	-0.68	0.12	0	-5.83	0
NF.type.Other	-0.92	0.14	0	-6.66	0



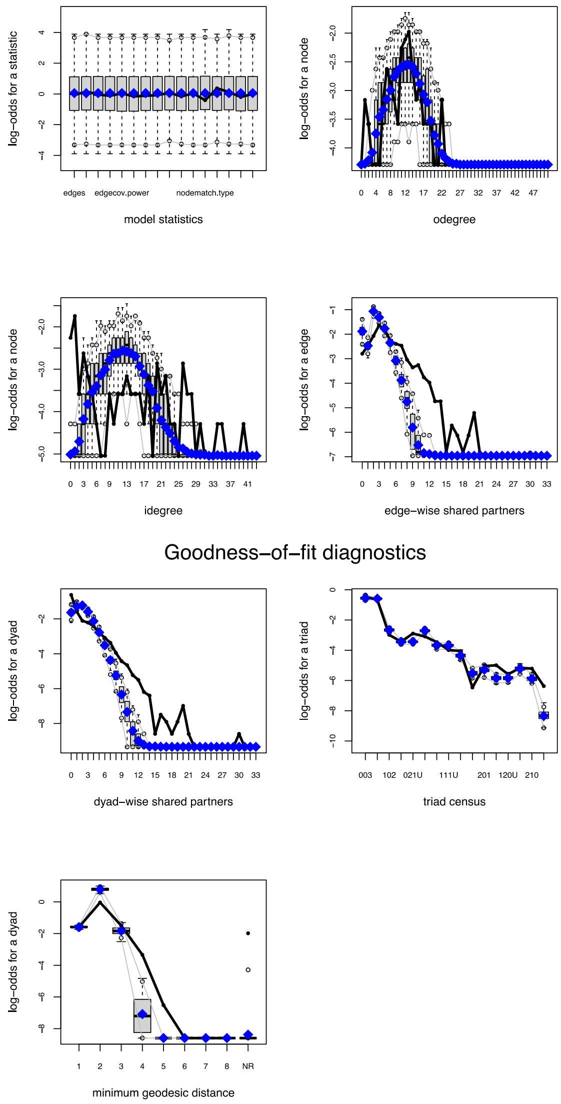


Case Alte Aare, hypothesis 3 & case Bolle, hypothesis 1

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-1.94	0.32	0	-6.14	0
mutual	0.78	0.18	0	4.33	0
esp1	-0.69	0.12	0	-5.63	0
EC.H3_similarity	-0.15	0.21	0	-0.71	0.48
EC.power	0.01	0.16	0	0.05	0.96
NM.location	0.11	0.13	0	0.87	0.38
NF.location.inter-cantonal	0.6	0.14	0	4.43	0
NF.location.other	0.88	0.44	0	1.98	0.05
NM.response	-0.06	0.11	0	-0.51	0.61
NF.response.add_later_no_answer	-0.43	0.25	0	-1.72	0.09
NF.response.normal_answer	0.71	0.15	0	4.85	0
NF.response.normal_no_answer	0.47	0.15	0	3.24	0
NM.type	-0.23	0.13	0	-1.73	0.08
NF.type.Federal_Office	-1.29	0.2	0	-6.4	0
NF.type.Municipality	-0.69	0.11	0	-6.4	0
NF.type.NGO_organization_association	-0.68	0.12	0	-5.67	0
NF.type.Other	-0.92	0.14	0	-6.69	0

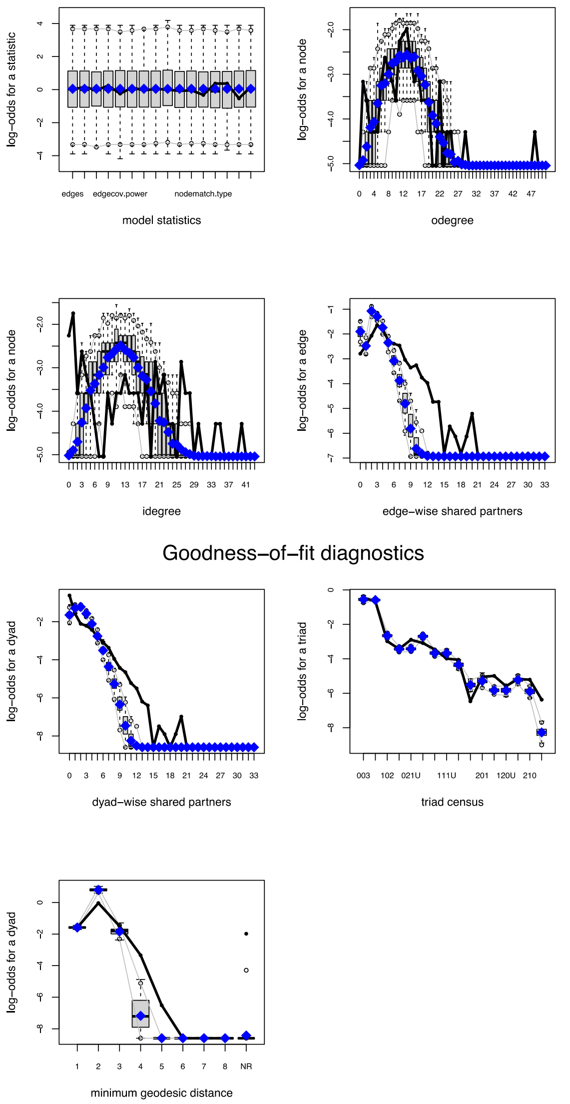


	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.14	0.38	0	-5.62	0
mutual	0.57	0.12	0	4.68	0
esp1	-1.1	0.12	0	-9.21	0
EC.H1_length	0.14	0.15	0	0.93	0.35
EC.power	0.52	0.11	0	4.83	0
NM.location	-0.24	0.15	0	-1.62	0.1
NF.location.Tessin	0.23	0.14	0	1.64	0.1
NM.response	-0.06	0.08	0	-0.75	0.45
NF.response.add_later_no_answer	-0.2	0.22	0	-0.91	0.36
NF.response.normal_answer	0.35	0.18	0	1.91	0.06
NF.response.normal_no_answer	0.15	0.18	0	0.8	0.42
NM.type	0.21	0.09	0	2.35	0.02
NF.type.Federal_Office	-0.12	0.12	0	-1	0.32
NF.type.Municipality	-0.18	0.09	0	-1.99	0.05
NF.type.NGO_organization_association	-0.28	0.07	0	-4.18	0
NF.type.Other	-0.43	0.07	0	-5.91	0

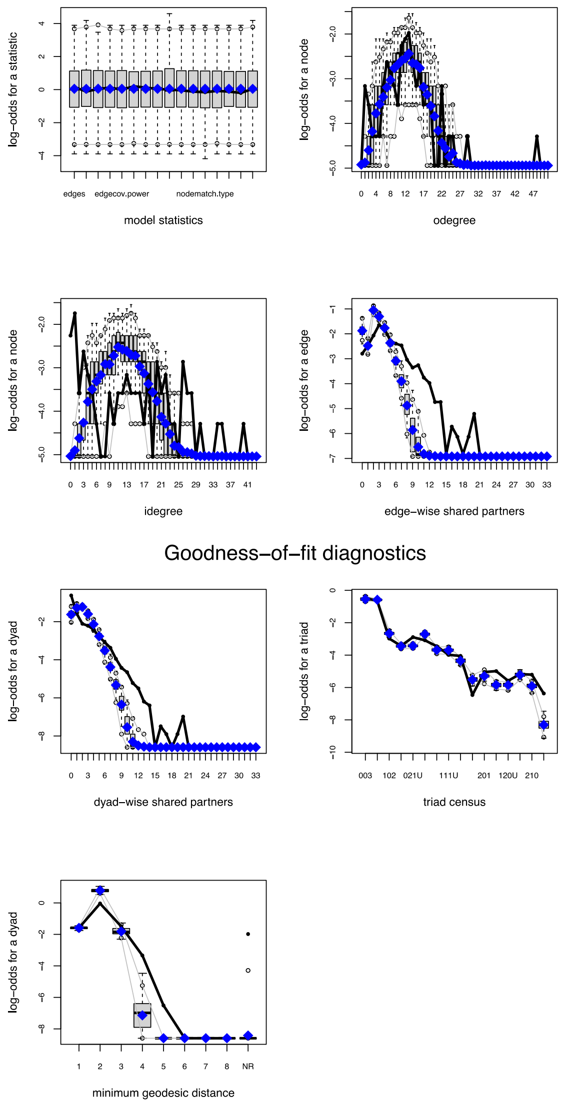


Case Bolle, hypotheses 2 & 3

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.15	0.39	0	-5.44	0
mutual	0.57	0.12	0	4.56	0
esp1	-1.1	0.12	0	-9.27	0
EC.H2_multiplexity	0.54	0.27	0	1.99	0.05
EC.power	0.52	0.11	0	4.82	0
NM.location	-0.23	0.15	0	-1.51	0.13
NF.location.Tessin	0.22	0.14	0	1.57	0.12
NM.response	-0.05	0.07	0	-0.71	0.48
NF.response.add_later_no_answer	-0.21	0.22	0	-0.93	0.35
NF.response.normal_answer	0.35	0.19	0	1.83	0.07
NF.response.normal_no_answer	0.14	0.19	0	0.74	0.46
NM.type	0.21	0.09	0	2.32	0.02
NF.type.Federal_Office	-0.11	0.12	0	-0.88	0.38
NF.type.Municipality	-0.17	0.09	0	-1.85	0.06
NF.type.NGO_organization_association	-0.28	0.07	0	-3.99	0
NF.type.Other	-0.43	0.07	0	-5.73	0



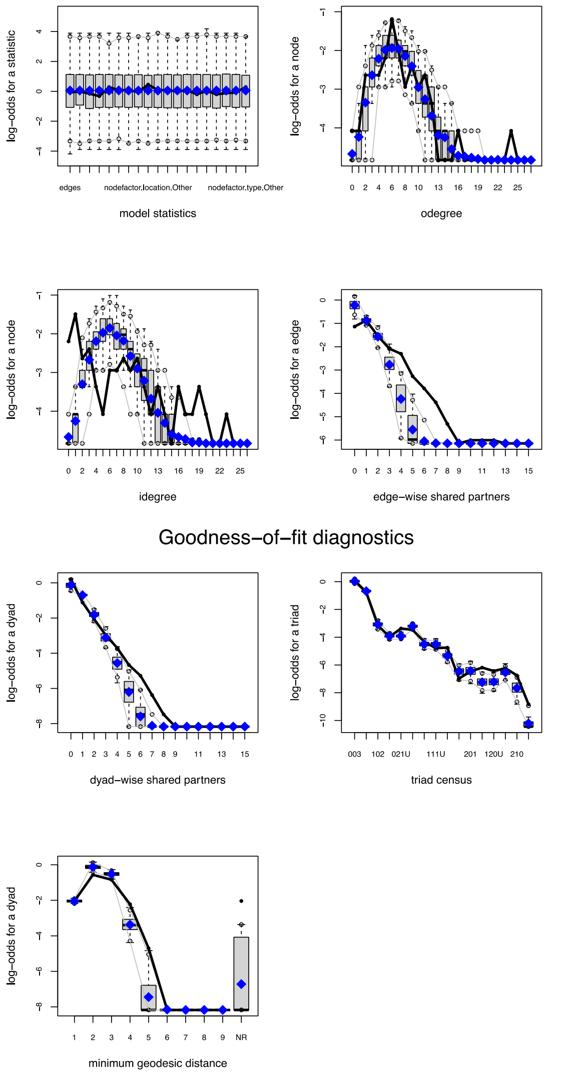
	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.14	0.39	0	-5.53	0
mutual	0.57	0.12	0	4.61	0
esp1	-1.1	0.12	0	-9.1	0
EC.H3_similarity	0.15	0.12	0	1.27	0.2
EC.power	0.53	0.11	0	5	0
NM.location	-0.24	0.16	0	-1.5	0.13
NF.location.Tessin	0.22	0.14	0	1.53	0.13
NM.response	-0.06	0.07	0	-0.78	0.44
NF.response.add_later_no_answer	-0.2	0.22	0	-0.91	0.36
NF.response.normal_answer	0.35	0.18	0	1.92	0.05
NF.response.normal_no_answer	0.15	0.18	0	0.8	0.42
NM.type	0.21	0.08	0	2.46	0.01
NF.type.Federal_Office	-0.11	0.12	0	-0.97	0.33
NF.type.Municipality	-0.18	0.09	0	-1.95	0.05
NF.type.NGO_organization_association	-0.28	0.07	0	-4.23	0
NF.type.Other	-0.43	0.07	0	-5.85	0

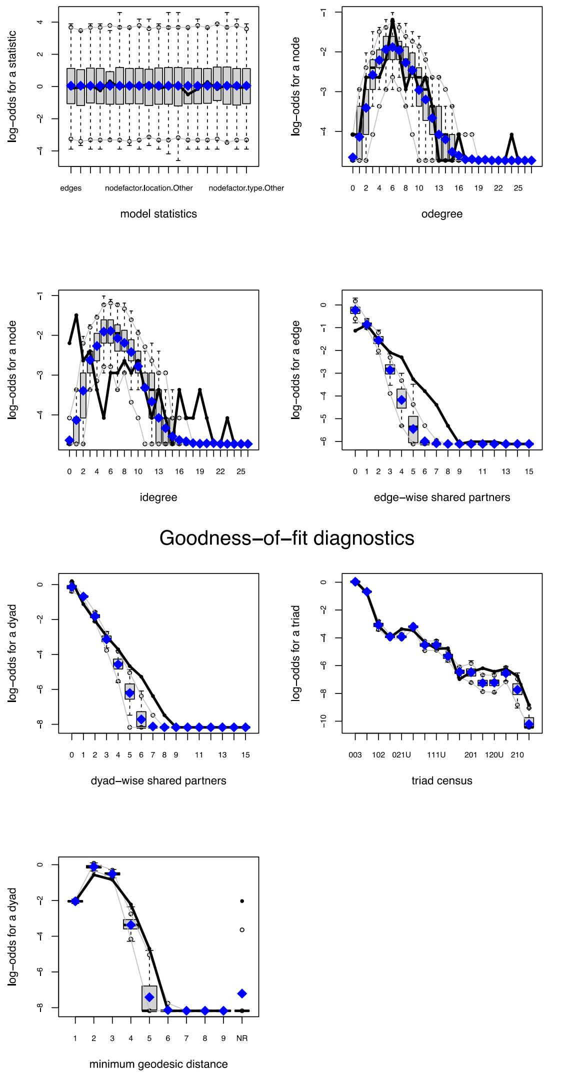


Case Murtensee, hypothesis 1 & 2

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.87	0.99	0	-3.89	0
mutual	0.73	0.19	0	3.81	0
esp1	-0.23	0.1	0	-2.18	0.03
EC.H1_length	0.21	0.25	0	0.81	0.42
EC.power	0.28	0.16	0	1.74	0.08
NM.location	0.18	0.11	0	1.55	0.12
NF.location.Fribourg	0.14	0.24	0	0.6	0.55
NF.location.inter-cantonal	0.15	0.24	0	0.63	0.53
NF.location.other	0.05	0.33	0	0.16	0.88
NF.location.Waadt	0.25	0.24	0	1.06	0.29
NM.response	-0.05	0.11	0	-0.46	0.65
NF.response.add_later_no_answer	0.55	0.47	0	1.17	0.24
NF.response.normal_answer	0.96	0.47	0	2.07	0.04
NF.response.normal_no_answer	0.93	0.46	0	2	0.05
NM.type	0.3	0.12	0	2.54	0.01
NF.type.Federal_Office	-0.45	0.2	0	-2.22	0.03
NF.type.Municipality	-0.12	0.12	0	-0.98	0.33
NF.type.NGO_organization_association	-0.32	0.11	0	-2.95	0
NF.type.Other	-0.41	0.11	0	-3.82	0

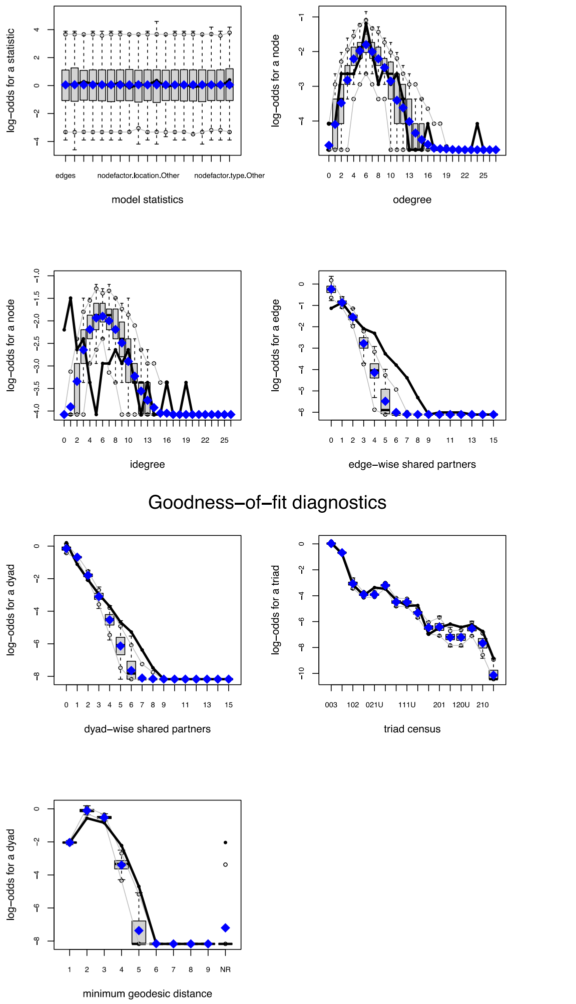
	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.88	1.03	0	-3.76	0
mutual	0.72	0.19	0	3.71	0
esp1	-0.23	0.11	0	-2.15	0.03
EC.H2_multiplexity	0.31	0.51	0	0.61	0.54
EC.power	0.27	0.16	0	1.7	0.09
NM.location	0.18	0.11	0	1.53	0.13
NF.location.Fribourg	0.15	0.23	0	0.63	0.53
NF.location.inter-cantonal	0.16	0.25	0	0.64	0.52
NF.location.other	0.06	0.33	0	0.17	0.87
NF.location.Waadt	0.26	0.24	0	1.07	0.28
NM.response	-0.05	0.11	0	-0.52	0.61
NF.response.add_later_no_answer	0.57	0.49	0	1.16	0.25
NF.response.normal_answer	0.97	0.47	0	2.04	0.04
NF.response.normal_no_answer	0.93	0.47	0	1.97	0.05
NM.type	0.31	0.12	0	2.53	0.01
NF.type.Federal_Office	-0.44	0.21	0	-2.13	0.03
NF.type.Municipality	-0.12	0.12	0	-1	0.32
NF.type.NGO_organization_association	-0.32	0.11	0	-3.03	0
NF.type.Other	-0.41	0.1	0	-3.92	0



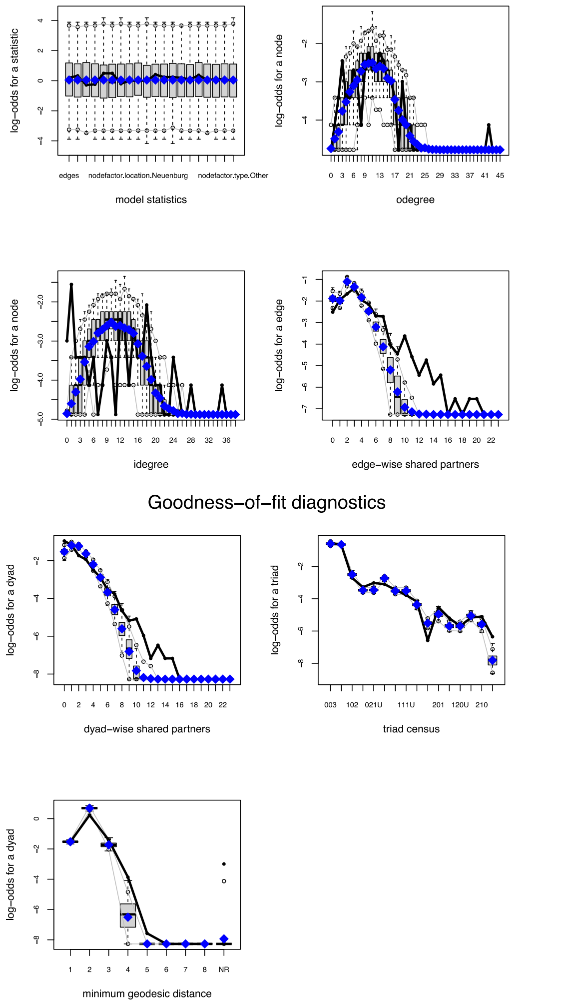


Case Murtensee, hypothesis 3 & case Neuchatel, hypothesis 1

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.86	1.03	0	-3.74	0
mutual	0.72	0.2	0	3.6	0
esp1	-0.23	0.1	0	-2.18	0.03
EC.H3_similarity	0.17	0.22	0	0.77	0.44
EC.power	0.27	0.17	0	1.61	0.11
NM.location	0.17	0.11	0	1.51	0.13
NF.location.Fribourg	0.15	0.23	0	0.67	0.5
NF.location.inter-cantonal	0.16	0.24	0	0.66	0.51
NF.location.other	0.06	0.32	0	0.19	0.85
NF.location.Waadt	0.26	0.23	0	1.12	0.26
NM.response	-0.05	0.11	0	-0.49	0.62
NF.response.add_later_no_answer	0.54	0.49	0	1.11	0.27
NF.response.normal_answer	0.96	0.47	0	2.04	0.04
NF.response.normal_no_answer	0.91	0.47	0	1.95	0.05
NM.type	0.3	0.12	0	2.59	0.01
NF.type.Federal_Office	-0.43	0.2	0	-2.15	0.03
NF.type.Municipality	-0.12	0.12	0	-0.99	0.32
NF.type.NGO_organization_association	-0.32	0.11	0	-2.92	0
NF.type.Other	-0.41	0.11	0	-3.83	0

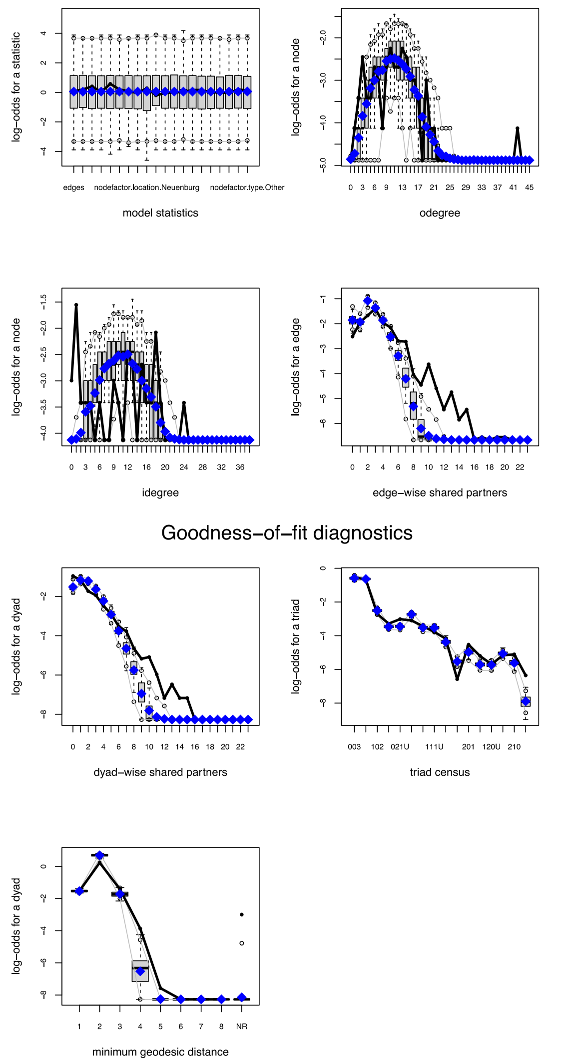


	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-4.15	0.93	0	-4.48	0
mutual	0.75	0.14	0	5.32	0
esp1	-0.64	0.11	0	-5.64	0
EC.H1_length	-0.33	0.2	0	-1.72	0.09
EC.power	0.21	0.11	0	1.88	0.06
NM.location	0.3	0.09	0	3.18	0
NF.location.Fribourg	0.56	0.28	0	2.01	0.04
NF.location.inter-cantonal	0.68	0.3	0	2.26	0.02
NF.location.Neuenburg	0.05	0.3	0	0.16	0.88
NF.location.other	0.62	0.36	0	1.71	0.09
NF.location.Waadt	0.44	0.28	0	1.55	0.12
NM.response	-0.08	0.09	0	-0.82	0.41
NF.response.add_later_no_answer	0.28	0.42	0	0.68	0.5
NF.response.normal_answer	1	0.39	0	2.61	0.01
NF.response.normal_no_answer	0.74	0.38	0	1.95	0.05
NM.type	-0.08	0.1	0	-0.75	0.45
NF.type.Federal_Office	-0.57	0.17	0	-3.45	0
NF.type.Municipality	-0.19	0.08	0	-2.31	0.02
NF.type.NGO_organization_association	-0.27	0.12	0	-2.27	0.02
NF.type.Other	-0.47	0.09	0	-5.13	0

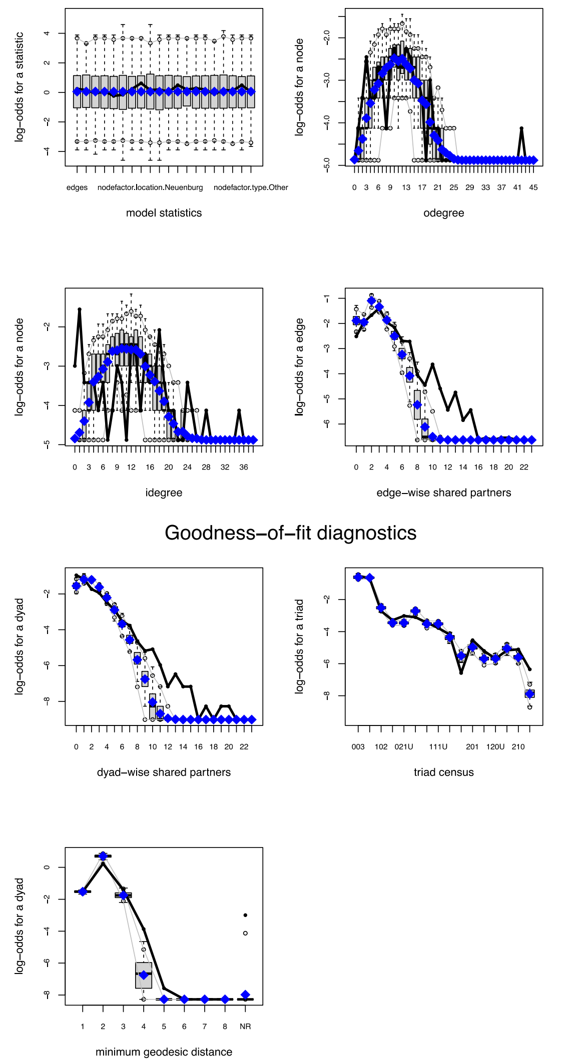


Case Neuchatel, hypotheses 2 & 3

	Estimate	Std. Error	MCMC %	Z value	Pr (>lzl)
edges	-4.2	0.91	0	-4.64	0
mutual	0.74	0.14	0	5.24	0
esp1	-0.64	0.11	0	-5.79	0
EC.H2_multiplexity	-0.48	0.39	0	-1.25	0.21
EC.power	0.21	0.11	0	1.87	0.06
NM.location	0.29	0.09	0	3.12	0
NF.location.Fribourg	0.57	0.27	0	2.08	0.04
NF.location.inter-cantonal	0.69	0.29	0	2.35	0.02
NF.location.Neuenburg	0.06	0.29	0	0.21	0.83
NF.location.other	0.63	0.36	0	1.78	0.08
NF.location.Waadt	0.44	0.28	0	1.6	0.11
NM.response	-0.07	0.09	0	-0.81	0.42
NF.response.add_later_no_answer	0.3	0.39	0	0.76	0.44
NF.response.normal_answer	1.02	0.37	0	2.77	0.01
NF.response.normal_no_answer	0.76	0.37	0	2.07	0.04
NM.type	-0.07	0.1	0	-0.72	0.47
NF.type.Federal_Office	-0.58	0.16	0	-3.52	0
NF.type.Municipality	-0.19	0.08	0	-2.28	0.02
NF.type.NGO_organization_association	-0.27	0.12	0	-2.35	0.02
NF.type.Other	-0.46	0.09	0	-4.9	0

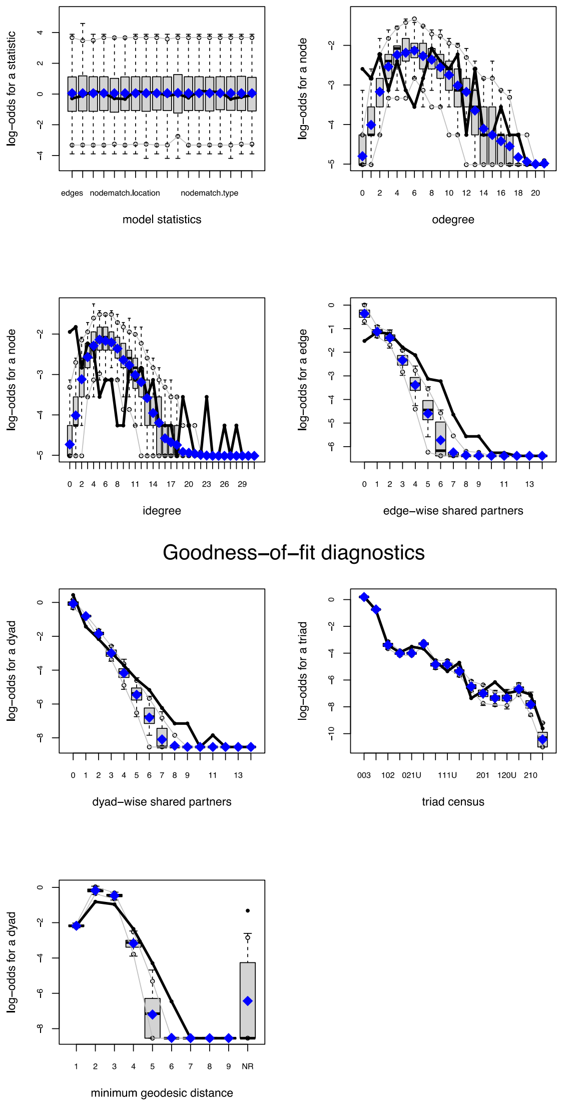


	Estimate	Std. Error	MCMC %	Z value	Pr (>lzl)
edges	-4.23	0.89	0	-4.74	0
mutual	0.74	0.14	0	5.29	0
esp1	-0.64	0.11	0	-5.63	0
EC.H3_similarity	-0.29	0.14	0	-1.99	0.05
EC.power	0.2	0.11	0	1.77	0.08
NM.location	0.3	0.09	0	3.19	0
NF.location.Fribourg	0.59	0.27	0	2.19	0.03
NF.location.inter-cantonal	0.7	0.29	0	2.4	0.02
NF.location.Neuenburg	0.08	0.29	0	0.27	0.79
NF.location.other	0.65	0.35	0	1.84	0.07
NF.location.Waadt	0.46	0.27	0	1.72	0.09
NM.response	-0.08	0.09	0	-0.84	0.4
NF.response.add_later_no_answer	0.33	0.41	0	0.81	0.42
NF.response.normal_answer	1.03	0.37	0	2.78	0.01
NF.response.normal_no_answer	0.77	0.37	0	2.1	0.04
NM.type	-0.08	0.1	0	-0.76	0.44
NF.type.Federal_Office	-0.57	0.17	0	-3.42	0
NF.type.Municipality	-0.19	0.08	0	-2.42	0.02
NF.type.NGO_organization_association	-0.27	0.11	0	-2.37	0.02
NF.type.Other	-0.47	0.09	0	-5.12	0

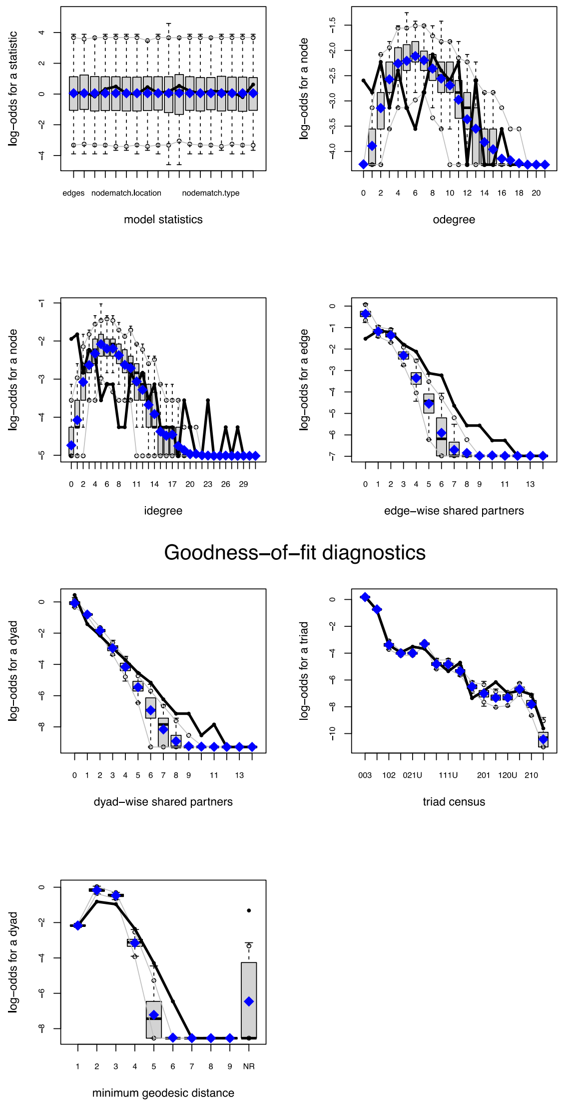


Case Reussebene, hypotheses 1 & 2

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.41	0.44	0	-7.75	0
mutual	0.15	0.19	0	0.8	0.43
esp1	-0.41	0.1	0	-4.18	0
EC.H1_length	0.1	0.21	0	0.49	0.63
EC.power	0.18	0.14	0	1.25	0.21
NM.location	1.09	0.1	0	10.76	0
NF.location.inter-cantonal	0.36	0.09	0	3.84	0
NF.location.Zug	0.07	0.09	0	0.79	0.43
NF.location.Zürich	-0.24	0.1	0	-2.44	0.01
NM.response	-0.46	0.12	0	-3.81	0
NF.response.add_later_no_answer	-0.04	0.35	0	-0.11	0.91
NF.response.normal_answer	1	0.22	0	4.54	0
NF.response.normal_no_answer	1.02	0.22	0	4.69	0
NM.type	0.22	0.11	0	1.99	0.05
NF.type.Federal_Office	-0.56	0.17	0	-3.3	0
NF.type.Municipality	-0.68	0.11	0	-6.11	0
NF.type.NGO_organization_association	-0.57	0.09	0	-6.04	0
NF.type.Other	-0.72	0.1	0	-6.95	0

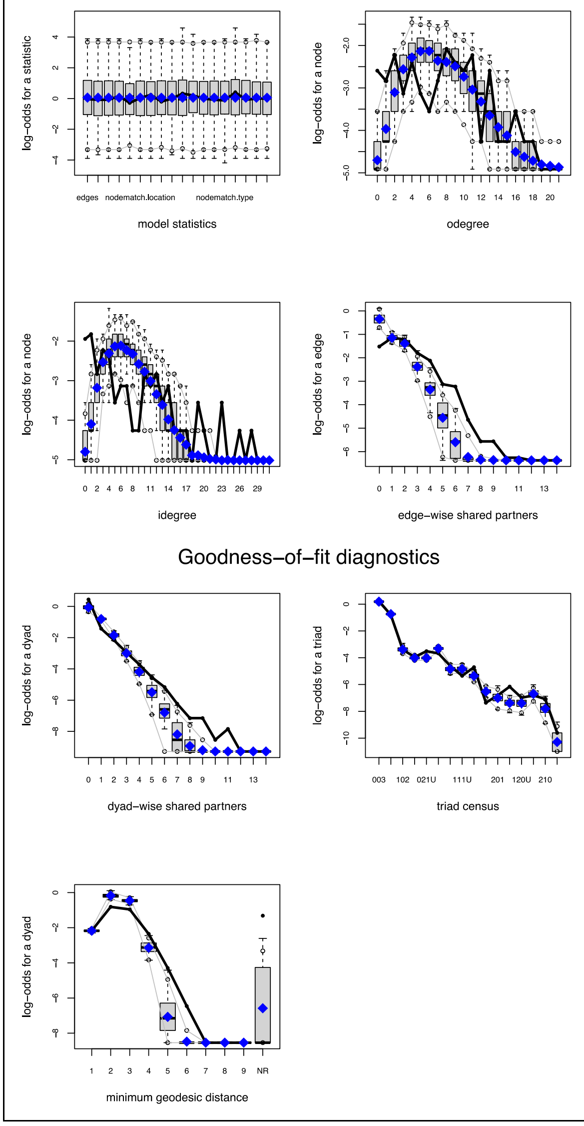


	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.4	0.44	0	-7.8	0
mutual	0.15	0.19	0	0.78	0.44
esp1	-0.41	0.1	0	-4.16	0
EC.H2_multiplexity	0.2	0.46	0	0.43	0.66
EC.power	0.18	0.14	0	1.25	0.21
NM.location	1.09	0.1	0	10.79	0
NF.location.inter-cantonal	0.36	0.09	0	3.78	0
NF.location.Zug	0.07	0.09	0	0.76	0.45
NF.location.Zürich	-0.24	0.1	0	-2.44	0.01
NM.response	-0.45	0.12	0	-3.75	0
NF.response.add_later_no_answer	-0.03	0.36	0	-0.08	0.94
NF.response.normal_answer	0.99	0.22	0	4.46	0
NF.response.normal_no_answer	1.01	0.21	0	4.73	0
NM.type	0.22	0.11	0	1.95	0.05
NF.type.Federal_Office	-0.55	0.17	0	-3.28	0
NF.type.Municipality	-0.68	0.11	0	-6.14	0
NF.type.NGO_organization_association	-0.57	0.09	0	-6.16	0
NF.type.Other	-0.73	0.11	0	-6.86	0

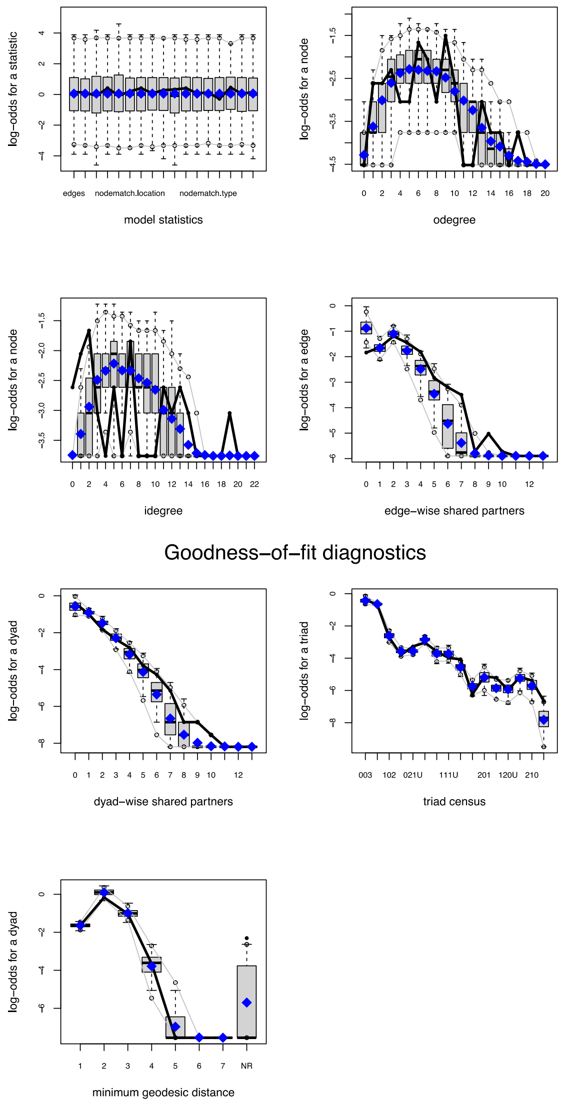


Case Reussebene, hypothesis 3 & case Rhonemündung, hypothesis 1

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.42	0.44	0	-7.74	0
mutual	0.15	0.18	0	0.8	0.42
esp1	-0.41	0.1	0	-4.34	0
EC.H3_similarity	0.21	0.21	0	1	0.32
EC.power	0.17	0.14	0	1.25	0.21
NM.location	1.09	0.1	0	10.62	0
NF.location.inter-cantonal	0.36	0.09	0	3.92	0
NF.location.Zug	0.08	0.09	0	0.83	0.4
NF.location.Zürich	-0.24	0.09	0	-2.49	0.01
NM.response	-0.45	0.12	0	-3.8	0
NF.response.add_later_no_answer	-0.05	0.35	0	-0.15	0.88
NF.response.normal_answer	0.99	0.22	0	4.42	0
NF.response.normal_no_answer	1.01	0.22	0	4.62	0
NM.type	0.23	0.11	0	2.06	0.04
NF.type.Federal_Office	-0.55	0.16	0	-3.37	0
NF.type.Municipality	-0.67	0.11	0	-6.06	0
NF.type.NGO_organization_association	-0.56	0.09	0	-6.18	0
NF.type.Other	-0.72	0.1	0	-7	0

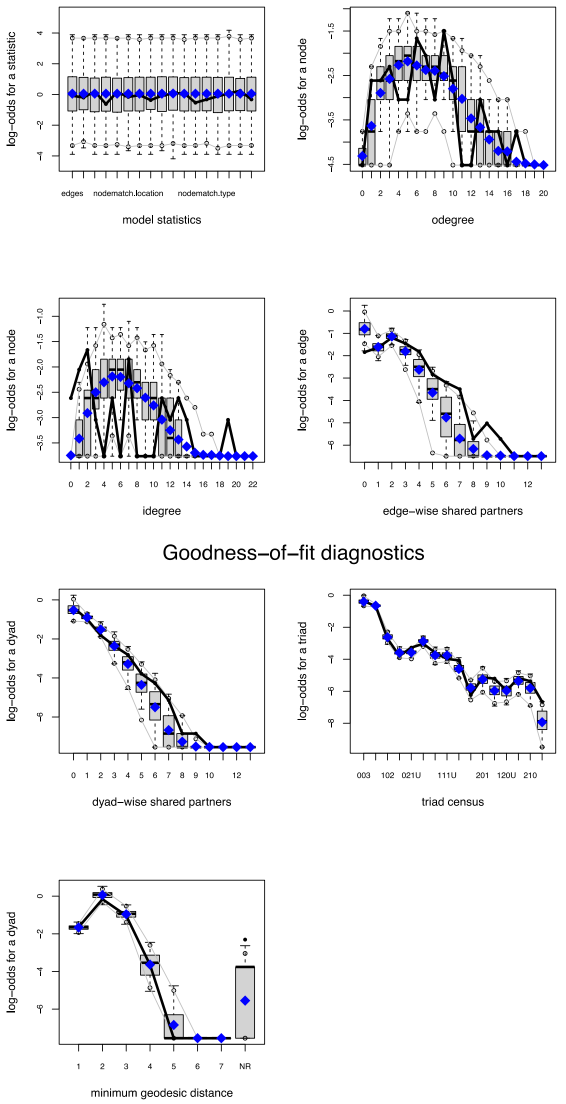


	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.62	0.73	0	-3.59	0
mutual	0.65	0.22	0	2.95	0
esp1	-0.73	0.14	0	-5.02	0
EC.H1_length	-0.19	0.32	0	-0.61	0.54
EC.power	0.37	0.17	0	2.16	0.03
NM.location	0.3	0.14	0	2.15	0.03
NF.location.Waadt	0.07	0.12	0	0.58	0.56
NF.location.Wallis	0	0.14	0	-0.01	0.99
NM.response	0.07	0.14	0	0.45	0.65
NF.response.add_later_no_answer	0.08	0.41	0	0.19	0.85
NF.response.normal_answer	0.63	0.37	0	1.69	0.09
NF.response.normal_no_answer	0.56	0.37	0	1.51	0.13
NM.type	0.11	0.15	0	0.73	0.47
NF.type.Federal_Office	-0.15	0.19	0	-0.76	0.44
NF.type.Municipality	-0.15	0.14	0	-1.05	0.29
NF.type.NGO_organization_association	-0.55	0.14	0	-3.99	0
NF.type.Other	-0.39	0.12	0	-3.33	0

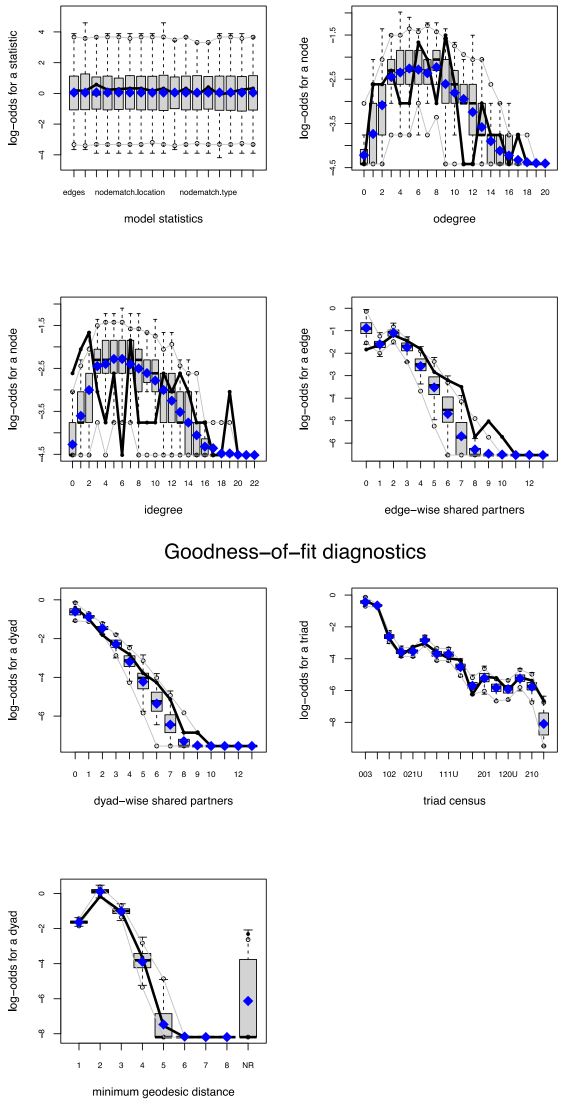


Case Rhonemündung, hypotheses 2 & 3

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.66	0.7	0	-3.81	0
mutual	0.66	0.21	0	3.09	0
esp1	-0.72	0.15	0	-4.9	0
EC.H2_multiplexity	-0.08	0.49	0	-0.16	0.87
EC.power	0.38	0.17	0	2.23	0.03
NM.location	0.3	0.14	0	2.17	0.03
NF.location.inter-cantonal	0.07	0.13	0	0.51	0.61
NF.location.other	0	0.15	0	-0.02	0.99
NM.response	0.08	0.14	0	0.56	0.57
NF.response.add_later_no_answer	0.09	0.4	0	0.23	0.82
NF.response.normal_answer	0.64	0.36	0	1.78	0.07
NF.response.normal_no_answer	0.57	0.36	0	1.59	0.11
NM.type	0.12	0.15	0	0.76	0.45
NF.type.Federal_Office	-0.15	0.18	0	-0.81	0.42
NF.type.Municipality	-0.16	0.14	0	-1.12	0.26
NF.type.NGO_organization_association	-0.55	0.13	0	-4.12	0
NF.type.Other	-0.39	0.12	0	-3.29	0



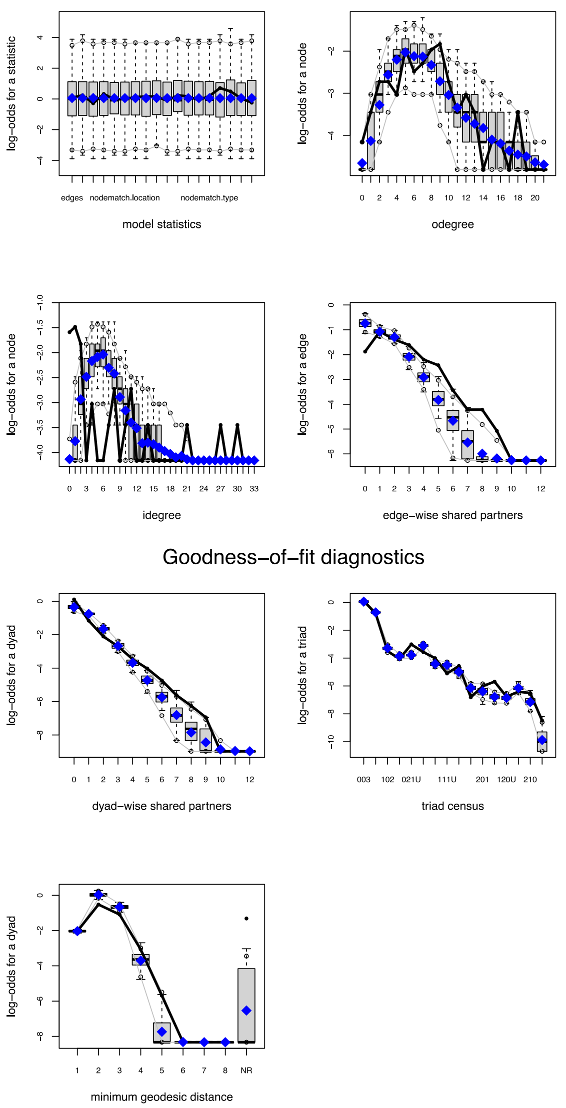
	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.61	0.69	0	-3.79	0
mutual	0.66	0.22	0	3.03	0
esp1	-0.72	0.14	0	-5.07	0
EC.H3_similarity	-0.2	0.25	0	-0.8	0.42
EC.power	0.38	0.17	0	2.23	0.03
NM.location	0.29	0.14	0	2.11	0.03
NF.location.inter-cantonal	0.07	0.13	0	0.56	0.58
NF.location.other	0	0.15	0	-0.02	0.99
NM.response	0.08	0.14	0	0.56	0.57
NF.response.add_later_no_answer	0.08	0.39	0	0.2	0.84
NF.response.normal_answer	0.63	0.35	0	1.79	0.07
NF.response.normal_no_answer	0.57	0.35	0	1.6	0.11
NM.type	0.12	0.15	0	0.8	0.42
NF.type.Federal_Office	-0.15	0.19	0	-0.82	0.41
NF.type.Municipality	-0.16	0.14	0	-1.16	0.25
NF.type.NGO_organization_association	-0.56	0.14	0	-3.99	0
NF.type.Other	-0.4	0.12	0	-3.43	0

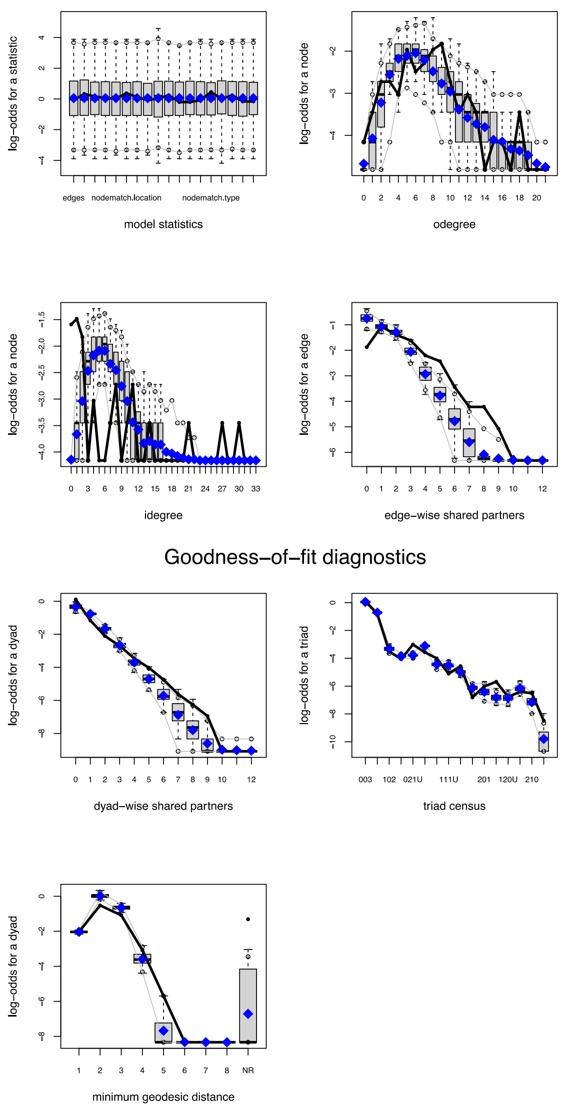


Case Sense, hypotheses 1 & 2

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.04	0.47	0	-4.37	0
mutual	0.19	0.19	0	0.98	0.32
esp1	-0.27	0.1	0	-2.82	0
EC.H1_length	0.24	0.22	0	1.12	0.26
EC.power	0.58	0.13	0	4.36	0
NM.location	0.54	0.11	0	4.93	0
NF.location.Fribourg	-0.16	0.07	0	-2.19	0.03
NF.location.inter-cantonal	0.08	0.13	0	0.61	0.54
NF.location.other	0.08	0.32	0	0.25	0.8
NM.response	-0.2	0.11	0	-1.9	0.06
NF.response.add_later_no_answer	-0.34	0.31	0	-1.1	0.27
NF.response.normal_answer	0.78	0.23	0	3.39	0
NF.response.normal_no_answer	0.45	0.23	0	1.96	0.05
NM.type	-0.32	0.13	0	-2.43	0.02
NF.type.Federal_Office	-0.83	0.22	0	-3.69	0
NF.type.Municipality	-0.77	0.1	0	-7.45	0
NF.type.NGO_organization_association	-0.59	0.13	0	-4.6	0
NF.type.Other	-0.95	0.13	0	-7.29	0

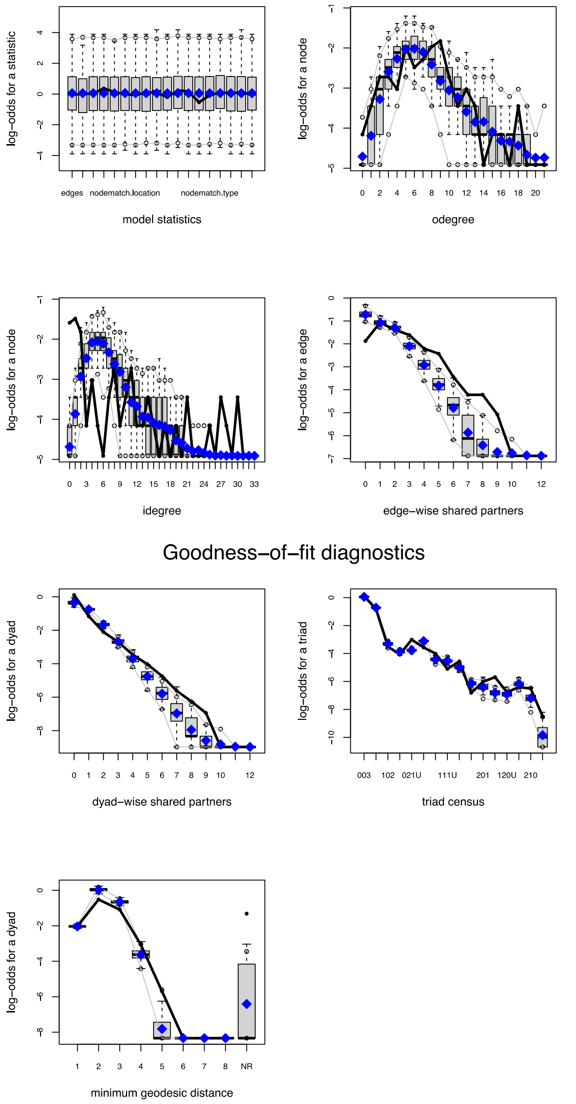
	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.04	0.47	0	-4.35	0
mutual	0.18	0.2	0	0.93	0.35
esp1	-0.27	0.1	0	-2.7	0.01
EC.H2_multiplexity	0.41	0.4	0	1.02	0.31
EC.power	0.58	0.13	0	4.31	0
NM.location	0.53	0.1	0	5.1	0
NF.location.Fribourg	-0.16	0.07	0	-2.11	0.03
NF.location.inter-cantonal	0.08	0.14	0	0.55	0.58
NF.location.other	0.06	0.32	0	0.2	0.84
NM.response	-0.21	0.11	0	-1.98	0.05
NF.response.add_later_no_answer	-0.34	0.31	0	-1.11	0.27
NF.response.normal_answer	0.79	0.23	0	3.43	0
NF.response.normal_no_answer	0.45	0.23	0	2	0.05
NM.type	-0.32	0.13	0	-2.41	0.02
NF.type.Federal_Office	-0.83	0.22	0	-3.78	0
NF.type.Municipality	-0.78	0.1	0	-7.51	0
NF.type.NGO_organization_association	-0.59	0.13	0	-4.62	0
NF.type.Other	-0.95	0.12	0	-7.6	0



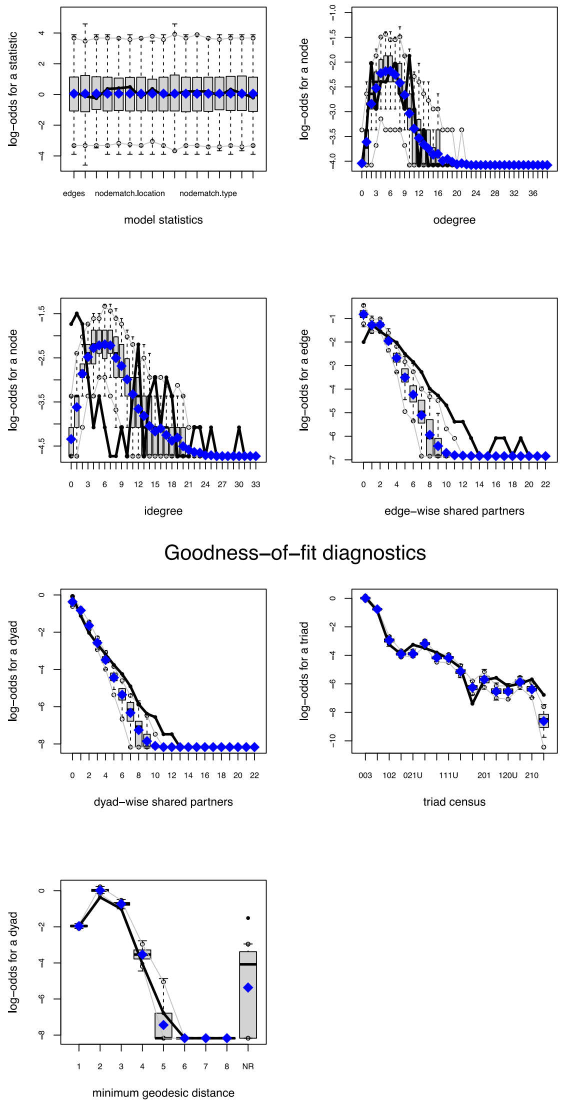


Case Sense, hypothesis 3 & Case Untere Saane, hypothesis 1

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.05	0.48	0	-4.3	0
mutual	0.18	0.2	0	0.92	0.36
esp1	-0.27	0.1	0	-2.68	0.01
EC.H3_similarity	0.19	0.17	0	1.08	0.28
EC.power	0.58	0.13	0	4.34	0
NM.location	0.53	0.1	0	5.11	0
NF.location.Fribourg	-0.16	0.07	0	-2.25	0.02
NF.location.inter-cantonal	0.08	0.13	0	0.62	0.53
NF.location.other	0.06	0.31	0	0.2	0.84
NM.response	-0.2	0.11	0	-1.85	0.06
NF.response.add_later_no_answer	-0.35	0.3	0	-1.15	0.25
NF.response.normal_answer	0.79	0.23	0	3.38	0
NF.response.normal_no_answer	0.46	0.23	0	1.97	0.05
NM.type	-0.32	0.13	0	-2.47	0.01
NF.type.Federal_Office	-0.83	0.23	0	-3.66	0
NF.type.Municipality	-0.78	0.1	0	-7.65	0
NF.type.NGO_organization_association	-0.59	0.12	0	-4.74	0
NF.type.Other	-0.95	0.13	0	-7.23	0

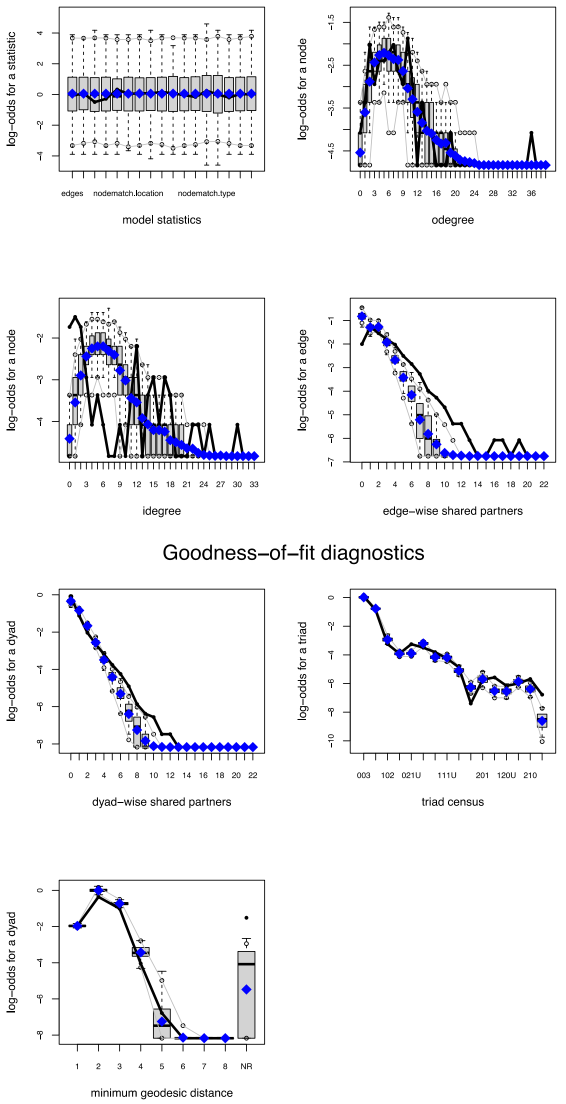


	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.21	0.74	0	-4.37	0
mutual	0.63	0.19	0	3.31	0
esp1	-0.37	0.11	0	-3.47	0
EC.H1_length	0.44	0.24	0	1.81	0.07
EC.power	0.36	0.14	0	2.59	0.01
NM.location	0.37	0.12	0	3.09	0
NF.location.inter-cantonal	0.57	0.11	0	5.02	0
NF.location.other	0.36	0.29	0	1.24	0.21
NM.response	-0.11	0.11	0	-1.04	0.3
NF.response.add_later_no_answer	0.19	0.4	0	0.47	0.64
NF.response.normal_answer	1.27	0.36	0	3.51	0
NF.response.normal_no_answer	0.69	0.36	0	1.91	0.06
NM.type	0.07	0.13	0	0.55	0.58
NF.type.Federal_Office	-0.76	0.18	0	-4.15	0
NF.type.Municipality	-0.77	0.12	0	-6.24	0
NF.type.NGO_organization_association	-0.69	0.12	0	-5.92	0
NF.type.Other	-0.8	0.13	0	-6.2	0

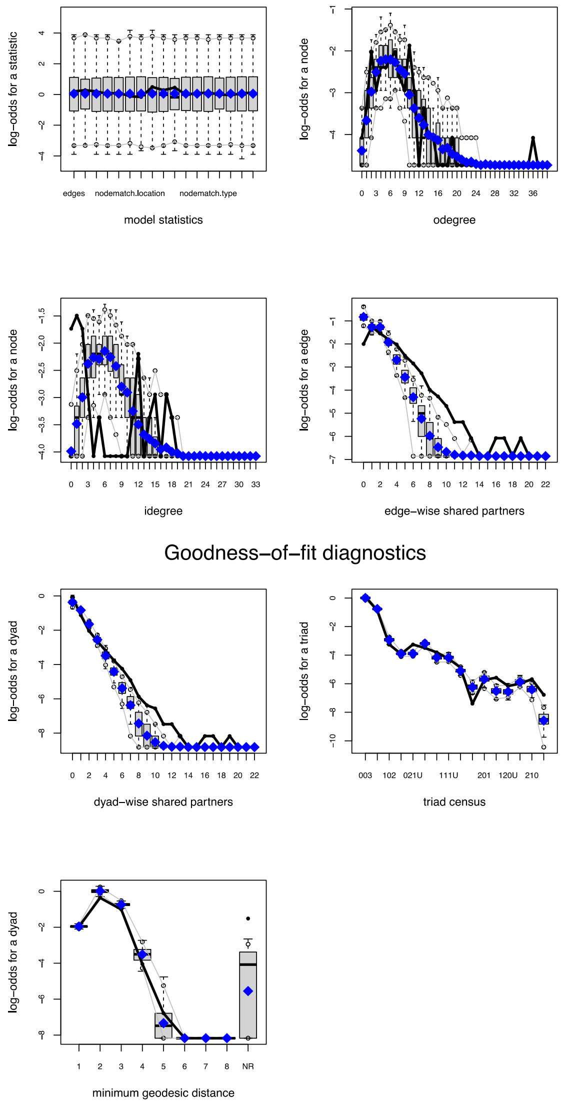


Case Untere Saane, hypotheses 2 & 3

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.23	0.71	0	-4.53	0
mutual	0.64	0.19	0	3.35	0
esp1	-0.37	0.11	0	-3.39	0
EC.H2_multiplexity	0.62	0.47	0	1.34	0.18
EC.power	0.36	0.14	0	2.51	0.01
NM.location	0.37	0.13	0	2.9	0
NF.location.inter-cantonal	0.57	0.12	0	4.81	0
NF.location.other	0.36	0.29	0	1.25	0.21
NM.response	-0.12	0.11	0	-1.08	0.28
NF.response.add_later_no_answer	0.19	0.38	0	0.51	0.61
NF.response.normal_answer	1.29	0.34	0	3.76	0
NF.response.normal_no_answer	0.72	0.36	0	2.02	0.04
NM.type	0.07	0.13	0	0.54	0.59
NF.type.Federal_Office	-0.76	0.18	0	-4.17	0
NF.type.Municipality	-0.77	0.13	0	-6.15	0
NF.type.NGO_organization_association	-0.7	0.12	0	-5.6	0
NF.type.Other	-0.8	0.14	0	-5.81	0



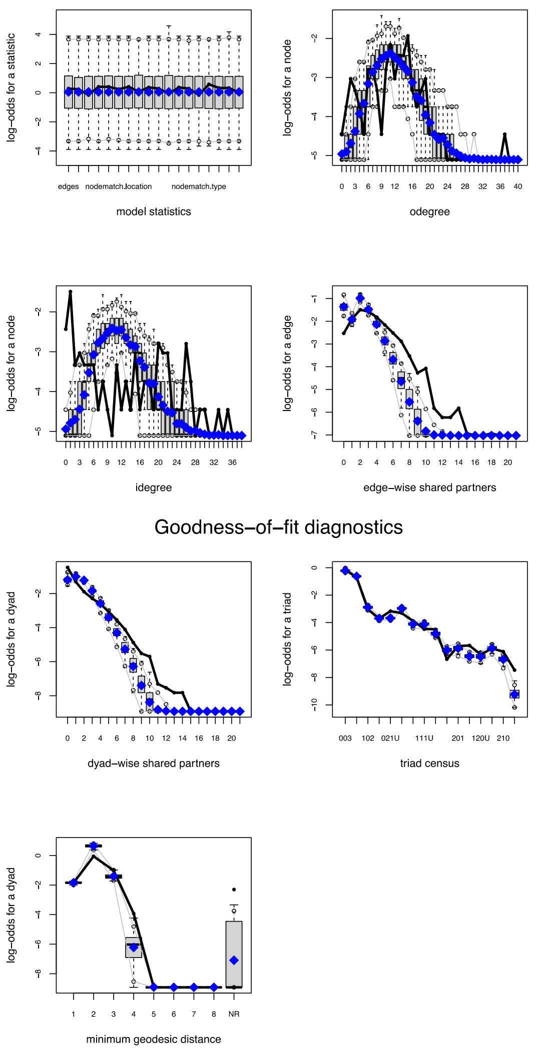
	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-3.23	0.73	0	-4.41	0
mutual	0.65	0.19	0	3.51	0
esp1	-0.37	0.11	0	-3.48	0
EC.H3_similarity	0.34	0.24	0	1.44	0.15
EC.power	0.36	0.14	0	2.58	0.01
NM.location	0.36	0.12	0	2.99	0
NF.location.inter-cantonal	0.56	0.11	0	5.03	0
NF.location.other	0.37	0.3	0	1.25	0.21
NM.response	-0.11	0.11	0	-1.03	0.3
NF.response.add_later_no_answer	0.2	0.4	0	0.5	0.62
NF.response.normal_answer	1.28	0.36	0	3.58	0
NF.response.normal_no_answer	0.7	0.36	0	1.97	0.05
NM.type	0.07	0.13	0	0.57	0.57
NF.type.Federal_Office	-0.74	0.19	0	-3.92	0
NF.type.Municipality	-0.76	0.13	0	-5.95	0
NF.type.NGO_organization_association	-0.69	0.12	0	-5.76	0
NF.type.Other	-0.8	0.13	0	-6.07	0



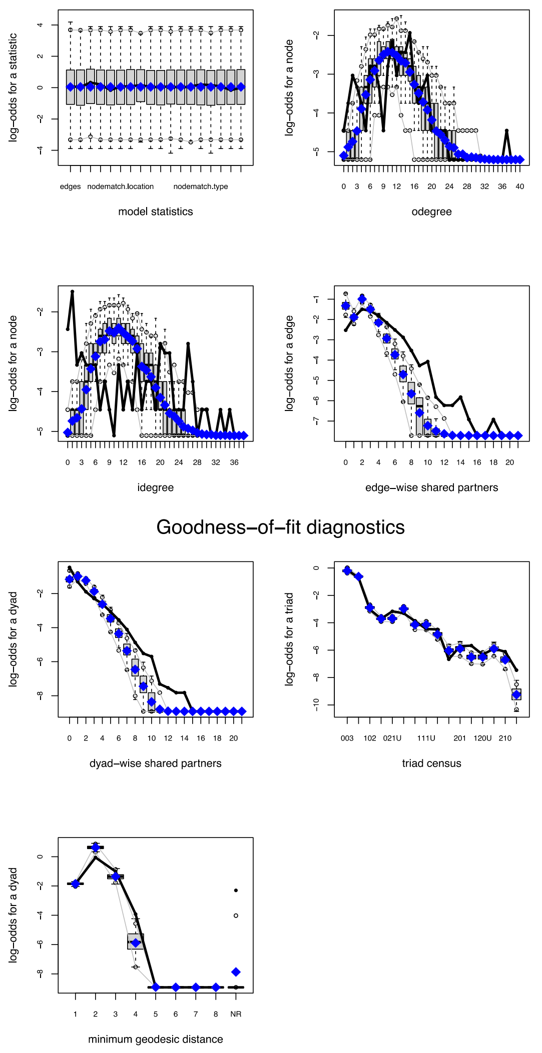
Additional ERGM results and GOF statistics not included in the analysis

Case Rhein, hypotheses 1 & 2

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-5.29	1.25	0	-4.24	0
mutual	0.61	0.12	0	4.94	0
esp1	-0.87	0.09	0	-9.75	0
EC.H1_length	-0.03	0.16	0	-0.17	0.86
EC.power	0.32	0.09	0	3.39	0
NM.location	0.38	0.07	0	5.73	0
NF.location.inter-cantonal	0.17	0.05	0	3.59	0
NF.location.other	0.2	0.24	0	0.83	0.41
NF.location.St. Gallen	0.12	0.04	0	2.8	0.01
NM.response	-0.09	0.07	0	-1.2	0.23
NF.response.add_later_no_answer	1.65	0.63	0	2.63	0.01
NF.response.normal_answer	1.85	0.62	0	2.98	0
NF.response.normal_no_answer	1.78	0.62	0	2.86	0
NM.type	0.06	0.08	0	0.76	0.45
NF.type.Federal_Office	-0.48	0.1	0	-4.58	0
NF.type.Municipality	-0.29	0.07	0	-4.14	0
NF.type.NGO_organization_association	-0.38	0.07	0	-5.63	0
NF.type.Other	-0.46	0.07	0	-6.29	0

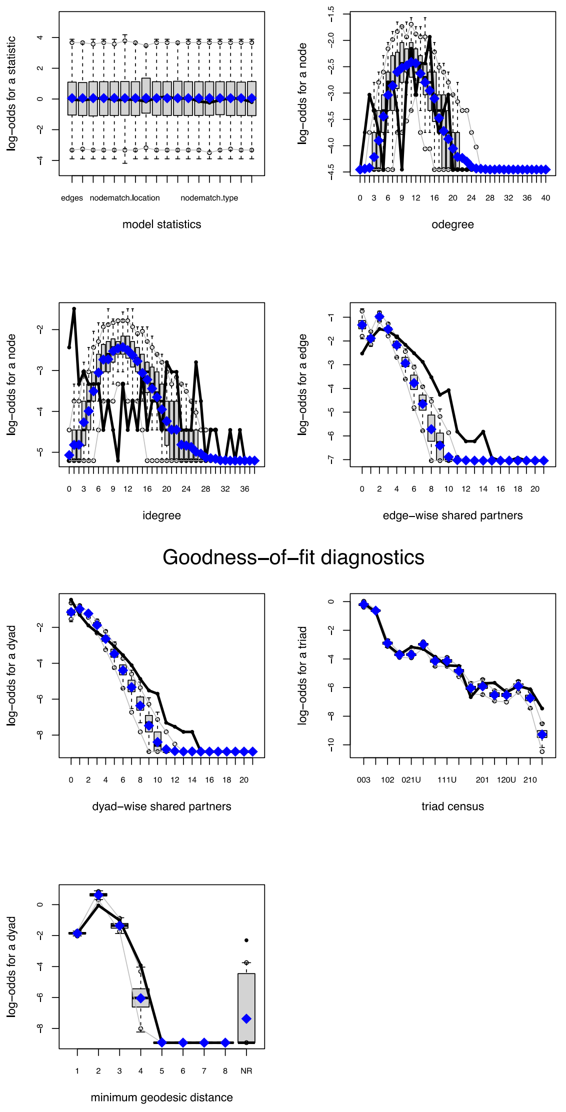


	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-5.26	1.21	0	-4.34	0
mutual	0.61	0.12	0	5.14	0
esp1	-0.87	0.09	0	-9.69	0
EC.H2_multiplexity	-0.02	0.33	0	-0.06	0.95
EC.power	0.32	0.09	0	3.47	0
NM.location	0.38	0.07	0	5.81	0
NF.location.inter-cantonal	0.17	0.05	0	3.63	0
NF.location.other	0.19	0.23	0	0.81	0.42
NF.location.St. Gallen	0.12	0.04	0	2.85	0
NM.response	-0.09	0.07	0	-1.2	0.23
NF.response.add_later_no_answer	1.64	0.61	0	2.69	0.01
NF.response.normal_answer	1.84	0.6	0	3.04	0
NF.response.normal_no_answer	1.76	0.6	0	2.92	0
NM.type	0.06	0.08	0	0.75	0.45
NF.type.Federal_Office	-0.48	0.1	0	-4.6	0
NF.type.Municipality	-0.29	0.07	0	-4.15	0
NF.type.NGO_organization_association	-0.38	0.07	0	-5.8	0
NF.type.Other	-0.46	0.07	0	-6.4	0

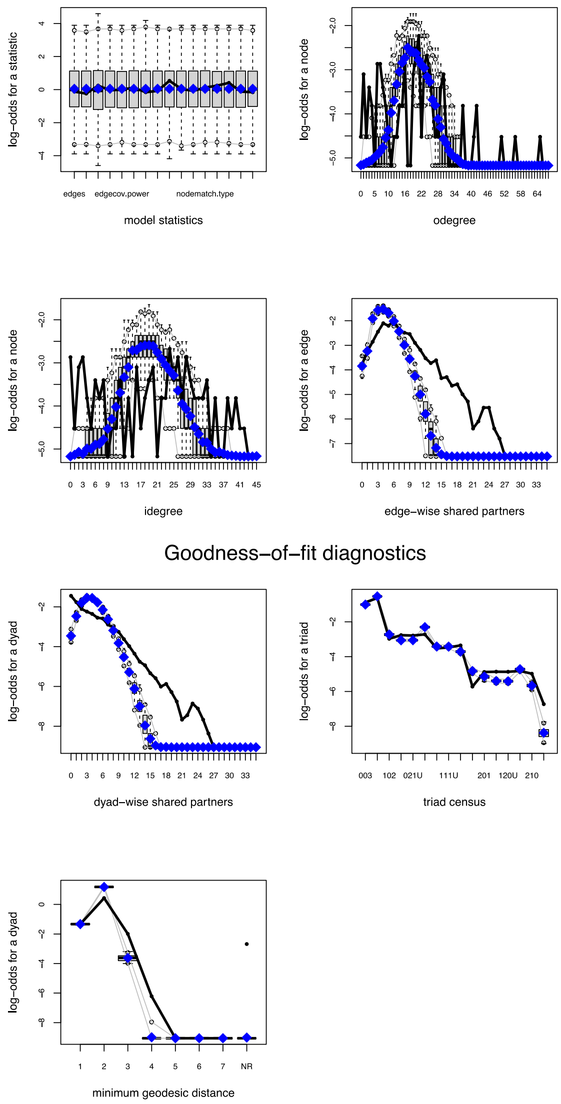


Case Rhein, hypothesis 3 & Case Maggia, hypothesis 1

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-5.28	1.24	0	-4.27	0
mutual	0.61	0.12	0	5.01	0
esp1	-0.87	0.09	0	-9.76	0
EC.H3_similarity	-0.04	0.16	0	-0.27	0.79
EC.power	0.32	0.09	0	3.5	0
NM.location	0.38	0.07	0	5.68	0
NF.location.inter-cantonal	0.17	0.05	0	3.51	0
NF.location.other	0.2	0.23	0	0.86	0.39
NF.location.St. Gallen	0.12	0.04	0	2.91	0
NM.response	-0.09	0.07	0	-1.17	0.24
NF.response.add_later_no_answer	1.65	0.62	0	2.66	0.01
NF.response.normal_answer	1.85	0.62	0	2.99	0
NF.response.normal_no_answer	1.77	0.62	0	2.87	0
NM.type	0.06	0.08	0	0.77	0.44
NF.type.Federal_Office	-0.48	0.11	0	-4.51	0
NF.type.Municipality	-0.29	0.07	0	-4.19	0
NF.type.NGO_organization_association	-0.38	0.06	0	-5.84	0
NF.type.Other	-0.46	0.07	0	-6.52	0



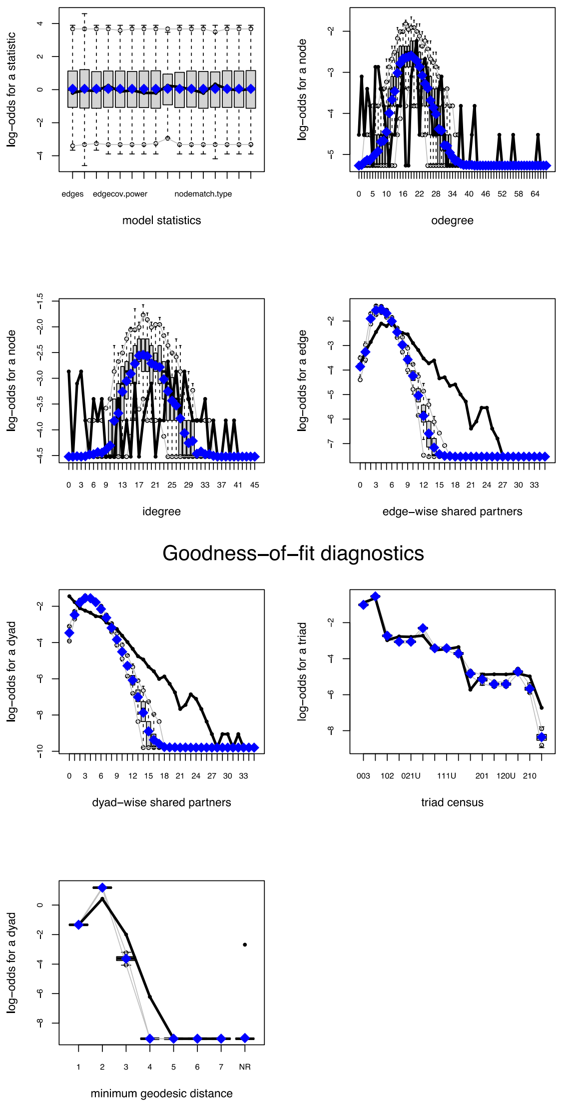
	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.4	0.4	0	-6.03	0
mutual	0.23	0.09	0	2.6	0.01
esp1	-0.61	0.13	0	-4.79	0
EC.H1_length	0.04	0.1	0	0.4	0.69
EC.power	0.16	0.08	0	2.14	0.03
NM.location	0.17	0.12	0	1.39	0.17
NF.location.Tessin	-0.08	0.12	0	-0.71	0.48
NM.response	0.02	0.05	0	0.28	0.78
NF.response.add_later_no_answer	0.27	0.27	0	0.99	0.32
NF.response.normal_answer	0.88	0.18	0	4.93	0
NF.response.normal_no_answer	0.81	0.18	0	4.62	0
NM.type	-0.04	0.07	0	-0.56	0.58
NF.type.Federal_Office	-0.29	0.13	0	-2.35	0.02
NF.type.Municipality	-0.26	0.06	0	-4.18	0
NF.type.NGO_organization_association	-0.49	0.07	0	-7.38	0
NF.type.Other	-0.63	0.07	0	-9.01	0

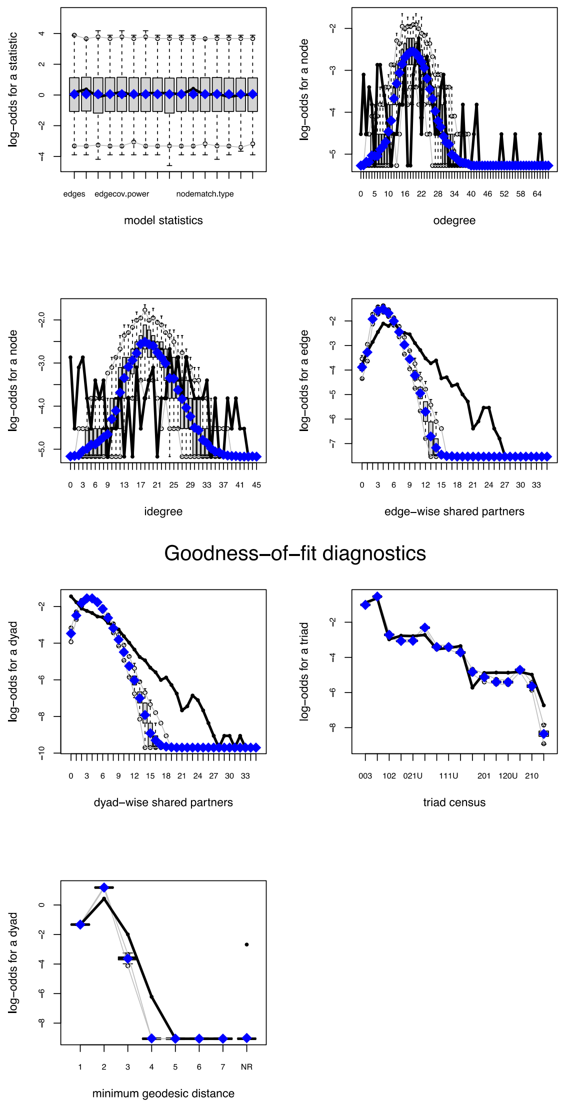


Case Maggia, hypotheses 2 & 3

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.4	0.41	0	-5.85	0
mutual	0.23	0.09	0	2.59	0.01
esp1	-0.62	0.13	0	-4.87	0
EC.H2_multiplexity	0.03	0.22	0	0.13	0.9
EC.power	0.17	0.08	0	2.18	0.03
NM.location	0.16	0.12	0	1.36	0.17
NF.location.Tessin	-0.08	0.12	0	-0.68	0.5
NM.response	0.02	0.06	0	0.39	0.7
NF.response.add_later_no_answer	0.26	0.27	0	0.95	0.34
NF.response.normal_answer	0.88	0.19	0	4.77	0
NF.response.normal_no_answer	0.81	0.18	0	4.4	0
NM.type	-0.04	0.07	0	-0.64	0.52
NF.type.Federal_Office	-0.3	0.12	0	-2.49	0.01
NF.type.Municipality	-0.27	0.06	0	-4.32	0
NF.type.NGO_organization_association	-0.49	0.07	0	-7.49	0
NF.type.Other	-0.64	0.06	0	-9.95	0

	Estimate	Std. Error	MCMC %	Z value	Pr (>|z|)
edges	-2.39	0.41	0	-5.83	0
mutual	0.24	0.09	0	2.6	0.01
esp1	-0.62	0.13	0	-4.75	0
EC.H1_length	0.01	0.1	0	0.07	0.94
EC.power	0.16	0.07	0	2.26	0.02
NM.location	0.17	0.12	0	1.44	0.15
NF.location.Tessin	-0.09	0.12	0	-0.78	0.44
NM.response	0.02	0.06	0	0.4	0.69
NF.response.add_later_no_answer	0.26	0.27	0	0.99	0.32
NF.response.normal_answer	0.89	0.18	0	4.86	0
NF.response.normal_no_answer	0.81	0.18	0	4.48	0
NM.type	-0.03	0.07	0	-0.47	0.64
NF.type.Federal_Office	-0.31	0.13	0	-2.45	0.01
NF.type.Municipality	-0.27	0.06	0	-4.14	0
NF.type.NGO_organization_association	-0.49	0.07	0	-7.33	0
NF.type.Other	-0.63	0.07	0	-9.13	0





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##################################################################
# 01_prep_data


# September, 2020

# Topic: create package (data_processed) of clean data for analysis based on:
# - exported data from limesurvey
# - information about conceptual map from airtable

# READ INSTRUCTIONS
# to run script select case from list:
# if file is called from other file then do replace existing case_name


# set-up ----
# load packages
library(here)
library(network)
library(statnet)
library(data.table)
library(dplyr)
library(tidyverse)
library(GGally)
library(igraph)
library(mlergm)

# load functions
source("utility_functions.R")

# load data
path_name <- paste(dirname(getwd()), "wetlands_data/data_processed/", sep = "/")
ergm_results_file <- list.files(path = path_name, pattern = "_prep_data_2_mice_complete")
session_name_file <- paste(path_name, ergm_results_file[length(ergm_results_file)], sep = "/")
load(session_name_file)

# prep hypotheses for individual cases ----
# create adjacency matrix from el and make them square

# prepare empty tables to fill in in loop
names_h_mat <- unique(c(general_collab_el$sender, general_collab_el$receiver))
dim_h_mat   <- length(names_h_mat)

empty_matrix_case_all    <- as.data.frame(matrix(0,
                                                  nrow = dim_h_mat, ncol = dim_h_mat,
                                                  dimnames = list(names_h_mat, names_h_mat)))

h1_length_mat   <- empty_matrix_case_all
h2_multip_mat   <- empty_matrix_case_all
h2_multip_w_mat <- empty_matrix_case_all
h3_homoge_mat   <- empty_matrix_case_all
h3_homoge_w_mat <- empty_matrix_case_all

# loop trough all cases to create the variables for the three hypotheses
for (case_name in case_name_loop) {

  # prepare data to create values for the hypotheses  ----

  # select values from ELs relevant for that specific cases and store as square mat
  concept_el_case         <- concept_el[concept_el$case == case_name,]
  actor_activity_el_case  <- actor_activity_el[actor_activity_el$case == case_name]

  # - delete when activities where filled in that are not relevant for this case
  remove_index <- which(is.na(match(actor_activity_el_case$receiver, concept_el_case$sender)))
  if (length(remove_index) > 0) {
    actor_activity_el_case <- actor_activity_el_case[-remove_index,]
  }

  sonet    <- create_adjacency_matrix(general_collab_el[general_collab_el$case == case_name])
  ecnet    <- create_adjacency_matrix(concept_el_case)
  acnet    <- create_adjacency_matrix(actor_activity_el_case)
  fonet    <- create_adjacency_matrix(actor_forum_el[actor_forum_el$case == case_name])

  sonet <- make_df_square(sonet)
  ecnet <- make_df_square(ecnet)
  acnet <- make_df_square(acnet)
  fonet <- make_df_square(fonet)

  # - remove actors from acnet that are not included in sonet because they have no ties
  irrelevant_actors <- rownames(acnet)[is.na(match(rownames(acnet), rownames(sonet)))]
  irrelevant_actors <- irrelevant_actors[is.na(match(irrelevant_actors, rownames(ecnet)))]

  if (length(irrelevant_actors) > 0) {
    irrelevant_actors_index <- unlist(lapply(irrelevant_actors, function(x) grep(x, rownames(acnet))))
    acnet <- acnet[-c(irrelevant_actors_index), -c(irrelevant_actors_index)]
  }

  # get all names across tables and store in array
  # - code for names
  # -- 1 = actor
  # -- 2 = activity
  # -- 3 = factor
  # -- 4 = target
  # -- 5 = forum
  full_names  <- unique(c(rownames(sonet), rownames(acnet), rownames(ecnet), rownames(fonet)))

  node_meber  <- c(rep(1, length(rownames(sonet))),
                   rep(2, length(rownames(acnet)) - length(intersect(rownames(sonet), rownames(acnet)))),
                   rep(3, length(rownames(ecnet)) - length(intersect(rownames(ecnet), rownames(acnet)))),
                   rep(5, length(rownames(fonet)) - length(intersect(rownames(fonet), rownames(sonet)))))
  node_meber_names  <- c(rep("actor", length(rownames(sonet))),
                         rep("activity", length(rownames(acnet)) - length(intersect(rownames(sonet), rownames(acnet)))),
                         rep("factor", length(rownames(ecnet)) - length(intersect(rownames(ecnet), rownames(acnet)))),
                         rep("forum", length(rownames(fonet)) - length(intersect(rownames(fonet), rownames(sonet)))))

  names_targets     <- concept_nodes$german[which(grepl("Target", concept_nodes$group_id) &
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                                                    grepl(case_name, concept_nodes$case_present))]
  names_targets     <- paste(names_targets, case_codes[case_name_loop == case_name], sep = "_")

  index_targets     <- unlist(sapply(names_targets, function(x) grep(paste("^", x, "$", sep = ""), full_names)))

  node_meber[index_targets]        <- 4
  node_meber_names[index_targets]  <- "target"

  # total number of actors, activities, factors, targets combined
  length_sonet <- sum(node_meber == 1 | node_meber == 2 | node_meber == 3 | node_meber == 4)

  # fill in full network (full_net) with data from all actor network (sonet) and the three sub networks (ecnet, acnet, and fonet)
  full_net    <- as.data.frame(matrix(0,
                                    nrow = length(full_names), ncol = length(full_names),
                                    dimnames = list(full_names, full_names)))
  full_net    <- fill_matching_values(sonet, full_net)
  full_net    <- fill_matching_values(ecnet, full_net)
  full_net    <- fill_matching_values(acnet, full_net)
  full_net    <- fill_matching_values(fonet, full_net)

  # make diag all zero
  diag(full_net) <- 0

  # plot and export network illustration
  network_illustration_case <- ggnet2(as.matrix(full_net),
                                    arrow.gap = 0.02,
                                    arrow.size = 3,
                                    node.size = 2,
                                    node.label = F,
                                    node.color = node_meber_names,
                                    palette = "Pastel1")
  ggsave(paste("illustrations/", format(Sys.time(), "%y%m%d"), "_", case_name, "_ml_network.pdf", sep = ""),
         plot = network_illustration_case)

  # H1 and H2 ----

  # get pos/neg tie values and fill them for both sides since valid for incoming/outgoing ties
  sign_mat <- as.data.frame(matrix(0,
                                 nrow = length_sonet, ncol = length_sonet,
                                 dimnames = list(full_names[1:length_sonet],full_names[1:length_sonet])))
  sign_mat[sign_mat == 0] <- NA

  for (i in 1:dim(concept_el_case)[1]) {
    if (concept_el_case$sign[i] != 0) {
      sign_mat[concept_el_case$sender[i], concept_el_case$receiver[i]] <- concept_el_case$sign[i]
      sign_mat[concept_el_case$receiver[i], concept_el_case$sender[i]] <- concept_el_case$sign[i]
    }
  }

  # prep df where all actors and ties from actors are 0 and only path between activities are possible
  full_net_wo_forums  <- full_net[1:length_sonet, 1:length_sonet]
  actors_zero_df      <- full_net_wo_forums

  # the actor-activitiy ties needed are implemented later (but only the ones from the two actors)
  actors_zero_df[1:sum(node_meber == 1),] <- 0

  # avoid backward loops from issues to actors
  actors_zero_df[(sum(node_meber == 1) + 1):dim(actors_zero_df)[1],1:sum(node_meber == 1)]  <- 0

  # prep empty df's for loop
  shortest_path_number    <- as.data.frame(matrix(NA,
                                                nrow = dim(sonet)[1], ncol = dim(sonet)[1],
                                                dimnames = list(rownames(sonet),colnames(sonet))))
  shortest_path_length    <- shortest_path_number
  shortest_path_number_w  <- shortest_path_number

  # loop to calc path variables for for H1_path_length and H2_path_multiplexity (standard and weighted)
  for (x in rownames(sonet)) {
    for (y in rownames(sonet)) {

      # fill in ties from relevant actors to activities
      actors_zero_df_temp <- actors_zero_df

      actors_zero_df_temp[x, (1 + sum(node_meber == 1)):dim(full_net_wo_forums)[2]] <- full_net_wo_forums[x, (1 + sum(node_meber ==
1)):dim(full_net_wo_forums)[2]]
      actors_zero_df_temp[y, (1 + sum(node_meber == 1)):dim(full_net_wo_forums)[2]] <- full_net_wo_forums[y, (1 + sum(node_meber ==
1)):dim(full_net_wo_forums)[2]]

      actors_zero_graph_temp <- graph_from_adjacency_matrix(as.matrix(actors_zero_df_temp), mode = "directed")

      # get name of all shortest paths
      shortest_path_options <- all_shortest_paths(actors_zero_graph_temp, x, y, mode = "all")$res

      # get shortest till shortest + 2 paths connecting two actors => weighted shortest path
      distance_min  <- distances(actors_zero_graph_temp, v = x, to = y, mode = "all")

      if (!is.infinite(distance_min)) {
        shortest_path_0 <- all_simple_paths(actors_zero_graph_temp, from = x, to = y, mode = "all", cutoff = distance_min + 0)
        shortest_path_1 <- all_simple_paths(actors_zero_graph_temp, from = x, to = y, mode = "all", cutoff = distance_min + 1)
        shortest_path_2 <- all_simple_paths(actors_zero_graph_temp, from = x, to = y, mode = "all", cutoff = distance_min + 2)

        shortest_path_number_w[x,y] <- sum(length(shortest_path_0)/(distance_min*1^2),
                                         length(shortest_path_1)/(distance_min*2^2),
                                         length(shortest_path_2)/(distance_min*3^2))

        shortest_path_number[x,y]      <- length(shortest_path_options)
      }

      # get number of shortest paths that are longer than zero and between two different actors
      if (length(shortest_path_options) > 0 & x != y) {

        # get length of shortest path
        shortest_path_length[x,y]   <- length(shortest_path_options[[1]]) - 1
      }}}

  # clean values from loop
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# - fix that min path length is 1
shortest_path_length <- shortest_path_length - 1

# - zeros filled in when no paths exists and for loops... replace them with NA
diag(shortest_path_number_w)                          <- NA
diag(shortest_path_number)                            <- NA

# - replace NA values with values that can be interpreted (corrected max/min values)
shortest_path_number[is.na(shortest_path_number)]     <- min(shortest_path_number, na.rm = T) - 1
shortest_path_number_w[is.na(shortest_path_number_w)] <- min(shortest_path_number_w, na.rm = T) - 1
shortest_path_length[is.na(shortest_path_length)]     <- max(shortest_path_length, na.rm = T) + 1

# - scale values
shortest_path_number_scale    <- range01(t(scale(t(shortest_path_number))))
shortest_path_number_w_scale  <- range01(t(scale(t(shortest_path_number_w))))
shortest_path_length_scale    <- abs(range01(t(scale(t(shortest_path_length)))) - 1) # small values are better

# - replace reintroduced NA's
shortest_path_number_scale[is.na(shortest_path_number_scale)]     <- 0
shortest_path_number_w_scale[is.na(shortest_path_number_w_scale)] <- 0
shortest_path_length_scale[is.na(shortest_path_length_scale)]     <- 0

# insert variables for first two hypotheses in DF
for (i in 1:dim(shortest_path_length_scale)[1]) {
  for (j in 1:dim(shortest_path_length_scale)[2]) {
    h1_length_mat[rownames(shortest_path_length_scale)[i],colnames(shortest_path_length_scale)[j]]        <- shortest_path_length_scale[i,j]
    h2_multip_mat[rownames(shortest_path_number_scale)[i],colnames(shortest_path_number_scale)[j]]        <- shortest_path_number_scale[i,j]
    h2_multip_w_mat[rownames(shortest_path_number_w_scale)[i],colnames(shortest_path_number_w_scale)[j]]  <- shortest_path_number_w_scale[i,j]
  }}

# H3 ----

# get target names
target_names <- unlist(concept_nodes[which(grepl("^Target$", concept_nodes$type) &
                                             grepl(case_name, concept_nodes$case_present) &
                                             !grepl("^NA_", concept_nodes$german_coded)),
                                     grepl("german_coded", colnames(concept_nodes))])

# select concepts for case
concept_nodes_notarget <- concept_nodes[!grepl("Target",concept_nodes$type),
                                        grepl("german|concept|type|case", colnames(concept_nodes))]

# get goal impact by activity
index_activities    <- sapply(full_names[node_meber == 2], function(x)
  which(grepl(paste("^", x, "$", sep = ""), concept_nodes_notarget$german_coded) &
          grepl(case_name, concept_nodes_notarget$case_present)))

concept_activities  <- concept_nodes_notarget[unlist(index_activities),]

# function to get path activity by goal
ties_pos_neg <- function(starting_nodes_names) {

  # prep emtpy DFs
  pos_neg_df_1  <- as.data.frame(matrix(NA, nrow = length(starting_nodes_names), ncol = 20))
  index_df_1    <- as.data.frame(matrix(NA, nrow = length(starting_nodes_names), ncol = 20))

  # start loop
  for (i0 in 1:length(starting_nodes_names)) {

    # step 1 - prep array if not yet existing
    index_0       <- which(full_net[starting_nodes_names[i0],] == 1)
    if (length(index_0) > 0) {
      array_1       <- array(NA)
      array_result  <- array(NA)
      index_1       <- array(NA)

      # step 2 - fill in arrays
      array_1   <- sapply(index_0, function(x)
        concept_el_case$sign[which(concept_el_case$sender == starting_nodes_names[i0] &
                                     concept_el_case$receiver == colnames(full_net)[x])])
      pos_neg_df_1[i0, 1:length(array_1)] <- array_1

      index_1   <- sapply(index_0, function(x)
        which(concept_el_case$sender == starting_nodes_names[i0] &
                concept_el_case$receiver == colnames(full_net)[x]))
      index_df_1[i0, 1:length(index_1)] <- index_1
    }}

  # clean arrays
  array_index     <- as.array(unlist(t(index_df_1)))[!is.na(unlist(t(index_df_1)))]
  receiver_nodes  <- as.array(unlist(concept_el_case$receiver[array_index]))
  array_result    <- as.array(unlist(t(pos_neg_df_1)))[!is.na(unlist(t(pos_neg_df_1)))]
  nr_outgoing     <- rowSums(!is.na(pos_neg_df_1), na.rm = T)

  # return data
  list_returne <- list(array_result, nr_outgoing, receiver_nodes)
  return(list_returne)
}

# select the names of the activites from the full_net
activities_start <- colnames(full_net)[node_meber == 2]

# prep list to fill in loop
result_list         <- list()
outgoing_list       <- list()
receiver_nodes_list <- list()
receiver_nodes_temp <- activities_start

# length dependent on size of conceptual map (best/mean = 15)
lm <- round(dim(concept_el_case)[1]/17)

# loop by the length of max path length in conceptual maps (lm) to run the function (ties_pos_neg)  and export/clean the output values
for (i in 1:lm) {
  output_temp               <- ties_pos_neg(receiver_nodes_temp)
  result_list[[i]]          <- output_temp[[1]]
  outgoing_list[[i]]        <- output_temp[[2]]
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  receiver_nodes_list[[i]]  <- output_temp[[3]]

  index_temp          <- unlist(sapply(full_names[node_meber == 4], function(x) grep(paste("^", x, "$", sep = ""), receiver_nodes_list[[i]])))
  receiver_nodes_temp <- receiver_nodes_list[[i]]
  receiver_nodes_temp[index_temp] <- paste(receiver_nodes_list[[i]][index_temp], "target", sep = "_")
}

# function to sum together the values from the ties_pos_neg function
rep_nodes_out <- function(sx_outgoing, sx_array_result, sx_receiver_nodes, sy_ingoing) {

  # prep emtpy array
  rep_nodes_out_temp <- array(NA)

  # combine all the existing values
  for (i in 1:length(sx_outgoing)[1]) {
    insert_value <- rep(i, sx_outgoing[i])
    if (length(insert_value) > 0) {
      if (sum(rep_nodes_out_temp, na.rm = T) == 0) {
        rep_nodes_out_temp[length(rep_nodes_out_temp):length(insert_value)]     <- insert_value
      } else {
        rep_nodes_out_temp[length(rep_nodes_out_temp) + 1:length(insert_value)] <- insert_value
      }}}

  # cal overall pos/neg
  if (is.data.frame(sy_ingoing)) {
    sx_array_result <- sy_ingoing[,2][rep_nodes_out_temp] * sx_array_result
  }

  # clean and fill in remaining information in DF
  rep_nodes_out_clean           <- data.frame(data.frame(sy_ingoing)[,1][rep_nodes_out_temp])
  rep_nodes_out_clean[,2]       <- sx_array_result
  rep_nodes_out_clean[,3]       <- sx_receiver_nodes
  colnames(rep_nodes_out_clean) <- c("start", "sign", "end")

  # return
  return(rep_nodes_out_clean)
}

# prep empty list, DF, and names for loop
output_table_list <- list()
goal_impact_df    <- data.frame()
output_table_temp <- activities_start

# start loop for run function (rep_nodes_out)
for (i in 1:lm) {

  # run function and store relevant names for next round
  output_table_list[[i]]  <- rep_nodes_out(outgoing_list[[i]], result_list[[i]], receiver_nodes_list[[i]], output_table_temp)
  output_table_temp       <- output_table_list[[i]]

  # combine the output data sets across loops
  if (i > 1) {
    df_temp         <- cbind(output_table_list[[i]], i)
    goal_impact_df  <- rbind(goal_impact_df,
                             df_temp[unlist(sapply(full_names[node_meber == 4],
                                                   function(x) grep(paste("^", x, "$", sep = ""), df_temp[,3]))),])
  }}

# construct exponential weight based on path length (i) that has min at 1/3 (longest path has shortes weight)
weight_norm       <- exp(goal_impact_df$i)
weight_norm       <- ((weight_norm - min(weight_norm))/(max(weight_norm) - min(weight_norm))) * (1 - 1/3) + 1/3
weight_norm       <- round(abs(weight_norm - 1) + 1/3, 2)
goal_impact_df$i  <- weight_norm

# impact of actors on goals based on activity
# - extract actor_activity mat from full net end prep empty DF
actor_activity    <- full_net[full_names[node_meber == 1], full_names[node_meber == 2]]
actor_goal_impact <- as.data.frame(matrix(NA,
                                          nrow = length(full_names[node_meber == 1]), ncol = length(target_names),
                                          dimnames = list(full_names[node_meber == 1], target_names)))
actor_goal_impact_w <- actor_goal_impact

# loop trough actor_activity mat
for (i in 1:dim(actor_activity)[1]) {

  # get colnames of activities in actor_activity mat
  names_activities  <- colnames(actor_activity)[actor_activity[i,] == 1]

  # - search for names_activities to get the indexes if names exist
  if (length(names_activities) > 0) {
    index_impact_activity <- unlist(sapply(names_activities, function(x) grep(paste("^", x, "$", sep = ""), goal_impact_df[,1])))

    # look for targets in index_impact_activity
    for (j in 1:length(target_names)) {
      index_temp <- goal_impact_df[index_impact_activity,3] == target_names[j]
      goals_temp <- cbind(goal_impact_df$sign[index_temp], goal_impact_df$i[index_temp])

      # fill in values in DFs
      if (length(goals_temp) != 0) {
        actor_goal_impact[i,j]    <- mean(goals_temp[1,])
        actor_goal_impact_w[i,j]  <- weighted.mean(goals_temp)
      }}}}

# only keep most dominant goals related to Biodiversity and Recreation
names_target_coded <- paste(c("Artenschutz_primar_seltene_Arten", "Biodiversitat", "Touristische_Attraktivitat", "Erholungswert"),
                            case_codes[case_name_loop == case_name],
                            sep = "_")

keep_col <- colnames(actor_goal_impact)[!is.na(match(colnames(actor_goal_impact), names_target_coded))]

actor_goal_impact   <- actor_goal_impact[,keep_col]
actor_goal_impact_w <- actor_goal_impact_w[,keep_col]

# replace NA's in cols with mean
for (i in 1:length(keep_col)) {
  actor_goal_impact[,i][is.na(actor_goal_impact[,i])]     <- mean(actor_goal_impact[,i], na.rm = T)
```

```
    actor_goal_impact_w[,i][is.na(actor_goal_impact_w[,i])] <- mean(actor_goal_impact_w[,i], na.rm = T)
  }

  # calc similarity matrix using Euclidean sim metric
  actor_goal_impact_sim   <- as.matrix(proxy::simil(actor_goal_impact, method = "Euclidean", by_rows = T))
  actor_goal_impact_w_sim <- as.matrix(proxy::simil(actor_goal_impact_w, method = "Euclidean", by_rows = T))

  actor_goal_impact_sim   <- as.data.frame(actor_goal_impact_sim)
  actor_goal_impact_w_sim <- as.data.frame(actor_goal_impact_w_sim)

  # scale
  actor_goal_impact_sim_scale     <- range01(scale(actor_goal_impact_sim))
  actor_goal_impact_w_sim_scale   <- range01(scale(actor_goal_impact_w_sim))

  # insert variables for third hypotheses (standard and weighted) in DFs
  for (i in 1:dim(actor_goal_impact_sim_scale)[1]) {
    for (j in 1:dim(actor_goal_impact_sim_scale)[2]) {
      h3_homoge_mat[rownames(actor_goal_impact_sim_scale)[i],colnames(actor_goal_impact_sim_scale)[j]]        <- actor_goal_impact_sim_scale[i,j]
      h3_homoge_w_mat[rownames(actor_goal_impact_w_sim_scale)[i],colnames(actor_goal_impact_w_sim_scale)[j]]  <- actor_goal_impact_w_sim_scale[i,j]
    }}
}

# prep network for combined cases ----

# extract mat from EL and make them square
sonet    <- create_adjacency_matrix(general_collab_el)
ecnet    <- create_adjacency_matrix(concept_el)
acnet    <- create_adjacency_matrix(actor_activity_el)
fonet    <- create_adjacency_matrix(actor_forum_el)

sonet <- make_df_square(sonet)
ecnet <- make_df_square(ecnet)
acnet <- make_df_square(acnet)
fonet <- make_df_square(fonet)

# remove actors from acnet that are not included in sonet becuase they have no ties
irrelevant_actors <- rownames(acnet)[is.na(match(rownames(acnet), rownames(sonet)))]
irrelevant_actors <- irrelevant_actors[grep(paste(case_codes, collapse = "$|"), irrelevant_actors)]
index_irrelevant  <- which(!is.na(match(irrelevant_actors,rownames(general_collab_mat_imp))))
index_exclude     <- unlist(lapply(irrelevant_actors[index_irrelevant], function(x) grep(x, rownames(acnet))))
acnet             <- acnet[-c(index_exclude), -c(index_exclude)]

# get all names across tables and store in array
# - code for names
# -- 1 = actor
# -- 2 = activity
# -- 3 = factor
# -- 4 = target
# -- 5 = forum
full_names  <- unique(c(rownames(sonet), rownames(acnet), rownames(ecnet), rownames(fonet)))

node_meber  <- c(rep(1, length(rownames(sonet))),
                 rep(2, length(rownames(acnet)) - length(intersect(rownames(sonet), rownames(acnet)))),
                 rep(3, length(rownames(ecnet)) - length(intersect(rownames(ecnet), rownames(acnet)))),
                 rep(5, length(rownames(fonet)) - length(intersect(rownames(fonet), rownames(sonet)))))
node_meber_names  <- c(rep("actor", length(rownames(sonet))),
                       rep("activity", length(rownames(acnet)) - length(intersect(rownames(sonet), rownames(acnet)))),
                       rep("factor", length(rownames(ecnet)) - length(intersect(rownames(ecnet), rownames(acnet)))),
                       rep("forum", length(rownames(fonet)) - length(intersect(rownames(fonet), rownames(sonet)))))

names_targets     <- concept_nodes$german_coded[which(grepl("Target", concept_nodes$group_id) &
                                                  grepl(case_name, concept_nodes$case_present))]
index_targets     <- unlist(sapply(names_targets, function(x) grep(paste("^", x, "$", sep = ""), full_names)))

node_meber[index_targets]        <- 4
node_meber_names[index_targets]  <- "target"

# fill in full network (full_net) with data from all actor network (sonet) and the three sub networks (ecnet, acnet, and fonet)
full_net    <- as.data.frame(matrix(0,
                                    nrow = length(full_names), ncol = length(full_names),
                                    dimnames = list(full_names, full_names)))
full_net    <- fill_matching_values(sonet, full_net)
full_net    <- fill_matching_values(ecnet, full_net)
full_net    <- fill_matching_values(acnet, full_net)
full_net    <- fill_matching_values(fonet, full_net)

# make diag all zero
diag(full_net) <- 0

# plot and export network illustration
network_illustration_case <- ggnet2(as.matrix(full_net),
                                    arrow.gap = 0.02,
                                    arrow.size = 3,
                                    node.size = 2,
                                    node.label = F,
                                    node.color = node_meber_names,
                                    palette = "Pastel1")
ggsave(paste("illustrations/", format(Sys.time(), "%y%m%d"), "_ml_network.pdf", sep = ""),
       plot = network_illustration_case)

# control variables ----

# CV: actor type
# - prep DF
actor_type <- as.data.frame(array(data = NA, dim = dim(sonet)[1], dimnames = list(rownames(sonet))))

# - fill in DF with type of actors
for (i in 1:dim(actor_type)[1]) {
  index <- which(match(general_collab_el$sender, rownames(actor_type)[i]) == 1)[1]
  actor_type[i,1] <- general_collab_el$sender_type[index]
  if (is.na(index)) {
    index <- which(match(general_collab_el$receiver, rownames(actor_type)[i]) == 1)[1]
    actor_type[i,1] <- general_collab_el$receiver_type[index]
  }}

# - remove infomration about which canton as not needed (comes later in seperate CV: location)
```

```
actor_type[,1] <- gsub("(Canton_).*", "Canton", actor_type[,1])

# CV: survey group
# - prep DF
survey_group <- as.data.frame(array(data = NA, dim = dim(sonet)[1], dimnames = list(rownames(sonet))))

# - fill in DF with survey group actors
for (i in 1:dim(survey_group)[1]) {
  index <- which(match(general_collab_el$sender, rownames(survey_group)[i]) == 1)[1]
  survey_group[i,1] <- general_collab_el$sender_group[index]
  if (is.na(index)) {
    index <- which(match(general_collab_el$receiver, rownames(survey_group)[i]) == 1)[1]
    survey_group[i,1] <- general_collab_el$receiver_group[index]
  }}

# CV: location
# - prep DF
location <- as.data.frame(array(data = NA, dim = dim(sonet)[1], dimnames = list(rownames(sonet))))

# - fill in DF with location actors are present
for (i in 1:dim(location)[1]) {
  index <- which(match(general_collab_el$sender, rownames(location)[i]) == 1)[1]
  location[i,1] <- general_collab_el$sender_location[index]
  if (is.na(index)) {
    index <- which(match(general_collab_el$receiver, rownames(location)[i]) == 1)[1]
    location[i,1] <- general_collab_el$receiver_location[index]
  }}

# CV: power
# - extract mat and make it squaere
power <- power_mat_clean
power <- make_df_square(power)

# - remove irrelevant actors
index_remove  <- which(is.na(match(rownames(power), rownames(sonet))))
power         <- power[-c(index_remove), -c(index_remove)]

# CV: common forums of actors
# - prep DF
common_forums  <- as.data.frame(matrix(NA,
                                       nrow = dim(sonet)[1], ncol = dim(sonet)[1],
                                       dimnames = list(rownames(sonet),colnames(sonet))))

# - fill in DF with common forums of actors
for (x in rownames(sonet)) {
  for (y in rownames(sonet)) {
    net_temp <- full_net[c(x,y),node_meber == 5]
    net_temp <- net_temp[,colnames(net_temp) != "Keine_der_oben_genannten_Foren"]

    common_forums[x,y] <- sum(colSums(net_temp) == 2)
  }}

# scale values and insert zeros for NAs
common_forums_scale <- range01(t(scale(t(common_forums))))
common_forums_scale[is.na(common_forums_scale)]   <- 0

# CV: beliefs and process assessment
# - extract beliefs and process assessment and make square
process_sim_scale         <- make_df_square(process_sim_scale)
beliefs_sim_scale         <- make_df_square(beliefs_sim_scale)

# - remove irrelevant actors
index_remove <- which(is.na(match(rownames(process_sim_scale), rownames(sonet))))

process_sim_scale         <- process_sim_scale[-c(index_remove), -c(index_remove)]
beliefs_sim_scale         <- beliefs_sim_scale[-c(index_remove), -c(index_remove)]


# fill up network ----

# get length and index of individual cases
case_length <- unlist(lapply(case_codes, function(x) sum(grepl(x, rownames(sonet)))))
case_index  <- lapply(case_codes, function(x) grep(x, rownames(sonet)))

# function to fill in values for ergm network
fill_net    <- function(collab_network, edge_network, index) {

  collab_network %v% "type"             <- actor_type[index,]
  collab_network %v% "survey_group"     <- survey_group[index,]
  collab_network %v% "location"         <- location[index,]

  edge_network %e% "H1_length"          <- round(h1_length_mat, 2)[index,index]
  edge_network %e% "H2_multiplexity"    <- round(h2_multip_mat, 2)[index,index]
  edge_network %e% "H2_multiplexity_w"  <- round(h2_multip_w_mat, 2)[index,index]
  edge_network %e% "H3_homogeneity"     <- round(h3_homoge_mat, 2)[index,index]
  edge_network %e% "H3_homogeneity_w"   <- round(h3_homoge_w_mat, 2)[index,index]

  edge_network %e% "common_forum"       <- round(common_forums_scale, 2)[index,index]
  edge_network %e% "power"              <- round(power, 2)[index,index]

  edge_network %e% "process_assessment" <- round(process_sim_scale, 2)[index,index]
  edge_network %e% "beliefs"            <- round(beliefs_sim_scale, 2)[index,index]

  return(list(collab_network, edge_network))

}

# prep empty list for loop
ergm_net_case <- list()

# loop to fill in netowkr for each individual case
for (i in 1:length(case_codes)) {

  # prep DF and networks to be filled in using fill_net function
  ones_matrix_case_actors <- as.data.frame(matrix(1,
                                                  nrow = case_length[i], ncol = case_length[i],
```

```
                                                       dimnames = list(rownames(sonet)[case_index[[i]]],colnames(sonet)[case_index[[i]]]))

  collab_net_case <- as.network(as.matrix(sonet[case_index[[i]], case_index[[i]]]),
                                directed = TRUE, loops = FALSE, matrix.type = "adjacency", na.omit = T)
  edge_net_case   <- as.network(as.matrix(ones_matrix_case_actors),
                                directed = TRUE, loops = FALSE, matrix.type = "adjacency", na.omit = T)

  # function to fill in variables
  ergm_net_case[[i]] <- fill_net(collab_net_case, edge_net_case, case_index[[i]])
}


# prep data for export ----
# save full data set
data_list_net <- c("ergm_net_case", "sonet")
file_name     <- "_network_data"
file_path     <- paste("data_processed/", format(Sys.time(), "%y%m%d"), file_name, ".RData", sep = "")
save(list = data_list_net, file = file_path)




################################################################
# 02_ergm


# September, 2020

# Topic: run ERGM and store results

# set-up ----
# load packages
library(here)
library(network)
library(statnet)
library(dplyr)
library(tidyverse)
library(gridExtra)
library(RGraphics)

# load function
path_name <- paste(dirname(getwd()), "wetlands_data/data_processed/", sep = "/")
ergm_results_file <- list.files(path = path_name, pattern = "_prep_data_2_mice_complete")
session_name_file <- paste(path_name, ergm_results_file[length(ergm_results_file)], sep = "/")
load(session_name_file)

file_name <- "_network_data"
file_list <- list.files(path = "data_processed/", pattern = file_name)
name_file <- paste("data_processed/", file_list[length(file_list)], sep = "")
load(name_file)

source("utility_functions.R")

# run ergm ----

# function to run ergm and export results
run_ergm <- function(name_hypothesis, name){

  # extract networks from case
  collab_net_case <- ergm_net_case[[i]][[1]]
  edge_net_case   <- ergm_net_case[[i]][[2]]

  # select and run ergm
  if (name == "esp") {
    ergm_result <- ergm(collab_net_case~edges + mutual +
                          esp(1) +
                          edgecov(edge_net_case, name_hypothesis) +
                          edgecov(edge_net_case, "power") +
                          nodematch("location") + nodefactor("location") +
                          nodematch("survey_group") + nodefactor("survey_group") +
                          nodematch("type") + nodefactor("type"),
                        control = control.ergm(seed = 123, MCMLE.maxit = 50))
    gof_export(ergm_result, paste(name, case_codes[i], name_hypothesis, sep = "_"))
  } else if (name == "esp_H123") {
    ergm_result <- ergm(collab_net_case~edges + mutual +
                          esp(1) +
                          edgecov(edge_net_case, "H1_length") +
                          edgecov(edge_net_case, "H2_multiplexity_w") +
                          edgecov(edge_net_case, "H3_homogeneity") +
                          edgecov(edge_net_case, "power") +
                          nodematch("location") + nodefactor("location") +
                          nodematch("survey_group") + nodefactor("survey_group") +
                          nodematch("type") + nodefactor("type"),
                        control = control.ergm(seed = 123, MCMLE.maxit = 40))
    gof_export(ergm_result, paste(name, case_codes[i], name_hypothesis, sep = "_"))
  }

  # return data
  return(ergm_result)
}


# prep list that will be filled in with ergm results
# - ergm by case and hypotheses
ergm_result_list_esp <- list()
for (i in 1:length(case_codes)) {
  list_returne                <- list()
  list_returne[[1]]           <- try(run_ergm("H1_length", "esp"))
  list_returne[[2]]           <- try(run_ergm("H2_multiplexity_w", "esp"))
  list_returne[[3]]           <- try(run_ergm("H3_homogeneity", "esp"))
  ergm_result_list_esp[[i]]   <- list_returne
}

# - ergm by case  and combined hypotheses
ergm_result_list_esp_H123 <- list()
for (i in 1:length(case_codes)) {
```

```
  list_returne                    <- list()
  list_returne[[1]]               <- try(run_ergm("", "esp_H123"))
  ergm_result_list_esp_H123[[i]]  <- list_returne
}


# prep data for export ----
# save all ergm outpus
data_list_net <- c(ls())[grep("ergm_result_list", c(ls()))]
file_name     <- "_ergm_results"
file_path     <- paste("data_processed/", format(Sys.time(), "%y%m%d"), file_name, ".RData", sep = "")
save(list = data_list_net, file = file_path)


#################################################################
# 00_utility_functions


# November, 2020

# Topic: collect functions that are used in different scripts
# => all functions (should) contain short description of variables used and list of scripts they are implemented in.

# READ INSTRUCTIONS
# always run first before start working on nw_analysis to make sure all functions are loaded


rename_based_on_codebook <- Vectorize(function(input,codebook,rawvar,codevar){
  #make sure there is only one coded entry in rawvar for input
  z <- codebook[[as.character(rawvar)]] %in% as.character(input)
  numberofentries <- sum(z, na.rm = TRUE)
  if (numberofentries > 1) {
    replacement <- paste("Warning: More than one entry for","",as.character(gsub(input,pattern = ",",replacement = "")),"","in codebook")
  }
  if (numberofentries == 0) {
    replacement <- paste("No entry for", as.character(input), "in codebook")
  }
  if (numberofentries == 1) {
    replacement <- as.character(codebook[[as.character(codevar)]][codebook[[as.character(rawvar)]] %in% as.character(input)])
  }
  return(replacement)
},vectorize.args = c("input"))

save_dot <- function(graphv, filename){
  dot_output <- generate_dot(graphv)
  dot_output <- gsub("\'","\"",dot_output) #because diagrammR does this in a way atom cannot handle
  cat(dot_output,file = paste(filename))
}

get_id_for_name <- Vectorize(function(name, name_id_map){
  name_id_map$id[name_id_map$name == as.character(name)]
},vectorize.args = c("name"))

get_name_for_id <- Vectorize(function(id, name_id_map){
  if (!(as.character(id) %in% name_id_map[["id"]])) {
    return(paste(as.character(id), " not in name-id mapping"))
  }
  else {
    mapped_name <- name_id_map[["name"]][name_id_map[["id"]] == as.character(id)]
    mapped_name
  }
},vectorize.args = c("id"))

# get_name_for_id("jaja", expert_ids)



# function to work with data_processed----

# function to create adjacency matrix using the first two col from el with potential additional elements
# optimized for el from data_processed, if used with other el adaption might be needed
# data_el: edge list that can included addtional elememnts (optimized el from data_processed)
create_adjacency_matrix <- function(data_el) {

  data_el <- apply(data_el, 2, function(x) x)

  sender_receiver <- data_el[,1:2]
  sender_receiver_t <- as_tibble(sender_receiver)

  adjacency_matrix <- matrix(0,
                             nrow = length(unique(sender_receiver_t$sender)),
                             ncol = length(unique(sender_receiver_t$receiver)))

  rownames(adjacency_matrix) <- unique(sender_receiver_t$sender)
  colnames(adjacency_matrix) <- unique(sender_receiver_t$receiver)

  adjacency_matrix[sender_receiver] <- 1
  adjacency_matrix_df <- as.data.frame(adjacency_matrix)

  return(adjacency_matrix_df)
}

# function to create squared adjacency matrix
# data_df: adjacency matrix with that is not square
make_df_square <- function(data_df) {

  data_df_order_row <- match(rownames(data_df), colnames(data_df))
  data_df_order_col <- match(colnames(data_df), rownames(data_df))

  data_df_add_row   <- which(is.na(data_df_order_row))
  data_df_add_col   <- which(is.na(data_df_order_col))

  data_df_names_row <- rownames(data_df)[data_df_add_row]
  data_df_names_col <- colnames(data_df)[data_df_add_col]

  data_df_mat_col <- matrix(0, nrow = length(data_df_names_col), ncol = dim(data_df)[2])
```

```
  rownames(data_df_mat_col) <- data_df_names_col
  colnames(data_df_mat_col) <- colnames(data_df)
  data_df <- rbind(data_df, data_df_mat_col)

  data_df_mat_row <- matrix(0, nrow = length(data_df_names_row), ncol = dim(data_df)[1])
  rownames(data_df_mat_row) <- data_df_names_row
  data_df <- cbind(data_df, t(data_df_mat_row))

  data_df <- data_df[order(rownames(data_df)),order(colnames(data_df))]


  return(data_df)
}

# function to fill in partial df into larger df. larger df needs to include other df
# data_df_to_match: partial df
# ml_mat_data: full df
fill_matching_values <- function(data_df_to_match, ml_mat_data){
  # test
  # data_df_to_match  <- shortest_distance_activity_2
  # ml_mat_data       <- ml_mat_wet_activi

  for (i in 1:dim(data_df_to_match)[1]) {
    for (j in 1:dim(data_df_to_match)[2]) {
      if (data_df_to_match[i,j] == 1) {
        # find also dublicated values which are indicated by .[number] and fill in value
        # rowname_ml_mat_wet_raw  <- gsub(pattern = "\\.\\d", replacement = "", rownames(data_df_to_match)[i])
        # colnames_ml_mat_wet_raw <- gsub(pattern = "\\.\\d", replacement = "", colnames(data_df_to_match)[j])
        ml_mat_data[rownames(data_df_to_match)[i],colnames(data_df_to_match)[j]] <- 1
      }}}
  return(ml_mat_data)
}

# function to export ergm results to pdf and jpg
# ergm_result: results from ergm function
# case_name: name of case, needed to export individually named documents
gof_export <- function(ergm_result, case_name) {

  # test
  # ergm_result <- ergm_result_a
  # case_name <- "ergm_result_a"

  # run GOF
  Model_GOF   <-  gof(ergm_result, GOF = ~distance + triadcensus + espartners + dspartners + idegree + odegree + model,
                      verbose = TRUE, interval = 5e+4,
                      control = control.gof.ergm(seed = 123))

  # get text elements
  pdf_title         <- case_name
  pdf_name          <- paste("ergm/", format(Sys.time(), "%y%m%d"), "_", pdf_title, ".pdf", sep = "")
  csv_name          <- paste("ergm/", format(Sys.time(), "%y%m%d"), "_", pdf_title, ".csv", sep = "")
  jpg_name          <- paste("ergm/", format(Sys.time(), "%y%m%d"), "_", pdf_title, ".jpg", sep = "")
  network_size      <- paste("network size:", network.size(ergm_result$network))
  network_densitiy  <- paste("network density:", round(network.density(ergm_result$network),2))
  iterations_nr     <- paste("iterations:", ergm_result$iterations)

  # summarize data from ergm
  summary_df            <- data.frame(round(coef(summary(ergm_result)), digits = 2))
  summary_df_colna      <- rownames(summary_df)
  summary_df_colna      <- gsub(pattern = "nodefactor", replacement = "NF",summary_df_colna)
  summary_df_colna      <- gsub(pattern = "nodecov", replacement = "NC",summary_df_colna)
  summary_df_colna      <- gsub(pattern = "nodematch", replacement = "NM",summary_df_colna)
  summary_df_colna      <- gsub(pattern = "edgecov", replacement = "EC",summary_df_colna)

  rownames(summary_df)  <- summary_df_colna

  # start pdf
  pdf(pdf_name)
  par(mfrow = c(2,2))

  # put all information into the pdf
  # write head of ergm
  text <- str_c("\n", pdf_title, network_size, network_densitiy, iterations_nr, sep = "\n     ")
  grid.arrange(splitTextGrob(text))

  # layout pdf
  core_value <- list(padding = unit(c(10, 0.0001), "mm"))

  # write table
  grid.table(summary_df, theme = ttheme_default(base_size = 8, core = core_value))

  # plot plots => decide which one...
  plot(Model_GOF , cutoff = 15, pretty_x = TRUE, plotlogodds = TRUE)

  # close pdf
  dev.off()

  # write csv
  write.csv(summary_df, csv_name)


  # export gof seperately
  # jpeg(jpg_name, width = 1500, height = 1500)
  #
  # # Create the plot
  # par(mfrow = c(3,3))
  # plot(Model_GOF, cex.lab = 1.6, cex.axis = 1.6, plotlogodds = TRUE)

  # Close  file
  # dev.off()
}

# function to source till limited point in document
# source_name: name of source file (xxx.R)
# endTag: string specifying last line to read
sourcePartial <- function(source_name, endTag) {
```

```
  lines <- readLines(source_name)
  st    <- grep("set-up ----",lines)
  en    <- grep(endTag,lines)
  tc    <- textConnection(lines[st:en])
  source(tc, encoding = "UTF-8")
  close(tc)
}

# function to clean names_new (for now only german)
# names: array with
clean_names <- function(names) {

  # clean
  names_clean <- gsub(pattern = "Ã¼", replacement = "u", names)
  names_clean <- gsub(pattern = "Ã", replacement = "U", names_clean)
  names_clean <- gsub(pattern = "Ã¶|Ã´", replacement = "o", names_clean)
  names_clean <- gsub(pattern = "Ã", replacement = "O", names_clean)
  names_clean <- gsub(pattern = "Ã|Ã|Ã", replacement = "A", names_clean)
  names_clean <- gsub(pattern = "Ã¤|Ã¢|Ã ", replacement = "a", names_clean)
  names_clean <- gsub(pattern = "Ã©|Ã¨|Ãª", replacement = "e", names_clean)
  names_clean <- gsub(pattern = "Ã", replacement = "e", names_clean)
  names_clean <- gsub(pattern = "Ã§", replacement = "c", names_clean)
  names_clean <- gsub(pattern = "Â°", replacement = "", names_clean)
  names_clean <- gsub(pattern = "&", replacement = "und", names_clean)
  names_clean <- gsub(pattern = ",", replacement = "_", names_clean)
  names_clean <- gsub(pattern = "â", replacement = "_", names_clean)
  names_clean <- gsub(pattern = "Â«|Â»", replacement = "", names_clean)

  names_clean <- gsub(pattern = "[(]|[)]", replacement = ".", names_clean)
  names_clean <- gsub(pattern = "[+]", replacement = ".", names_clean)

  names_clean <- gsub(pattern = ".*_\\[", replacement = "", names_clean)
  names_clean <- gsub(pattern = "]", replacement = "", names_clean)
  names_clean <- gsub(pattern = "\\[\\{.*", replacement = "", names_clean)
  names_clean <- gsub(pattern = " ", replacement = "_", names_clean)
  names_clean <- gsub(pattern = " ", replacement = "_", names_clean)
  names_clean <- gsub(pattern = " ", replacement = "_", names_clean)
  names_clean <- gsub(pattern = "  ", replacement = "_", names_clean)
  names_clean <- gsub(pattern = " [/]", replacement = "/", names_clean)
  names_clean <- gsub(pattern = "[/]", replacement = "/__", names_clean)
  names_clean <- gsub(pattern = "_$", replacement = "", names_clean)
  names_clean <- gsub(pattern = "_[/]", replacement = "/", names_clean)
  names_clean <- gsub(pattern = "__", replacement = "_", names_clean)
  names_clean <- gsub(pattern = "__", replacement = "_", names_clean)
  names_clean <- gsub(pattern = "__", replacement = "_", names_clean)
  names_clean <- gsub(pattern = "^_", replacement = "", names_clean)


  # export - to GlobalEnv
  return(names_clean)
}

# function to create similarity matrix fro ergms (only with orgnames = survey_data_clean$ORGNAME_survey)
# table_to_sim: table for input in simil function
# method: similarity method
# - summary(pr_DB)
# - pr_DB$get_entry("Jaccard")
# names: row & colnames
sim_scale_mat <- function(table_to_sim, method, names) {

  table_sim <- proxy::simil(table_to_sim, method = method, by_rows = T)

  table_sim_scale                           <- scale(table_sim)
  table_sim_scale[is.na(table_sim_scale)]   <- 0

  rownames(table_sim_scale) <- names
  colnames(table_sim_scale) <- names

  return(table_sim_scale)
}

# function to create similarity matrix fro ergms (only with orgnames = survey_data_clean$ORGNAME_survey)
# table_to_sim: table with (col and) rownames
sort_df <- function(data_sort) {
  # data_sort <- power_df

  if (dim(data_sort)[1] == dim(data_sort)[2]) {
    data_sorted <- data.frame(data_sort[order(rownames(data_sort)), order(colnames(data_sort))])
  } else {
    data_sorted <- data.frame(data_sort[order(rownames(data_sort)),])
    rownames(data_sorted) <- sort(rownames(data_sort))
  }

  return(data_sorted)
}

# function for imputing
# table_to_sim: table with (col and) rownames
# - data_impute: data frame to be imputed
# - one ore multiple arrays with addtional informations (yet only with one array tested)
# (- added variable to specify imputation method)
# case_name_x: used for selection of method
impute_df <- function(data_impute, additional_informations_df, case_name_x){
  #  test
  # data_impute <- cbind(sonet_case, power_df)
  # additional_informations_df <- actor_type

  # get name
  file_name <- deparse(substitute(data_impute))

  # save names
  c_names <- colnames(data_impute)
  r_names <- rownames(data_impute)

  # ad actor type to help guessing
  data_impute <- cbind(data_impute, as.numeric(as.factor(additional_informations_df[,1])))
```

```r
  colnames(data_impute) <- c(paste("c", seq(1,length(colnames(data_impute))), sep = "_"))
  rownames(data_impute) <- c(paste("r", seq(1,length(rownames(data_impute))), sep = "_"))


  # data_to_imputex <- data_impute[-c(which(rowSums(data_to_impute, na.rm = T) == 0)),-c(which(colSums(data_to_impute, na.rm = T) == 0))]

  # impute missing data - run imputation
  # if I only need the first model then just make one
  # method meth='pmm'is standard but "norm" also works well
  mice_method <- "pmm"

  data_imputed <- mice::mice(data_impute, m = 1, maxit = 50, meth = mice_method, seed = 123)

  # clean data
  data_imp_clean <- complete(data_imputed,1)[,1:(dim(data_impute)[2] - 1)]
  colnames(data_imp_clean) <- c_names
  rownames(data_imp_clean) <- r_names

  # finish
  return(data_imp_clean)
}

# center data from 0 to 1
# - x: df to be arranged from 0 to 1
range01 <- function(x){
  (x - min(x, na.rm = T)) / (max(x, na.rm = T) - min(x, na.rm = T))
}

# reomve NA's and inf's from data fram
# - data_df: any data set
remove_na_inf <- function(data_df){
  # test
  # data_df <- H3_homog_log_scale
  # start
  data_df[is.na(data_df)]         <- 0
  data_df[is.infinite(data_df)]   <- 0

  return(data_df)
}

# create edgel list from matrix
# - mat_to_el: matrix or data frame with 0/1
make_el <- function(mat_to_el){
  edge_list           <- data.table::CJ(rownames(mat_to_el), colnames(mat_to_el),unique = TRUE)
  colnames(edge_list) <- c("sender","receiver")
  edge_list$value     <- apply(edge_list,1,function(x) mat_to_el[x[1],x[2]])
  edge_list           <- edge_list[edge_list$value == 1,c(1,2)]

  return(edge_list)
}


# get mode from vector
# - v: vector
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}
```