BARG Bayesian Analysis Report for: The network embedding of effective actors in Swiss wetlands governance

Mario Angst University of Zurich, Digital Society Initiative
Martin Huber Eawag aquatic research, University of Bern

Bayesian Analysis Reporting Guidelines (BARG) list of key reporting points closely following Kruschke [1] for the manuscript titled "The network embedding of effective actors in Swiss wetlands governance". We include points and steps not applicable in order to be transparent about what we deemed not applicable. The requirements of step 6 (Reproducibility) are not addressed in detail as they are addressed in an online repository accessible at https://github.com/marioangst/effective_navigation_public.

BARG Step 1. Explain the model

A. Data variables. Explain the dependent (predicted) variables

We use a survey item where actors were asked on a four-point Likert scale whether they strongly agreed, agreed, disagreed or strongly disagreed with the statement "my organization is involved in decisions that have an impact on [name of the case] to a satisfactory degree" (exact German wording: "Stimmen Sie den folgenden Aussagen zu? a) Meine Organisation ist in Entscheidungen, die die [Name Fallstudie] betreffen, genügend einbezogen").

All variable distributions: Figure 1

All collaboration networks are plotted in Figure 2 .

To measure *bonding* ties per actor, we use the number of closed triads an actor is involved in their non-negative collaboration network.

To measure *bridging* ties per actor, we rely on a local measurement of betweenness centrality in each actor's collaboration network. We calculate betweenness for each actor based on their so-called ego network of order two (thus based on a network subset including all network contacts and their connections up to two contacts removed - collaborators of collaborators), using all types of ties.

We measure an actor's generalized *power* over the governance process in each case by relying on the assessment of all other surveyed actors in the case. Actors were asked to indicate for all other actors in the case (including actors they did not collaborate with) whether they considered them influential in terms of governance outcomes. We used the number of times an actor was indicated as powerful by others to generate an individual score for ascribed power for each actor.

We normalize bonding, bridging and ascribed power by case. This accounts for the fact that absolute numbers of triad counts, local betweenness and ascribed power by other members of the network are not directly comparable between cases as they may depend on the size and properties of the collaboration networks in each case. As essentially all of this measures are counts and strictly non-negative, we also log-transform them.

Across all ten cases, we identified a total of 12 overarching wetlands governance issues through exploratory expert interviews with 2-3 experts per case. Not all issues were relevant for each case, given bio-physical differences and differing usage patterns. For example, forestry and timber harvesting were only relevant in one specific case. Thus, not all issues appeared in every survey.

- We measure the *top priority issue for each actor* based on a survey question, where respondents were asked to rate how important issues were to them in a survey item that asked them to rank issues in order based on the question: "which goals in [case study name] are most important to your organization?" (exact German wording: "Welche Ziele an der [Name Fallstudie] sind für Ihre Organisation besonders wichtig? Ordnen Sie die untenstehenden Ziele so, dass das wichtigste Ziel zuoberst steht").
- In order to assess how actors evaluate the *status of their top priority* issue we utilize information form a survey item that asked respondents to indicate how they rated the current state of goal achievement for each wetlands governance issue present in a given case on a three point scale ranging from "goal achieved", over "neutral" to "goal not achieved (exact German wording: "Unten sehen Sie mögliche Ziele für die Auengebiete an der [Name Fallstudie]. Wie gut werden diese Ziele Ihrer Meinung nach erreicht?")

Previous research on governance networks has shown repeatedly that different types of actors face very different opportunities and constraints in their ability to influence outcomes and processes of governance [2, 3, 4, 5]. Given this, we included actor type as an actor attribute manually coded by the researchers involved in data gathering, combining the jurisdictional level and societal sector of an actor to arrive at four main types of actors relevant for wetlands governance in our case. These were local-level municipalities, higher-level governmental agencies, local and higher-level non-governmental organizations as well as a "other" category including mostly local companies and service providers.

B. Likelihood function and parameters. For every model, explain the likelihood function and all the parameters, distinguishing clearly between parameters of primary theoretical interest and ancillary parameters. If the model is multilevel, be sure that the hierarchical structure is clearly explained, along with any covariance structure if multivariate parameter distributions are used

This is provided in the main text.

C. Prior distribution. For every model, explain and justify the prior distribution of the parameters in the model

We used weakly informative normal(0,5) priors for all τ and β parameters [6]. For the monotonic effect used in β_7, we relied on the `brms` default dirichlet(1) prior, assuming equal probability of increases in categories for all categories. For the varying intercept α parameters, we also used the relatively uninformative `brms` default student-t(3,0,2.5) priors.

Figure 3 contains prior and posterior predictive checks of the model. These show that the priors used are indeed very weakly informative. Before being updated with empirical data, the model fails absolutely in predicting the empirically observed outcome. After being updated, it achieves a very high predictive performance, indicating that the data contains enough information to overwhelm the prior completely.

Two variables we use contained missing values. First, 14.3% of respondents (n = 50) did not provide an answer with regard to our main outcome variable, satisfaction with inclusion in the governance process. We excluded these respondents from the analysis (row-wise deletion). Additionally, 23.4% did either not choose a top priority issue or not assess the status of the issue. We imputed values for these respondents (if they were not deleted in the first step, leading to n = 56 imputed values) before model fitting using 20 multiple imputations in `mice` [7]. In comparison to a model where row-wise deletion was applied instead, results did not change drastically (the main results plot 4 is reproduced for a model without imputations in figure 4).

D. Formal specification. Include a formal specification (mathematical or computer code) of the likelihood and prior, located either in the main text or in in publicly and persistently accessible online supplementary information

The linear predictor is reported in the main text. Computer code is accessible in open online repository under `https://github.com/marioangst/effective_navigation_public`

E. Prior predictive check. Especially when using informed priors but even with broad priors, it is valuable to report a prior predictive check to demonstrate that the prior really generates simulated data consistent with the assumed prior knowledge

Figure 3

BARG Step 2. Report details of the computation

A. Software. Report the software used, including any specific added packages or plugins

We fit all models in the `R`[8] package `brms`[9, 10].

B. MCMC chain convergence. Report evidence that the chains have converged, using a convergence statistic such as PSRF, for every parameter or derived value

We fit models Markov Chain Monte Carlo (MCMC) to derive the posterior distribution, using 4 chains with 2000 iterations and a burn-in of 1000. $\widehat{R}$ values were consistently one for all parameters, indicating that chains converged successfully.

C. MCMC chain resolution. Report evidence that the chains have high resolution, using the ESS, for every parameter or derived value

Tail effective sample size (ESS) was well above the recommended 400 [11] for all parameters and is reported in table 1.

D. If not MCMC

not applicable

BARG Step 3. Describe the posterior distribution

A. Posterior predictive check. Provide a posterior predictive check to show that the model usefully mimics the data.

See figure 3

B. Summarize posterior of variables. For continuous parameters, derived variables and predicted values, report the central tendency and limits of the credible interval. Explicitly state whether you are using density-based values (mode and HDI) or quantile-based values (median and ETI), and state the mass of the credible interval (for example, 95%)

See Figures 5, 6, 7, 8 and 9 show posterior distributions of the primary parameters of the model (parameter groups τ, α and β).

C. BF and posterior model probabilities

not applicable

BARG Step 4. Report decisions (if any) and their criteria

not applicable

BARG Step 5. Report sensitivity analysis

A. For broad priors. If the prior is intended to be vague or only mildly informed so that it has minimal influence on the posterior, show that other vague priors produce similar posterior results

The posterior is not sensitive to alternative prior specifications. Introducing variation in prior settings by both making weakly informative priors broader or more restrictive, as well as for introducing variation to default prior settings does not fundamentally alter the posterior distribution of parameters (Figure 10).

B. For informed priors

not applicable

C. For default priors. If using a default prior, show the effect of varying its settings. Be sure that the range of default priors constitutes theoretically meaningful priors, and consider whether they mimic plausible empirically informed priors.

Figure 10

D. BFs and model probabilites

not applicable

E. Decisions

not applicable

BARG Step 6. Make it reproducible

All modeling steps can be replicated using data and code provided in the open online repository https://github.com/marioangst/effective_navigation_public.

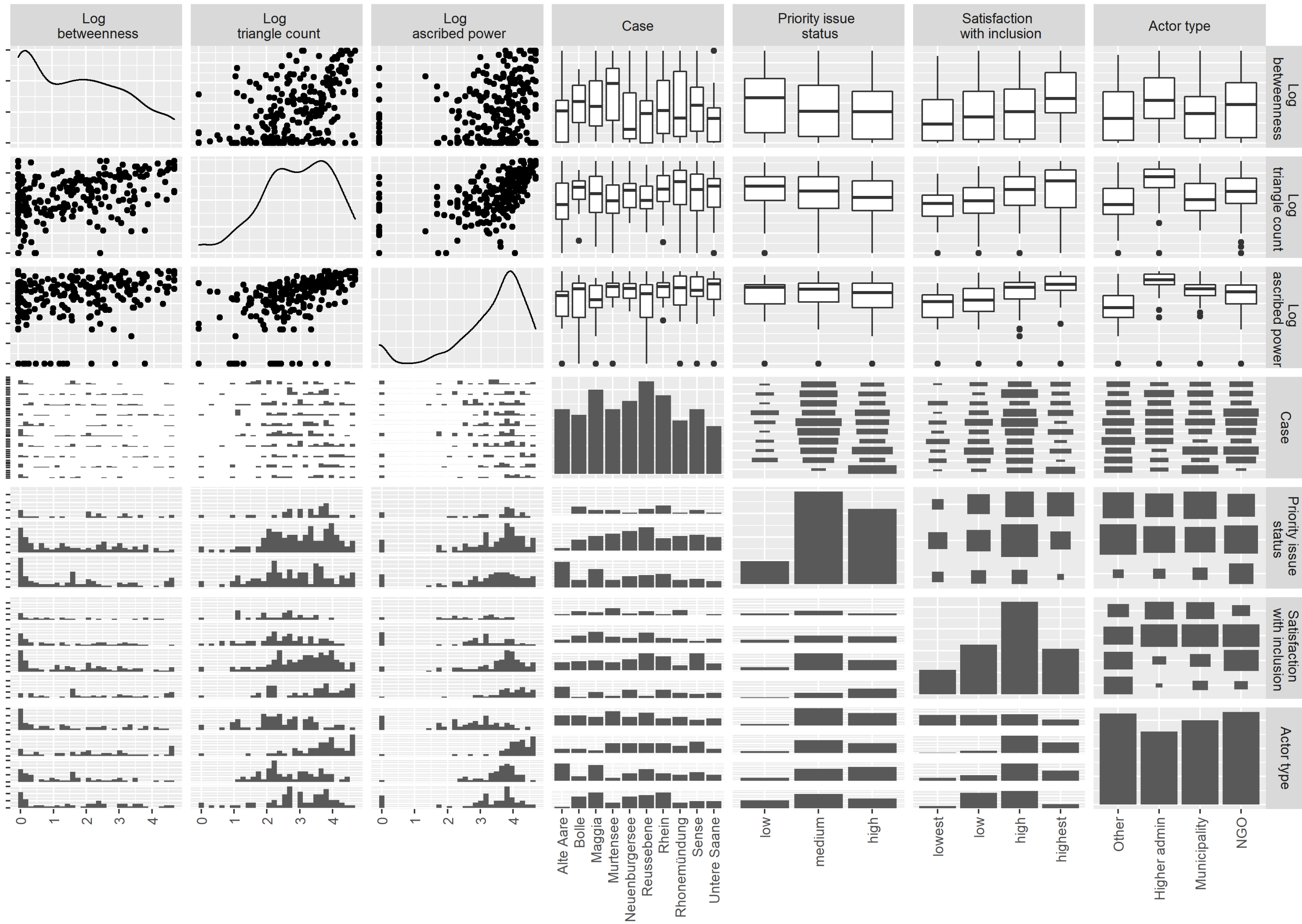

Figure 1: Distributions (diagonal) and pairwise interactions (off diagonal) for all variables used in modeling. Only complete cases (n = 243) are shown.

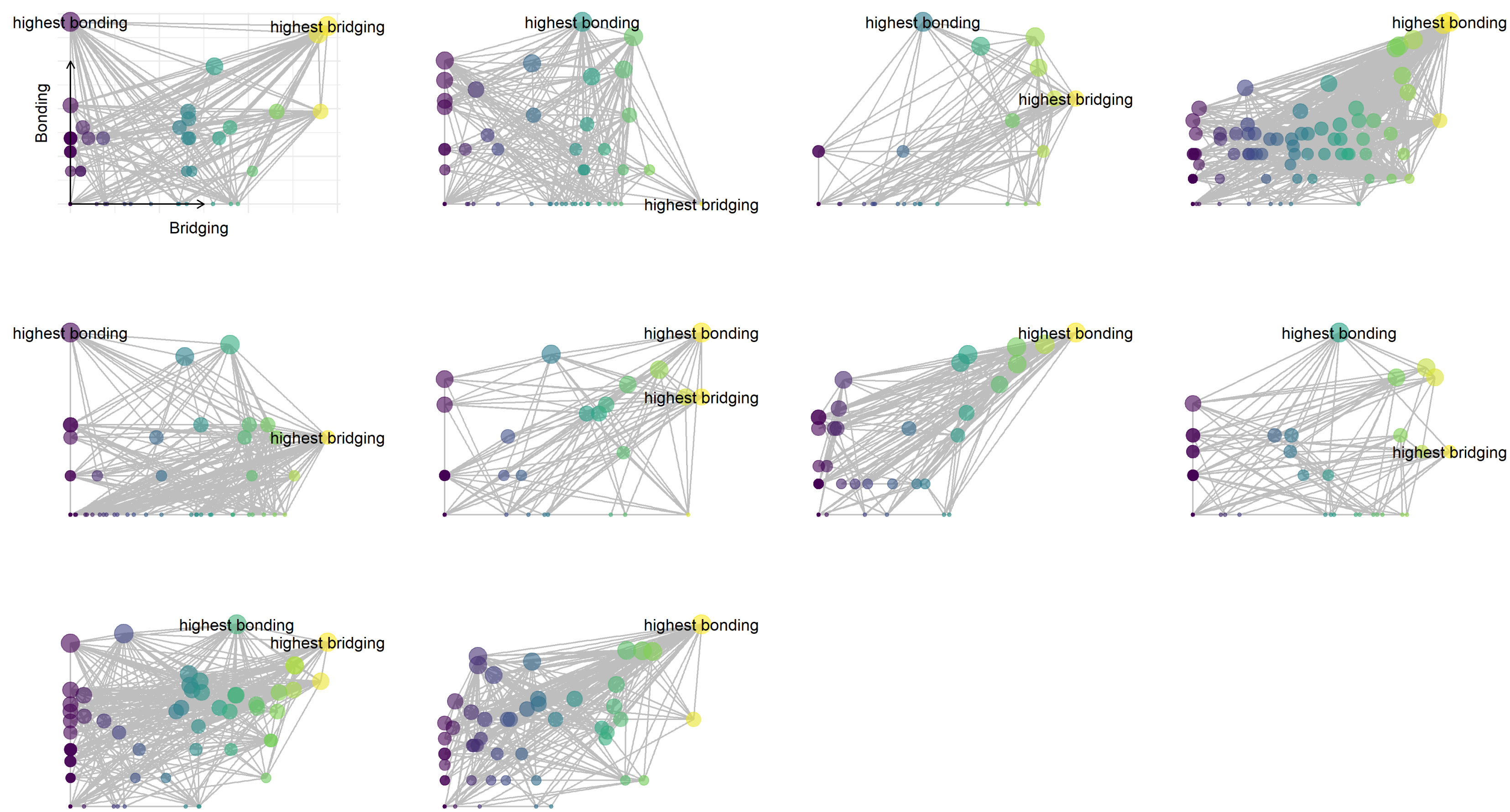

Figure 2: Network plots of collaboration networks across all ten cases with functional structure in terms of bridging versus bonding social capital emphasized in node placement. Isolates not shown. If only highest bonding is labeled, highest bonding equals highest bridging in the case. The size of nodes relates to bonding social capital measured as log-scaled triangle count. The color of nodes relates to bridging social capital as log-scaled betweenness in an actor's ego network of order 2.

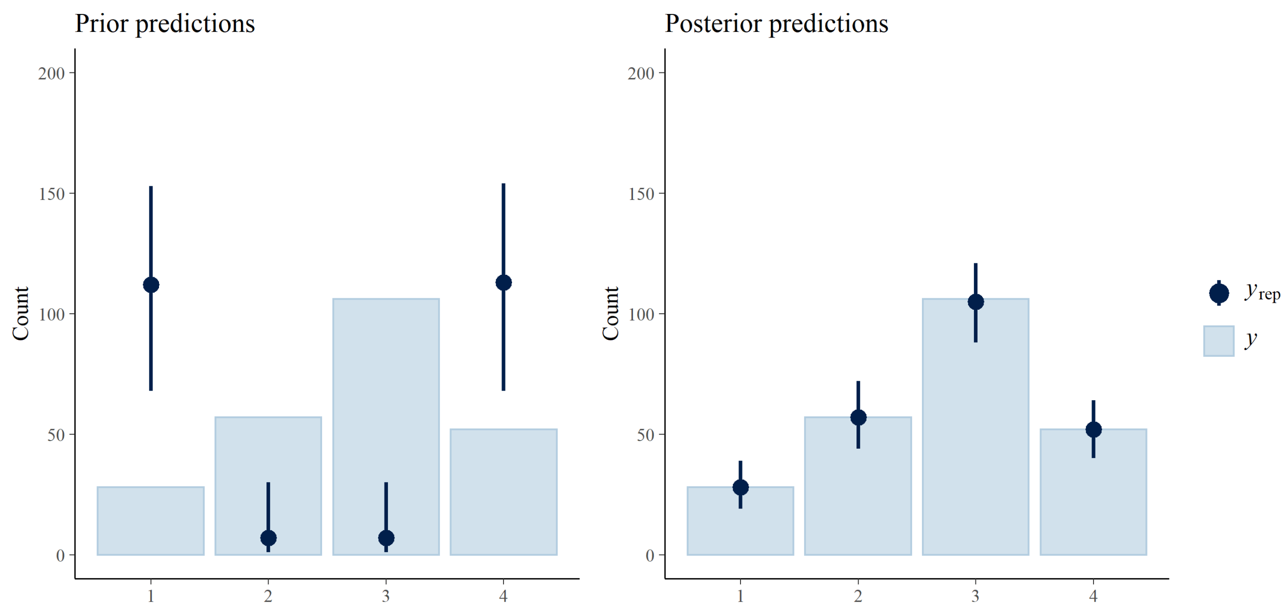

Figure 3: Prior (left panel) vs posterior predictions (right panel) of regression model (y_{rep}) versus empirical distribution y of outcome categories.

Parameter	Tail ESS
CDF threshold 1	25485
CDF threshold 2	19110
CDF threshold 3	20677
Log betweenness	49073
Log triangle count	48529
Log ascribed power	45167
Actor type: municipality	58232
Actor type: NGO	46689
Actor type: Other	58935
Betweenness x Triangle count interaction	55492
Betweenness x Power interaction	47166
Triangle count x Power interaction	45172
Status of priority goal (monotonic predictor)	1896

Table 1: Tail effective sample size for main model parameters

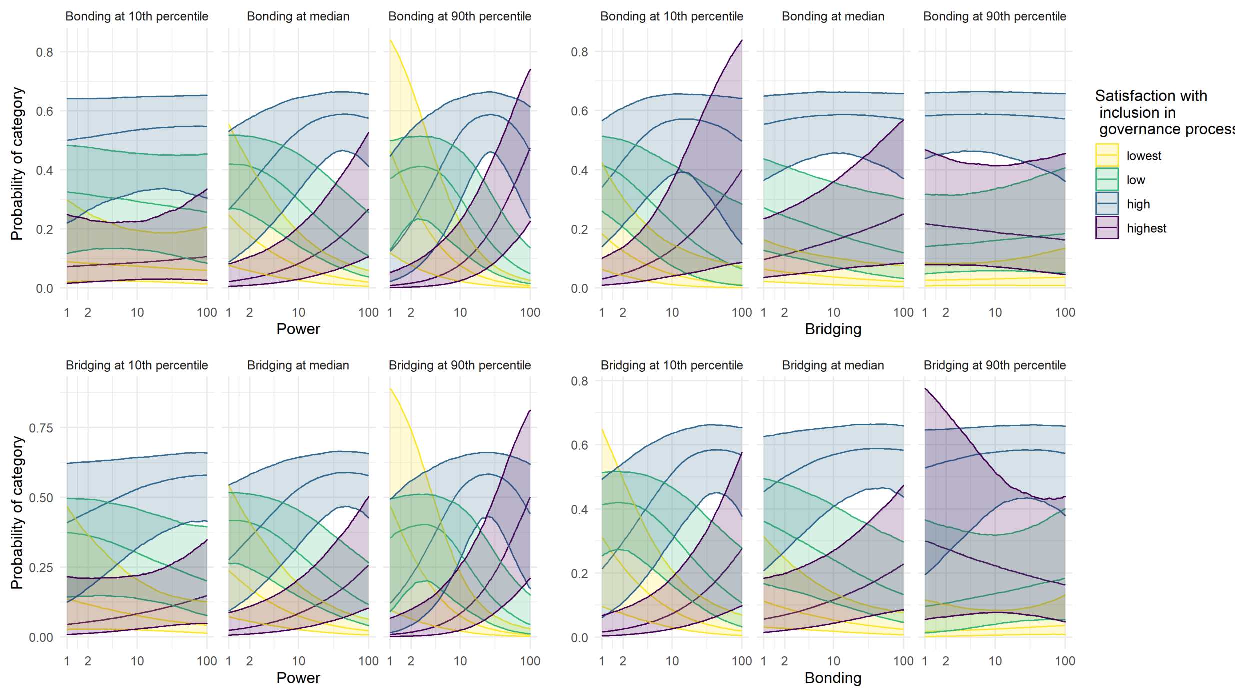

Figure 4: Conditional effects of power, bonding and bridging on effectiveness of individual actors, measured as their satisfaction with inclusion in the governance process *for model without imputation*.
Plots show posterior predictions from multi-level ordinal regression modeling at the population level (marginalized over levels). Solid lines within ribbons show the median posterior density. Ribbons indicate the 88% credibility interval. As the model used is an ordinal regression model, predictions are given in the form of combinations of predicted probabilities for each outcome category for each combination of variables. These probabilities are indicated by color.
Reading example, using the middle panel of the top left plot: For a value of actor power of 10 (x axis), with bonding held at its median value (middle panel), the mean probability (solid line within ribbon) of the actor falling within the "highest" (first) category in terms of satisfaction with their inclusion in the governance process (violet line) is roughly 10% (y axis) while it is slightly above 50% for the "high" (second) category (blue line).
For predictions, the predictor of interest (x axis, all log scaled) was varied over the whole empirically observed range. To show pairwise interactions, this procedure was repeated three times for low, median and high values of a second predictor of interest (indicated in the panel titles). All other variables were held at mean (for metric) or most common (for non-metric) values.

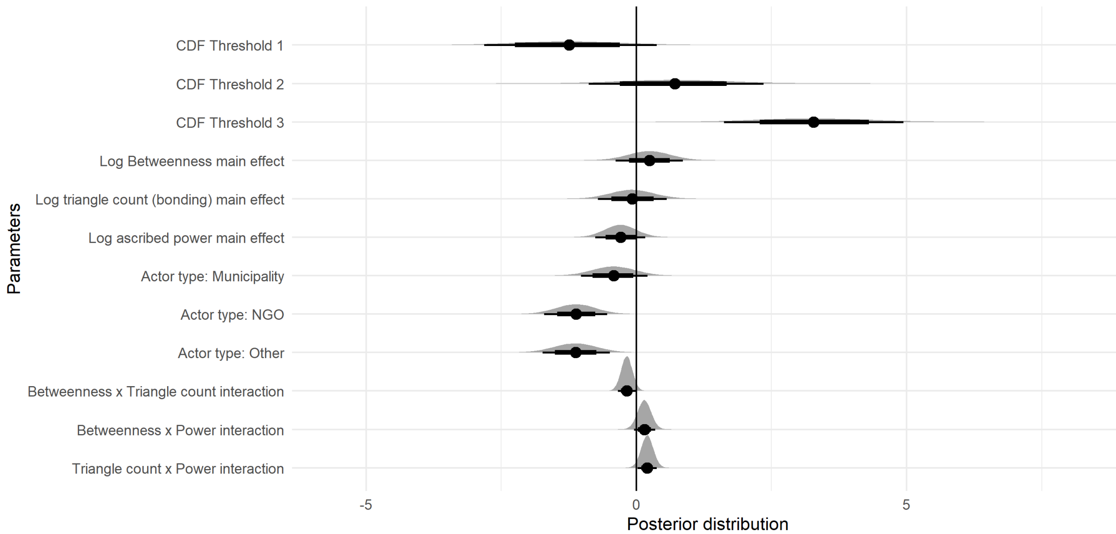

Figure 5: Posterior distribution of β and τ_k (CDF threshold) parameters. The highest posterior density intervals are shown. Point estimates (dots) are medians. Thick horizontal bars indicate 66% credible intervals, thin horizontal lines indicate 88% credible intervals.

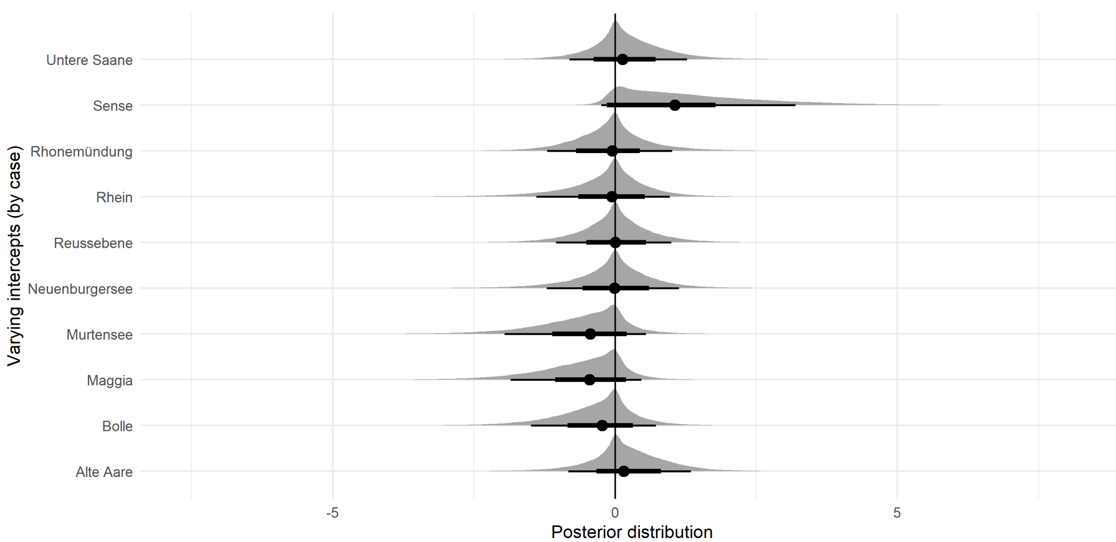

Figure 6: Posterior distribution of $\alpha_{1[\text{case}]}$, varying intercepts parameters by case. The highest posterior density intervals are shown. Point estimates (dots) are medians. Thick horizontal bars indicate 66% credible intervals, thin horizontal lines indicate 88% credible intervals.

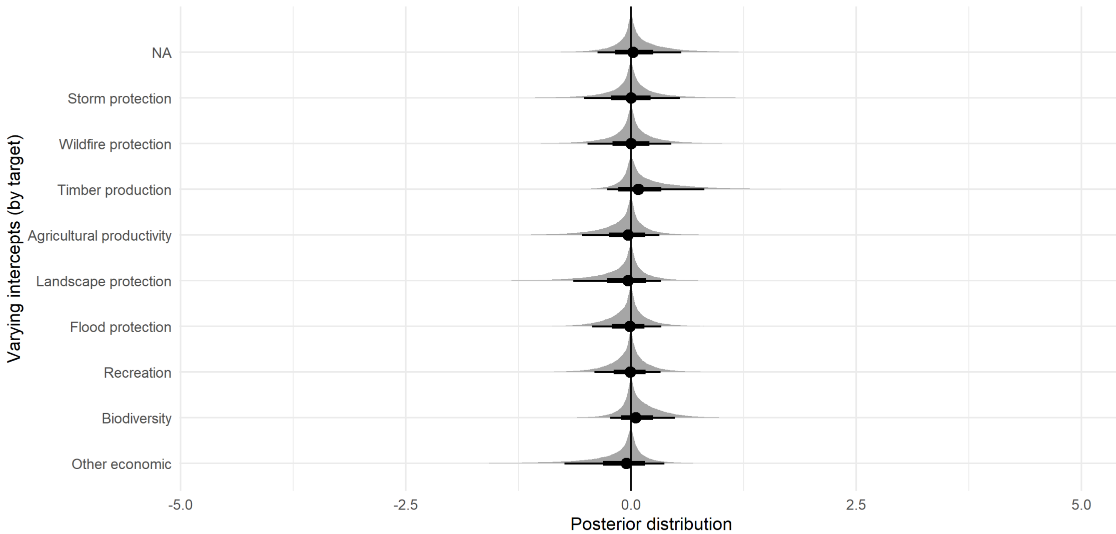

Figure 7: Posterior distribution of $\alpha_{2[\text{issue}]}$, varying intercepts parameters by case. The highest posterior density intervals are shown. Point estimates (dots) are medians. Thick horizontal bars indicate 66% credible intervals, thin horizontal lines indicate 88% credible intervals.

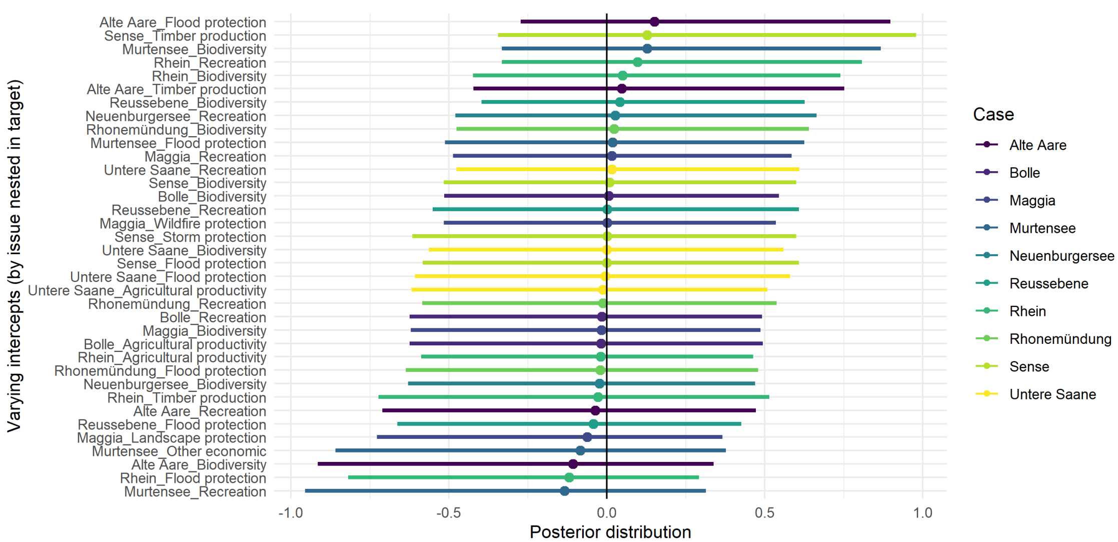

Figure 8: Posterior distribution of $\alpha_{3[\text{case,issue}]}$, varying intercepts parameters by issue nested within case. The highest posterior density intervals are shown. Point estimates (dots) are medians. Thick horizontal bars indicate 88% credible intervals.

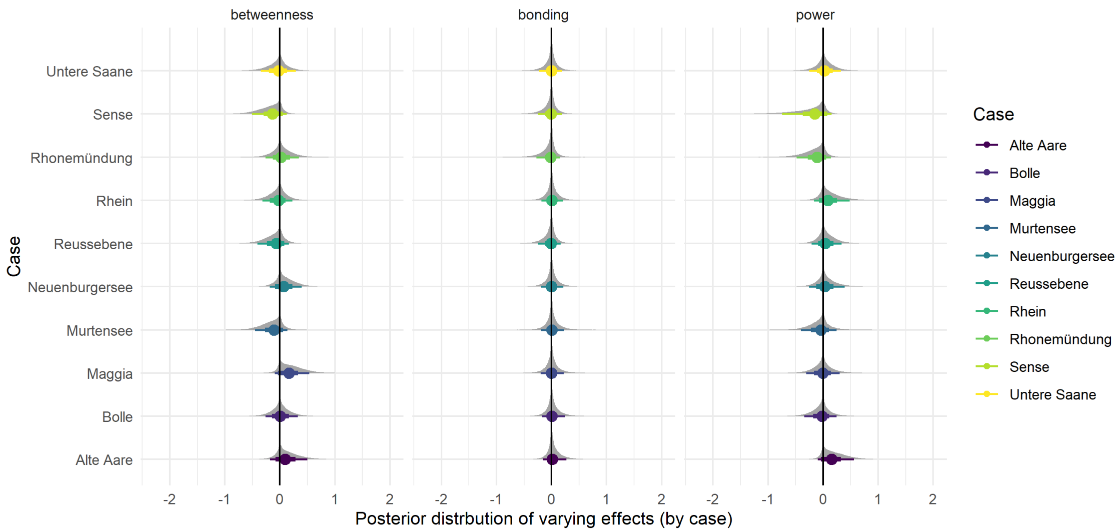

Figure 9: Posterior distribution of varying slopes parameters for the the three main variables of theoretical interest (bonding as log triangle count, bridging as log betweenness and log ascribed power) by case. The highest posterior density intervals are shown. Point estimates (dots) are medians. Thick horizontal bars indicate 66% credible intervals, thin horizontal lines indicate 88% credible intervals.

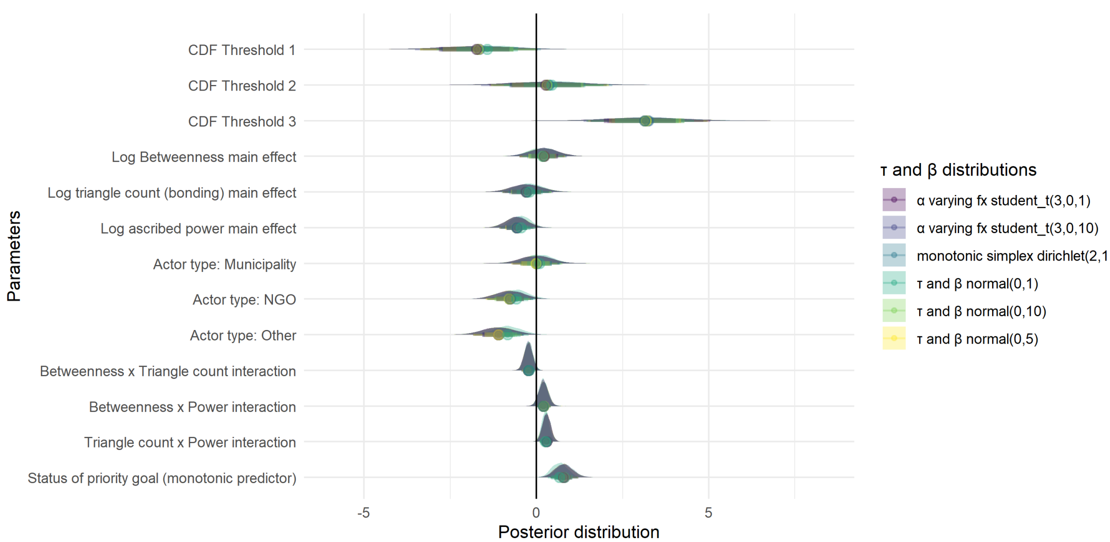

Figure 10: Sensitivity of posterior distribution of β and τ_k parameters to different prior settings. Variation was introduced both by making weakly informative priors for β and τ more restrictive or broader and by introducing variation on default parameters for the dirichlet distribution on the monotonic effect simplex parameter and for the student-t distribution on the varying intercept and slopes parameters of the multi-level model. The highest posterior density intervals are shown. Point estimates (dots) are medians. Thick horizontal bars indicate 66% credible intervals, thin horizontal lines indicate 88% credible intervals. Sensitivity was assessed on a model without imputation for computational efficiency.

References

[1] John K. Kruschke. “Bayesian Analysis Reporting Guidelines”. In: *Nature Human Behaviour* 5 (10) (2021), pp. 1282–1291.

[2] Adrienne Héritier and Dirk Lehmkuhl. “Introduction: The Shadow of Hierarchy and New Modes of Governance”. In: *Journal of Public Policy* 28 (1) (2008), pp. 1–17.

[3] Stuart Kininmonth, Arvid Bergsten, and Örjan Bodin. “Closing the collaborative gap: Aligning social and ecological connectivity for better management of interconnected wetlands”. In: *AMBIO* 44 (1) (2015), pp. 138–148.

[4] J. M. Fliervoet et al. “Analyzing Collaborative Governance Through Social Network Analysis: A Case Study of River Management Along the Waal River in The Netherlands”. In: *Environmental Management* 57 (2) (2016), pp. 355–367.

[5] Mario Angst et al. “Connectors and Coordinators in Natural Resource Governance: Insights from Swiss Water Supply”. In: *Ecology and Society* 23 (2) (2018), p. 1.

[6] Andrew Gelman et al. “A Weakly Informative Default Prior Distribution for Logistic and Other Regression Models”. In: *Annals of Applied Statistics* 2 (4) (2008), pp. 1360–1383.

[7] Stef van Buuren and Karin Groothuis-Oudshoorn. “mice: Multivariate Imputation by Chained Equations in R”. In: *Journal of Statistical Software* 45 (3) (2011), pp. 1–67.

[8] R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria, 2021.

[9] Paul-Christian Bürkner. “Advanced Bayesian Multilevel Modeling with the R Package brms”. In: *The R Journal* 10 (1) (2018), pp. 395–411.

[10] Paul-Christian Bürkner. “brms: An R Package for Bayesian Multilevel Models Using Stan”. In: *Journal of Statistical Software* 80 (1) (2017), pp. 1–28.

[11] Aki Vehtari et al. “Rank-Normalization, Folding, and Localization: An Improved $\widehat{R}$ for Assessing Convergence of MCMC (with Discussion)”. In: *Bayesian Analysis* 16 (2) (2021), pp. 667 –718.