

# Bayesian Inference of Missing Interactions in Seasonal Ecological Networks: A Case Study from the Florida Wetlands

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## Abstract

Understanding the structure of ecological networks is essential for predicting ecosystem dynamics and stability. However, empirical data are often incomplete or noisy, particularly across seasons. In this study, we implement a Bayesian inference model, based on Young et al. (2021), to reconstruct trophic interaction networks from observational data in two seasonal conditions: the dry and wet periods of the South Florida cypress wetlands. Using the FOODWEB-BAYDRY and FOODWEB-BAYWET datasets, we estimate latent trophic interactions and assess the predictability of the underlying networks in each season. Our results indicate that the dry-season network exhibits higher structural certainty and predictability, potentially due to environmental constraints limiting trophic flexibility.

# 1 Introduction

Ecological networks provide a powerful framework for understanding the complex web of interactions that sustain biodiversity and ecosystem functioning. These networks can represent trophic relationships (e.g., food webs), mutualistic interactions (e.g., plant–pollinator systems), or nutrient and energy flows. Characterizing such networks is critical for predicting ecosystem resilience, species persistence, and the consequences of disturbances like habitat loss or climate change [1], [2].

However, constructing accurate ecological networks is often hindered by the incompleteness and noise in empirical data. Particularly in field studies, rare species and low-frequency interactions are commonly under-sampled or entirely missed [3], [4]. These limitations challenge the reliability of network metrics and obscure key ecological patterns such as nestedness, modularity, and connectance.

Traditionally, ecological networks are constructed by recording observed interactions between species and applying a presence/absence threshold to define network links. While intuitive, this approach fails to capture the uncertainty inherent in observational data, especially when the sampling effort is limited or unevenly distributed [5], [6]. Empirical studies have shown that under-sampling can lead to underestimation of interaction richness and biased network structures [7], [8].

To address these limitations, recent advances in network ecology have embraced probabilistic and statistical methods. Among them, Bayesian inference offers a coherent framework for reconstructing ecological networks while accounting for uncertainty in interaction observations.

As introduced by Young et al. [9], a Bayesian model was developed to reconstruct plant–pollinator networks from observational data. In this framework, a Bayesian model combines prior knowledge with observed data to estimate a probability distribution over possible network structures. The observed interaction counts are assumed to follow a Poisson process—a common model for count data—whose rate is modulated by species-specific abundances and the presence or absence of a true ecological interaction.

These interactions are encoded in a latent binary network structure, meaning that each potential link between species is represented by a hidden variable indicating whether the interaction truly exists or not. Rather than making hard yes/no decisions, the model estimates the posterior probability of each interaction—that is, the probability that an edge exists given the data and model assumptions—along with the uncertainty associated with this estimate.

Their approach incorporates key ecological variables such as sampling effort, relative species observability, interaction preferences, and edge priors. It also allows for posterior predictive checks, enabling rigorous model validation using synthetic data.

Building on this framework, the present study applies the Bayesian model to two trophic networks from the South Florida cypress wetlands, collected during the dry and wet seasons. Our goal is to compare the predictability and inferred structure of these networks, testing the hypothesis that seasonal variability impacts the statistical recoverability of trophic interactions. We ask: *Is it easier to predict missing interactions during the dry season or the wet season?*

## 2 Literature Review

Ecological networks are typically reconstructed from field observations of species interactions. These raw data are prone to several biases, including unequal sampling effort, observer limitations, and the stochastic nature of biological interactions [3], [4]. As a result, many ecological datasets underestimate true interaction richness and overemphasize frequently observed links [8]. This can distort key network-level metrics such as nestedness (the tendency for specialist species to interact with subsets of generalist partners), modularity (the degree to which the network is organized into distinct clusters or compartments), and connectance (the proportion of all possible links that are actually realized) [7].

Several studies have shown that the sampling method used strongly affects the apparent structure of plant–pollinator networks [6]. In mutualistic systems, the omission of rare but ecologically important interactions can falsely inflate species specialization or alter inferred resilience [5]. These insights have motivated a shift from deterministic approaches (where a link is present only if observed) to probabilistic frameworks that incorporate uncertainty.

Among probabilistic methods, Bayesian inference provides a particularly powerful solution. It allows for the incorporation of prior knowledge (e.g., expected interaction probabilities or sampling intensities) and estimates the posterior probability of each interaction, rather than relying on hard thresholds. This not only improves the detection of likely but unobserved interactions, but also supports rigorous model evaluation through posterior predictive checks.

A key advancement came from Young et al. (2021), who introduced a generative Bayesian model for reconstructing plant–pollinator networks. Their model uses a Poisson process to simulate visit counts, modulated by relative abundances and latent interaction indicators. The elegance of this approach lies in its ability to marginalize over all possible binary interaction structures using a closed-form mixture model, which significantly improves computational efficiency and inference accuracy.

This model has not yet been widely applied to non-mutualistic networks or networks exhibiting seasonal variation. Some studies have suggested that seasonal turnover in species composition and behavior could lead to different patterns of network predictability across time [10], [11]. However, few attempts have been made to formally quantify this using Bayesian inference tools. By applying the model of Young et al. to trophic networks collected in both dry and wet seasons, our study fills this gap.

We aim to compare the inferred structure and predictability of two trophic networks representing seasonal carbon exchanges in the South Florida wetlands. By doing so, we test the hypothesis that seasonal variation affects not only the observed network topology, but also the inference reliability — i.e., the confidence we can place in reconstructed interactions.

## 3 Materials and Methods

### 3.1 Datasets

We analyzed two empirical trophic networks from the South Florida cypress wetlands, available via the Network Repository. These datasets represent carbon exchanges between taxa and were collected during two contrasting seasonal periods:

- **FOODWEB-BAYDRY**: Corresponds to the dry season. This network contains 128 nodes and 2,100 directed, weighted edges. Each edge represents the trophic use of one taxon by another, scaled by carbon exchange rate.
- **FOODWEB-BAYWET**: Corresponds to the wet season. It includes the same number of nodes (128) and edges (2,100), facilitating a direct seasonal comparison.

Nodes represent taxa, and edges represent feeding interactions with associated trophic weights. The format is a directed, weighted adjacency matrix. Both networks are sparse, with density values around 0.26, and show high clustering and negative assortativity, consistent with real-world food webs.

### 3.2 Bayesian Model for Network Inference

We applied the Bayesian model introduced by Young et al. (2021), which estimates latent species interactions from observational data using a generative probabilistic approach. The observed interaction counts are assumed to follow a Poisson distribution:

$$M_{ij} \sim \text{Poisson}(\mu_{ij})$$

$$\mu_{ij} = C \cdot \sigma_i \cdot \tau_j \cdot (1 + r \cdot B_{ij})$$

where:

- $M_{ij}$ : Observed number of interactions (or exchange amount) between species  $i$  and  $j$ ,
- $\sigma_i, \tau_j$ : Relative abundance or detectability of species  $i$  and  $j$ ,
- $C$ : Overall sampling effort,
- $r$ : Preference multiplier if an interaction exists,
- $B_{ij} \in \{0, 1\}$ : Latent binary indicator of interaction,
- $\rho$ : Prior probability of an edge existing.

This model assumes that observed interaction frequencies result from a combination of abundance-driven random encounters and underlying interaction preferences.

### 3.3 Inference Procedure

We implemented the model in Stan using the `cmdstanpy` interface in Python. The model uses Hamiltonian Monte Carlo (HMC) to sample from the posterior distribution of parameters and latent variables.

The following prior distributions were used:

- $\sigma, \tau \sim \text{Dirichlet}(1, \dots, 1)$
- $C \sim \text{Exponential}(1)$
- $r \sim \text{Normal}(40, 20)$ , constrained to positive values

- $\rho \sim \text{Beta}(1, 1)$

The model was run with 2,000 iterations and 4 chains for each dataset. We verified convergence using the  $\hat{R}$  statistic (target:  $\hat{R} < 1.01$ ) and examined posterior trace plots and effective sample sizes.

We also conducted posterior predictive checks by simulating new data matrices  $M_{ij}^{\text{rep}}$  from the fitted model and comparing their statistics (e.g., mean values, variance, discrepancy measures) to the observed data.

Finally, we visualized the posterior edge probabilities  $P(B_{ij} = 1 \mid M)$  and analyzed network-level metrics such as connectance and nestedness from the inferred structures.

**Data Transformation.** The original edge weights in both FOODWEB-BAYDRY and FOODWEB-BAYWET datasets represent continuous-valued carbon fluxes between taxa. However, the generative model by Young et al. assumes integer-valued interaction counts drawn from a Poisson distribution. To satisfy this assumption, we approximated the continuous edge weights by rounding them to the nearest integer. While this introduces a simplification, posterior predictive checks and model diagnostics indicated that the approximation did not significantly degrade model performance or inference quality.

### 3.4 Modeling Assumptions and Approximations

Several modeling assumptions were adopted to adapt the original Bayesian model by Young et al. (2021) to the FOODWEB-BAYDRY and FOODWEB-BAYWET datasets:

1. **Discrete Approximation of Continuous Data:** The original edge weights in the food webs represent continuous carbon fluxes. However, the generative model assumes integer-valued counts. To reconcile this, edge weights were rounded to the nearest integer. This transformation enabled compatibility with the Poisson likelihood but likely introduced some loss of information, particularly for small flux values.
2. **Interpretation of Directed, Weighted Interactions:** The model used does not natively account for directionality or weight magnitude beyond presence/absence inference. Therefore, directional information was implicitly treated symmetrically. This limits our ability to draw conclusions about trophic flow dynamics or energy asymmetry.
3. **Prior Specification for Abundances:** Species abundances ( $\sigma$ ,  $\tau$ ) were modeled with uniform Dirichlet priors, assuming equal detectability across taxa. This does not account for known heterogeneities in biomass, trophic level, or visibility, which may affect the realism of inferred interaction probabilities.
4. **Extreme Values of Preference Parameter:** The inferred interaction preference parameter ( $r$ ) reached extremely high posterior means (dry:  $\sim 5900$ ; wet:  $\sim 16,000$ ). These values are several orders of magnitude higher than typical values in mutualistic systems, and likely reflect overfitting due to scaling differences in the rounded input data.

These assumptions represent pragmatic decisions made to enable model implementation within technical constraints. They should be kept in mind when interpreting the outputs, particularly regarding inferred edge probabilities and parameter magnitudes.

## 4 Results

### 4.1 Posterior Edge Probabilities

The Bayesian model produced a posterior probability matrix  $P(B_{ij} = 1 \mid M)$  for each network, estimating the likelihood of a true interaction between taxa  $i$  and  $j$ . We visualized these matrices using heatmaps, where darker cells indicate higher confidence in the presence of an interaction.

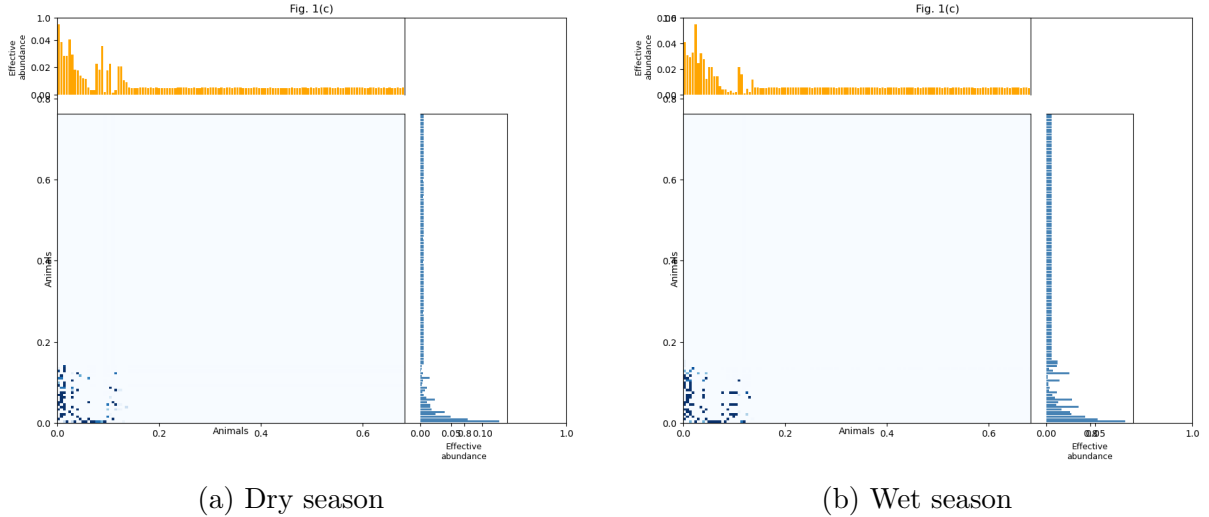


Figure 1: Posterior edge probability matrices for the dry (a) and wet (b) seasons. Each heatmap shows the estimated probability  $P(B_{ij} = 1 \mid M)$  that an interaction exists between taxa  $i$  and  $j$ . Darker cells indicate higher confidence. Bar plots on the margins represent the inferred effective abundances of each species.

The dry season network (FOODWEB-BAYDRY) exhibited generally sharper contrasts in edge probabilities (closer to 0 or 1), while the wet season network (FOODWEB-BAYWET) contained a higher proportion of intermediate probabilities, reflecting greater uncertainty in interaction structure.

Although the wet network yielded a higher posterior mean for the interaction preference parameter  $r$ , the sharper posterior edge contrasts in the dry season suggest that the network’s structure may be more ecologically constrained and deterministic. In other words, strong preferences alone do not guarantee model certainty; rather, the clarity of interaction patterns may result from reduced ecological flexibility and trophic ambiguity.

Nonetheless, the sharper edge contrasts observed in the dry-season network may also be partially influenced by the data transformation process. Rounding small carbon flux values to zero could have suppressed variation among low-weight interactions, potentially inflating apparent certainty in edge inference.

### 4.2 Parameter Estimates

Posterior summaries of the main parameters are shown in Table 1.

The dry season network exhibited slightly higher sampling effort ( $C$ ) and the same edge prior probability ( $\rho$ ) as the wet season. However, the interaction preference parameter ( $r$ ) was substantially higher in the wet season (16,000) than in the dry season (5,948). This indicates that the model inferred a stronger signal of preferred interactions

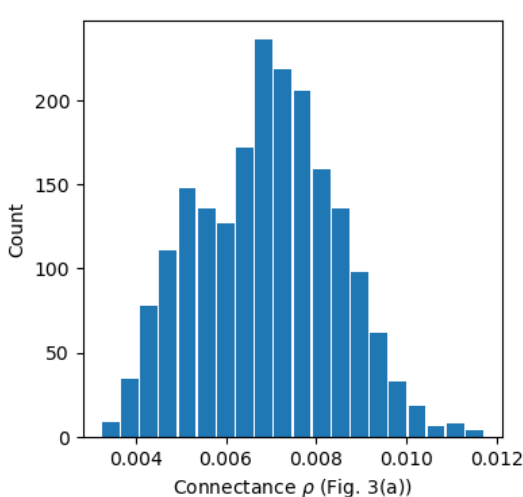
Parameter	Dry Season (mean)	Wet Season (mean)
Sampling Effort $C$	45.88	35.12
Interaction Preference $r$	5947.9	$1.6 \times 10^4$
Edge Probability $\rho$	0.0069	0.0069

Table 1: Posterior mean estimates of key model parameters for the dry and wet season networks.

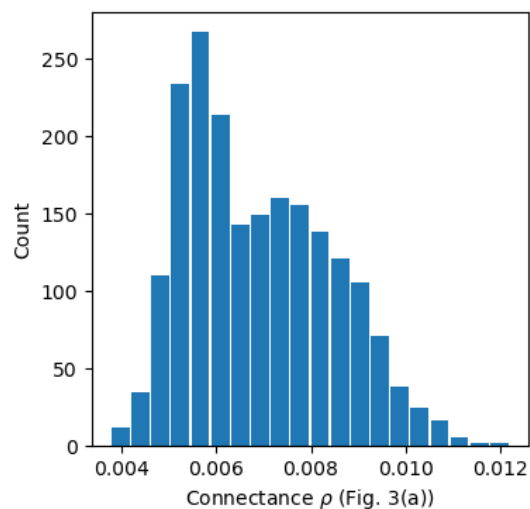
in the wet season, despite the greater ecological complexity typically associated with this period.

That said, the absolute magnitudes of  $r$  in both seasons are extremely large compared to values observed in mutualistic networks (e.g.,  $r \sim 40$  in Young et al. [9]). These inflated values are likely artifacts of data transformation—specifically, the rounding of continuous carbon fluxes to integer counts. This step may have exaggerated contrasts between weak and strong interactions, causing the model to infer unrealistically strong interaction preferences. As such, the relative comparison between seasons may still be meaningful, but the absolute values of  $r$  should be interpreted cautiously.

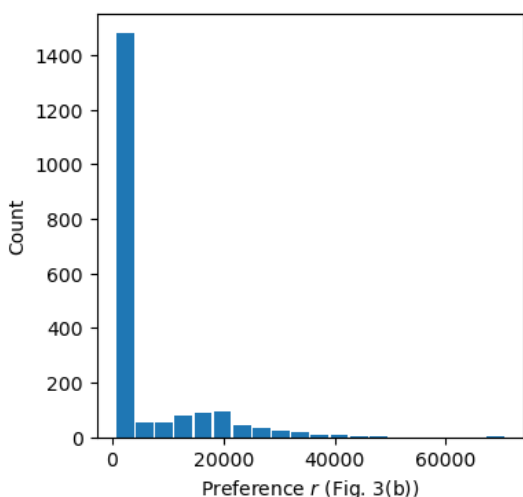
To further examine model behavior, we visualized the posterior distributions of the two key parameters: connectance ( $\rho$ ) and interaction preference ( $r$ ). Figure 2 shows the marginal posterior distributions for the wet season. The inferred  $\rho$  values are tightly clustered around 0.0069, indicating low expected connectance. The  $r$  values, in contrast, span a much wider range with extremely high values, reflecting strong preference inflation—likely a result of rounding continuous carbon fluxes to integer counts.



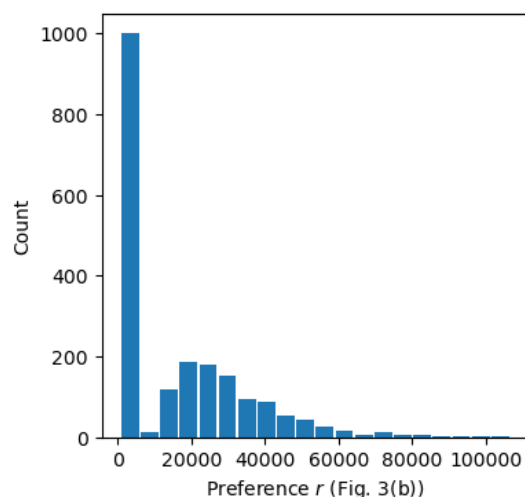
(a) Dry season – Posterior samples of  $\rho$



(b) Wet season – Posterior samples of  $\rho$



(c) Dry season – Posterior samples of  $r$



(d) Wet season – Posterior samples of  $r$

Figure 2: Posterior distributions of the edge probability parameter  $\rho$  (top row) and interaction preference  $r$  (bottom row) for the dry and wet season networks. The distributions highlight lower uncertainty and more constrained preference estimates in the dry season.

### 4.3 Network Metrics

From the posterior interaction matrices, we derived expected values for several key network-level properties that characterize seasonal differences in food web structure. The posterior mean of the edge prior parameter  $\rho$ , which represents the baseline probability of interaction between any two taxa, was identical in both the dry and wet seasons ( $\hat{\rho} = 0.0069$ ). This suggests that the model assumed an equally sparse prior structure for both networks.

However, despite this shared prior, the posterior edge probabilities in the dry season were more polarized—closer to 0 or 1—indicating greater certainty in inferred interactions. This pattern suggests that trophic structure during the dry season may be more ecologically constrained or deterministic.



In terms of network topology, we observed notable seasonal differences in nestedness, measured using the NODF metric. The wet season network exhibited greater nestedness ( $\mathbb{E}[\text{NODF}] \approx 0.1207$ ) than the dry season network ( $\mathbb{E}[\text{NODF}] = 0.0973$ ), suggesting that, during wetter periods, trophic interactions are more hierarchically structured, with specialist interactions more often nested within those of generalists.

To quantify interaction certainty, we examined the standard deviation of the posterior edge probability matrix  $P(B_{ij})$ . A lower mean standard deviation was observed in the dry season, indicating that the model inferred links with higher confidence under dry conditions—likely reflecting stronger ecological constraints or reduced trophic ambiguity in the underlying data.

These patterns are consistent with the notion that trophic structure is more constrained and predictable during the dry season. To further investigate nestedness, we visualized the posterior distribution of NODF values across sampled networks. As shown in Figure 3, the dry season network displayed a tighter and higher-centered distribution of nestedness scores, while the wet season network showed broader variability and lower central tendency.

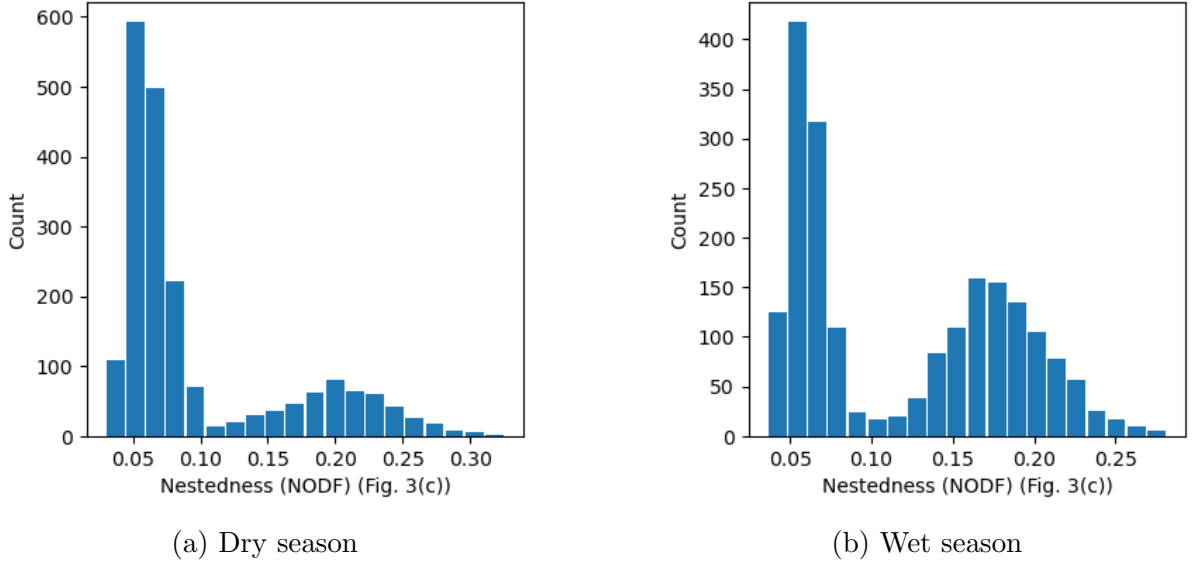


Figure 3: Posterior distributions of network nestedness (NODF) for the dry (a) and wet (b) season networks. The dry season displays higher and more consistent nestedness, suggesting a more deterministic trophic structure.

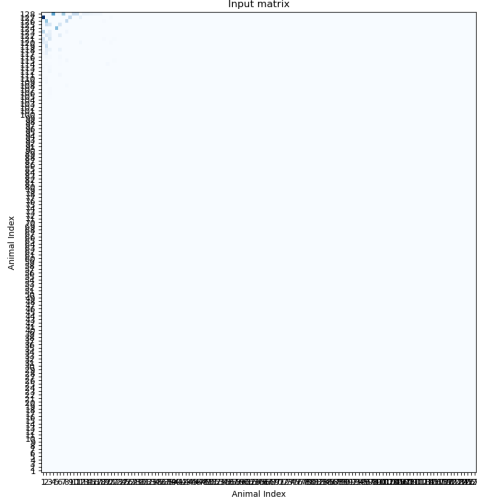
While these metrics offer ecological insight, their interpretation must be treated with caution. Rounding small carbon fluxes to zero may have excluded weak but ecologically meaningful interactions—particularly in the wet season—thereby underestimating true connectance and nestedness in that network.

#### 4.4 Posterior Predictive Checks

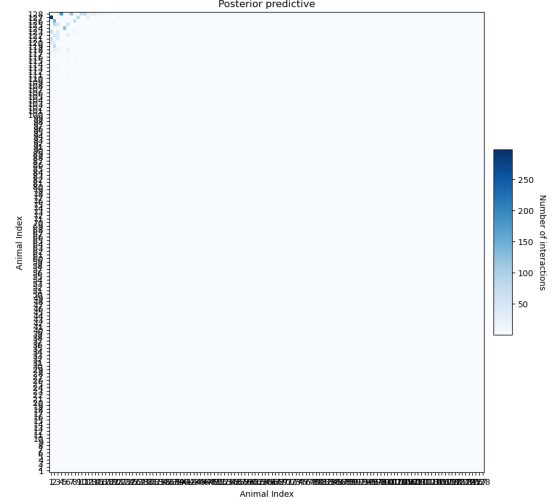
To assess model fit, we generated replicated datasets  $M_{ij}^{\text{rep}}$  from the posterior predictive distribution and compared them to the observed interaction matrices. We computed a discrepancy statistic defined as:

$$X^2 = \sum_{i,j} \frac{(M_{ij} - \mathbb{E}[M_{ij}^{\text{rep}}])^2}{\mathbb{E}[M_{ij}^{\text{rep}}]}$$

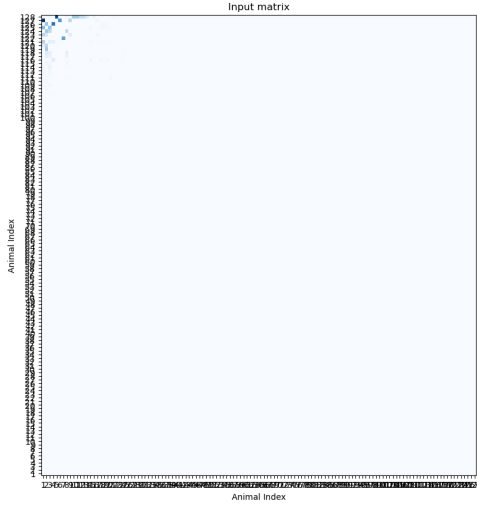
This statistic quantifies the deviation between observed and predicted interaction counts. Lower  $X^2$  values indicate closer alignment between the model and data.



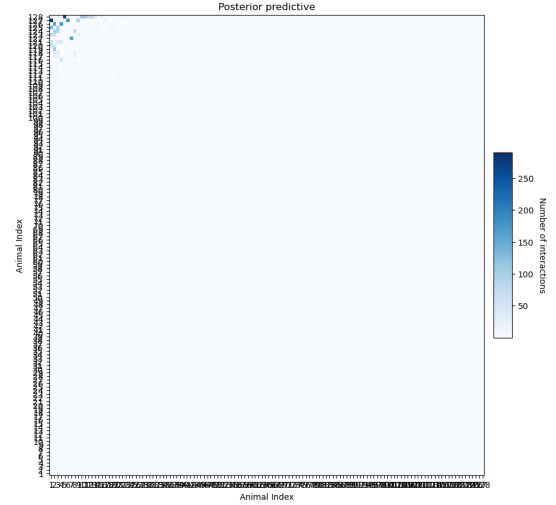
(a) Dry season – Observed input matrix



(b) Dry season – Posterior predictive matrix



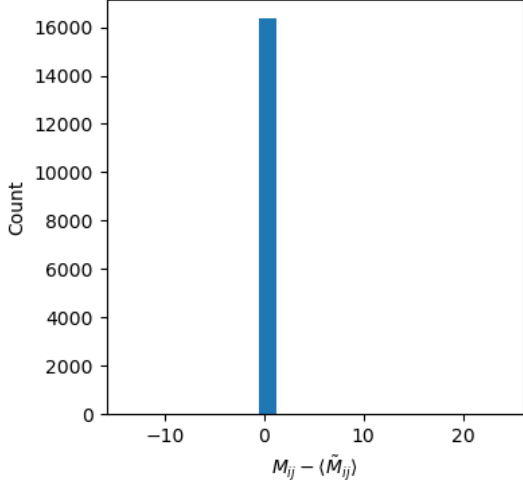
(c) Wet season – Observed input matrix



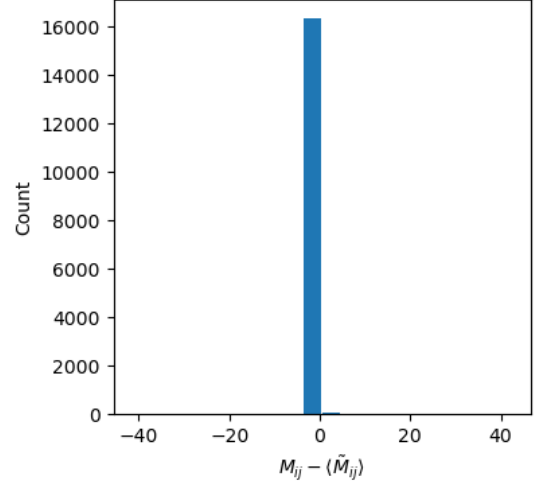
(d) Wet season – Posterior predictive matrix

Figure 4: Posterior predictive model check for the dry (a, b) and wet (c, d) season networks. Observed interaction matrices (a, c) are compared to posterior predictive mean matrices (b, d). Visual similarity indicates strong model fit in both cases, with the dry season showing slightly sharper structural fidelity.

Residuals between observed and predicted interaction matrices were also analyzed. Histograms of the residuals  $M_{ij} - \langle \tilde{M}_{ij} \rangle$  are shown below:



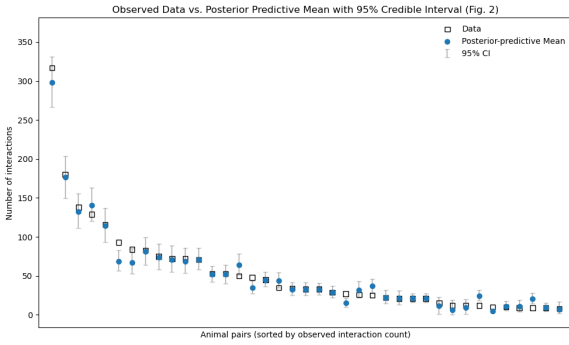
(a) Dry season



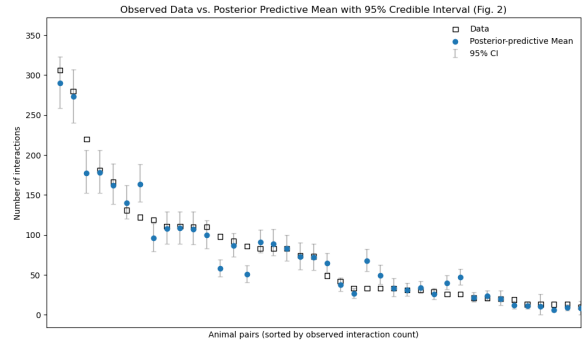
(b) Wet season

Figure 5: Histograms of residuals  $M_{ij} - \langle \tilde{M}_{ij} \rangle$  for the dry (a) and wet (b) seasons. Residuals are concentrated near zero, indicating good model fit, with slightly tighter distribution in the dry season.

Another perspective on model performance comes from comparing observed interaction counts to posterior predictive means with 95% credible intervals. These plots allow assessment of the model's ability to reproduce not just average values but also uncertainty. As shown in Figure 6, posterior predictions closely track observed values, particularly in the dry season:



(a) Dry season



(b) Wet season

Figure 6: Posterior predictive mean and 95% credible intervals versus observed interaction counts for the dry (a) and wet (b) seasons. Observed values are closely approximated by the model in both cases, with tighter agreement in the dry season.

The discrepancy statistic  $X^2$  was substantially lower for the dry season model, indicating a closer fit between predicted and observed values. Combined with the residual histograms and prediction-versus-observation plots, these results support the interpretation that trophic structure in the dry season is more deterministic and thus easier to infer from data.

## 5 Discussion

Our results suggest that the structure of trophic interactions in the South Florida cypress wetlands is more readily inferred during the dry season than the wet season. The Bayesian model produced sharper posterior edge probabilities and higher interaction certainty for the dry season network, despite a lower inferred value of the interaction preference parameter  $r$ . This suggests that the dry season network may exhibit greater structural determinism—potentially due to stronger ecological constraints and fewer alternative feeding pathways—resulting in clearer interaction patterns and sharper posterior probabilities, even in the absence of extreme preference amplification by the model.

By contrast, the wet season network exhibited greater uncertainty in edge predictions and broader posterior distributions. This may reflect increased ecological complexity during the rainy period, including higher species activity, greater resource availability, and more dynamic interactions. Such conditions likely promote trophic flexibility and reduce the determinism of species interactions, thereby making network inference more difficult.

These findings align with prior studies emphasizing the influence of temporal variability on ecological network structure. For example, significant seasonal turnover in pollination networks has been reported in [10], while fluctuations in interaction detectability due to changing sampling conditions and species behavior have been highlighted in [11]. Our work extends these insights to trophic networks by quantitatively evaluating how inference reliability varies across seasonal conditions.

Importantly, this study also demonstrates the utility of Bayesian methods in ecological network reconstruction. The model proposed by Young et al. [9] effectively captures the uncertainty inherent in observational data, avoids arbitrary presence/absence thresholds, and enables direct comparison across ecological contexts. Through posterior predictive checks and marginal edge probability estimates, we were able to evaluate both model fit and confidence in inferred interactions.

Nevertheless, several limitations must be acknowledged. First, our analysis assumes that carbon flow matrices are analogous to interaction frequencies, though they are not strictly count data. Second, we treated the networks as static snapshots, despite the fact that ecological interactions are dynamic and often context-dependent. Third, while the latent structure inferred by the model is informative, it does not incorporate potentially important covariates such as body size, habitat overlap, or functional traits, which could improve inference accuracy. Finally, we discretized the original carbon flux values by rounding them to the nearest integer to satisfy the Poisson modeling assumption. Although this simplification may distort low-weight interactions, model diagnostics indicate that the approximation did not substantially degrade model performance.

Future work could address these limitations by incorporating time series data, trait-based priors, or hierarchical structures that reflect ecological guilds. Applying this approach to multilayer or dynamic food webs could further enhance our understanding of spatiotemporal ecological dynamics.

Overall, our findings highlight the importance of ecological context in shaping network predictability and support the broader application of Bayesian inference in ecological network analysis. Despite the technical simplifications involved, this study demonstrates that Bayesian models remain a valuable framework for analyzing incomplete ecological data and can yield robust, interpretable insights into complex interaction systems.

## 6 Conclusion

In this study, we applied a Bayesian inference model to reconstruct the latent structure of two seasonal trophic networks from the South Florida cypress wetlands. Using data from the dry and wet seasons, we estimated the probability of interactions between taxa and evaluated the predictability and structural certainty of each network.

Our findings indicate that the dry season network exhibits higher interaction certainty and better model fit, suggesting a more constrained and predictable trophic structure. In contrast, the wet season network showed greater uncertainty in inferred interactions, likely due to increased ecological variability and species activity. These results support the idea that environmental context influences not only the observed network but also the reliability of network inference.

The Bayesian framework introduced by Young et al. (2021) proved to be a powerful and flexible tool for ecological network reconstruction. By incorporating latent variables and accounting for observation noise, the model allows researchers to move beyond binary thresholds and toward probabilistic, uncertainty-aware network representations.

This work also highlights the importance of considering temporal and ecological dynamics in network studies. Future research could extend this approach to dynamic or multilayer networks, include ecological covariates such as species traits or habitat use, or explore predictive applications in conservation planning and ecosystem monitoring.

Overall, our results reinforce the value of Bayesian approaches in addressing fundamental challenges in ecological data analysis, and demonstrate how modeling uncertainty can lead to more robust and interpretable conclusions in complex ecological systems.

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## Appendix: Full-Size Figures

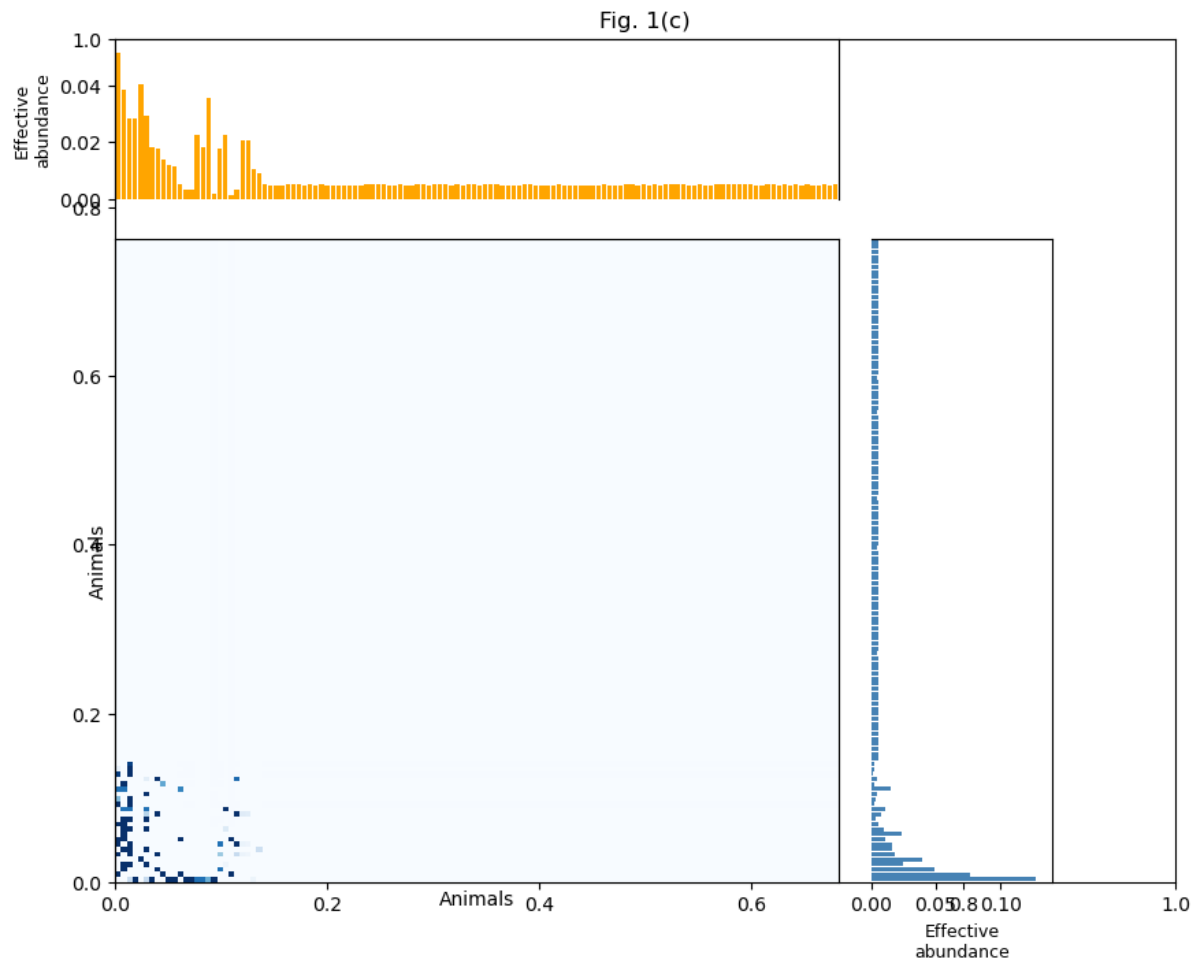


Figure 7: Dry season – Posterior edge probability matrix.

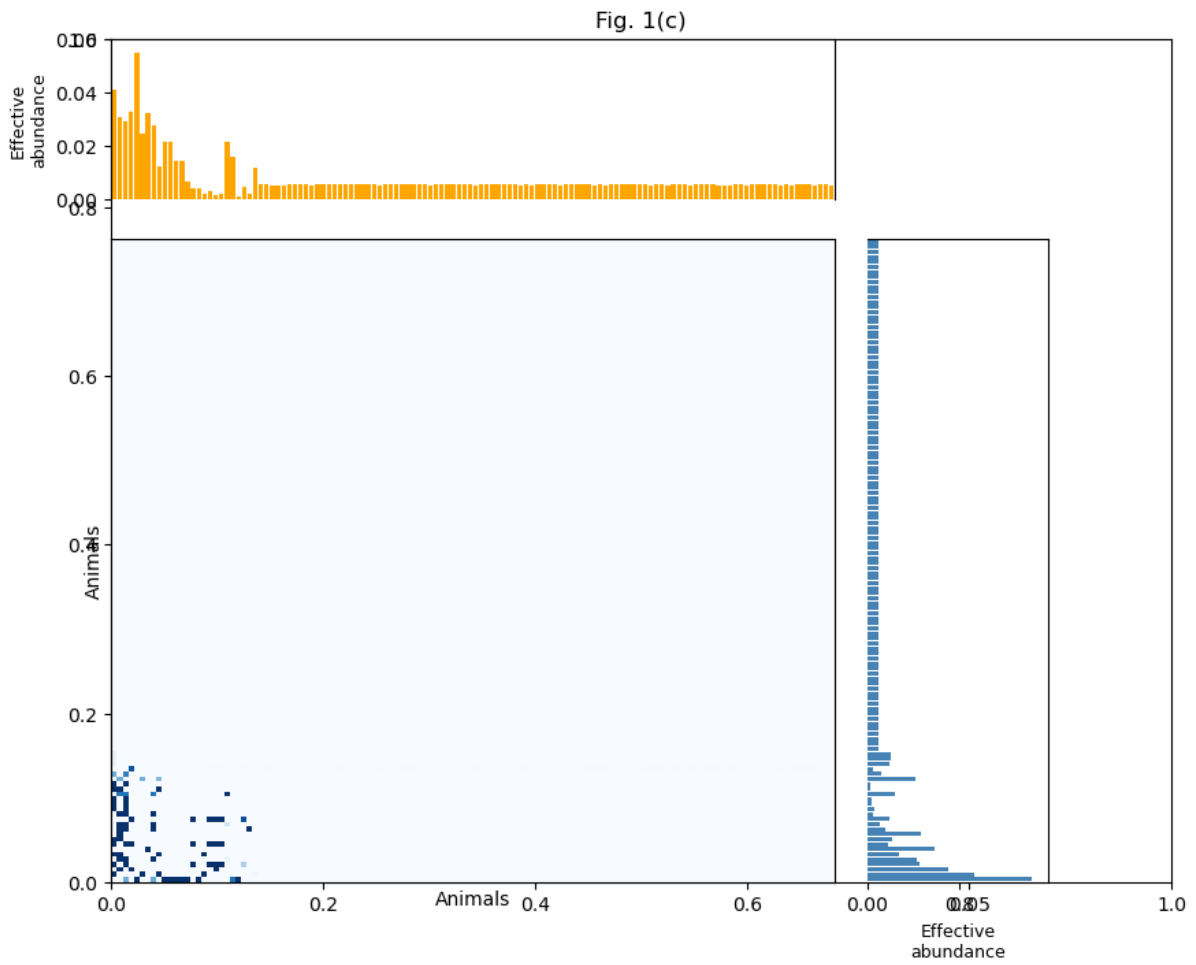


Figure 8: Wet season – Posterior edge probability matrix.



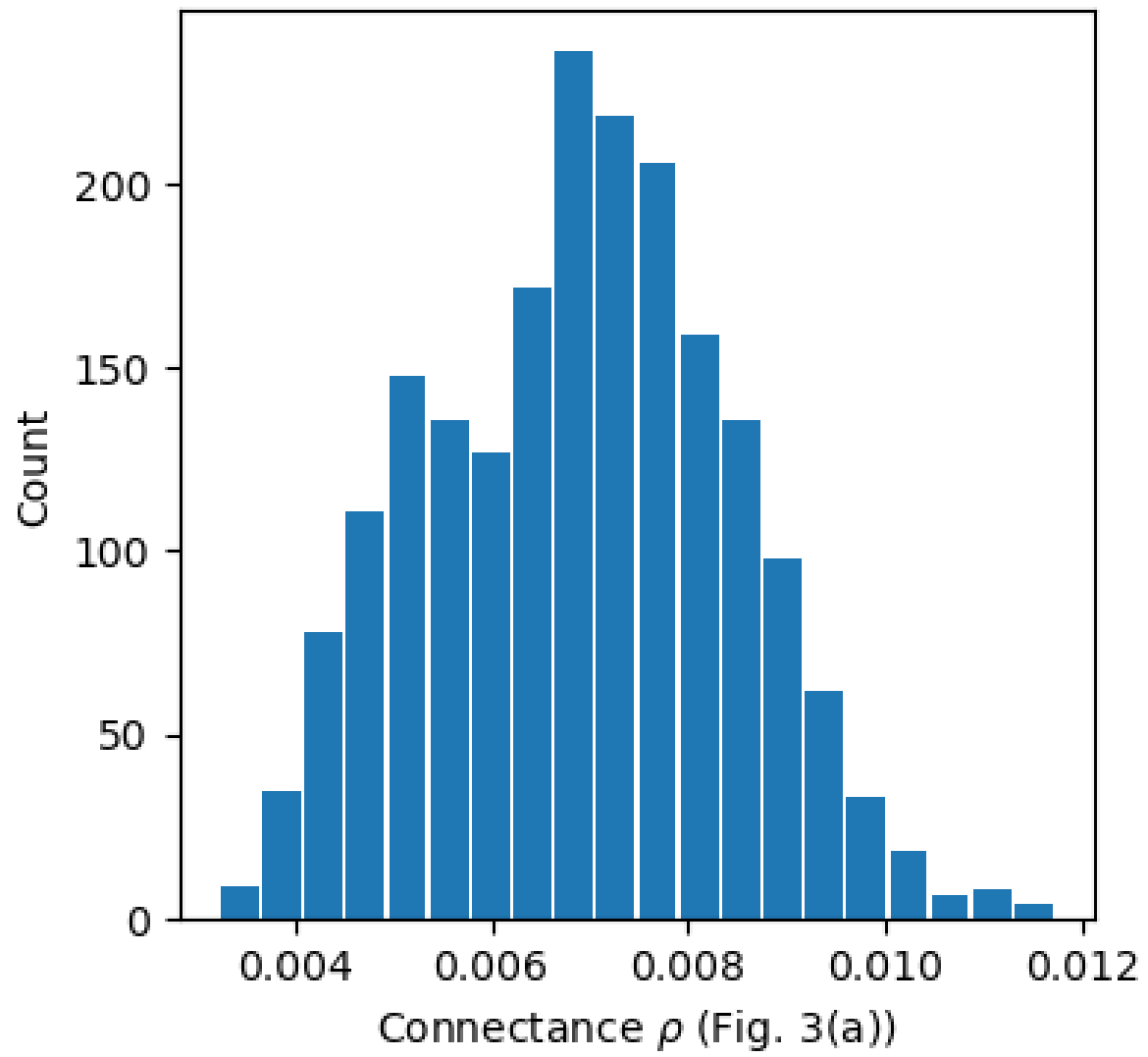


Figure 9: Dry season – Posterior samples of  $\rho$ .

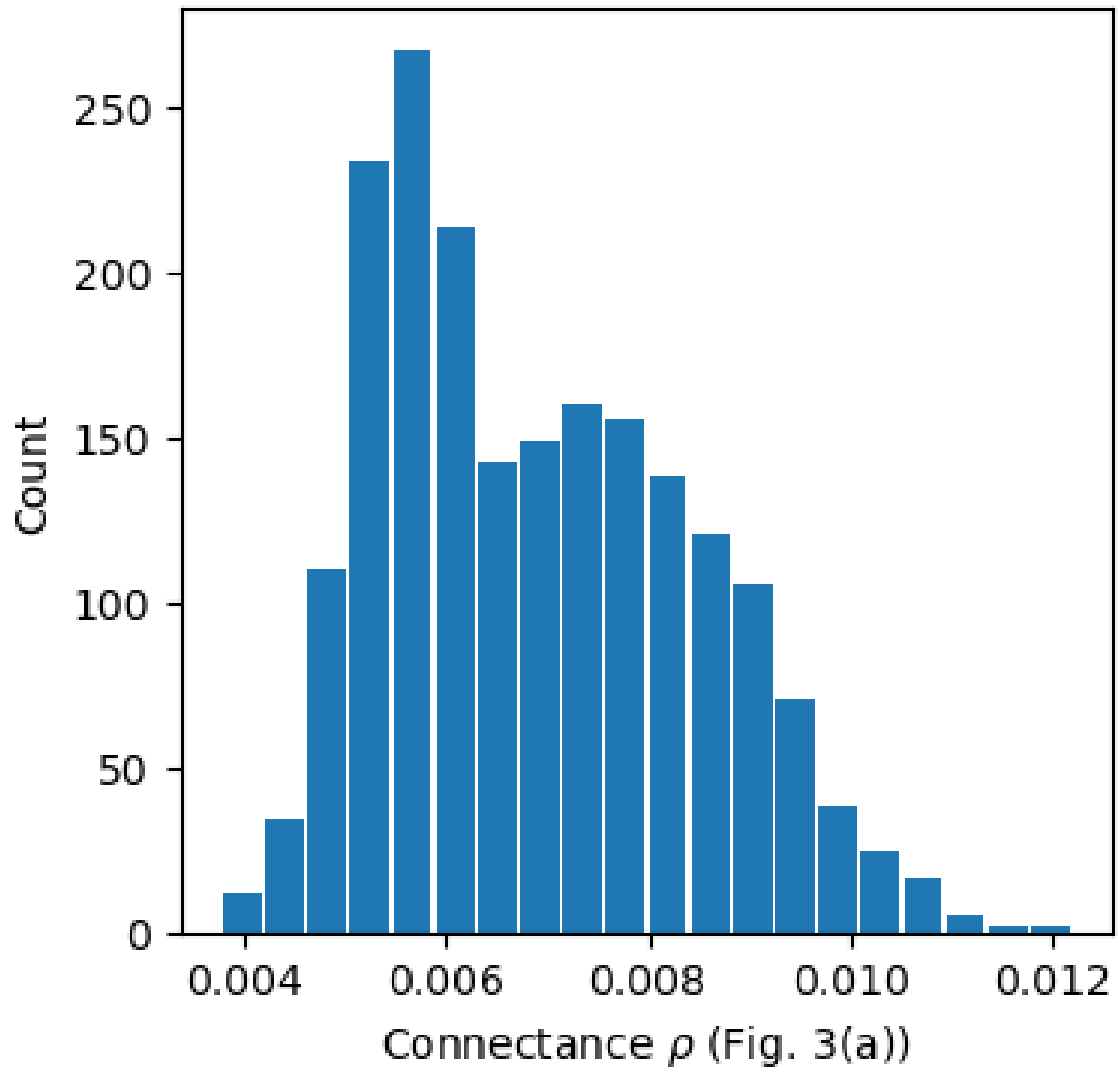


Figure 10: Wet season – Posterior samples of  $\rho$ .

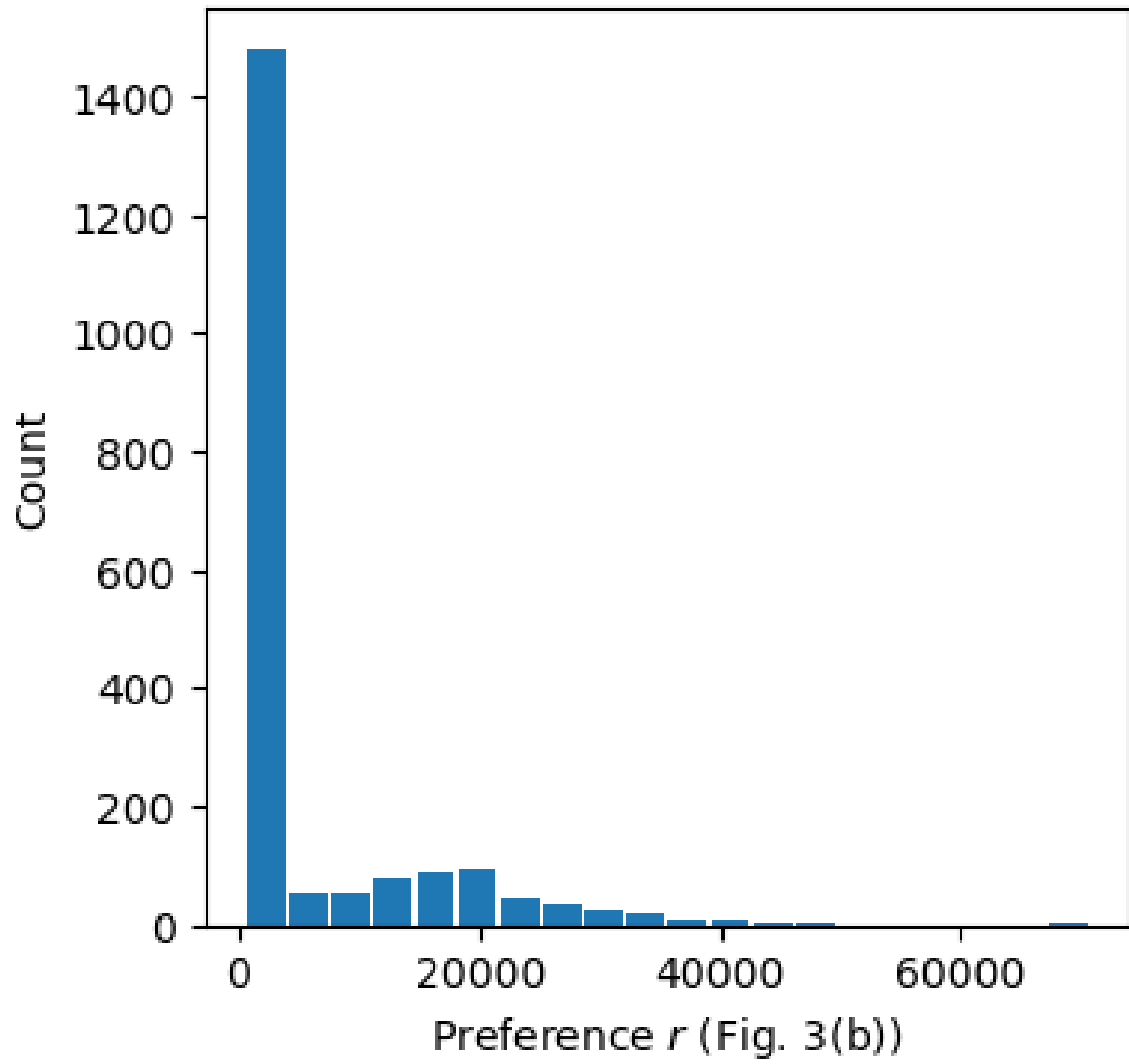


Figure 11: Dry season – Posterior samples of  $r$ .

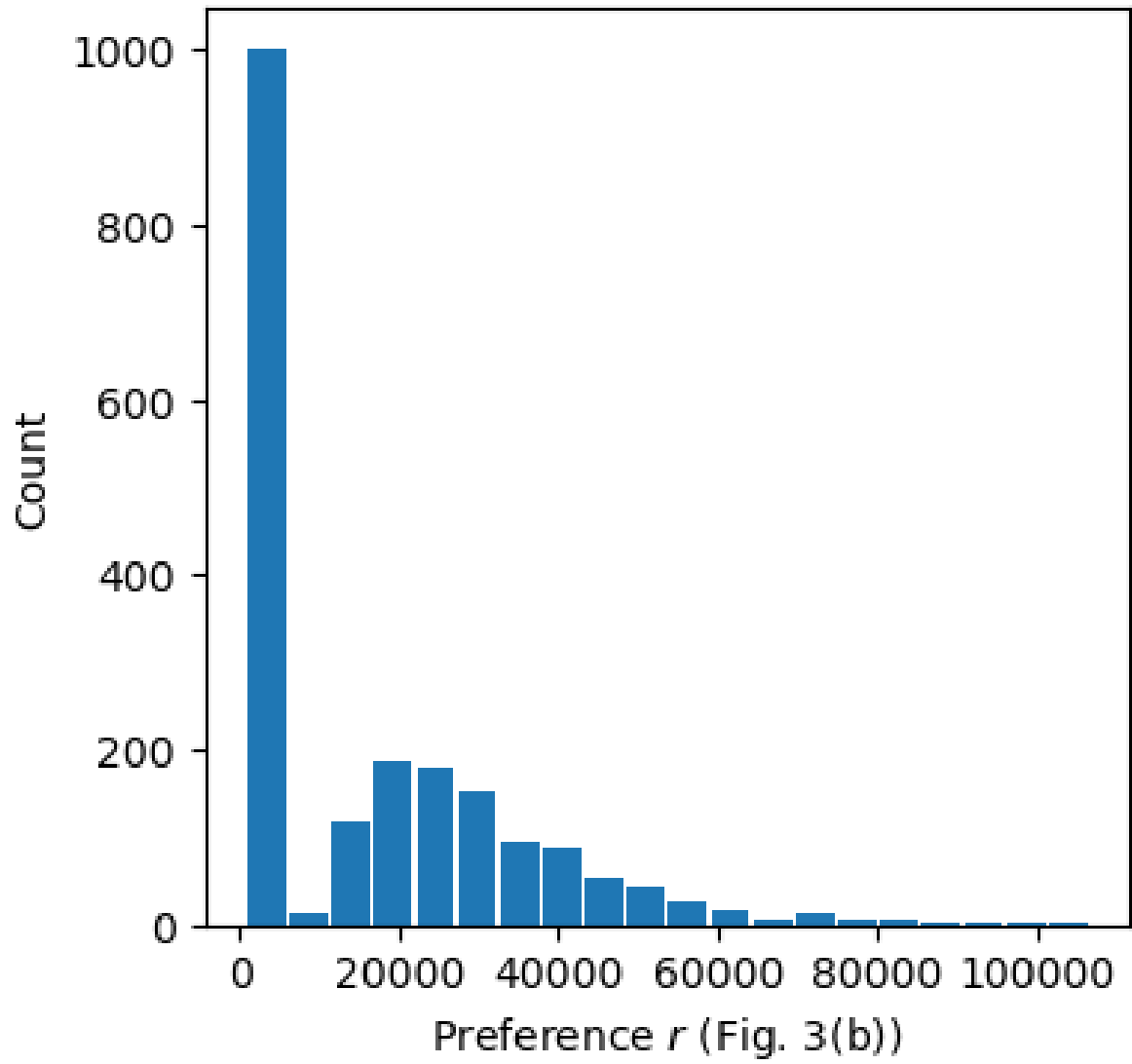


Figure 12: Wet season – Posterior samples of  $r$ .

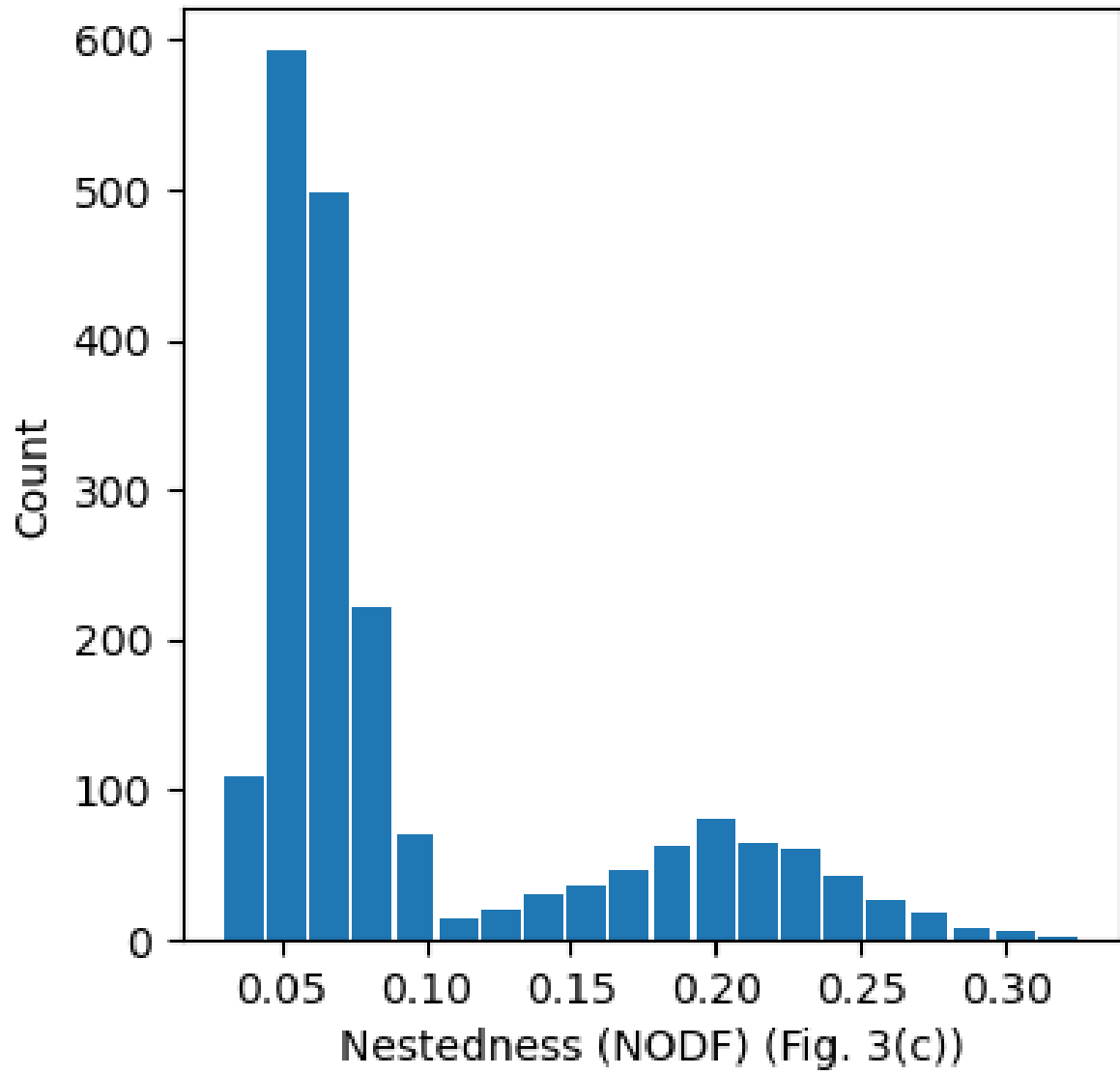


Figure 13: Dry season – Posterior distribution of NODF.

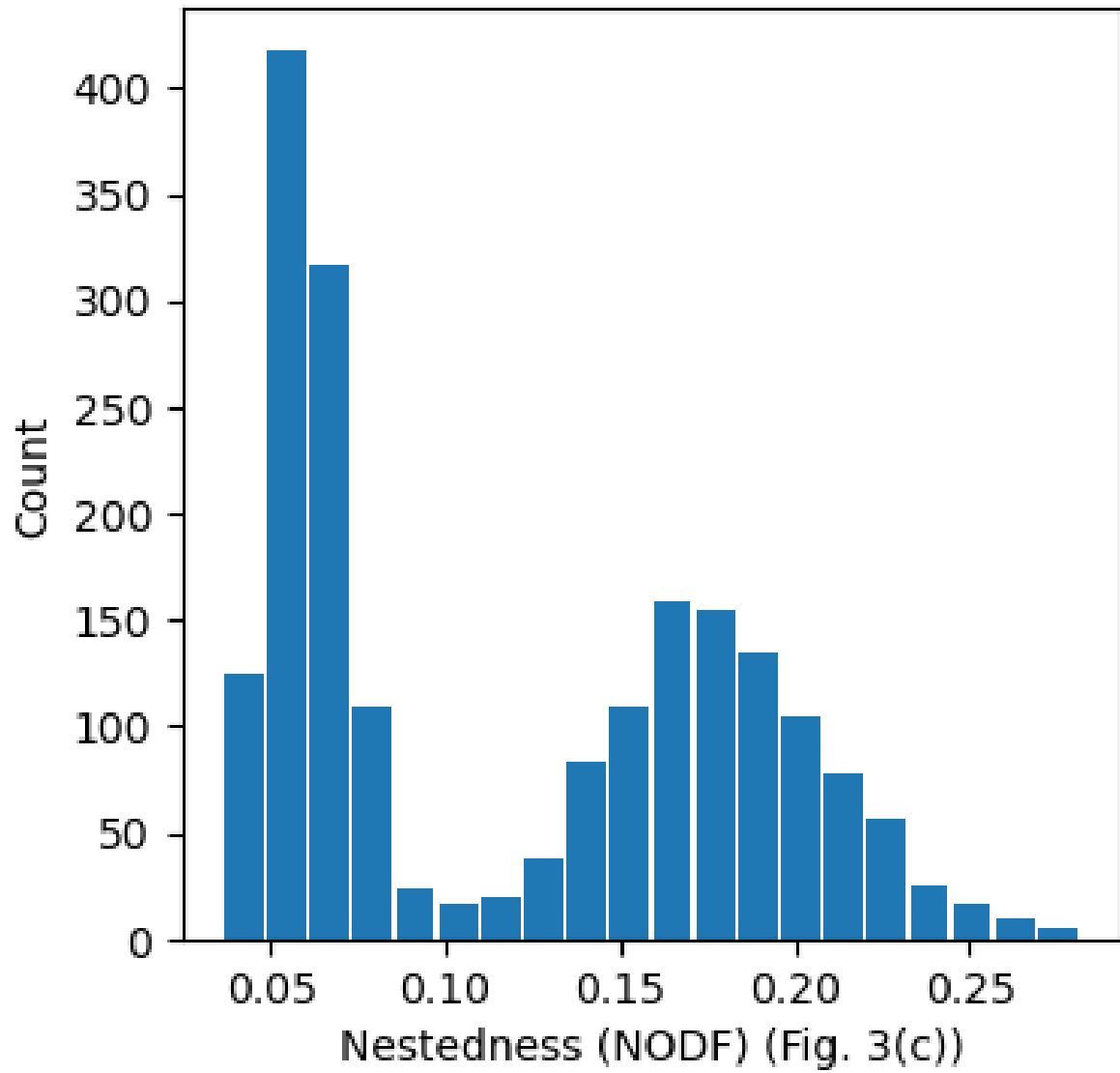


Figure 14: Wet season – Posterior distribution of NODF.

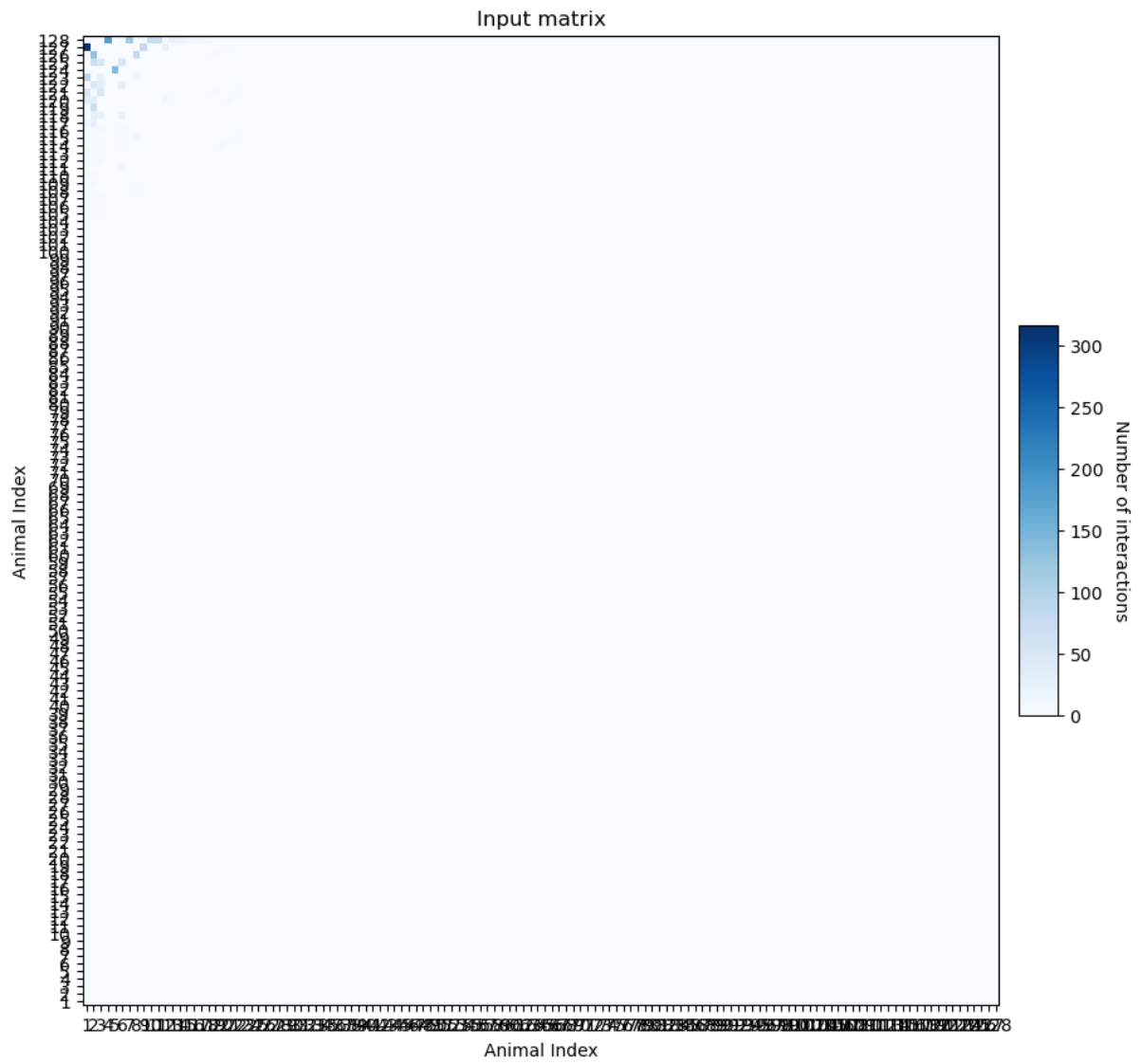


Figure 15: Dry season – Observed input matrix.

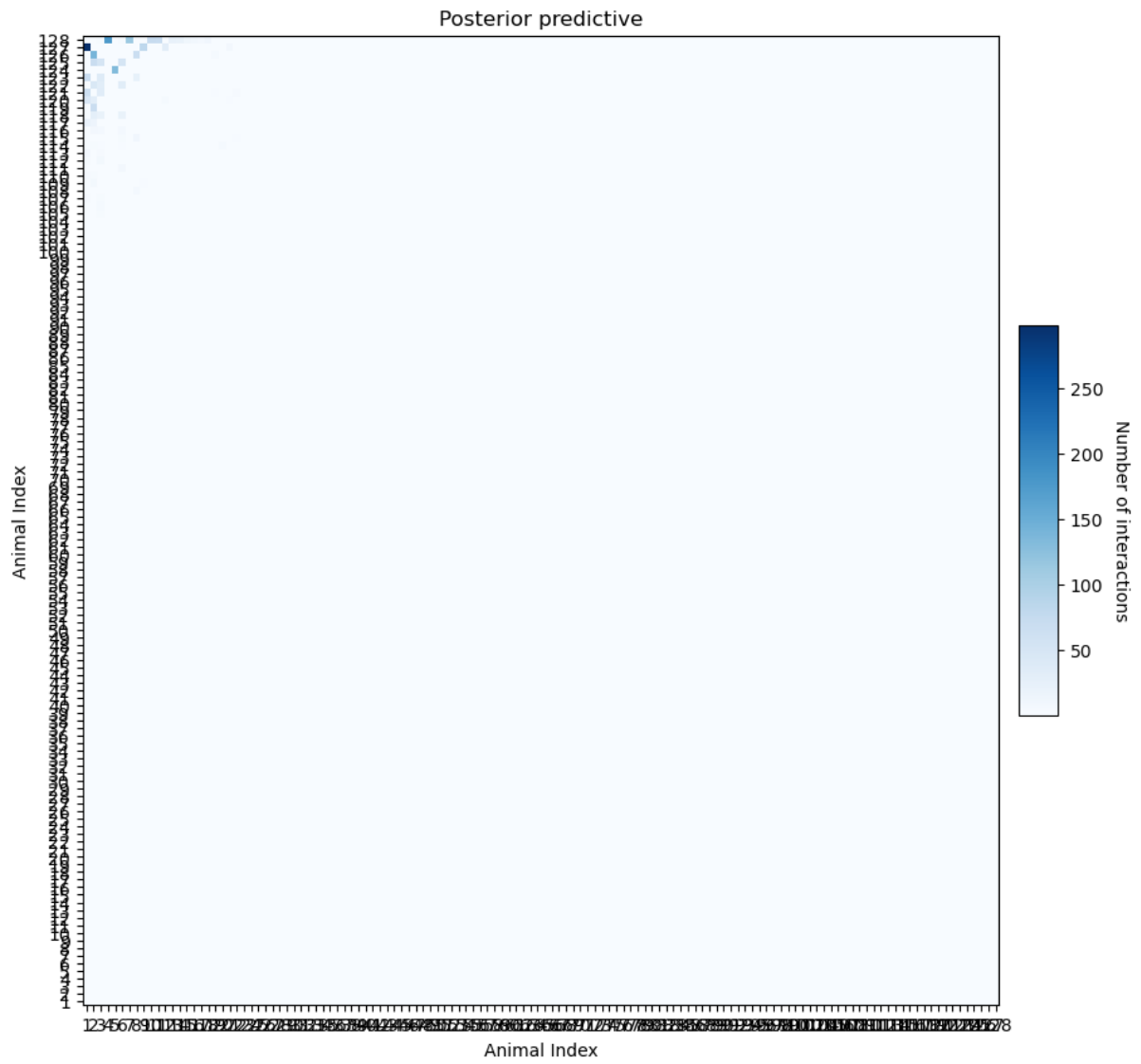


Figure 16: Dry season – Posterior predictive matrix.



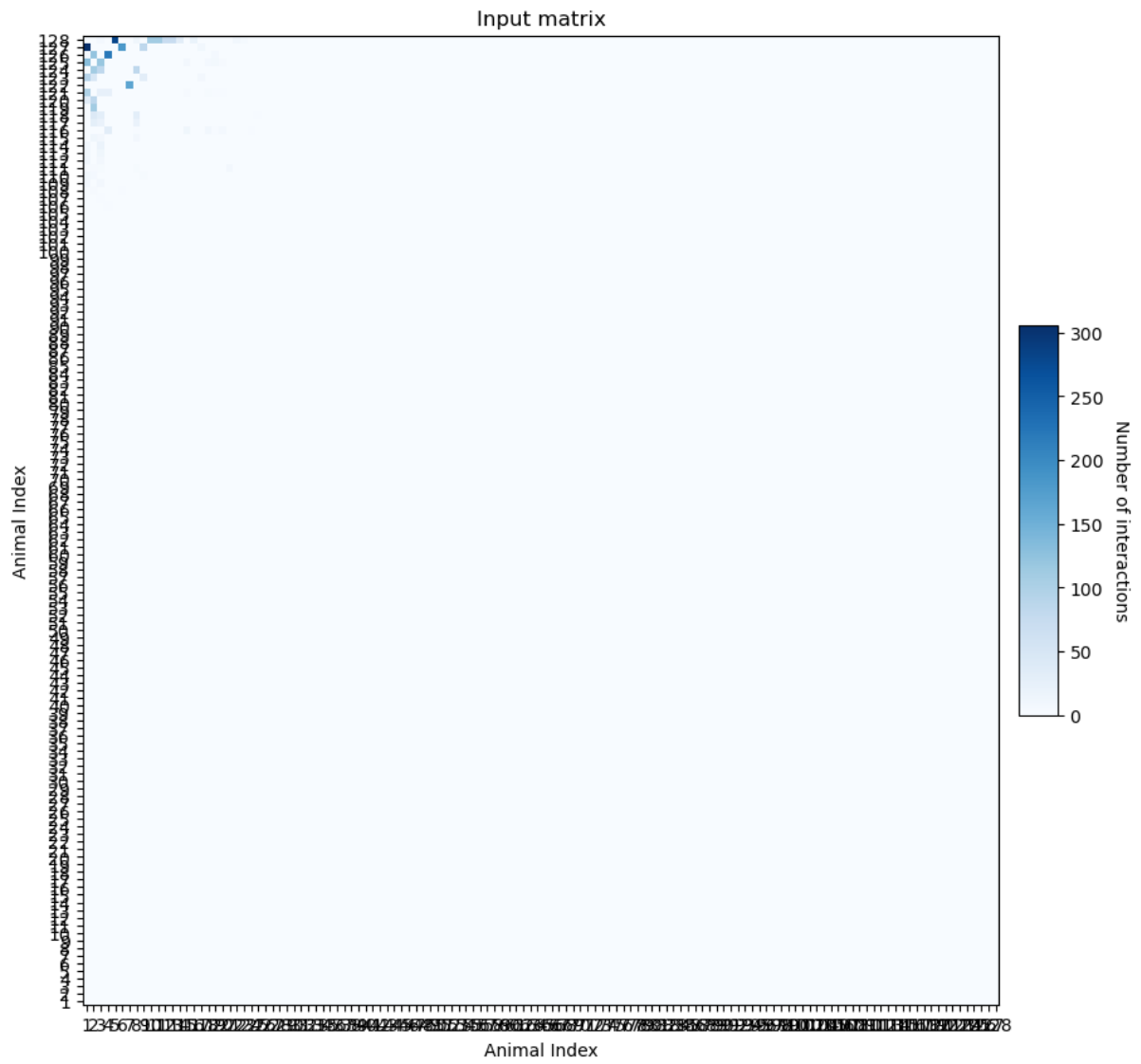


Figure 17: Wet season – Observed input matrix.

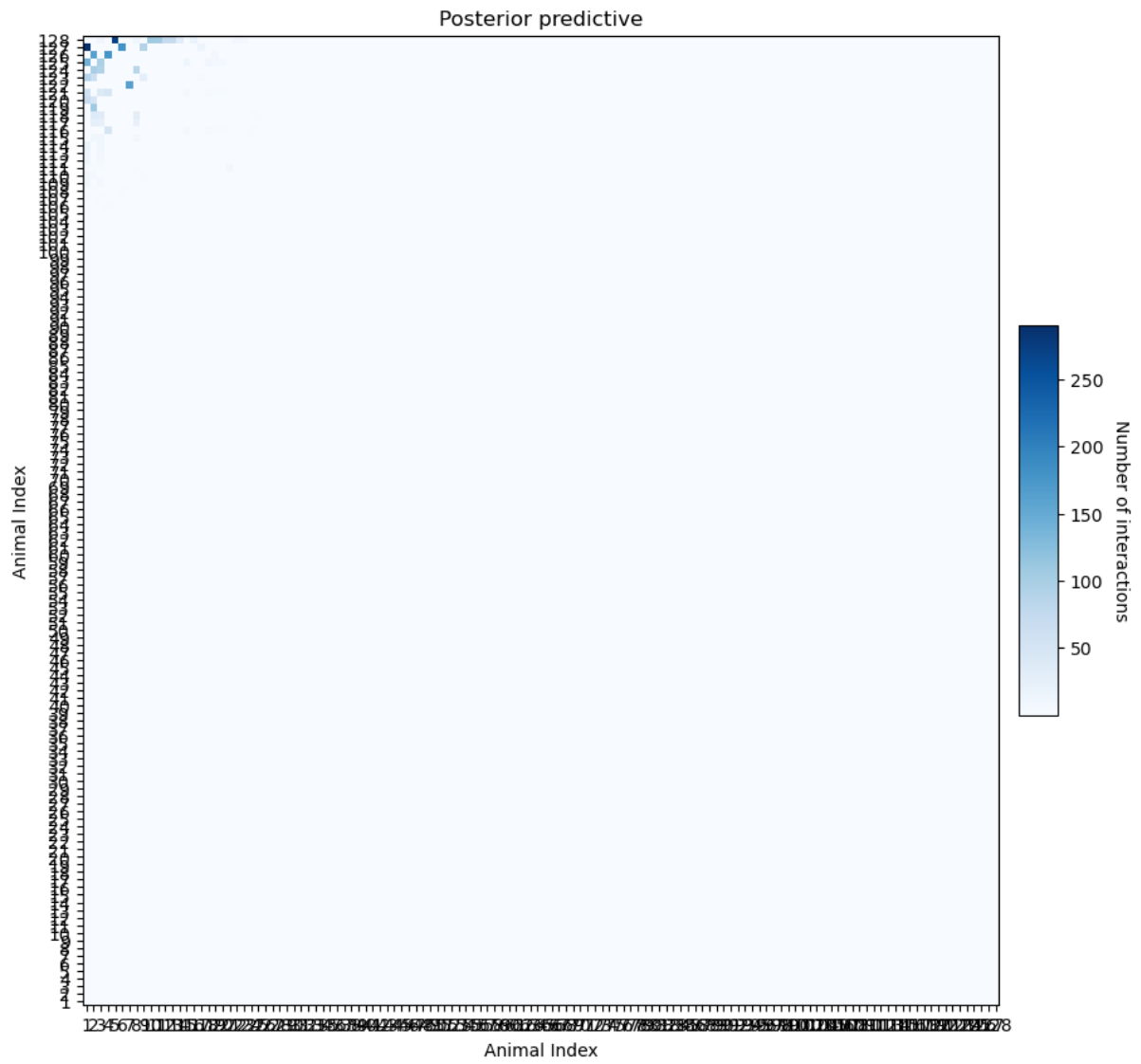


Figure 18: Wet season – Posterior predictive matrix.

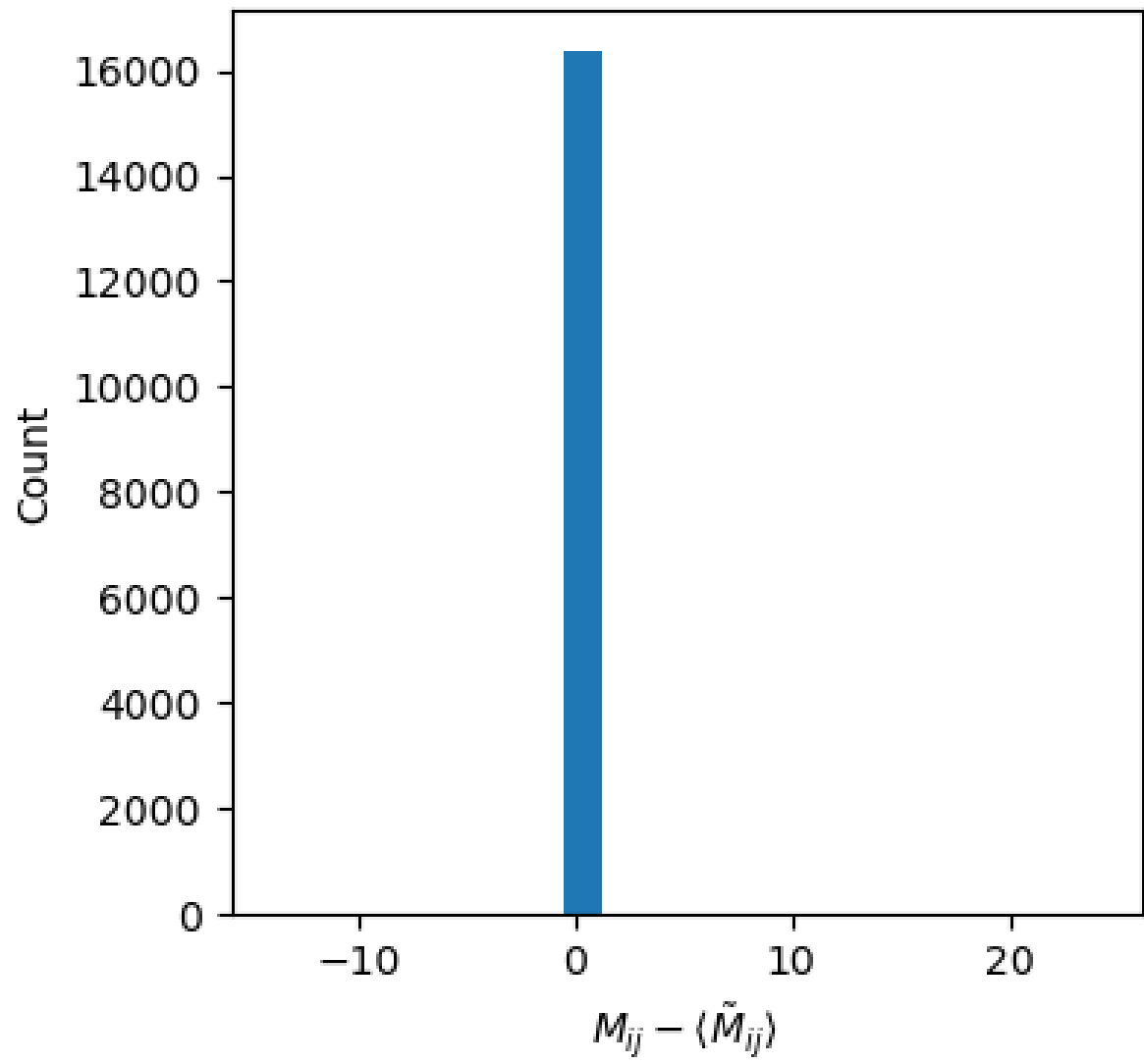


Figure 19: Dry season – Residuals histogram.

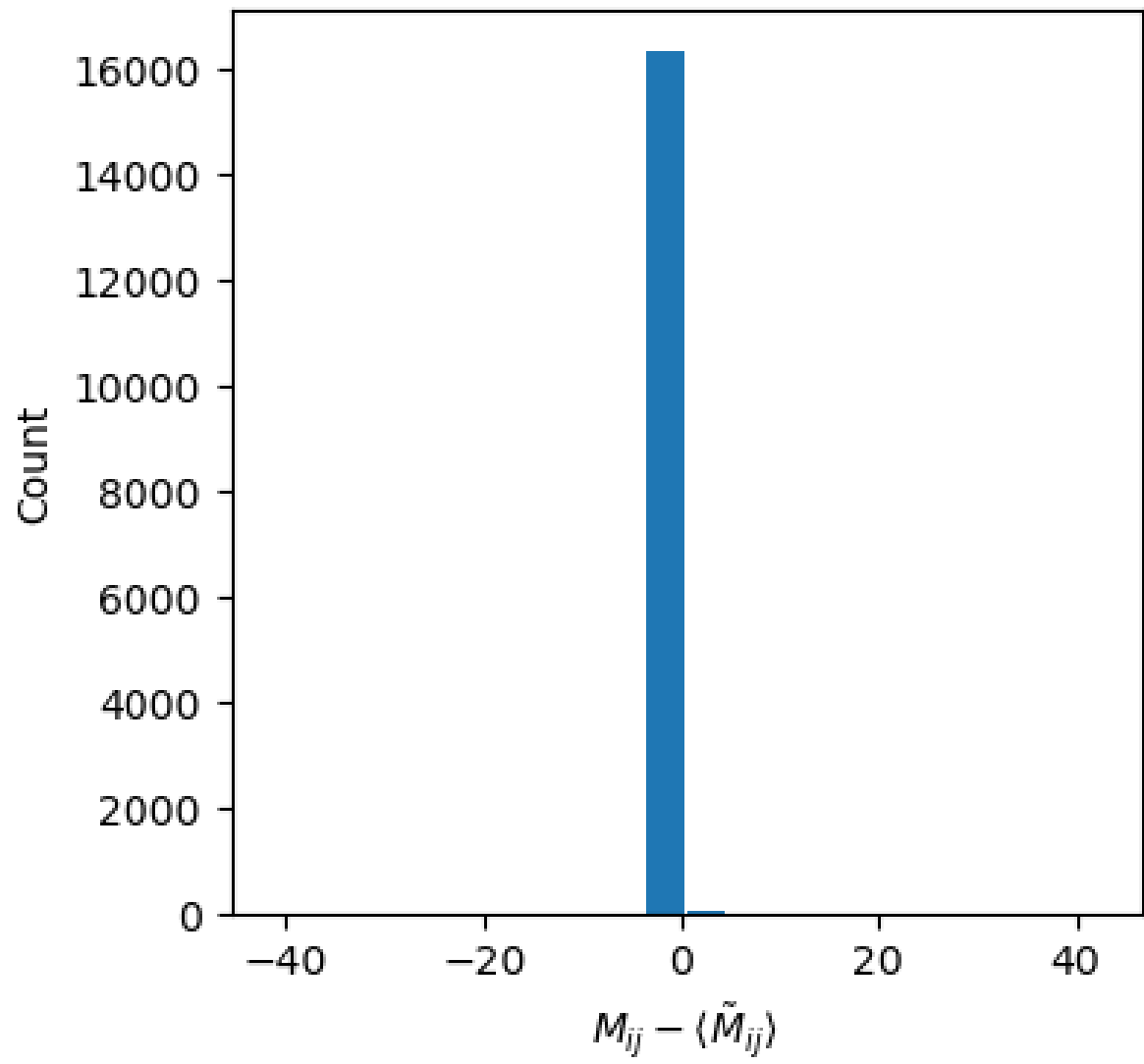


Figure 20: Wet season – Residuals histogram.

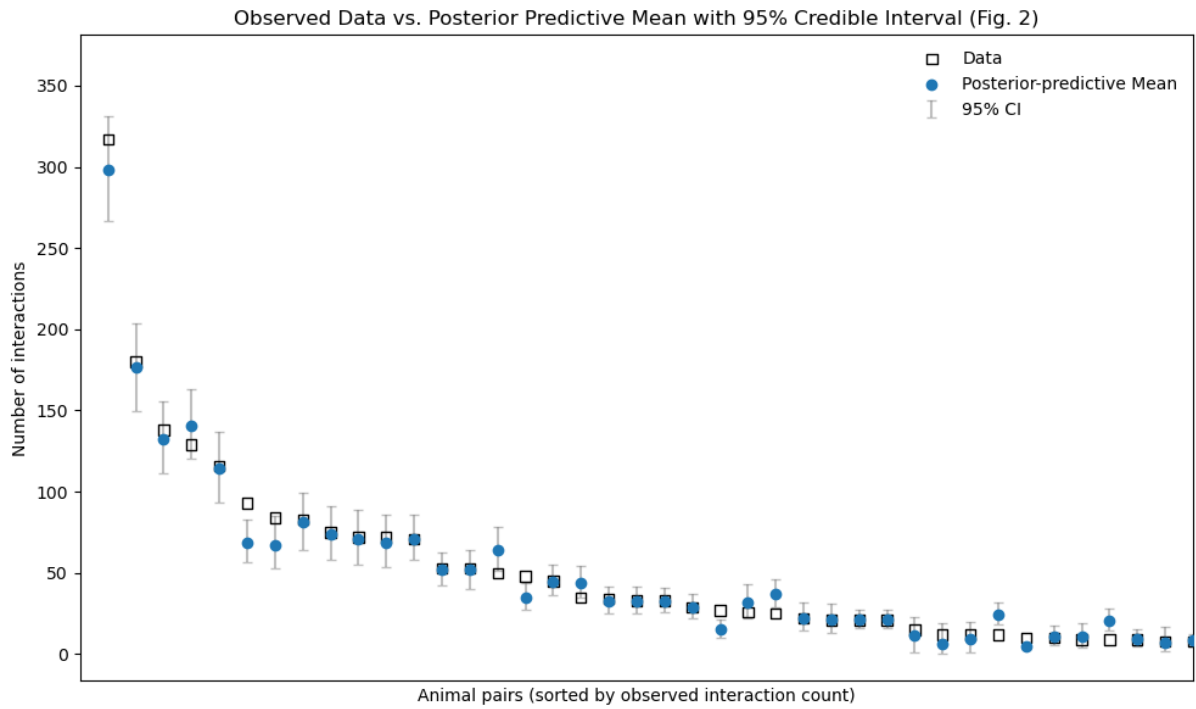


Figure 21: Dry season – Posterior predictive vs. observed counts with 95% credible intervals.

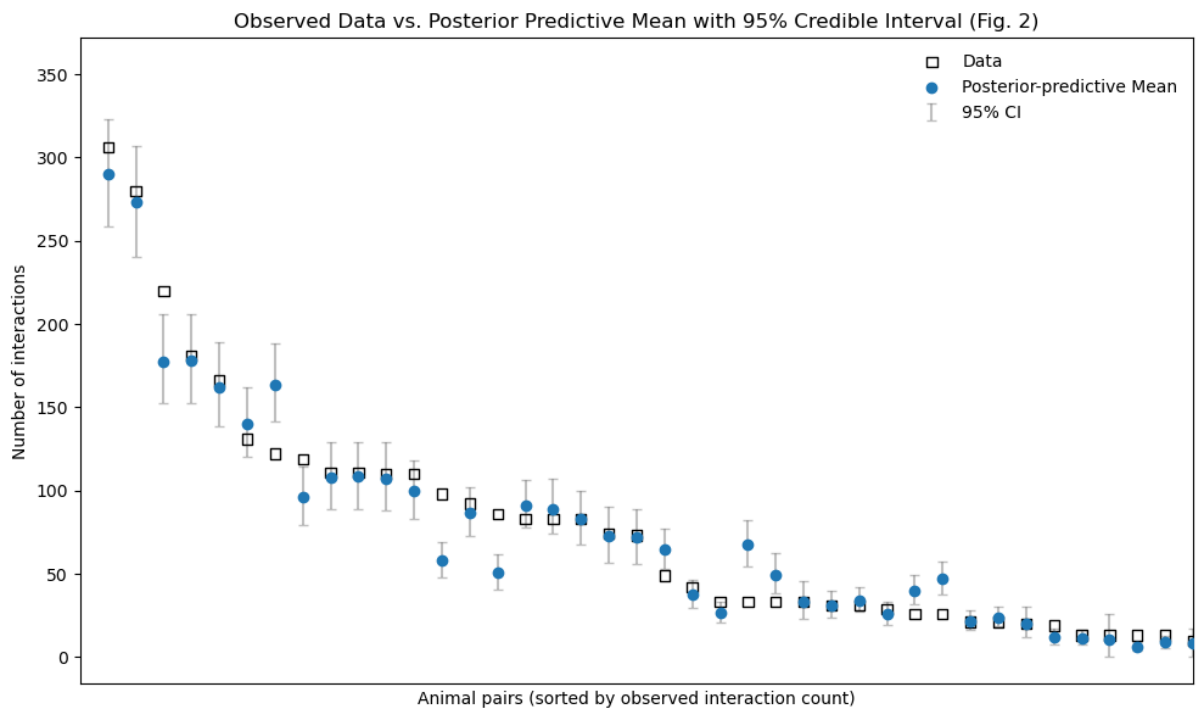


Figure 22: Wet season – Posterior predictive vs. observed counts with 95% credible intervals.