

How well do different statistical frameworks predict species- and community-level patterns?

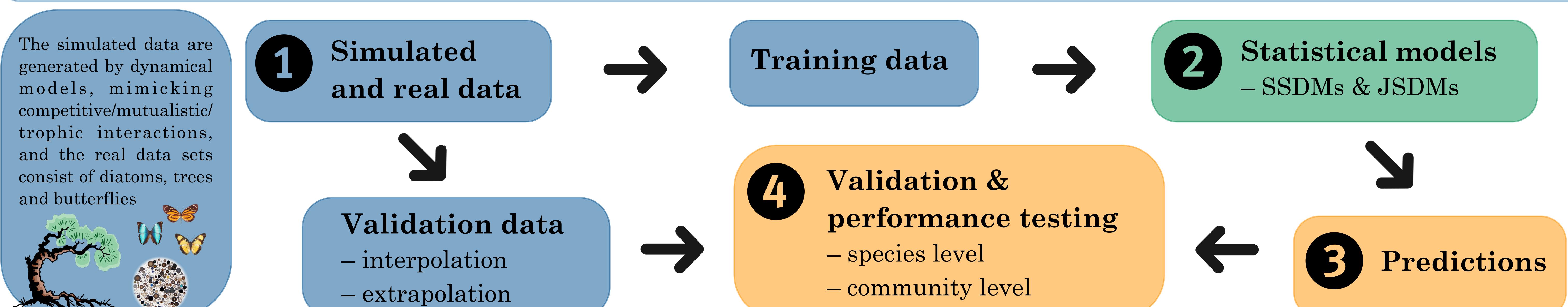


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The idea is to compare various statistical frameworks in terms of their predictive performance



2 Models

Stacked species distribution models

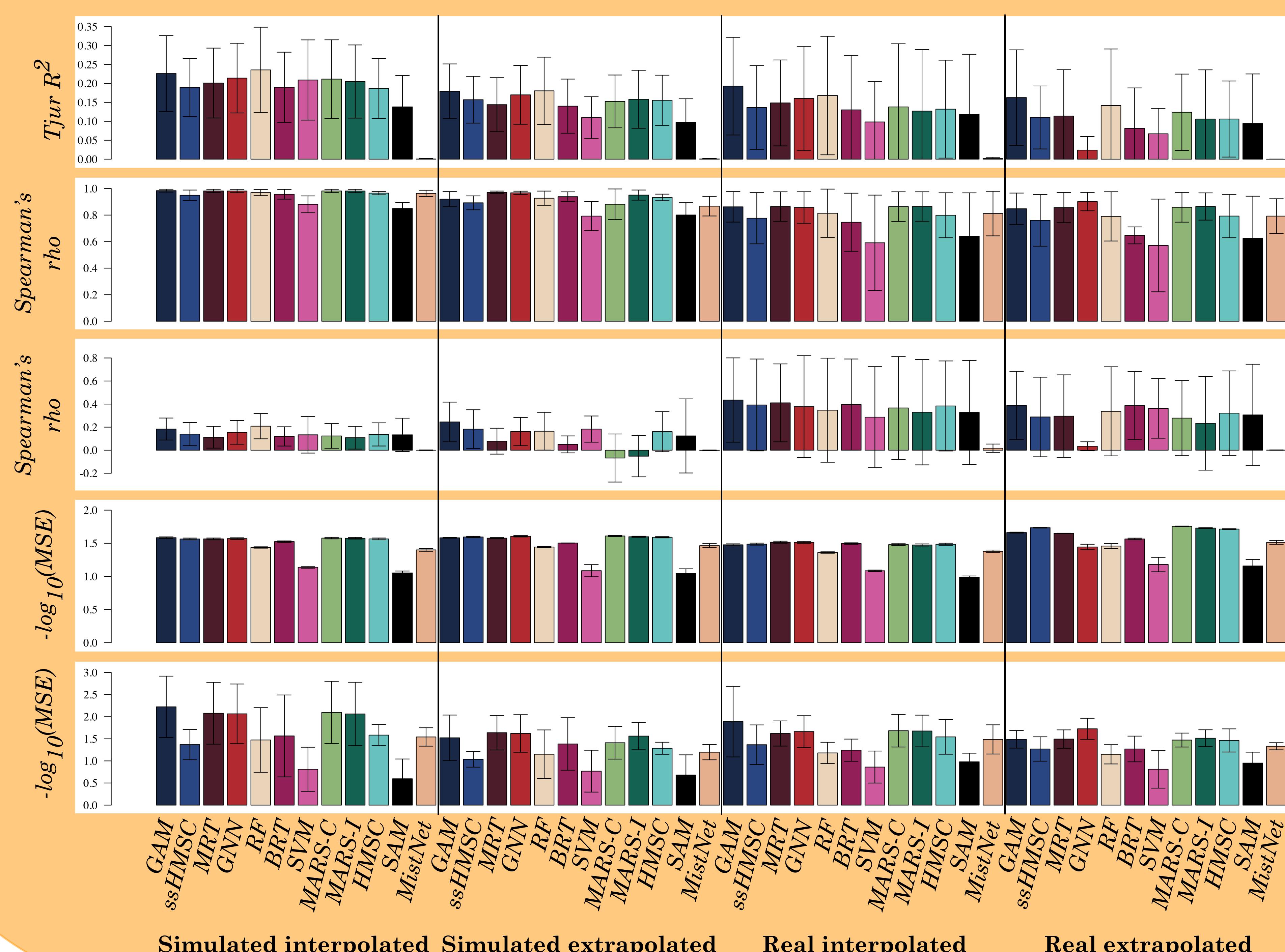
- Generalized additive models¹
 - Generalized linear models²⁻⁵
 - Multivariate regression trees⁶⁻⁷
 - Gradient nearest neighbour⁸
 - Random forests⁹
 - Boosted regression trees¹⁰
 - Support vector machines¹¹
 - Multivariate adaptive regression splines¹²

Joint species distribution models

- Hierarchical modelling of species communities²⁻⁵
 - Species archetype models¹³⁻¹⁵
 - Stochastic feedforward neural network¹⁶

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Predictions, validation & performance



(a) *Tijur R² values*

The mean t -values.

(b) Species prevalence

Species prevalence.
The mean Spearman's correlations between predicted and true species prevalences

(c) Species richness.

The mean Spearman's correlations between predicted and true species richnesses.

(d) *Bray-Curtis dissimilarity.*

The mean squared error of the Bray-Curtis dissimilarity index values.

(e) *Co-occurrence index.*

The mean squared error of the co-occurrence indices over species pairs.

We conclude, that even though there are differences in the predictive performance between the models, we so far see no clear division between stacked and joint models in general. Most models seem to perform consistently well, but some perform varyingly regarding accuracy and generality (e.g. GNN, MARS, MistNet). Further development in both model fitting procedures and performance testing is needed in order to obtain some more conclusive results.

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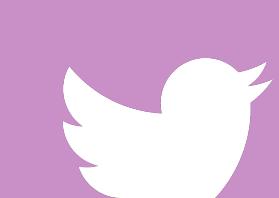
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