1. Posterior distributions (probabilistic estimations that take into account uncertainty of model conditions based on observed data – covariate effects and species cooccurrence - responses to each other and to environmental conditions)
   1. Each curve is a posterior prediction of percent cover – model driven inference to determine if different through time
   2. NOT in this case
   3. Real data
2. Conceptual figure impose 20% increase\* and then assess if current model can detect it without refitting the model
   1. Preserves
      1. Model uncertainty (posterior variability etc)
      2. Baseline structure (covariate effects, co-occurrence of species etc)
      3. Efficient, don’t need to refit the model 100s of times

\*don’t do this manually by adding to meanCover. Simulate implicitly by changing the covariate input and having GJAM leverage learned coefficients to predict what a 20% change looks like

More on posteriors

* Bayes, don’t estimate a single value for a parameter (likek a regression coefficient or sp abundance).
* Do: estimate a range of plausible values based on:
  + Observed data
  + Model structure
  + Priors
  + \*this range is called the posterior distribution – how probable different values are for a quantity you care about after seeing the data
* This work:
  + Want: Estimate percent cover in a given plot in year
  + Do: fit gjam and generates posterior distributions for all coefficients – effect of year on the sp
  + Then generate posterior distributions for predicted abundance