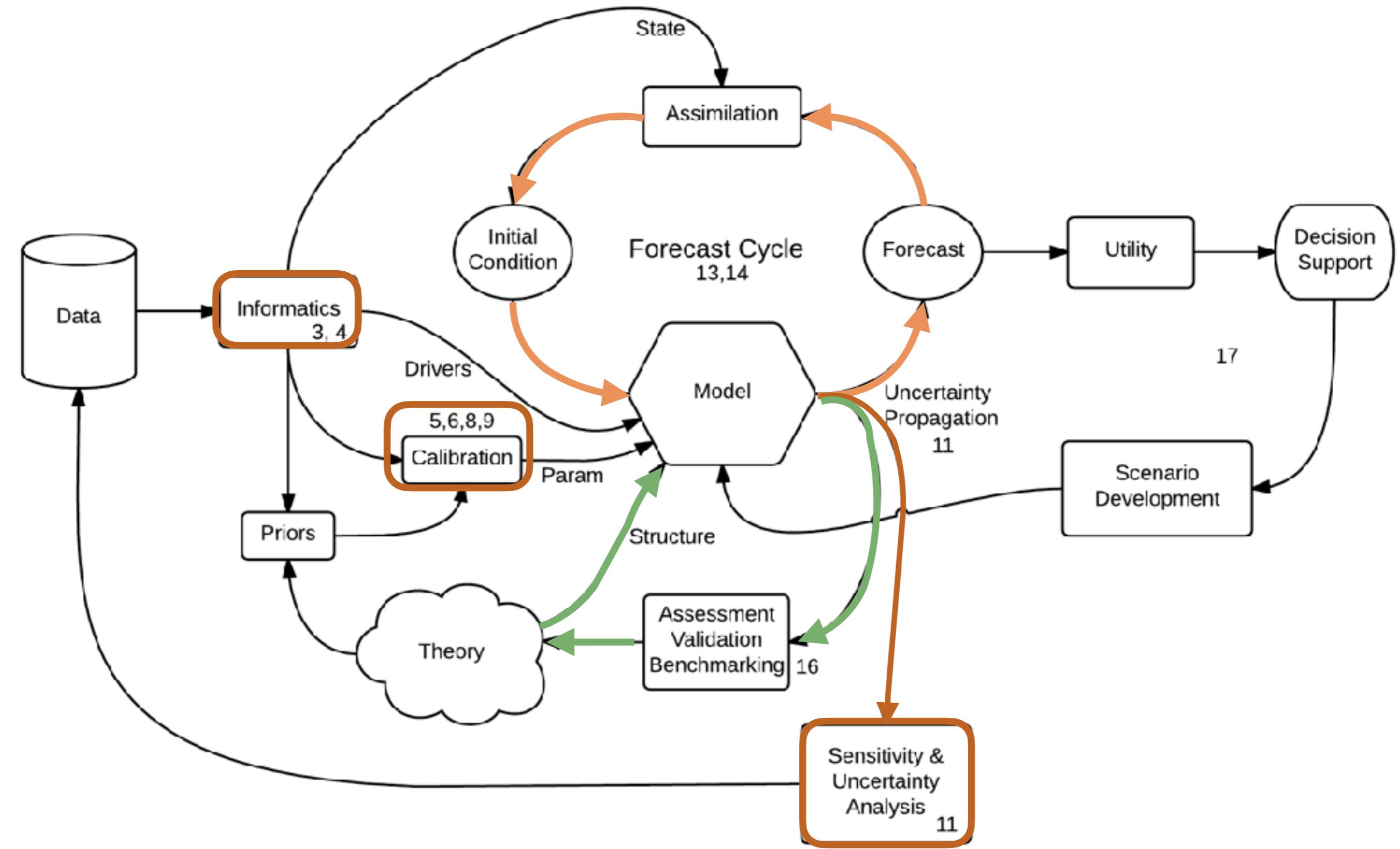
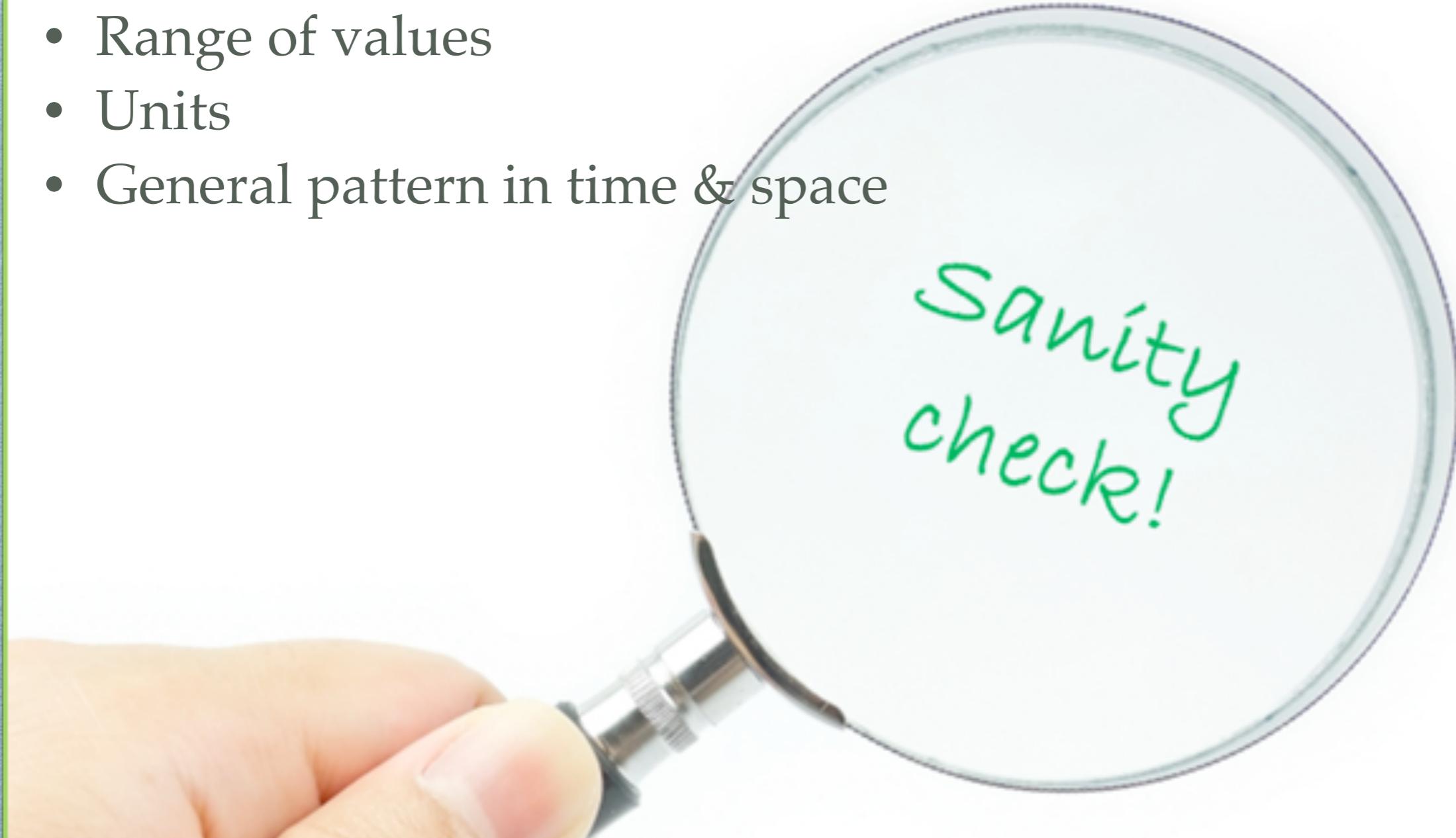


Assessing Model Performance

Lesson 11



- Range of values
- Units
- General pattern in time & space

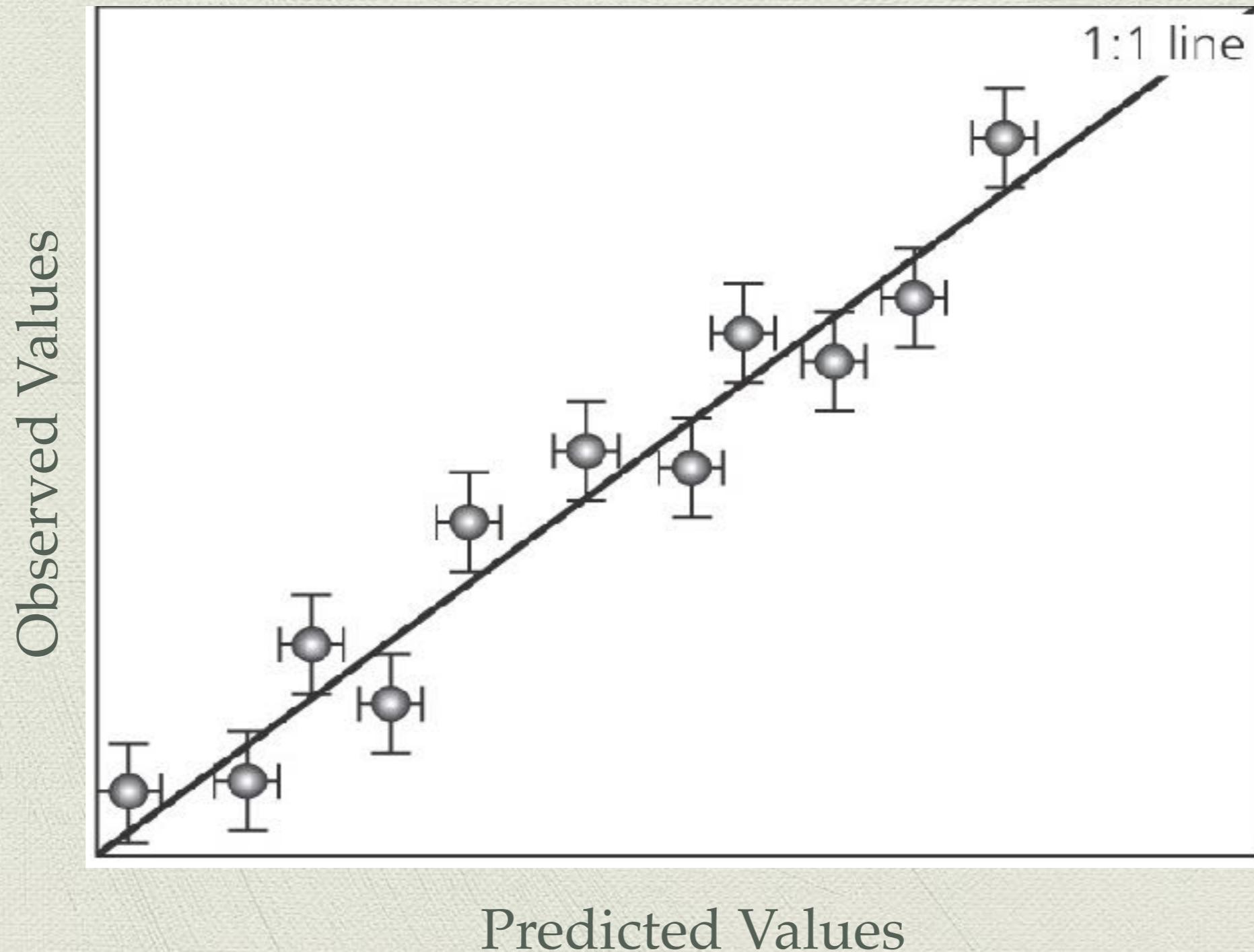


Step 1: Is the model
output reasonable?

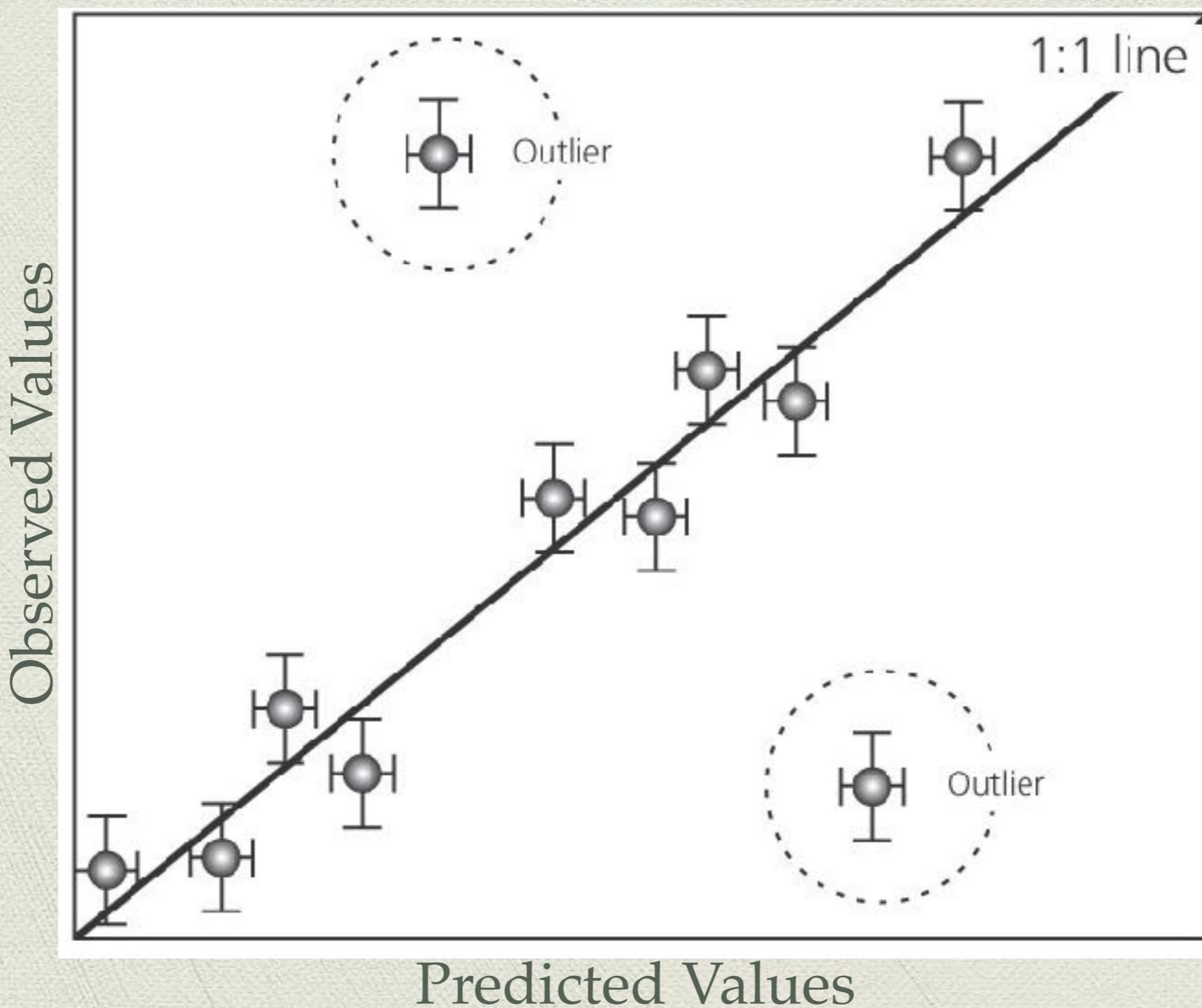


Step 2: Graphical
comparisons to data

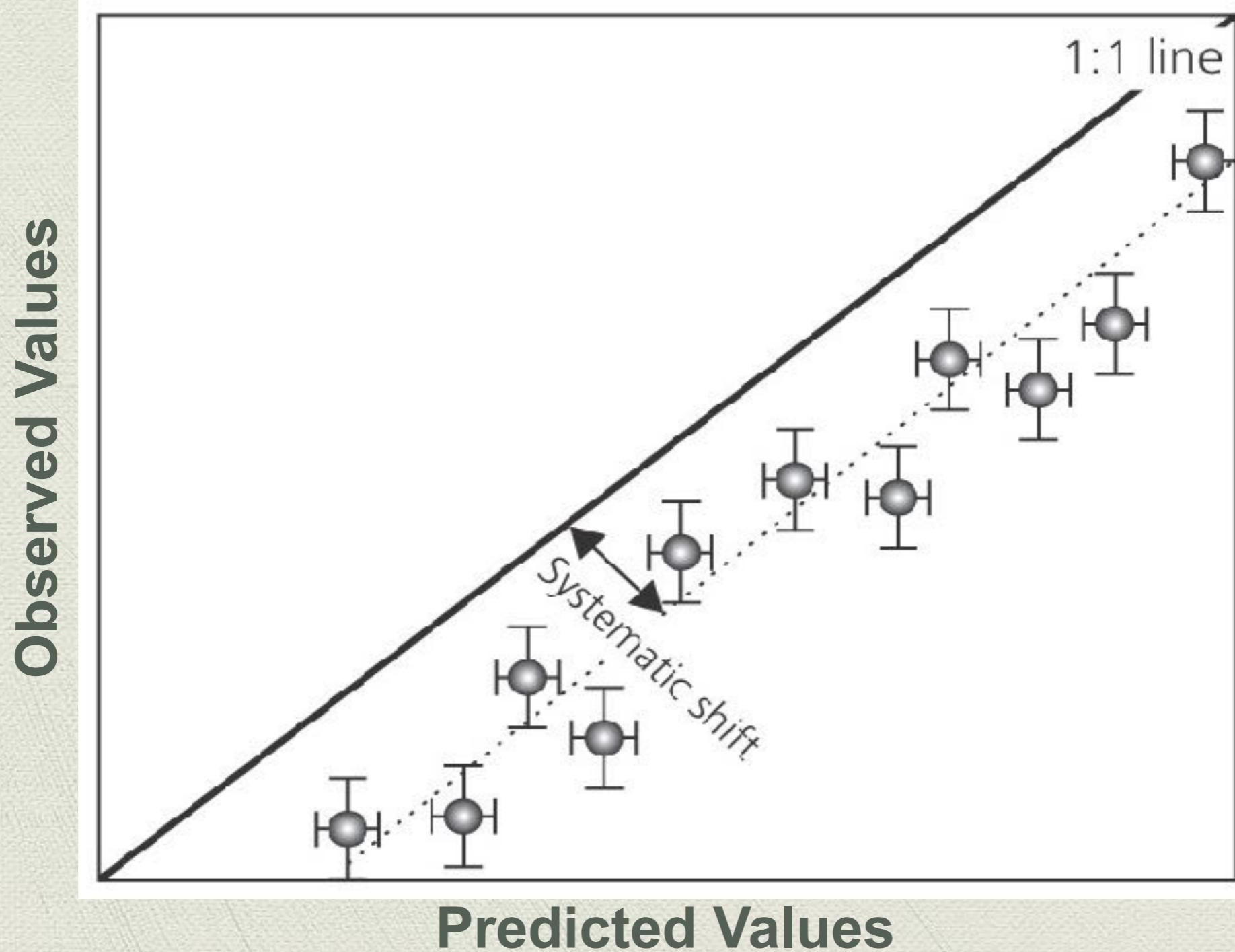
Accuracy of Prediction



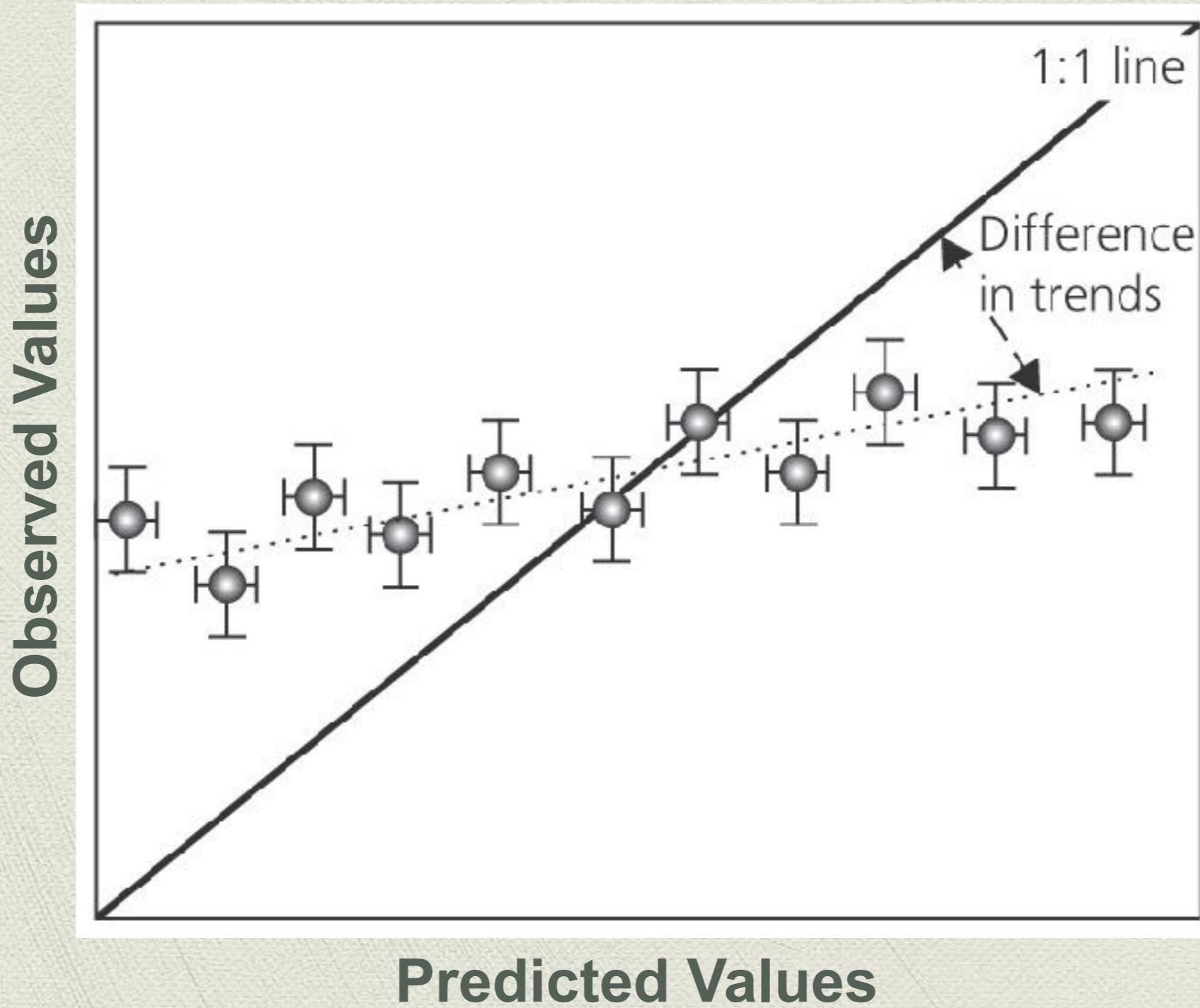
Identify Outliers



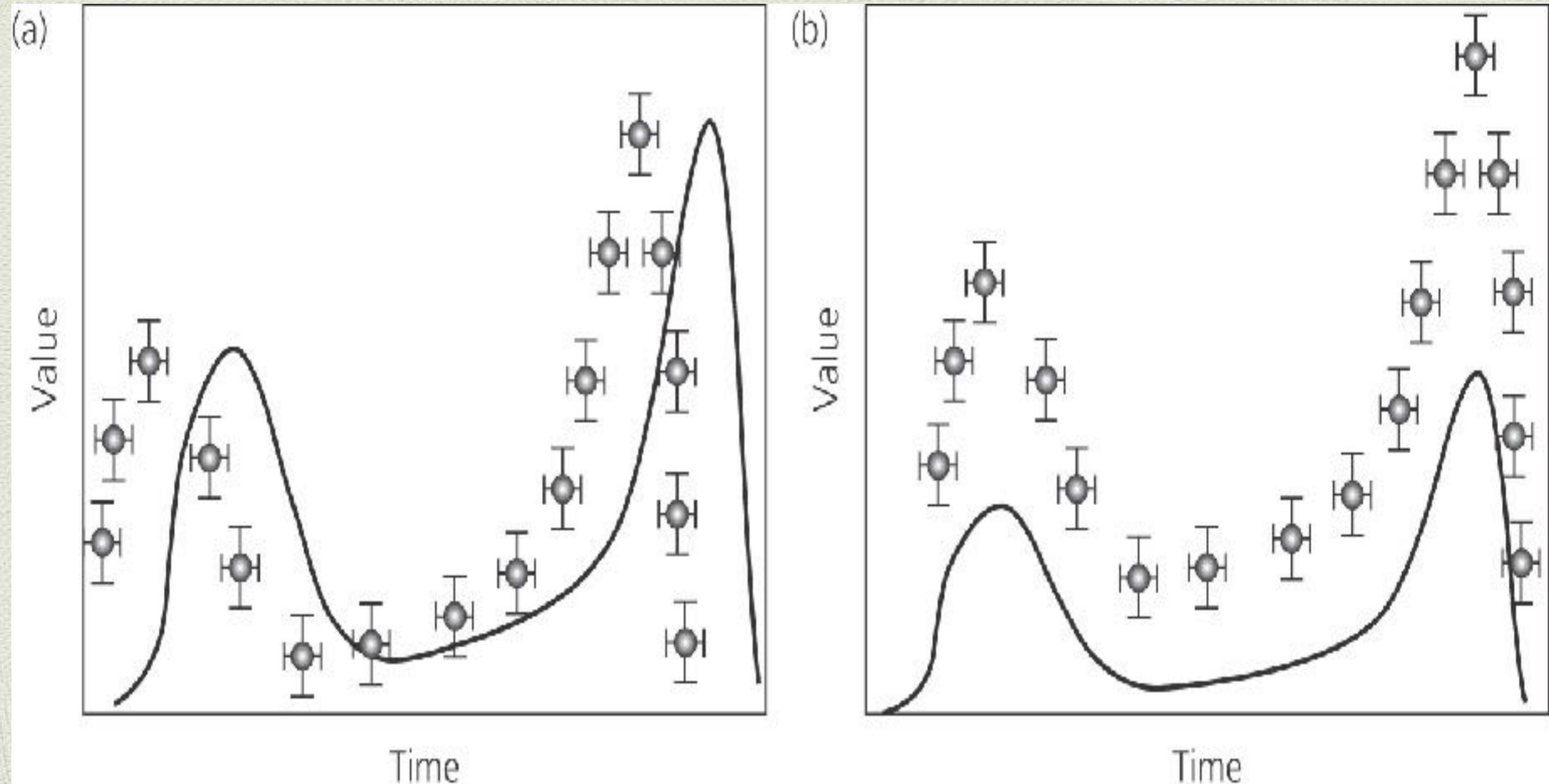
Assess Biases

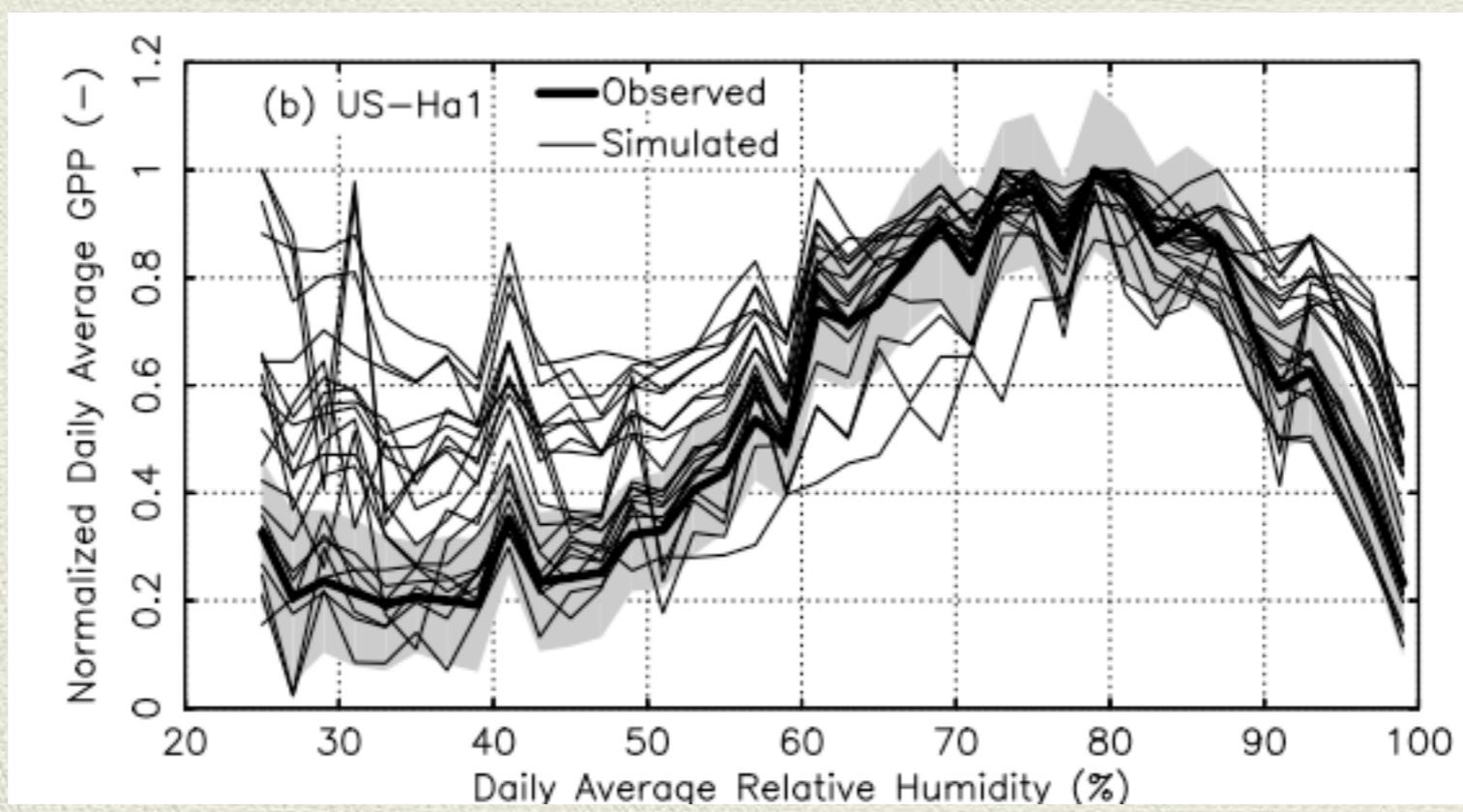
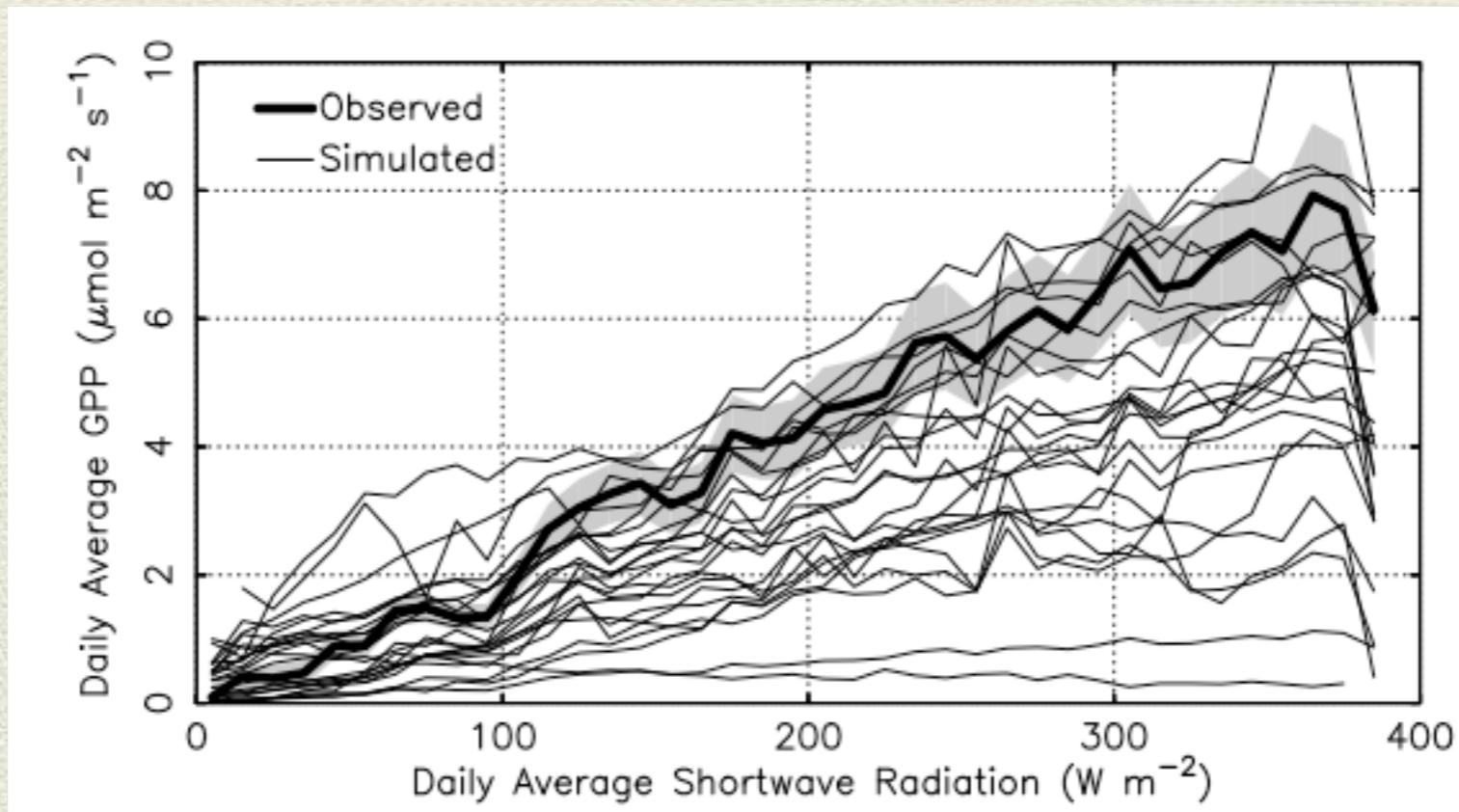


Miscalibration



Dynamics & Drivers







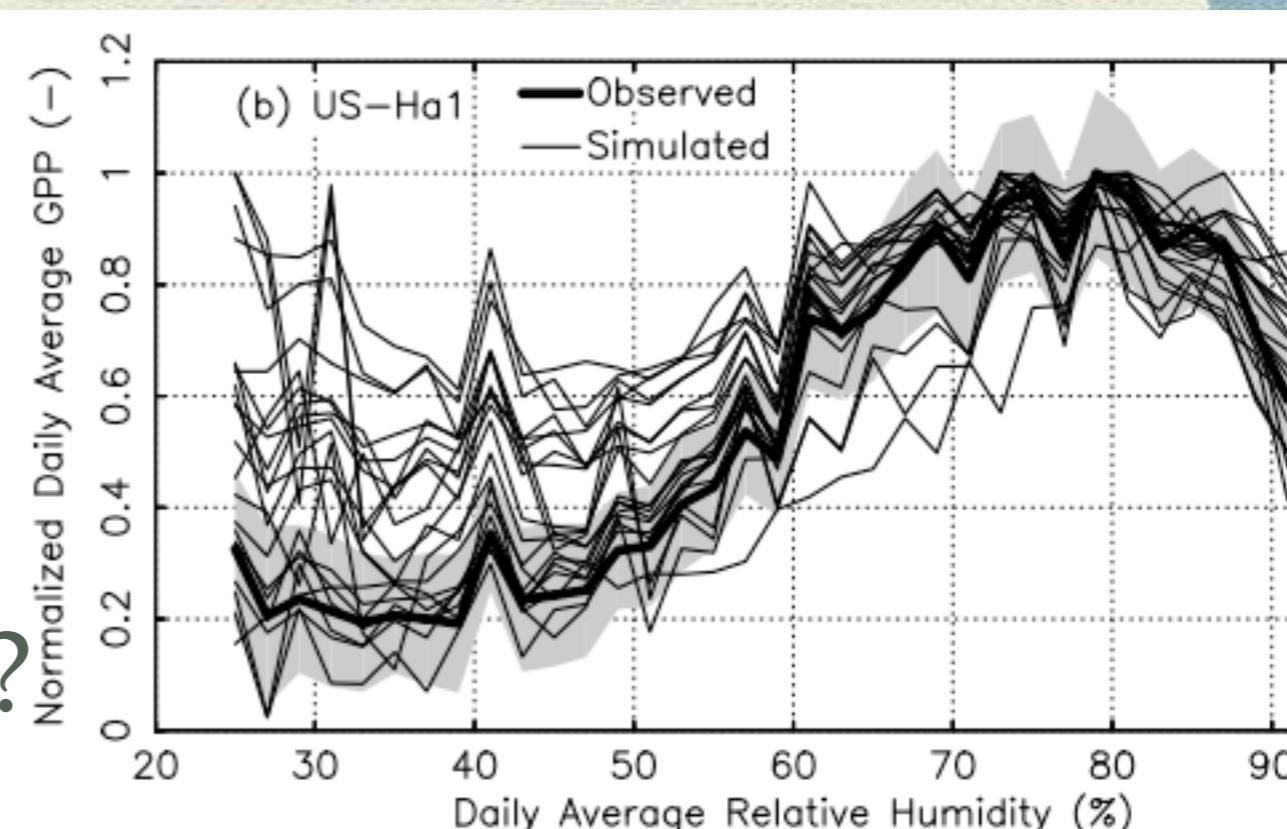
Diagnosing a model is
Hypothesis Testing

- ◆ Why would a model fail at low humidity?

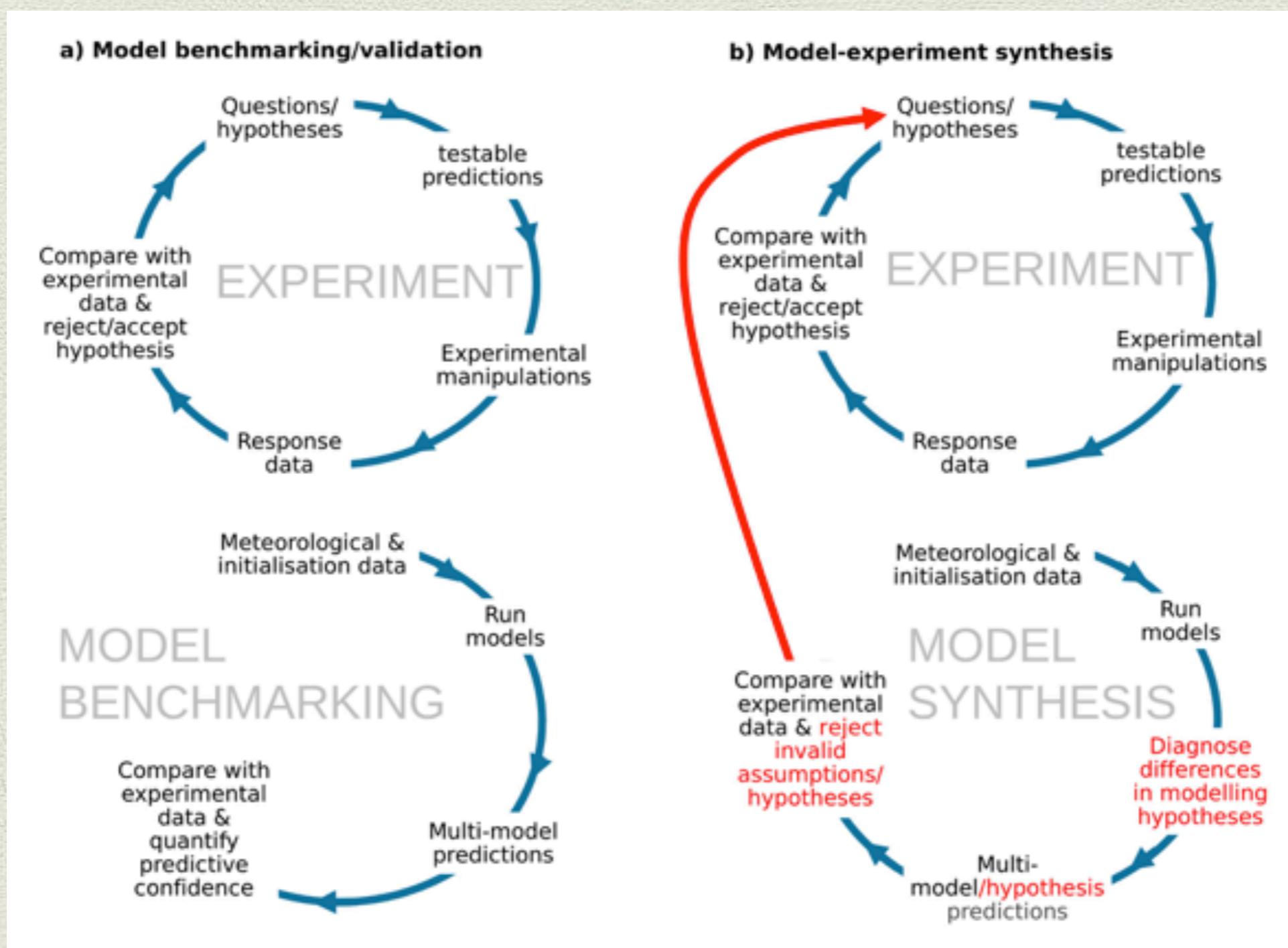
- ◆ Stomatal sensitivity too low?

- ◆ Too much soil moisture?

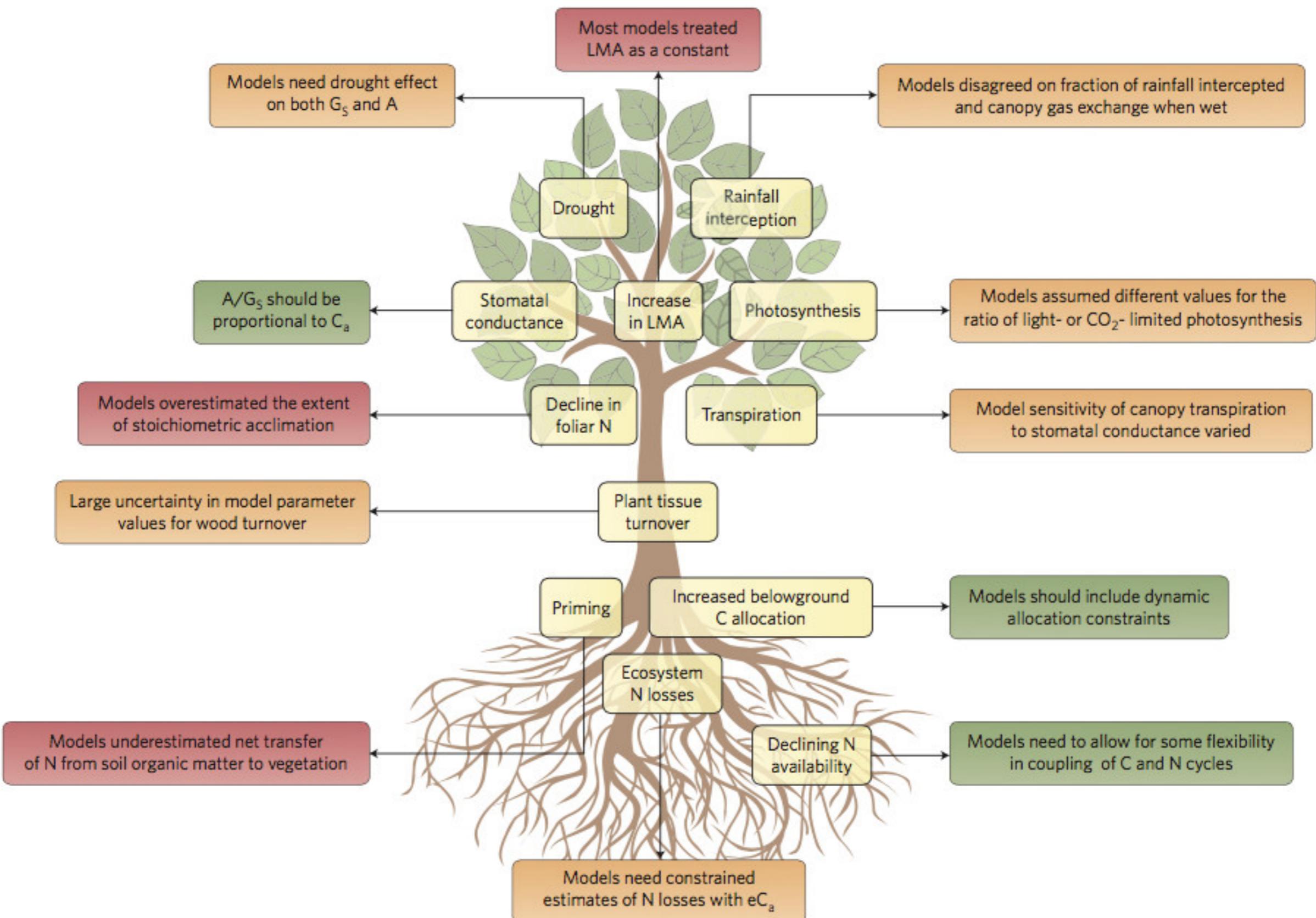
- ◆ What experiments would I run in the model to test this?



Focus on key assumptions



Walker et al 2014

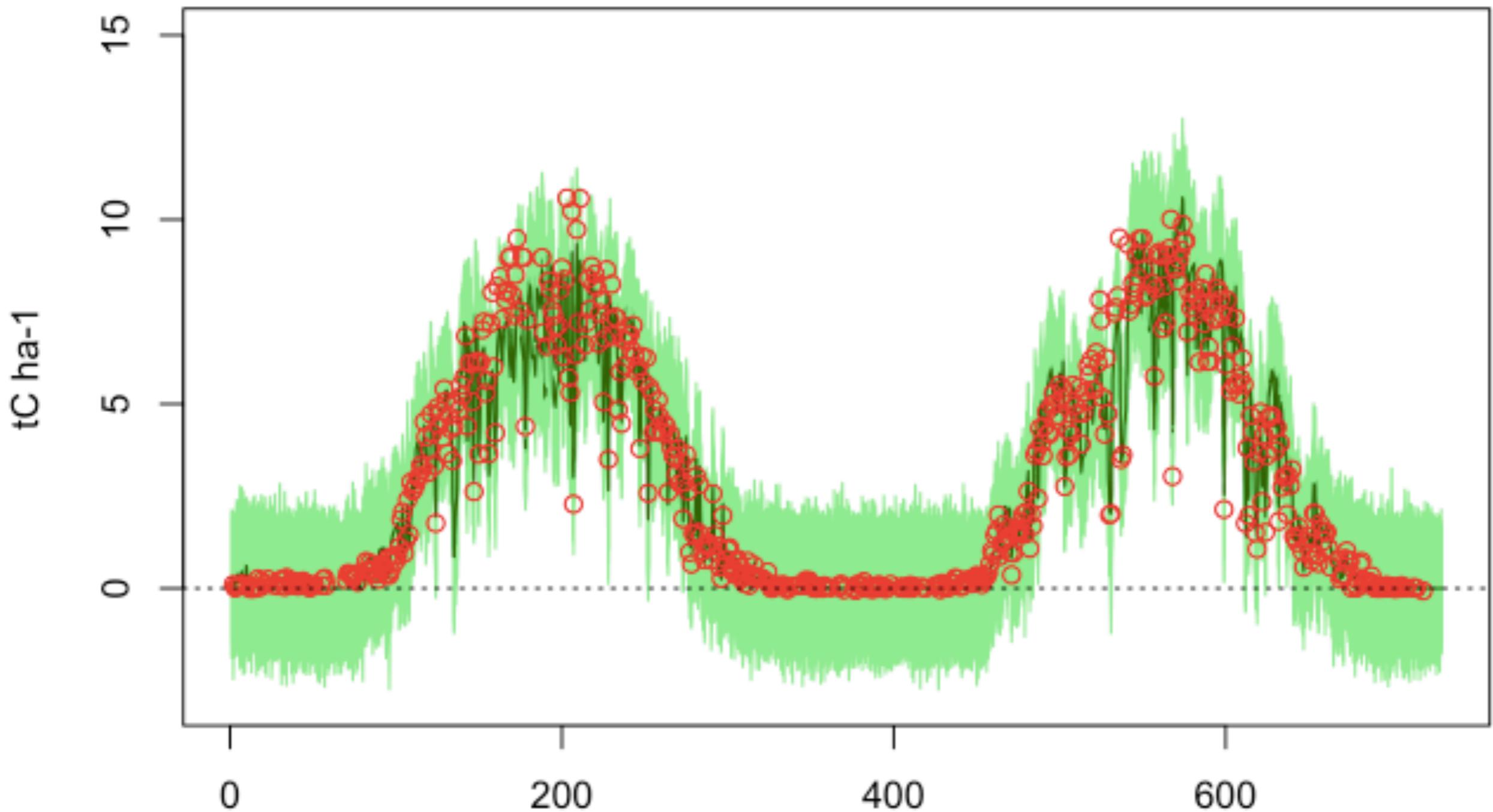


“data simulated under a model should look similar to data gathered in the real world.”

Conn et al 2018

IN THE FITTING, WE ASSUMED IID NORMAL ERRORS

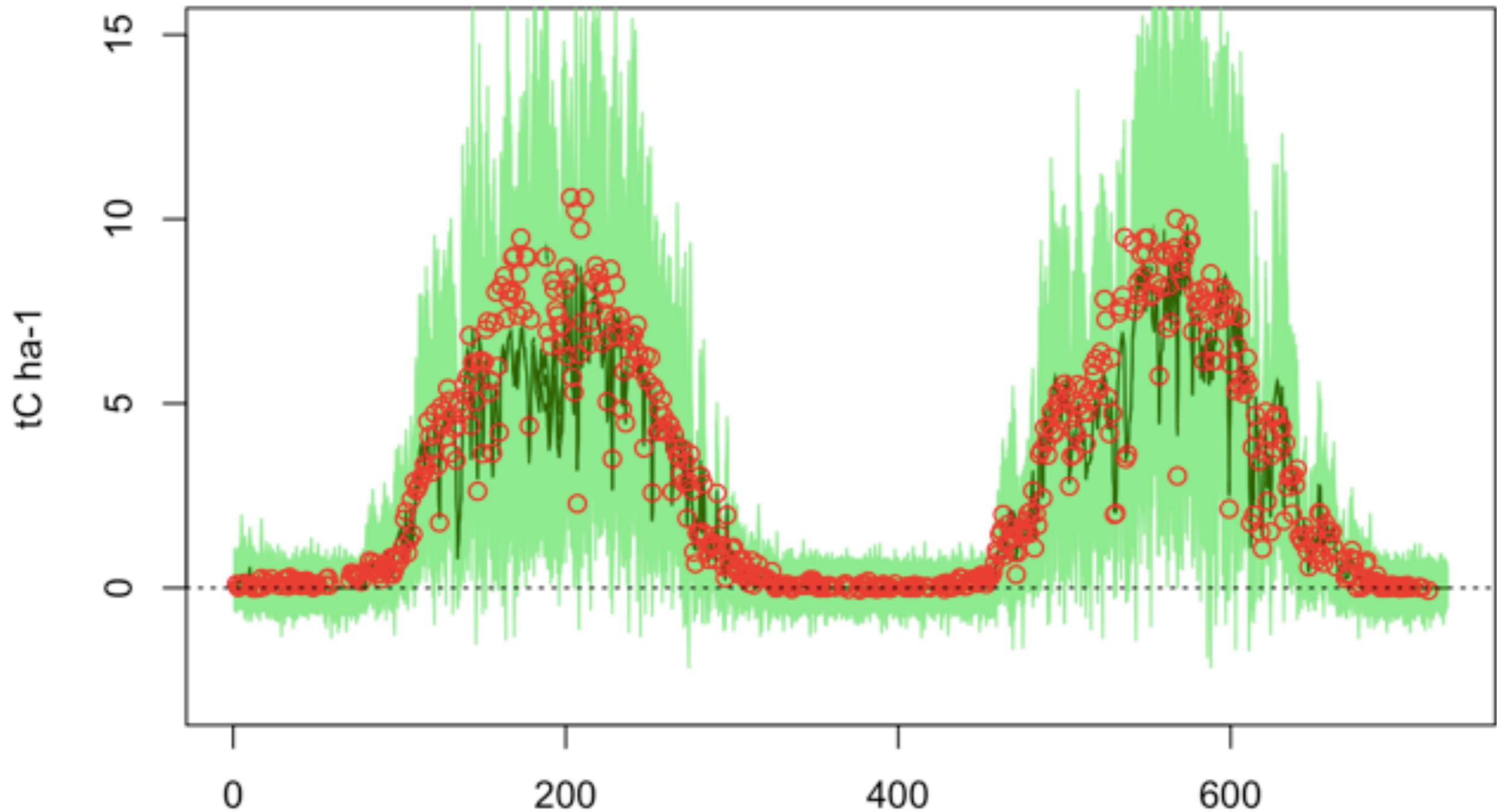
GPP



Does that seem like an adequate description of the data?

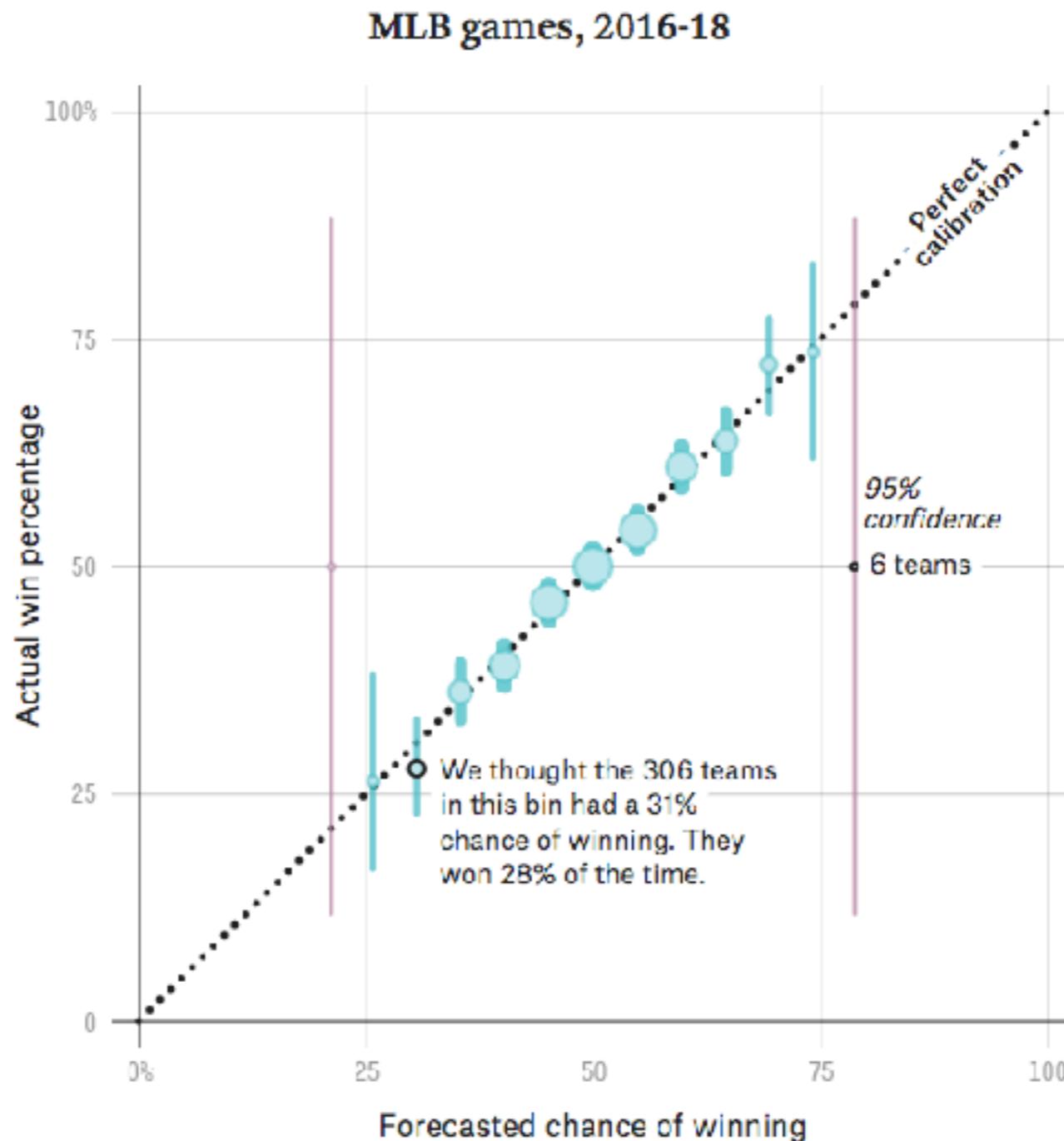
IN THIS FITTING, WE ASSUMED EXPONENTIAL ERRORS WITH
NON-CONSTANT VARIANCE

GPP



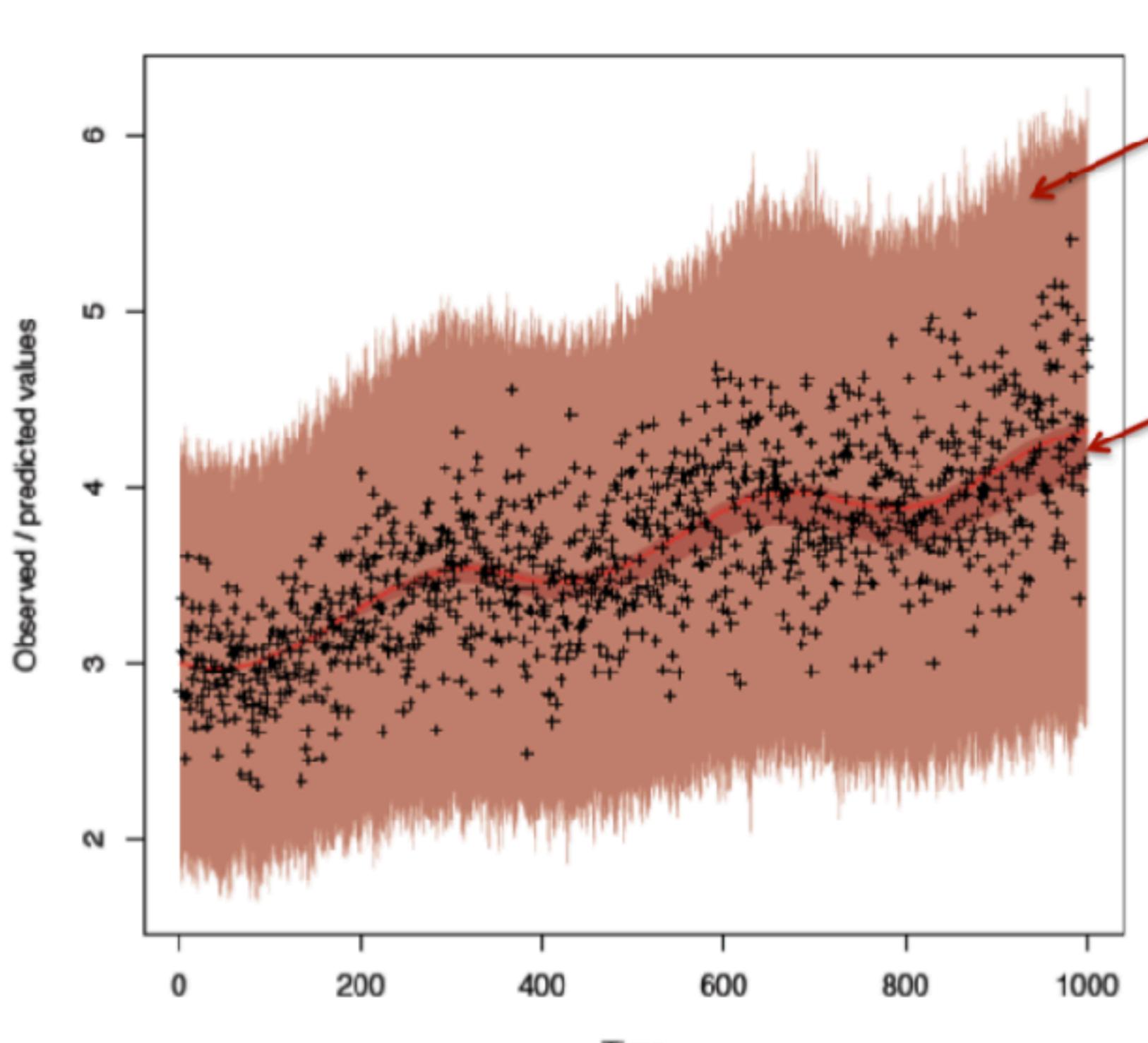
Does that seem like an adequate description of the data?

How Good Are FiveThirtyEight Forecasts?



Bayesian p-value / prediction interval

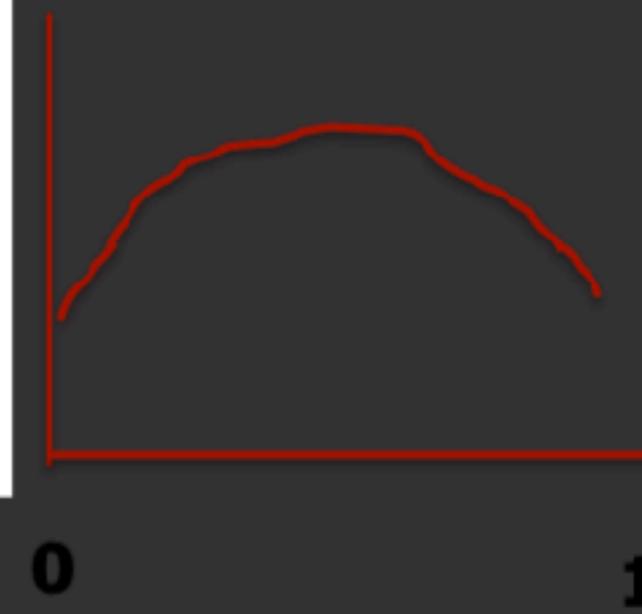
- Posterior predictive distribution is the uncertainty of the „true“ value
- **Prediction interval** is the expected variance of the observed values = PPD + error
 - Shows us what distribution we would expect for the data
- Bayesian p-value is when we use PPD + error to calculate the value of the cdf of the observed data
 - Distribution should be flat (uniform)
 - „Bayesian residuals“



PPD + Error

Posterior
Predictive
Distribution

Distribution of ecdf
values for residuals





Step 3: Quantitative Skill Assessment

Error Statistics

- ◆ Root Mean Square Error (RMSE)

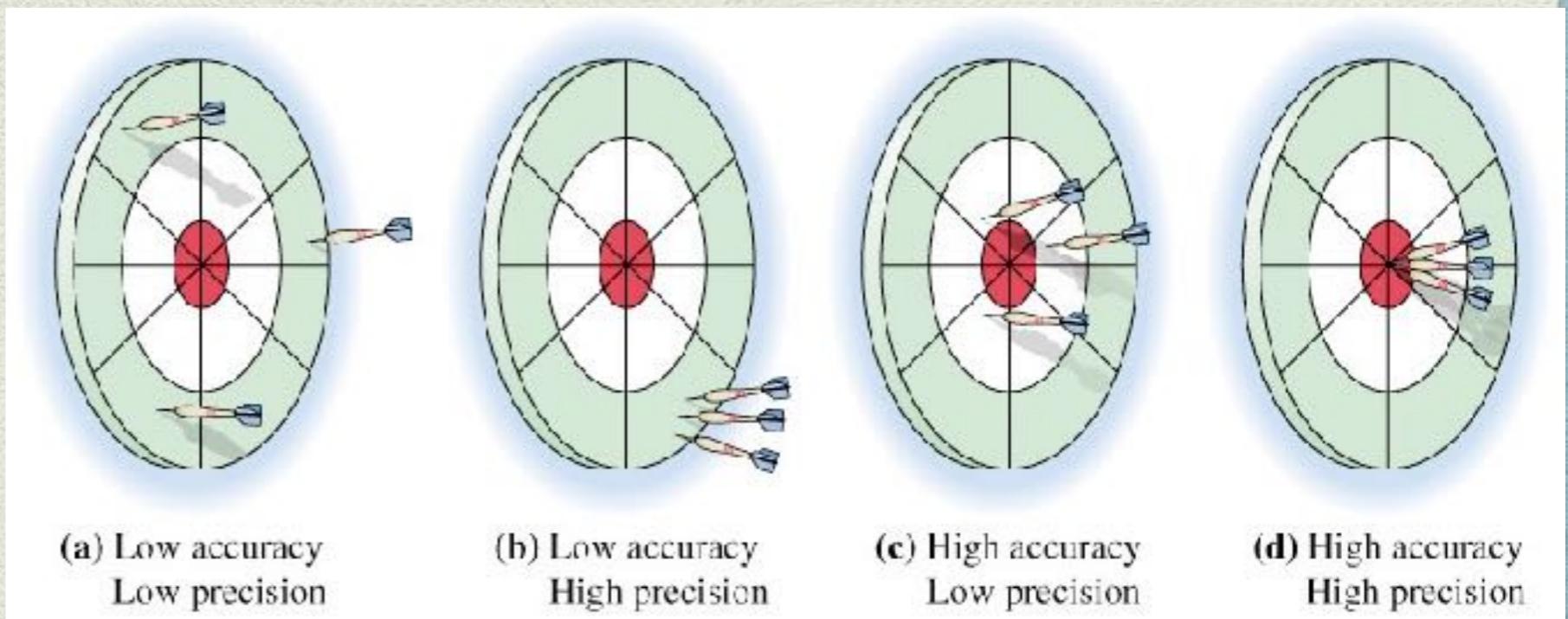
$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{x}_i)^2}$$

- ◆ Bias

- ◆ Correlation (r)

- ◆ R^2

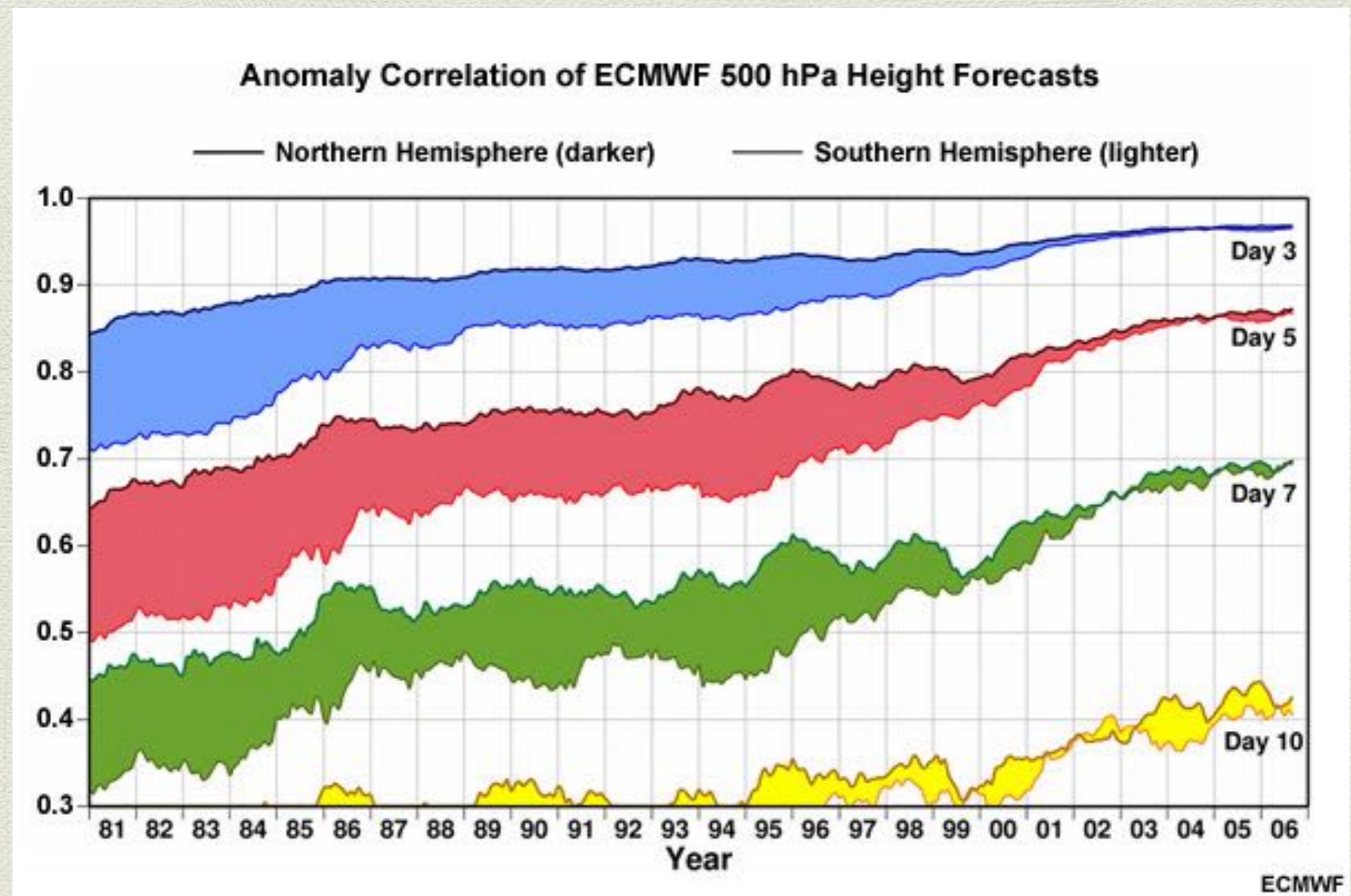
- ◆ Regression slope



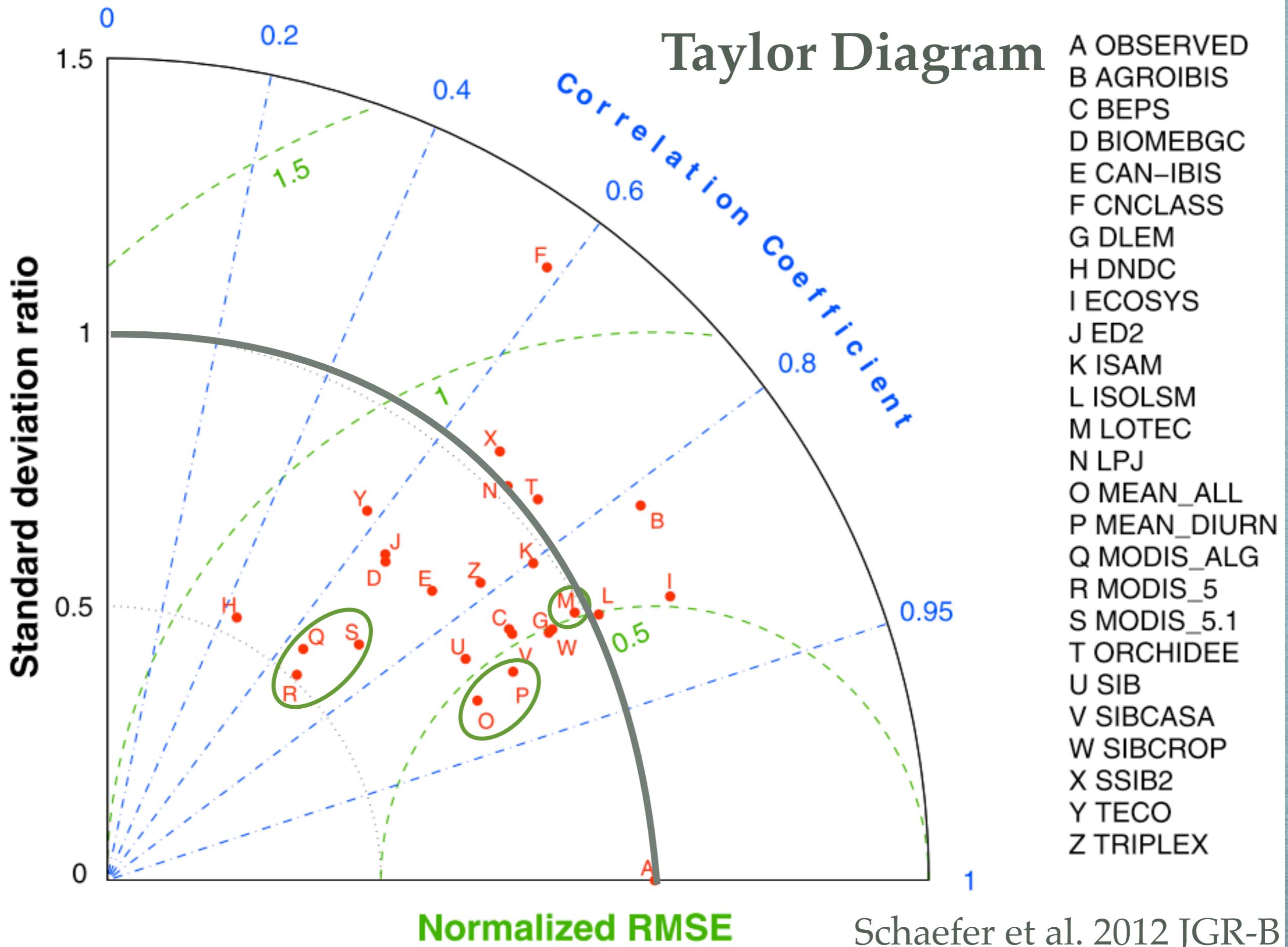
Proper: based on the metric used for calibration

Local: depends on data that could actually be collected

Correlation



Taylor Diagram

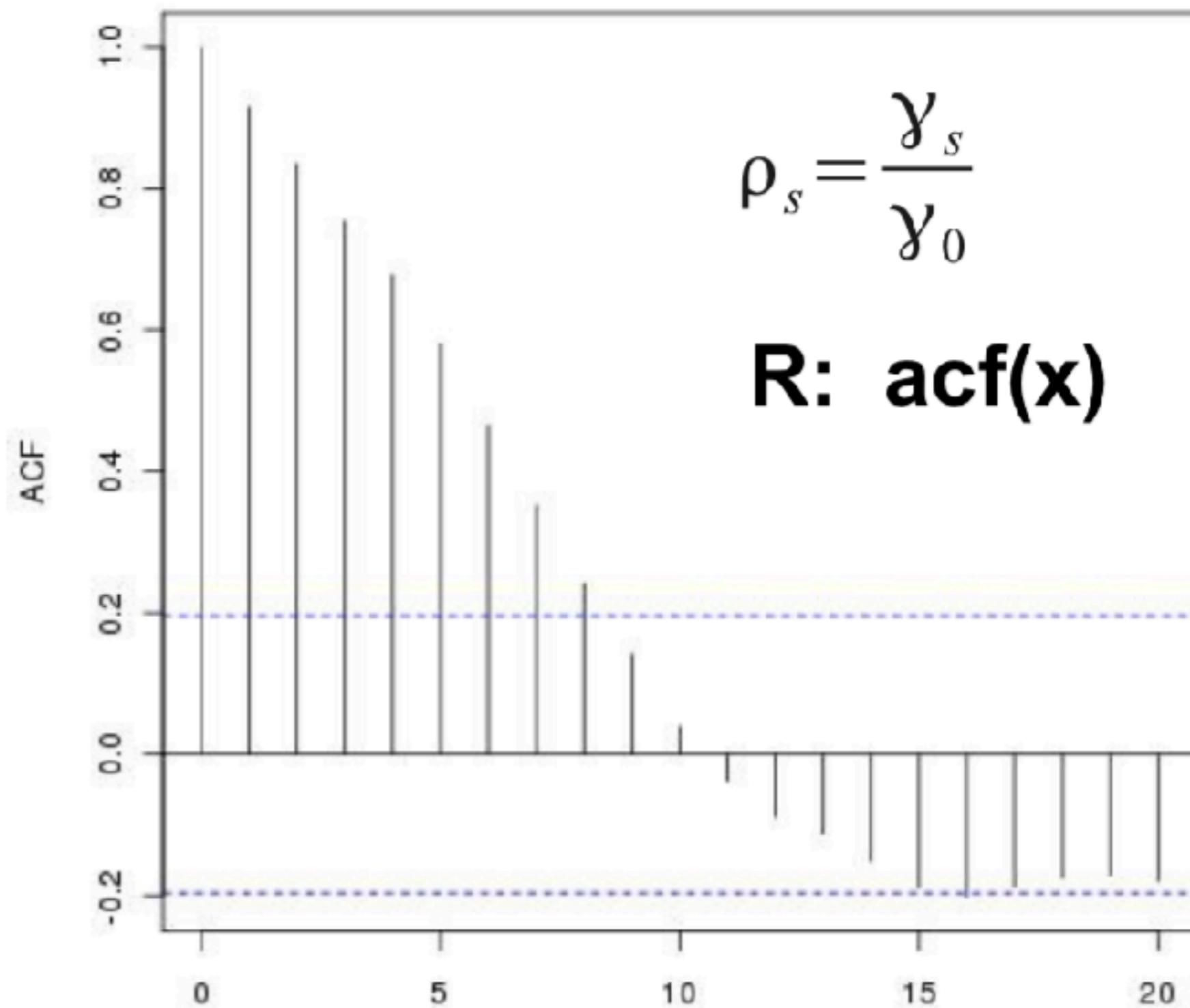


Normalized RMSE

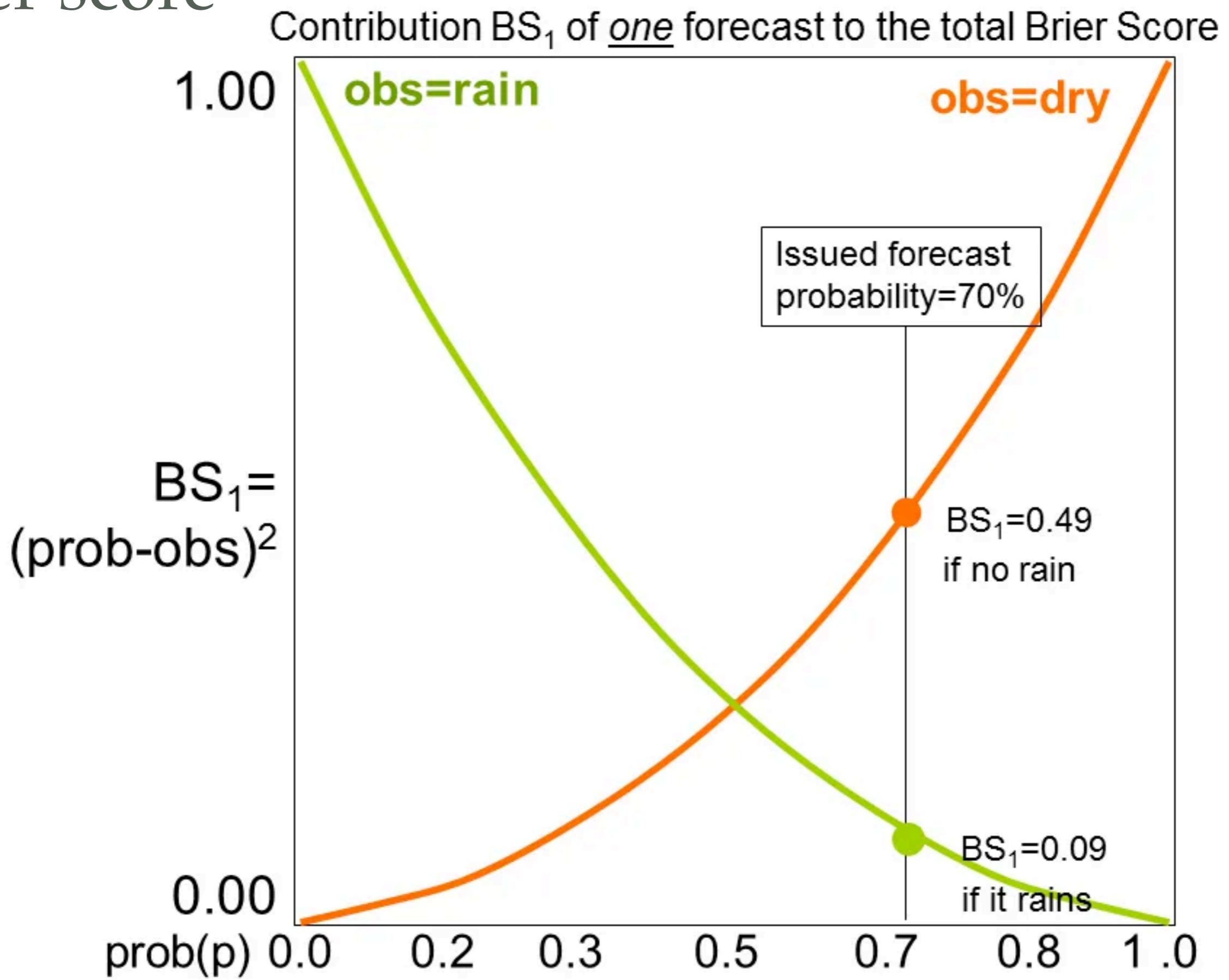
Schaefer et al. 2012 JGR-B

Autocorrelation

Correlogram

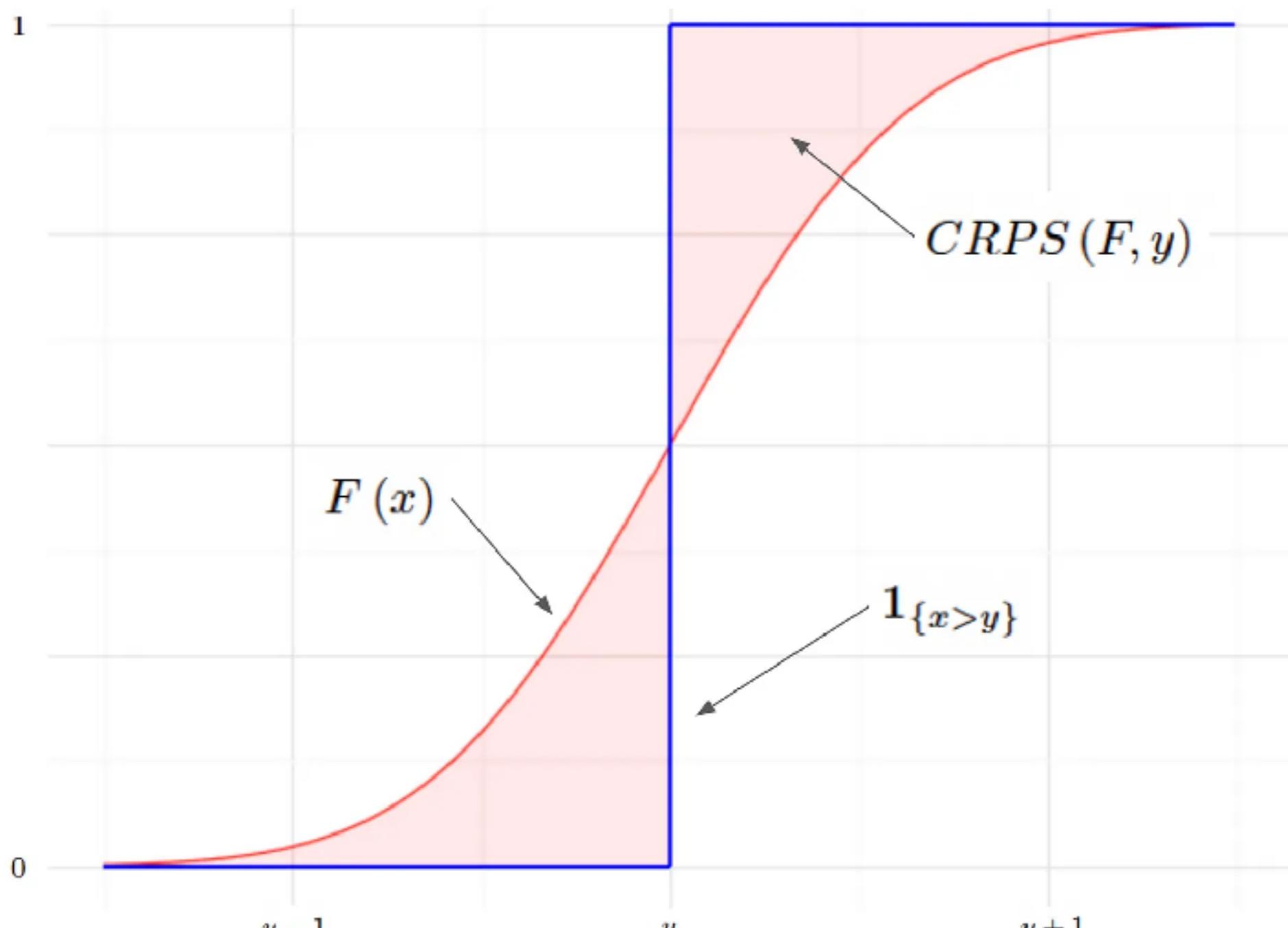


Brier score



Continuous Ranked Probability Score

$$\text{CRPS}(F, x) = - \int_{-\infty}^{\infty} (F(y) - \mathbf{1}\{y \geq x\})^2 dy$$



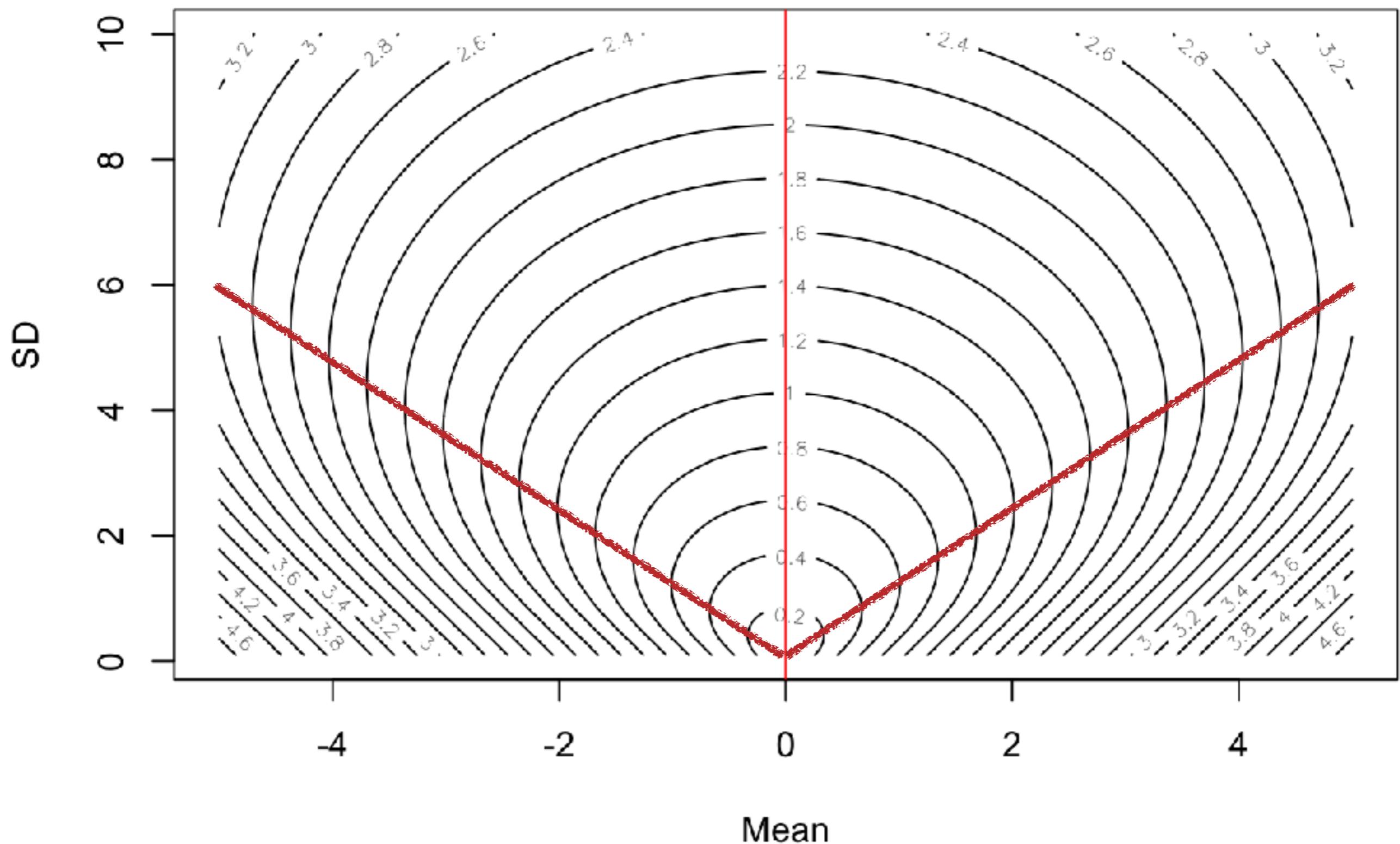
Continuous Ranked Probability Score

$$\text{CRPS}(F, x) = - \int_{-\infty}^{\infty} (F(y) - 1\{y \geq x\})^2 dy$$

$$\text{CRPS}(\hat{F}_m, y) = \frac{1}{m} \sum_{i=1}^m |X_i - y| - \frac{1}{2m^2} \sum_{i=1}^m \sum_{j=1}^m |X_i - X_j|$$

Ensemble member **Data**

Mean Absolute Error **Penalty for ensemble spread**

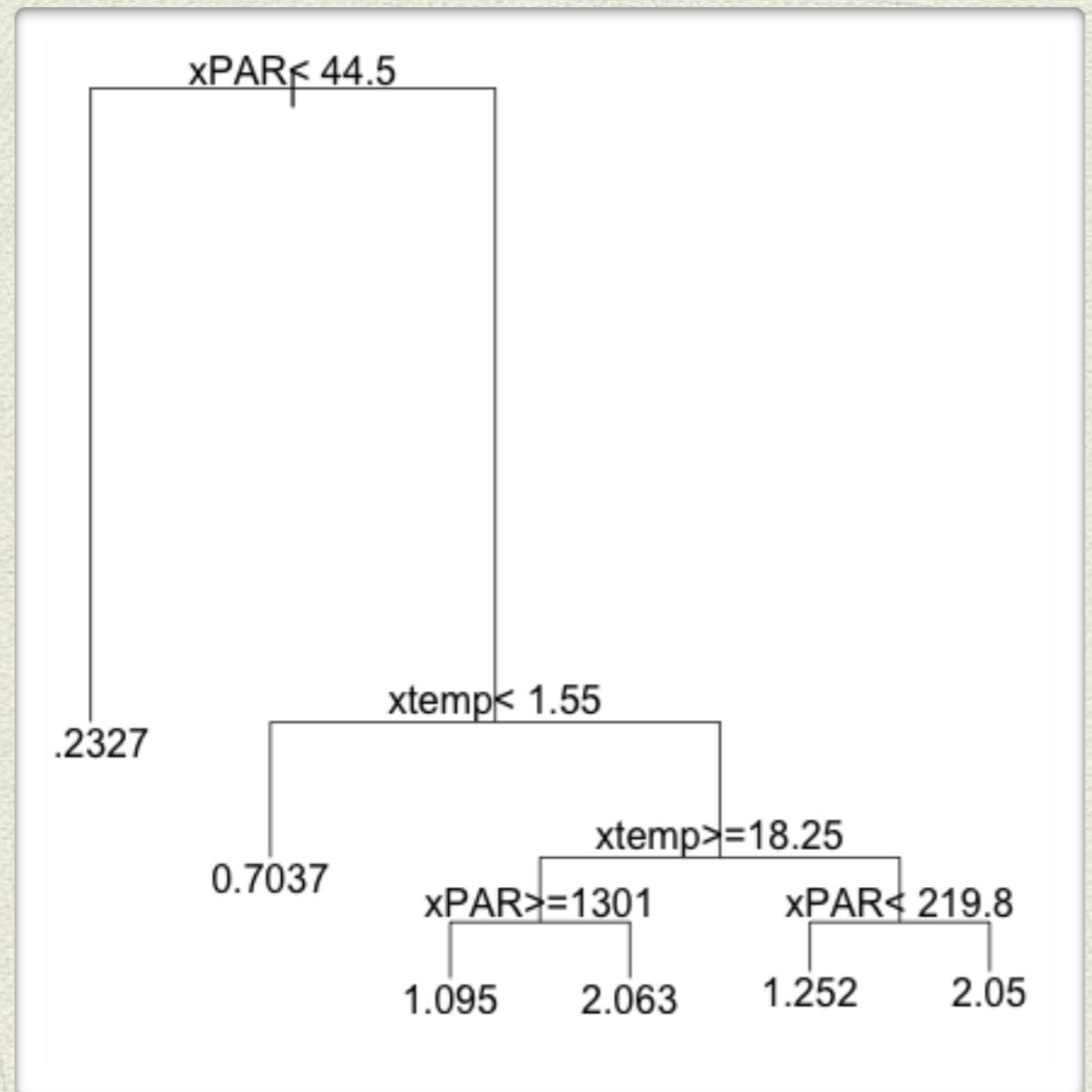


Data mining the residuals

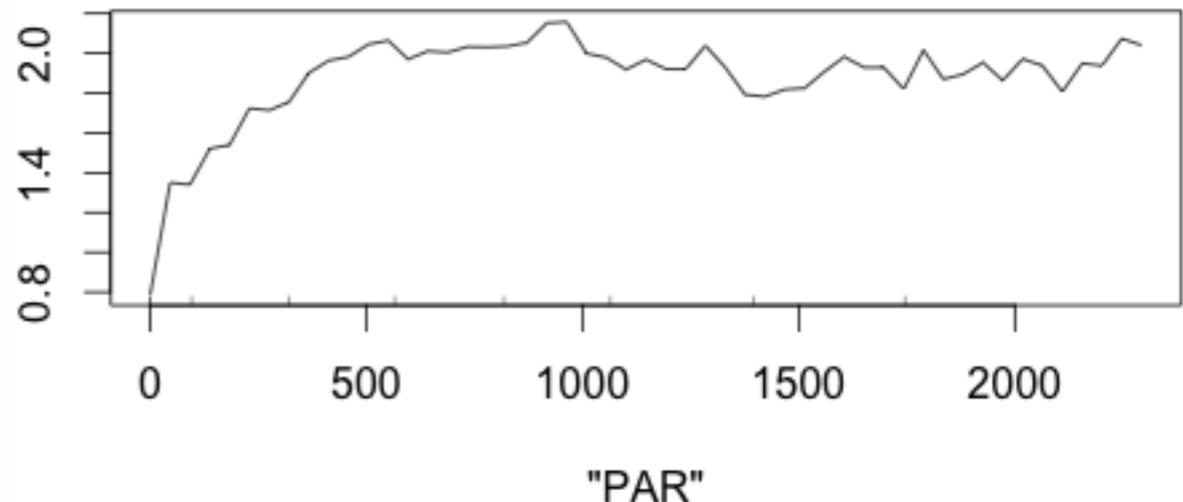
- ◆ Wide variety of Data Mining algorithms in use
- ◆ Large debate about use in process modeling and forecasting
- ◆ Potentially useful for generating hypothesis about when/where model fails
- ◆ CART
- ◆ GAM
- ◆ Random Forests
- ◆ Boosted regression trees / XGBoost
- ◆ Artificial Neural Network
- ◆ Deep Learning

Random Forest

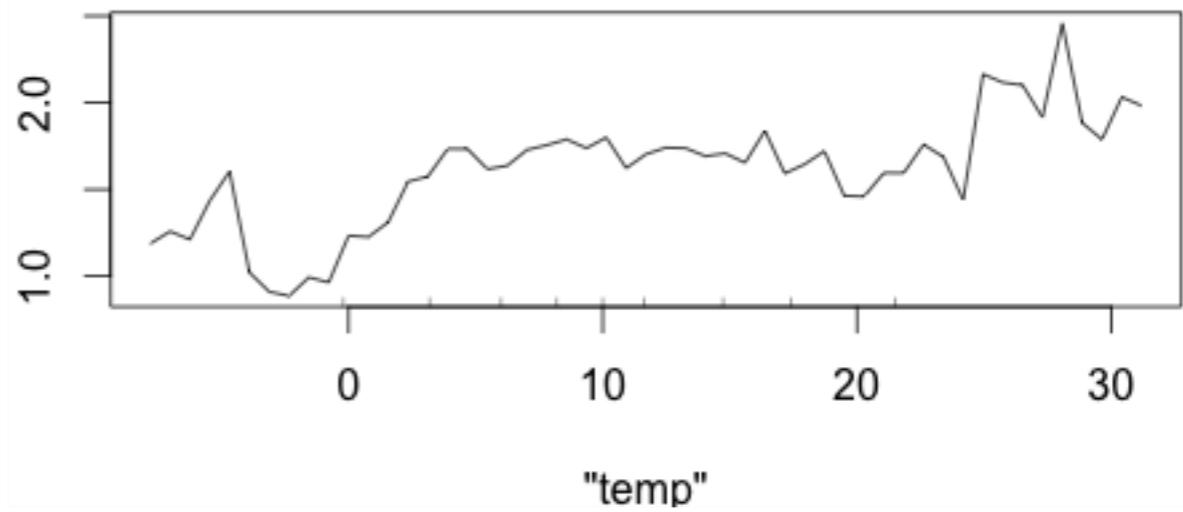
CART



Partial Dependence on "PAR"

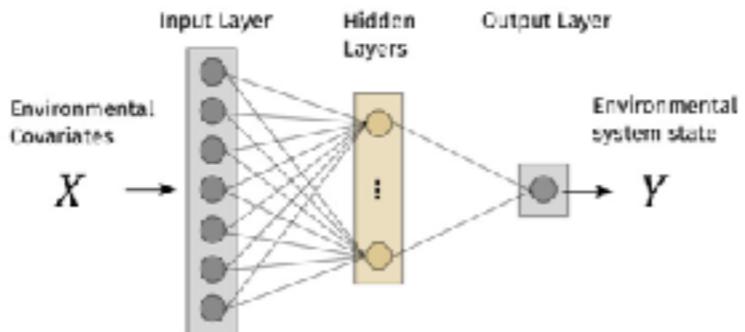


Partial Dependence on "temp"

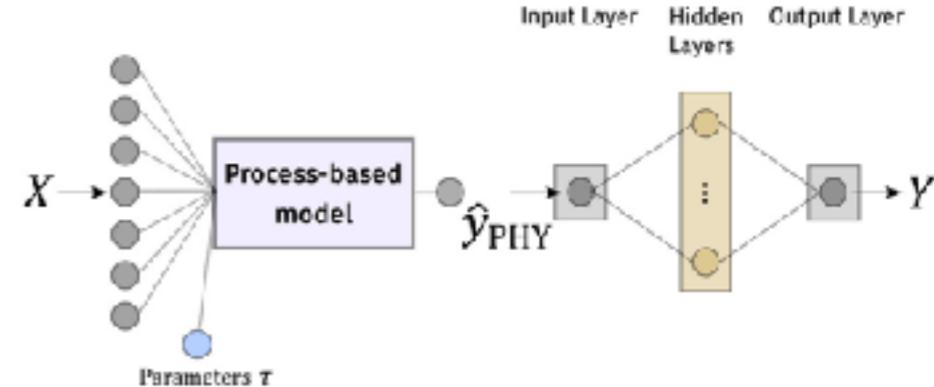


Hybrid Models (Process + NN)

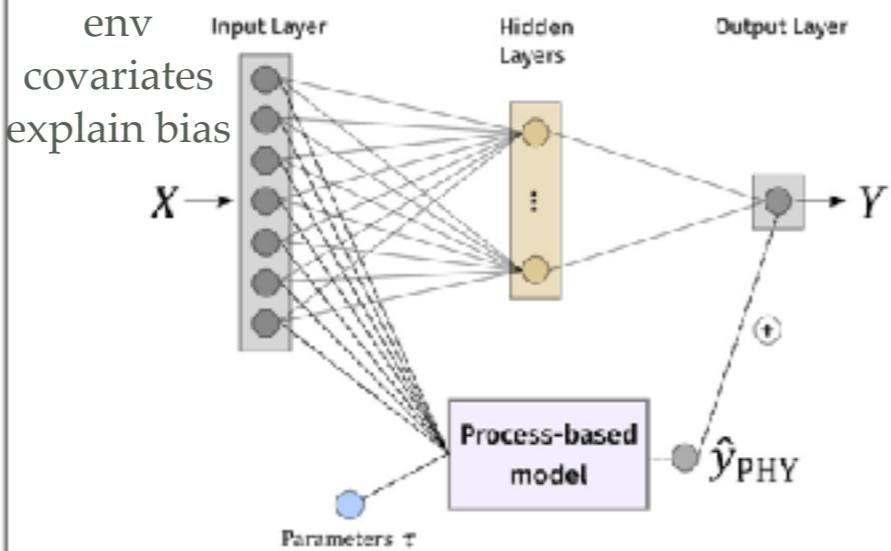
A. Naïve Neural Network



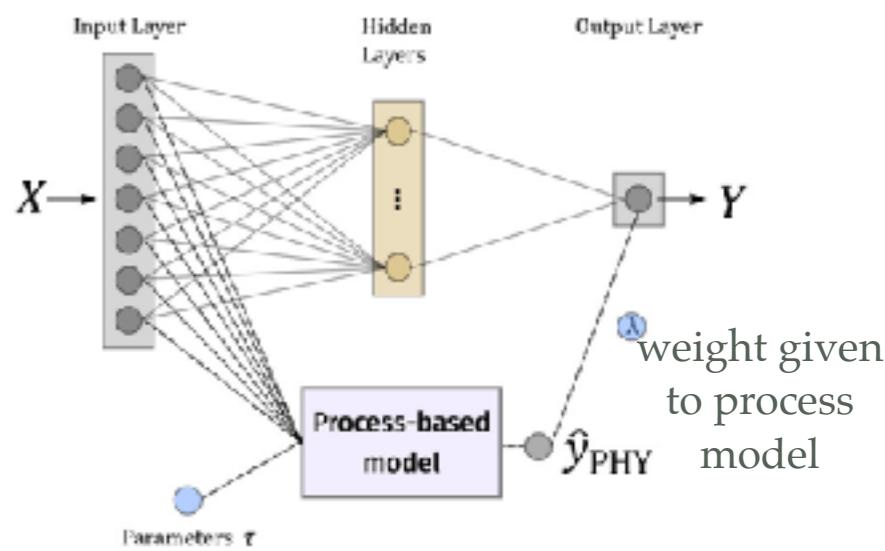
B. Bias Correction



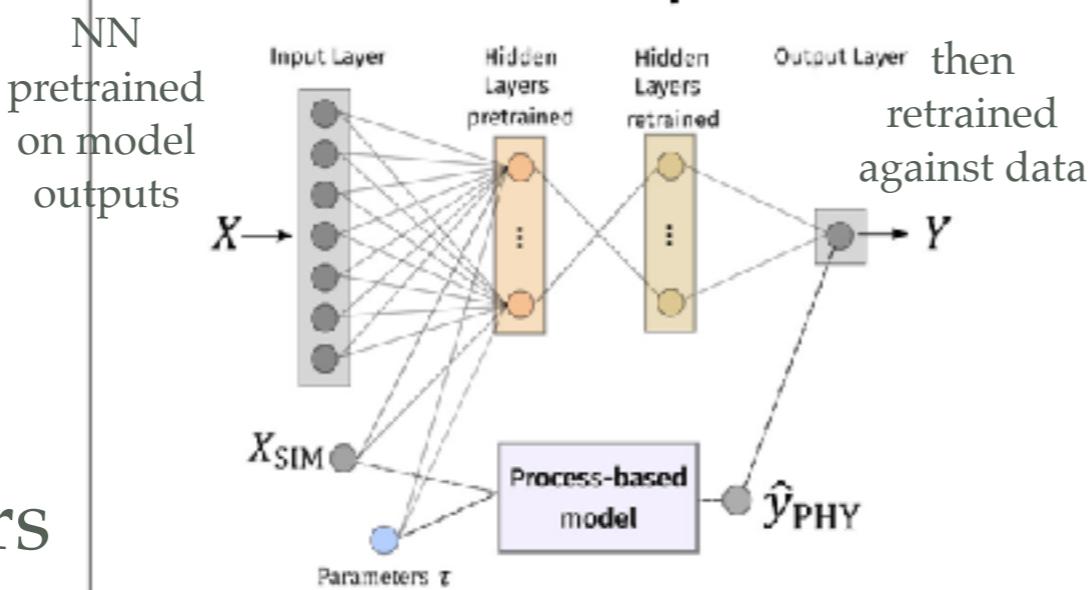
C. Parallel Physics



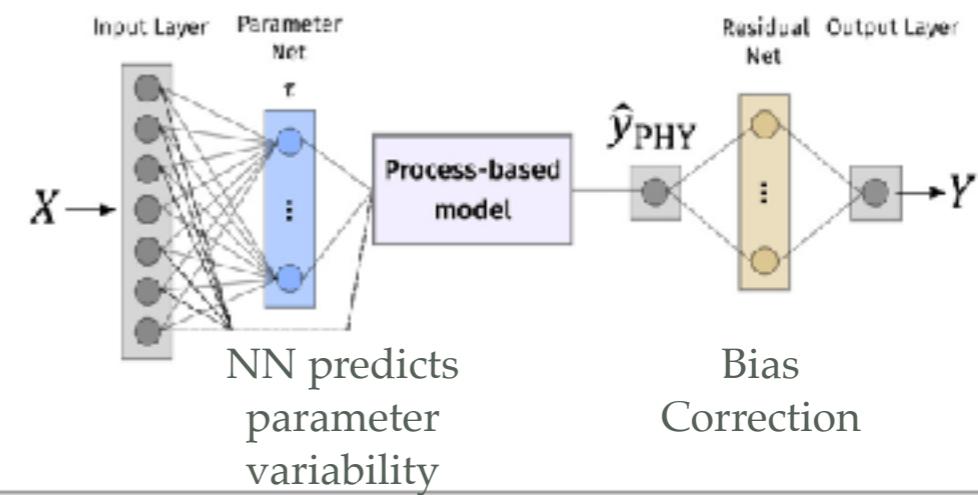
D. Physics Regularisation



E. Domain Adaptation

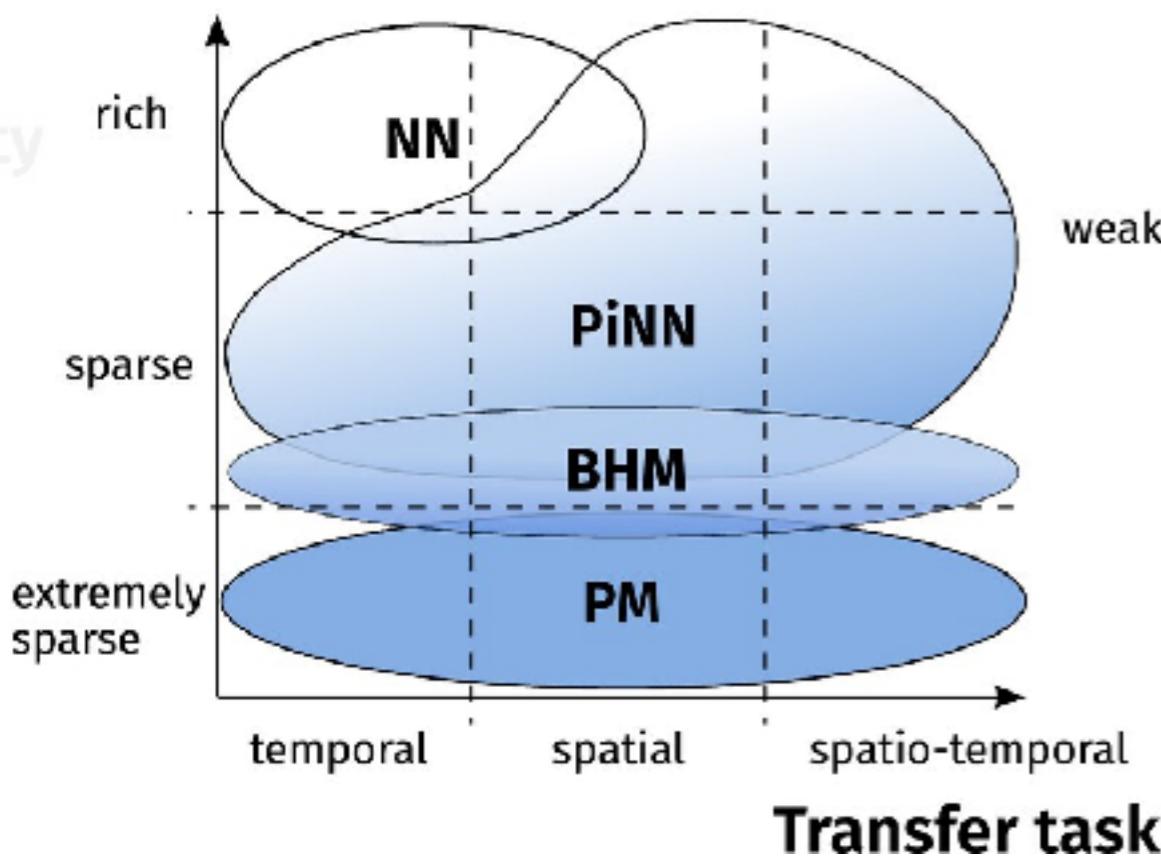


F. Physics Embedding



Expected performance sweet spots

Data Availability



Theory constraint of PiNNs

