

# A framework for evaluating uncertainty in crop model predictions

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# Most forecasters

recognize the importance of providing interval forecasts as well as (or instead of) point forecasts.

- to understand limitations of forecast
- to compare forecasting methods
- We need to associate a realistic measure of quality with crop model forecasts

# Vocabulary

- Error versus uncertainty:
  - Error is a number (true – simulated)
  - Uncertainty is a distribution
  - But don't rely on English, rely on equations

# Define prediction uncertainty

- Prediction uncertainty is the distribution of  $Y-f(X;\theta)$ 
  - where  $Y$  is the true value (e.g. yield)
  - $f(X; \theta)$  is the predictor (our model)
    - $f$  is model structure
    - $X$  is input vector
    - $\theta$  is parameter vector

The predictor is completely determined by these 3 elements

# MSEP

- It's not convenient to work with a distribution.
- A simple summary of prediction uncertainty is the mean squared error of prediction.

- For some specific  $X$

This means that the value of  $X$   
(weather, soil, etc) is fixed

$$\text{MSEP}(X) = E\{[Y - f(X; \theta)]^2 \mid X\}$$

Our criterion of prediction uncertainty

$$\text{MSEP}(X) = E\{[Y - f(X; \theta)]^2 \mid X\}$$

- The output  $Y$  is a random variable
  - $Y$  can have a range of values, even once  $X$  is given
  - Because input variables don't explain everything
- But what about the model? Fixed or random?

# Fixed or random model?



# Fixed or random model?

- That is the main topic of this talk
  - How to estimate MSE in each case
  - Advantages and drawbacks of each
- The two possibilities correspond to very different ways of thinking about, and estimating, prediction uncertainty.
  - So the choice is important.
- All work related to prediction uncertainty is based on one or the other
  - Even though it isn't said like that



# Fixed predictor $f(X; \theta)$

- We have one specific model (fixed)
- With given parameter values (fixed)
- Assume that the inputs are known without uncertainty

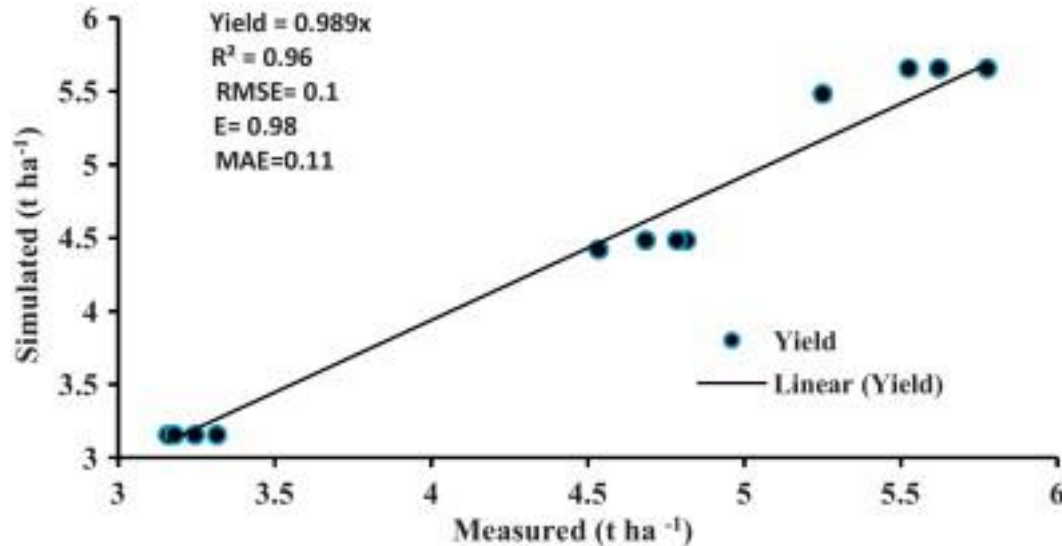
# Estimation of MSEP

- Compare hindcasts with observations
- Can't estimate for each  $X$  (only have  $y_i$  for a few  $X$ )
- So estimate average over all predictions
- Estimator is  $MSE = (1/n) \sum [y_i - f(X_i; \theta)]^2$
- Estimates  $MSEP_{\text{fixed}} = E[MSEP_{\text{fixed}}(X)]$

# Fixed model, in practice

- MSE (or RMSE) is most common criterion in model “evaluation” or “model validation” or “model performance”.
- This estimates  $MSEP_{\text{fixed}}$  (assumes fixed model)
  - There are other distance measures based on hindcasts, but they also estimate properties of prediction uncertainty assuming fixed model

# One example (from very many)



	RMSE	E	MAE	R2
Grain yield (t ha <sup>-1</sup> )	0.1	0.98	0.11	0.96
Biomass (t ha <sup>-1</sup> )	0.75	0.95	1.08	0.9
WP (kg ha <sup>-1</sup> mm <sup>-1</sup> )	1.2	0.74	0.71	0.77

Abedinpour et al. 2012.

# Features of $MSEP_{\text{fixed}}$

- Assumption (often implicit) is that past errors are representative of future errors
  - So this is an estimate of prediction uncertainty
- Only calculate average  $MSEP$ 
  - One value for all predictions
  - **Average** of past errors is representative of **average** of future errors
- For MSE to be unbiased estimate of  $MSEP_{\text{fixed}}$ , requires independence between evaluation and calibration errors.
  - Not easy to insure
  - In example, calibrate in 2009, evaluate for same field in 2010
  - Prediction error for other sites?

# Random predictor $f(X;\theta)$

- There are multiple alternative models.
  - Distribution: Simplest assumption - all equally probable
- Input variables measured or estimated with error
  - Distribution: from measurement sd or literature or multiple models (future climate)
- Parameter vector
  - From literature, from calibration (frequentist or Bayesian)

# $MSEP_{\text{random}}(X)$ is sum of two terms

- bias: error, averaged over  $X$ , of predictor averaged over equations, inputs, parameters,
- variance: uncertainty in predictor due to uncertainties in equations, inputs, parameters

bias term

variance term

$$MSEP_{\text{random}}(X) = E \left\{ \left[ \left( y - E[f(X; \theta) | X] \right)^2 \right] | X \right\} + \text{var} [f(X; \theta) | X]$$

# Estimation, random model

- Variance term
  - Do a computer experiment
  - This is specific for each  $X$
  - Calculate variance of simulated values

structure	$\theta$	$X$	$y(X)$
model 1	$\theta_{11}, \theta_{12}, \dots$	$X_1, X_2$	$Y_{111}, Y_{121}, \dots$
:			
model M	$\theta_{M1}, \theta_{M2}, \dots$	$X_1, X_2$	$Y_{M11}, Y_{M21}, \dots$

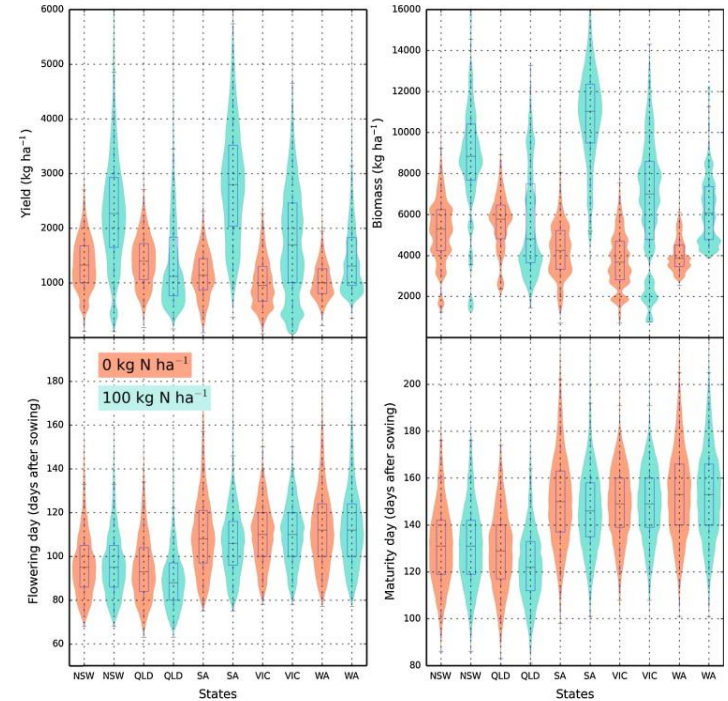
} calculate  
variance



- Bias term
  - Use hindcasts, compared to data
  - This estimates average over  $X$

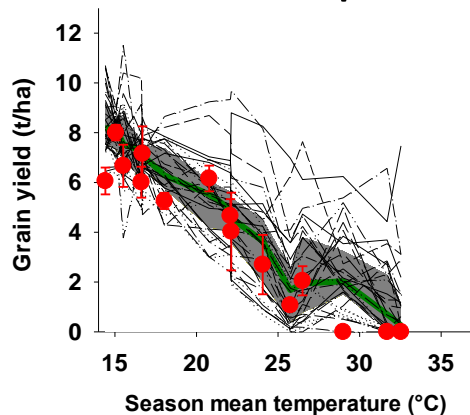
# Random model in practice

- Several studies with parameter and/or input uncertainty
  - These studies estimate only the variance term.
    - Ignore structure uncertainty
    - Ignores bias term



Zhao et al. 2014.

- Many recent studies with model structure uncertainty (multi-model ensembles)
  - Estimate variance term
    - Ignore uncertainty in inputs and parameters
  - Error of mean of models estimates bias term
    - Small compared to variance term



Asseng et al. 2014

# Features of $\text{MSEP}_{\text{random}}(X)$

- This is mean squared error for a specific  $X$
- But averaged over distribution of predictors
- That is the trade-off
- Note that standard statistical prediction intervals in regression treat model parameters as random. Bayesian credible intervals also.

# An example of the difference between fixed and random models

	AR 2009	AR 2010
$MSEP_{\text{fixed}}$		
model 1. MSEP	0.19	0.19
model 2. MSEP	2.02	2.02
$MSEP_{\text{random}}(X)$		
bias term	0.23	0.23
variance term	1.55	2.77
sum= $MSEP_{\text{random}}(X)$	1.78	3.00

# Conclusions

- $\text{MSEP}_{\text{random}}$  has both a variance term and a bias term, need to estimate both
  - Usual studies don't add bias
  - And only look at part of variance
- $\text{MSEP}_{\text{random}}(X)$  has important advantages
  - It shows how prediction uncertainty varies with the prediction situation (with  $X$ )
  - $\text{MSEP}_{\text{random}}$  allows separate estimation of effects of structure, input and parameter uncertainty

# Going forward

- Estimate  $\text{MSEP}_{\text{random}}(X)$  systematically
  - Can help answer question: is model good enough for this specific application
  - Useful even if only part of uncertainty taken into account
  - Can be compared with  $\text{MSEP}_{\text{fixed}}$
- Further work needed
  - More experience with size of bias term relative to variance
  - A major problem is estimating parameter uncertainty. This may be very important



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