Decadal Prediction Information

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Overview

Uncertainty in projections from Global Climate Models:
- quantifying it (a Bayesian approach) and propagating it

Examples of short term probabilistic projections:

1) Temperature and precipitation change for water resources management;

2) Temperature and precipitation change for food security/ agricultural impacts.

About probabilistic projections in a Bayesian framework

I.   What is the uncertain quantity, H, I'm after, and do I have any knowledge, independent of the data I'm going to use, that can shape a-priori its probability distribution, $P(H)$?

II.   What data do I have, and how does it relate, statistically, to H? What is the distribution of the data, given a specific value for H? What is the likelihood of the data, $P(D|H)$?

III.   How do I update my prior into a new distribution informed by the data, $P(H|D)$? How do I actually apply Bayes theorem?

More concretely

I.   I want to forecast temperature over North America in the next 20 years. Do I have any a-priori knowledge of what that is going to be like? IPCC-AR4 ensemble? Continuation of current trend? What is its a-priori probability distribution, P(H)?

II.   What is the decadal-prediction model ensemble saying? What am I going to look at? Temperature forecasts, straightforwardly? ENSO/NAO indices? If the real temperature was "h" how do I expect the model data to behave? What is the likelihood of the data, P(D | H=h)?

I.   How do I compute Bayes theorem, and update my prior into a new distribution informed by the data, P(H|D)? Markov Chain Montecarlo algorithms.

What are we going to look for in the model output?
Temperature for temperature, precipitation for precipitation?

Indices of which we have some sense of the predictability and teleconnection patterns?

It all boils down to decide on H and to determine a P(D|H)

What we want to forecast

What we can say about model output relation to H

An example:

Joint projections of temperature and precipitation

using the CMIP3 ensemble

What is H and what does P(D|H) look like

- We choose H to be the true climate signal time series (decadal averages of temperature and precipitation). We expect it to be a piecewise linear trend with an elbow at 2000, to account for the possibility that future trends will be different from current trends.

- Superimposed to the piecewise linear trends is a bivariate gaussian noise with a full covariance matrix, which introduces correlation between temperature and precipitation: that is what we observe and what GCMs simulate, our D.

- GCMs may have systematic additive bias, assumed constant along the length of the simulation;

- after the bias in each GCM simulation is identified and accounted for, the variability around the true climate signal is model-specific;

- observed decadal averages provide a good estimate of the current series, their correlation, and of their uncertainty.

P(D|H) looks like:

$$O_t^T \sim N[\mu_t^T; \eta^T]$$
$$O_t^P \sim N[\mu_t^P + \beta_{xo}(O_t^T - \mu_t^T); \eta^P]$$
$$X_{jt}^T \sim N[\mu_t^T + d_j^T; \phi_j^T]$$
$$X_{jt}^P \sim N[\mu_t^P + \beta_{xj}(X_{jt}^T - \mu_t^T - d_j^T) + d_j^P; \phi_j^P]$$

$$\begin{pmatrix} \mu_t^T \\ \mu_t^P \end{pmatrix} \equiv \begin{pmatrix} \alpha^T + \beta^T t + \gamma^T (t - T_o)\chi_t \\ \alpha^P + \beta^P t + \gamma^P (t - T_o)\chi_t \end{pmatrix}$$

We derive a joint posterior distribution for all of the parameters,
In particular for the time series of temperature and precipitation
signals:

$$\begin{pmatrix} \mu_t^T \\ \mu_t^P \end{pmatrix}$$

and a posterior predictive distribution for a new model's projection:

$$\begin{pmatrix} X_{*t}^T \\ X_{*t}^P \end{pmatrix}$$

Probabilistic projections
for temperature and precipitation

Global DJF averages

Full trajectories from 1950 to 2100

Changes by 2080-2100 vs.
1980-2000.
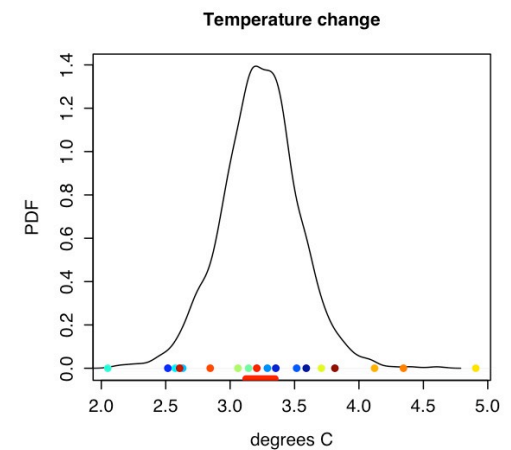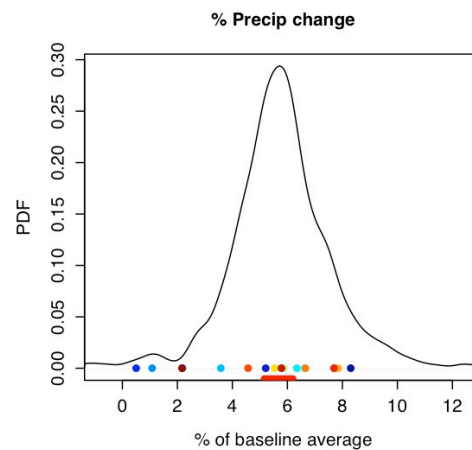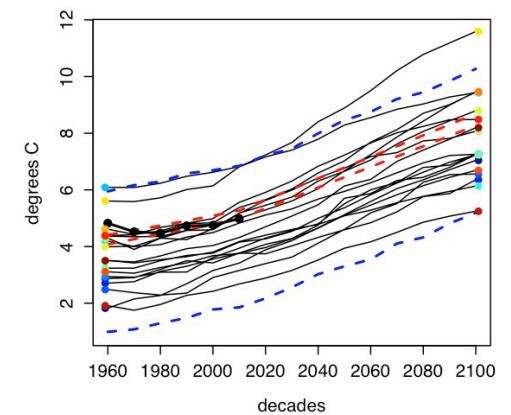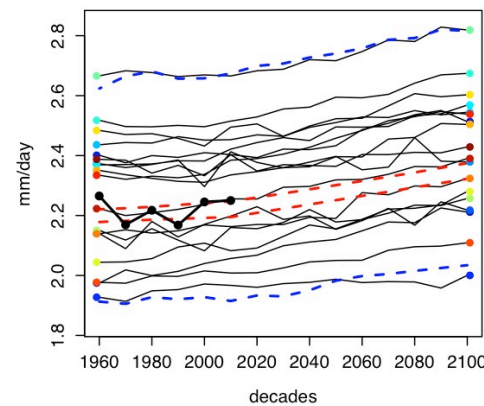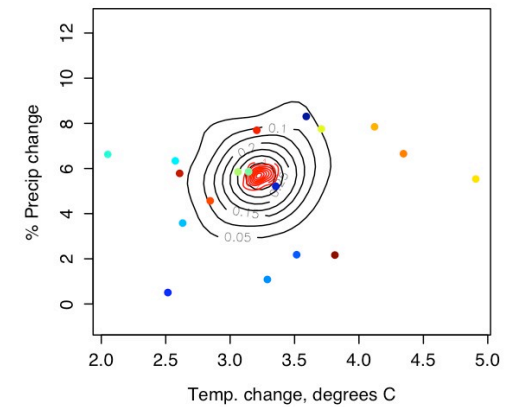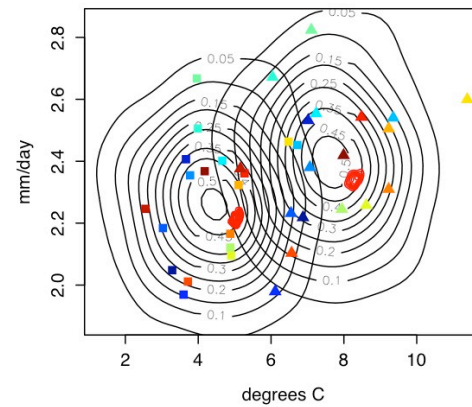
Climate Scenarios:
From frequencies to time series

- GCM ensemble projections are given as frequency distributions of decadal averages or linear trends

- Impact models (hydro, demand, ecosystem, etc) need time series of P, T, RH, wind speed over area of interest, oftenat a much higher frequency

- Spatial and temporal consistency

Need to generate multivariate weather data

Future temperature scenarios through a biased resampling approach:
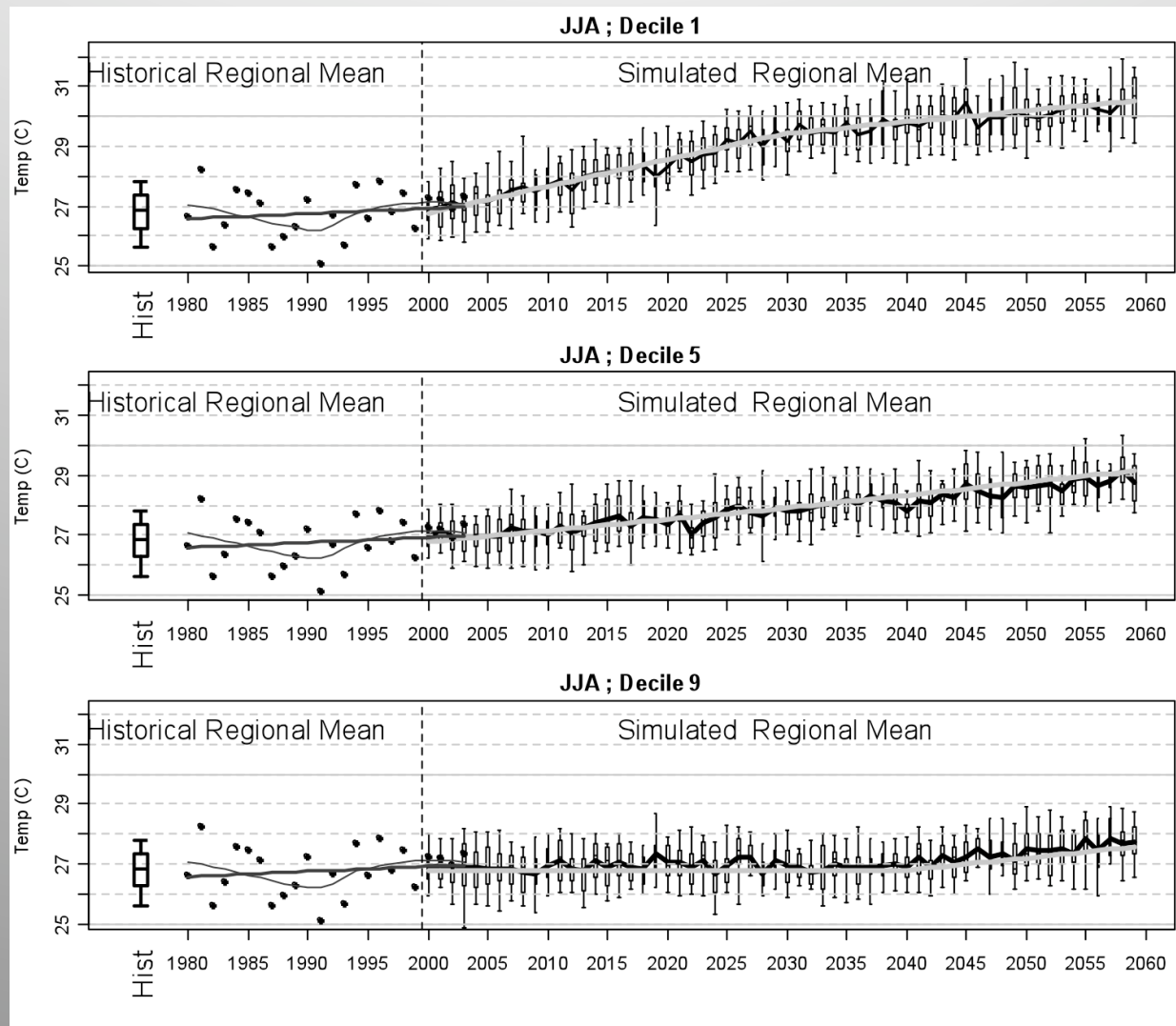
Future precipitation scenarios through a biased resampling approach:
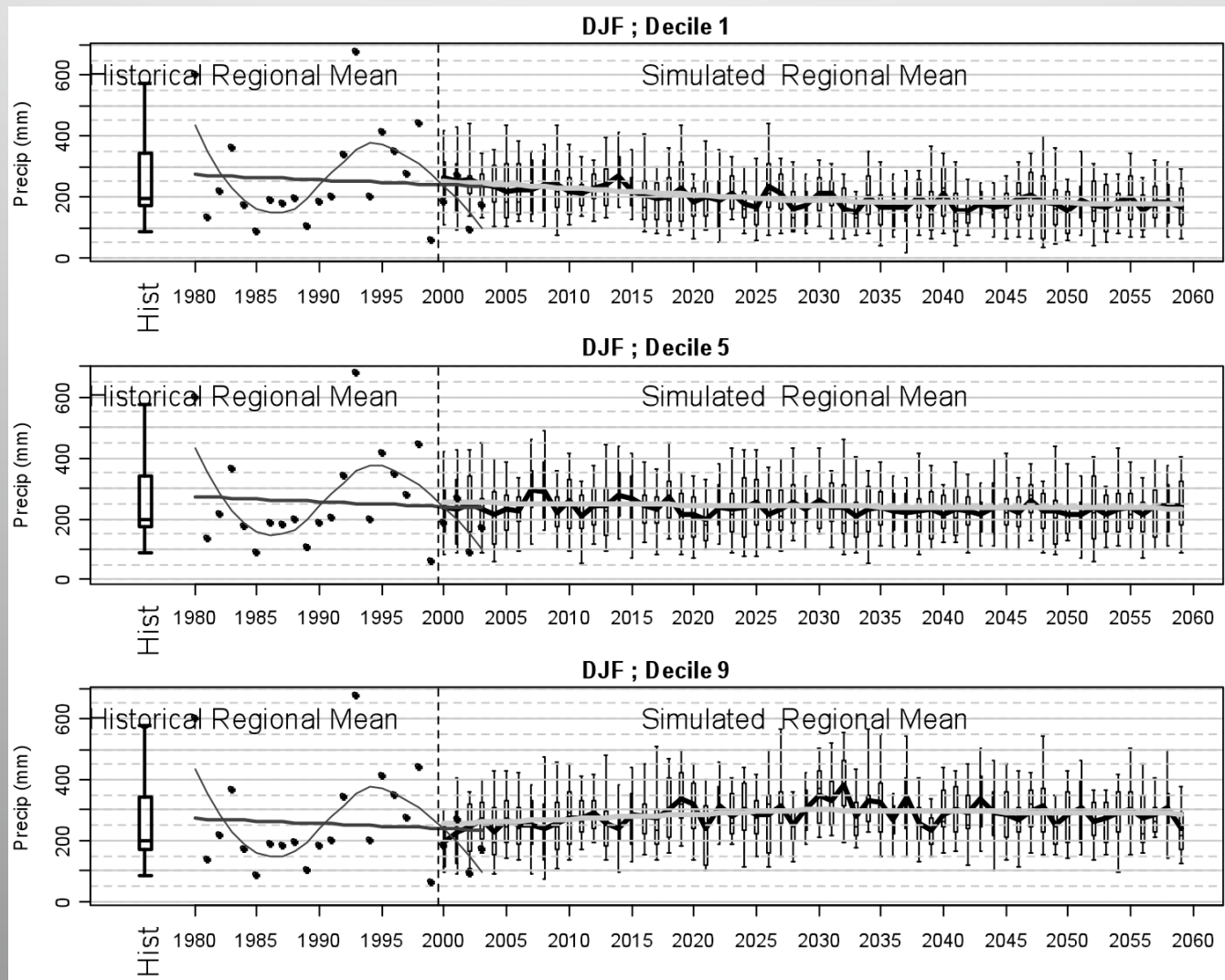
Each of the synthetic time series (many for each decile of the probability distribution of temperature change over Northern California) is fed into a water resources management model, producing probabilistic impact projections.
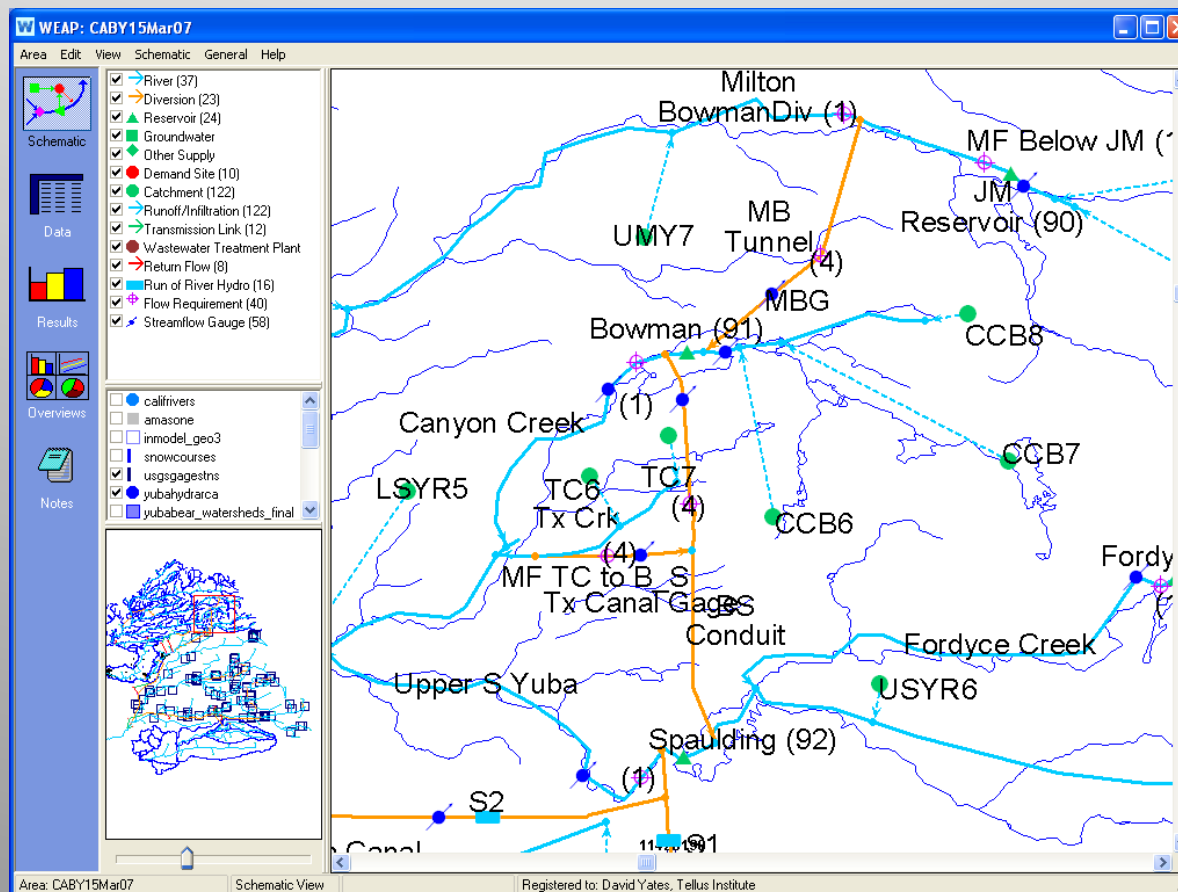
Translating GCM projections into agricultural impacts

We estimate empirical models of crop yield changes:
e.g., Barley
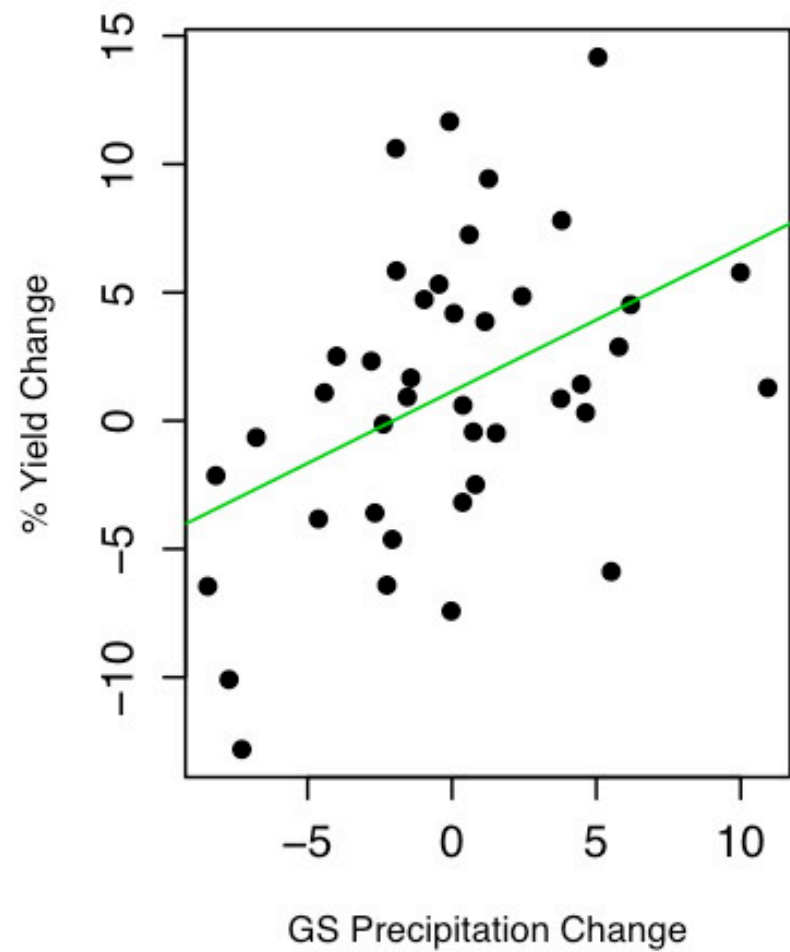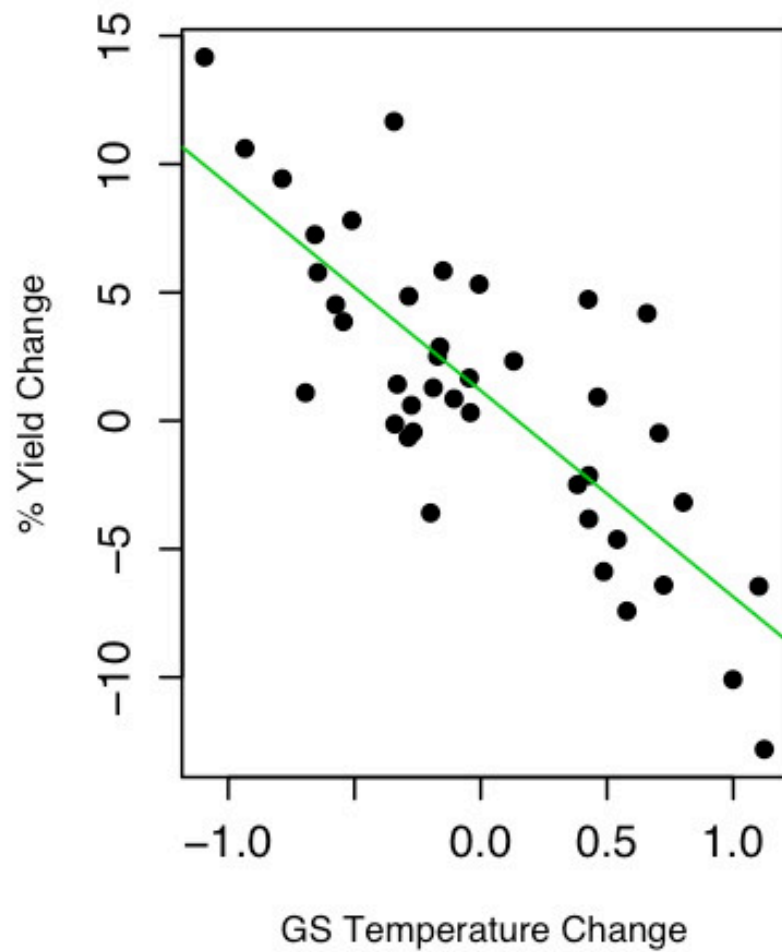
Each dot on the graphs

Global yield of barley (annual statistic, FAO)
Average temperature (and precipitation)
     aggregated over all barley-growing regions,
     for the crop-specific growing season

Except, these are actually changes from year to year
(first difference time series).

$$\Delta Y_i = \beta \Delta T_i + \gamma \Delta P_i + \varepsilon_i$$

We estimate the coefficients on the basis of observed data

We then plug in

$$(\Delta T_i, \Delta P_i)$$

from the joint probability distribution estimated from climate models' output

We thus obtain a probability distribution for

$$\Delta \hat{Y}_i$$

the change in yield.
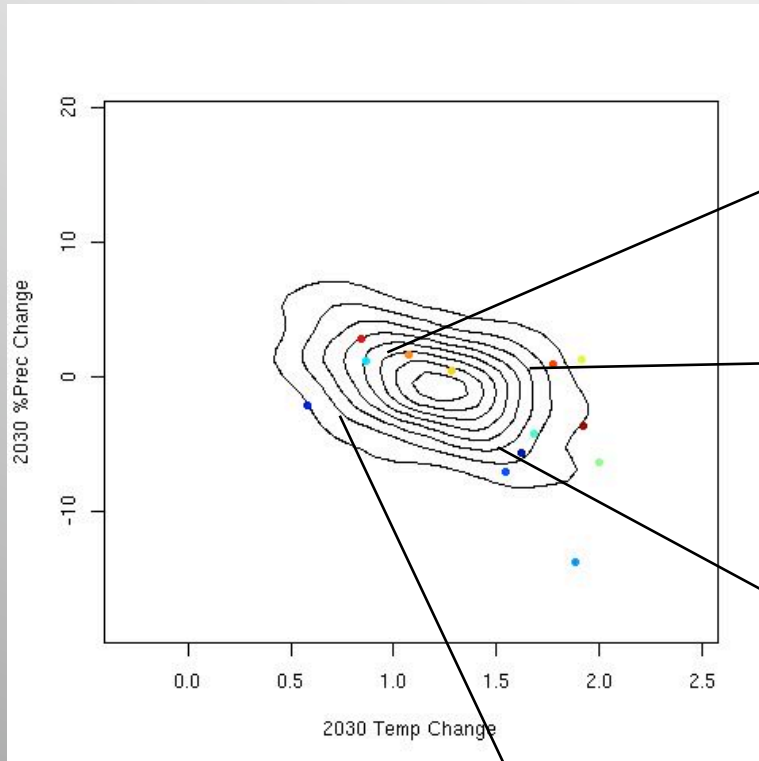
Areas where barley is grown
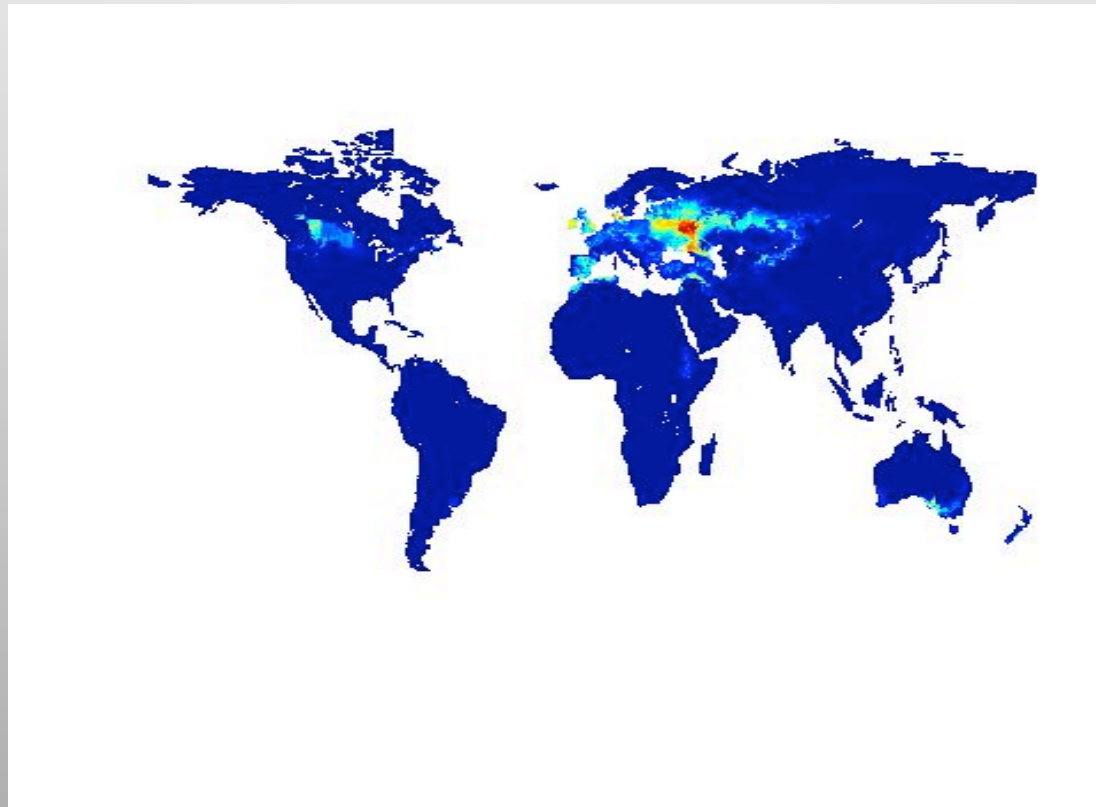
We aggregate GCM output (temperature and precip) over these regions and over barley's growing season

Results from Bayesian analysis of GCM output
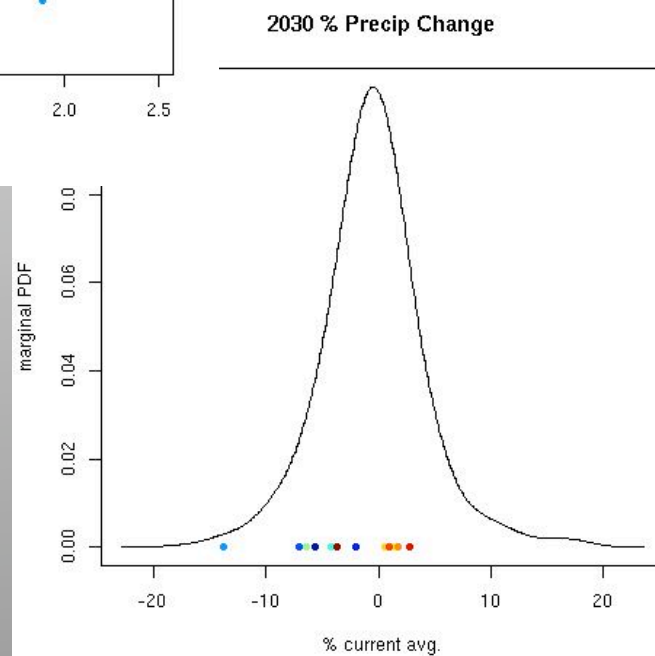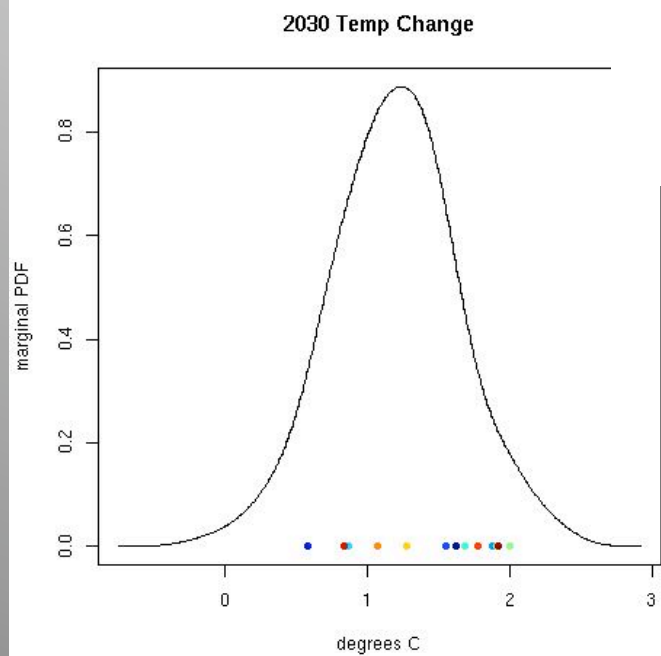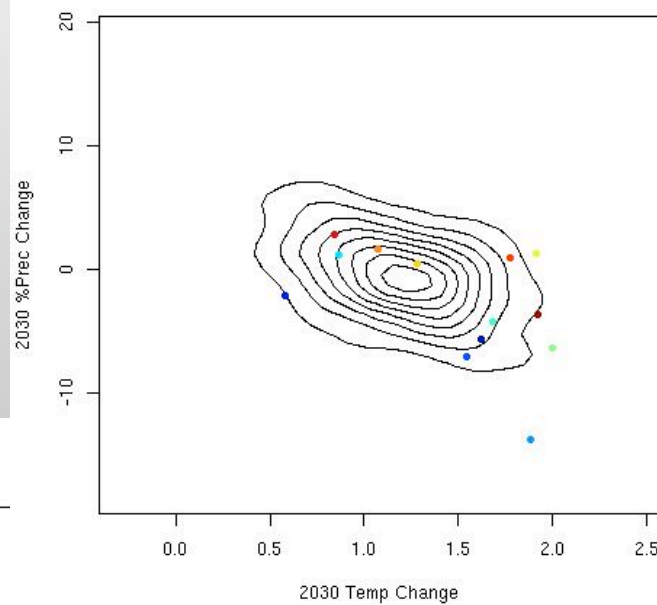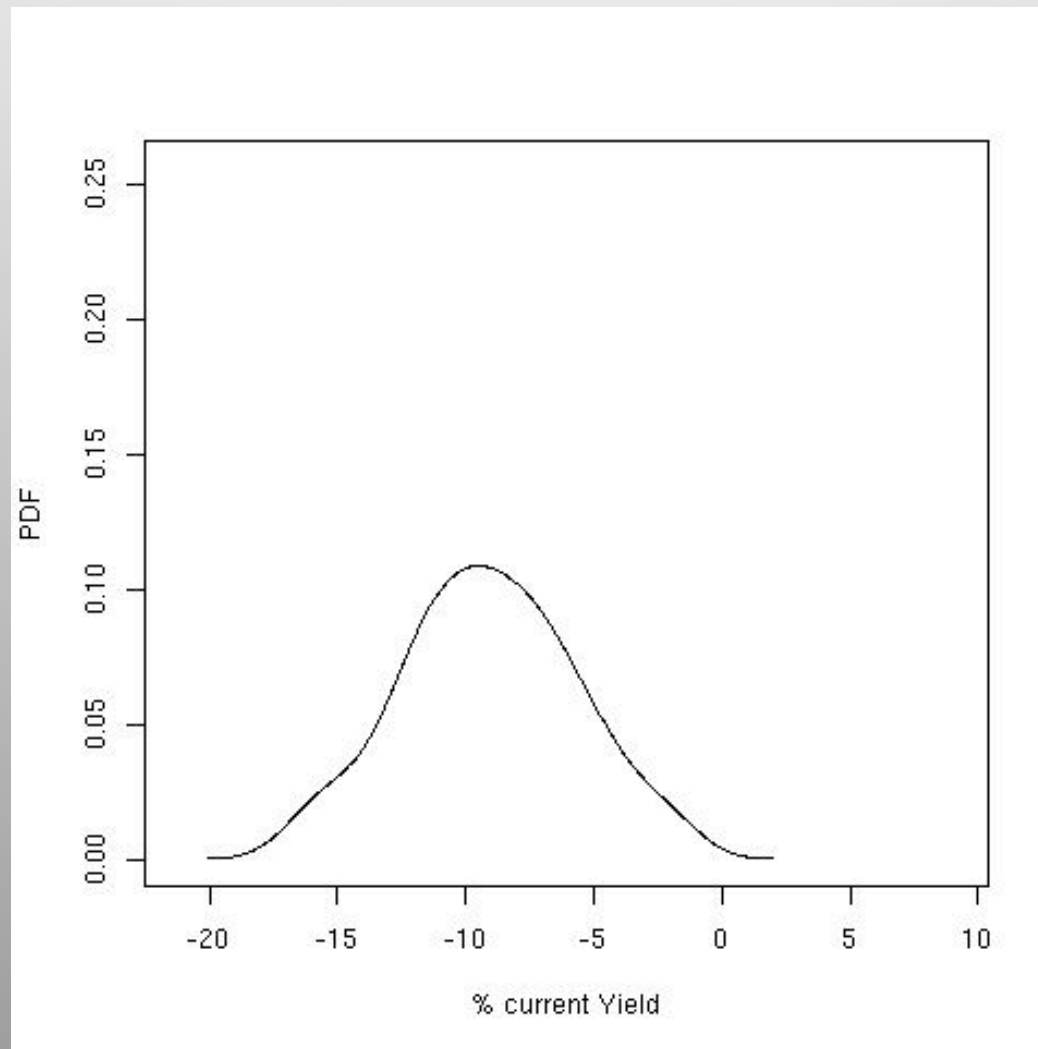
Sampling from uncertain climate projections

$$\Delta Y_1 = \hat{\beta}\Delta T_1 + \hat{\gamma}\Delta P_1$$

$$\Delta Y_2 = \hat{\beta}\Delta T_2 + \hat{\gamma}\Delta P_2$$

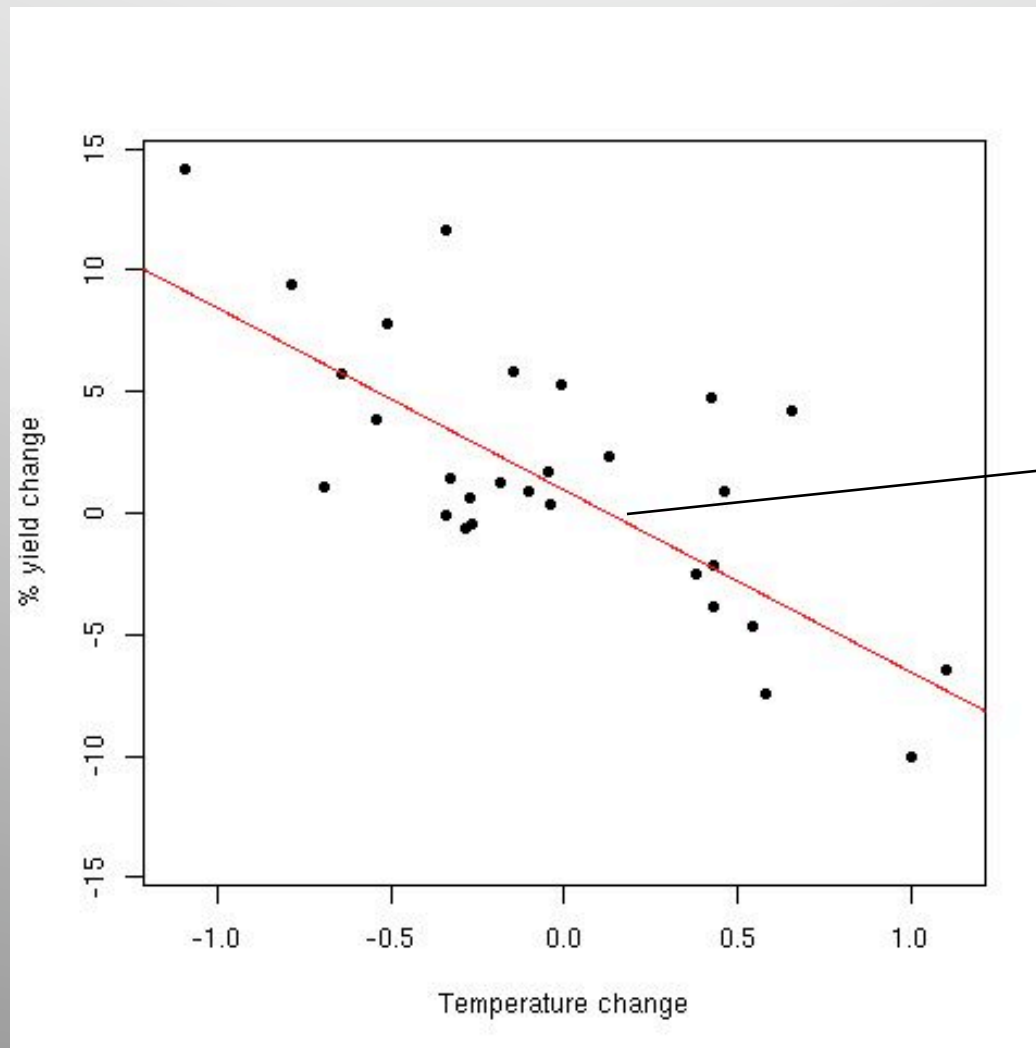$$\Delta Y_3 = \hat{\beta}\Delta T_3 + \hat{\gamma}\Delta P_3$$

$$\Delta Y_{1000} = \hat{\beta}\Delta T_{1000} + \hat{\gamma}\Delta P_{1000}$$

A probability distribution of yield changes in the face of uncertain climate projections
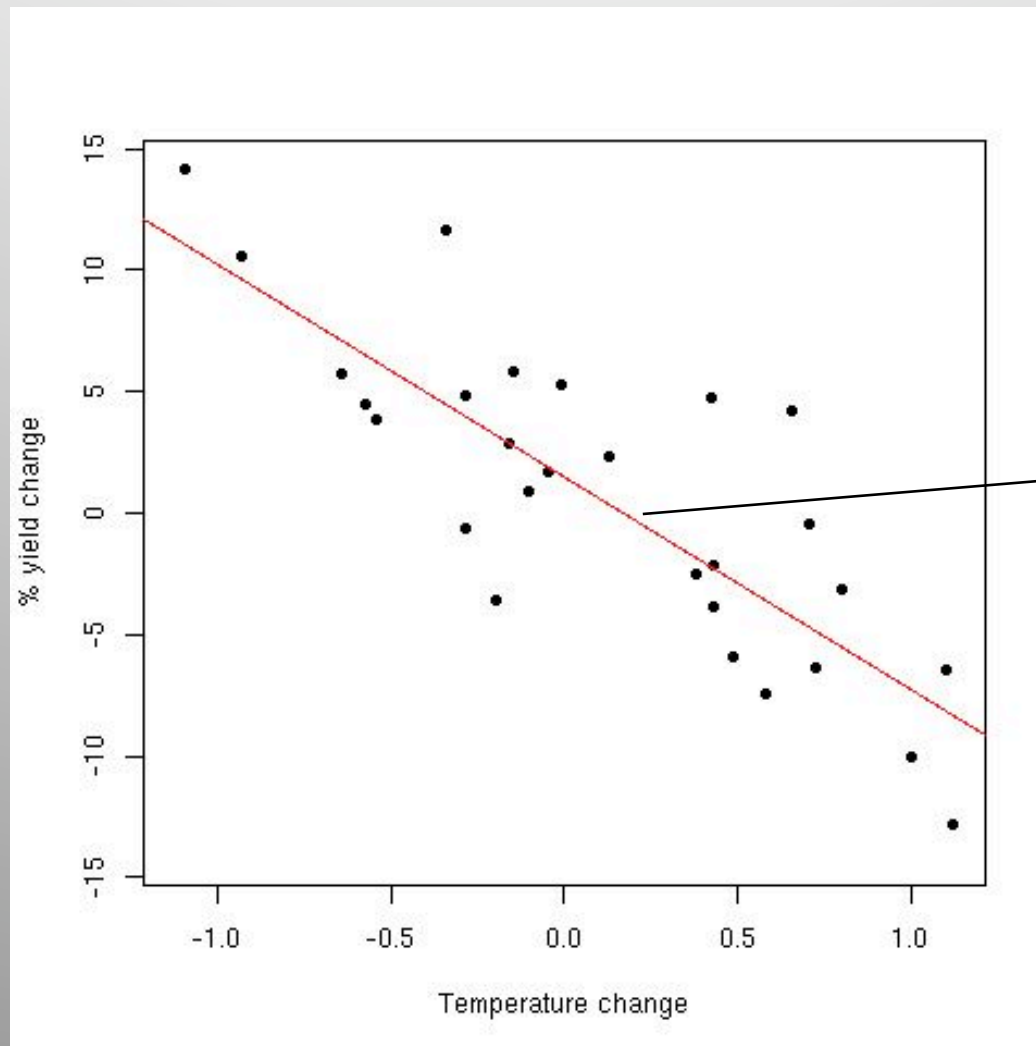
Uncertainties in crop response to climate variability
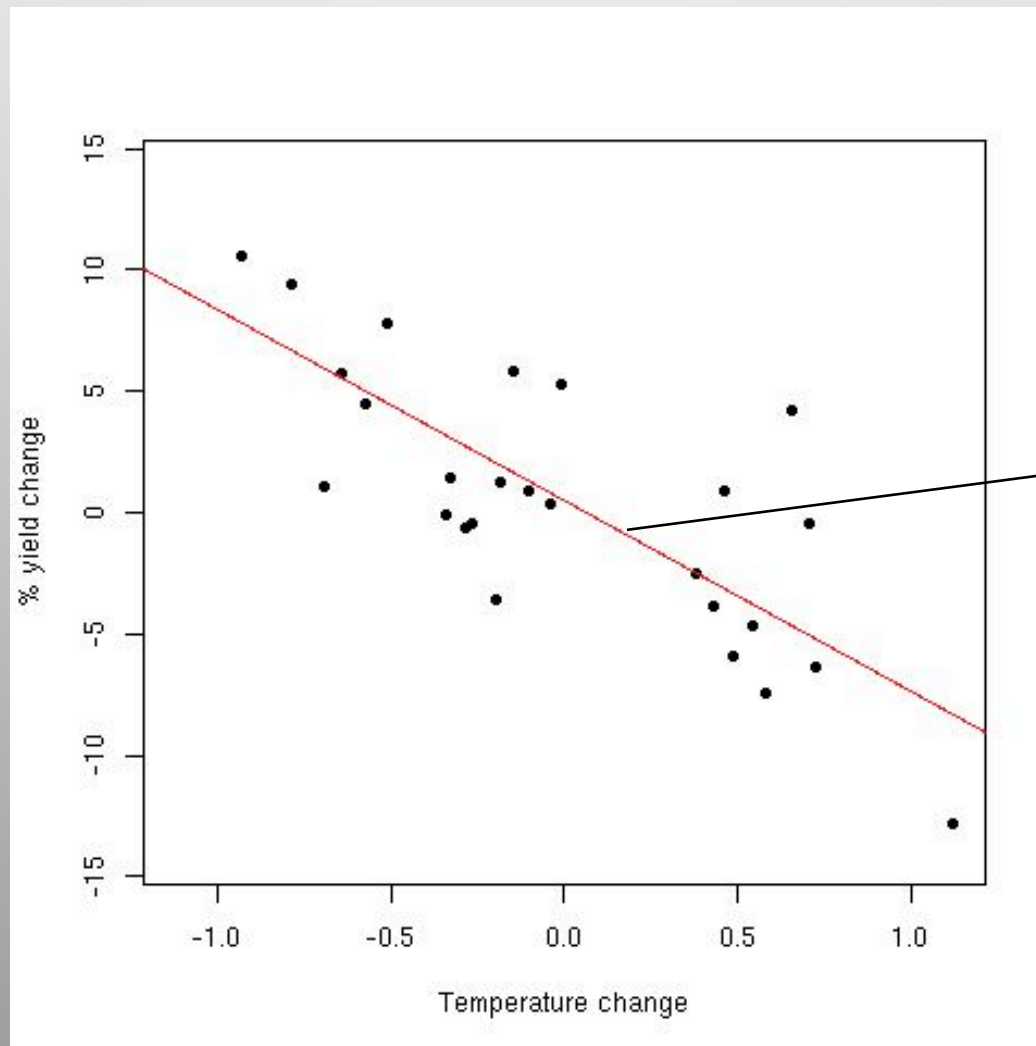
Uncertainties in crop response to climate variability
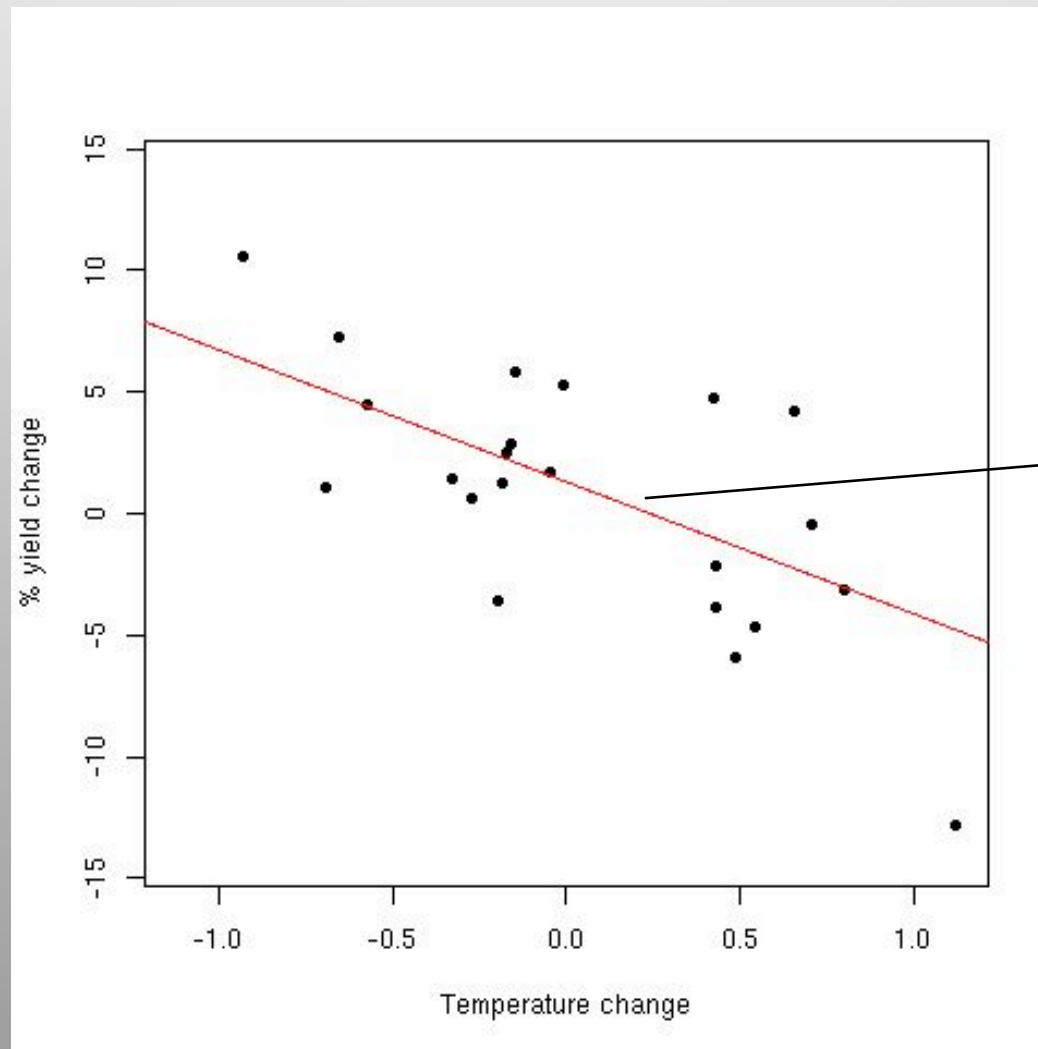
Uncertainties in crop response to climate variability
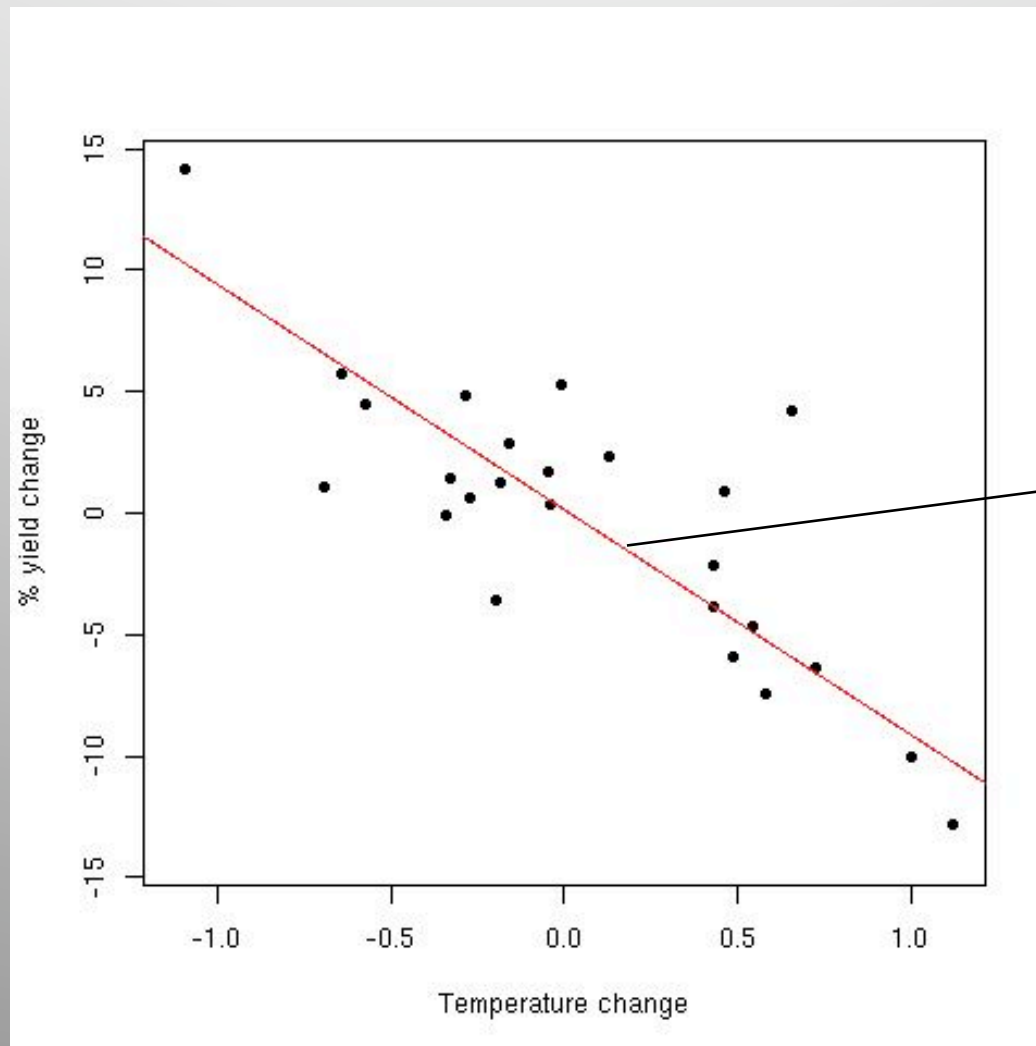
Uncertainties in crop response to climate variability

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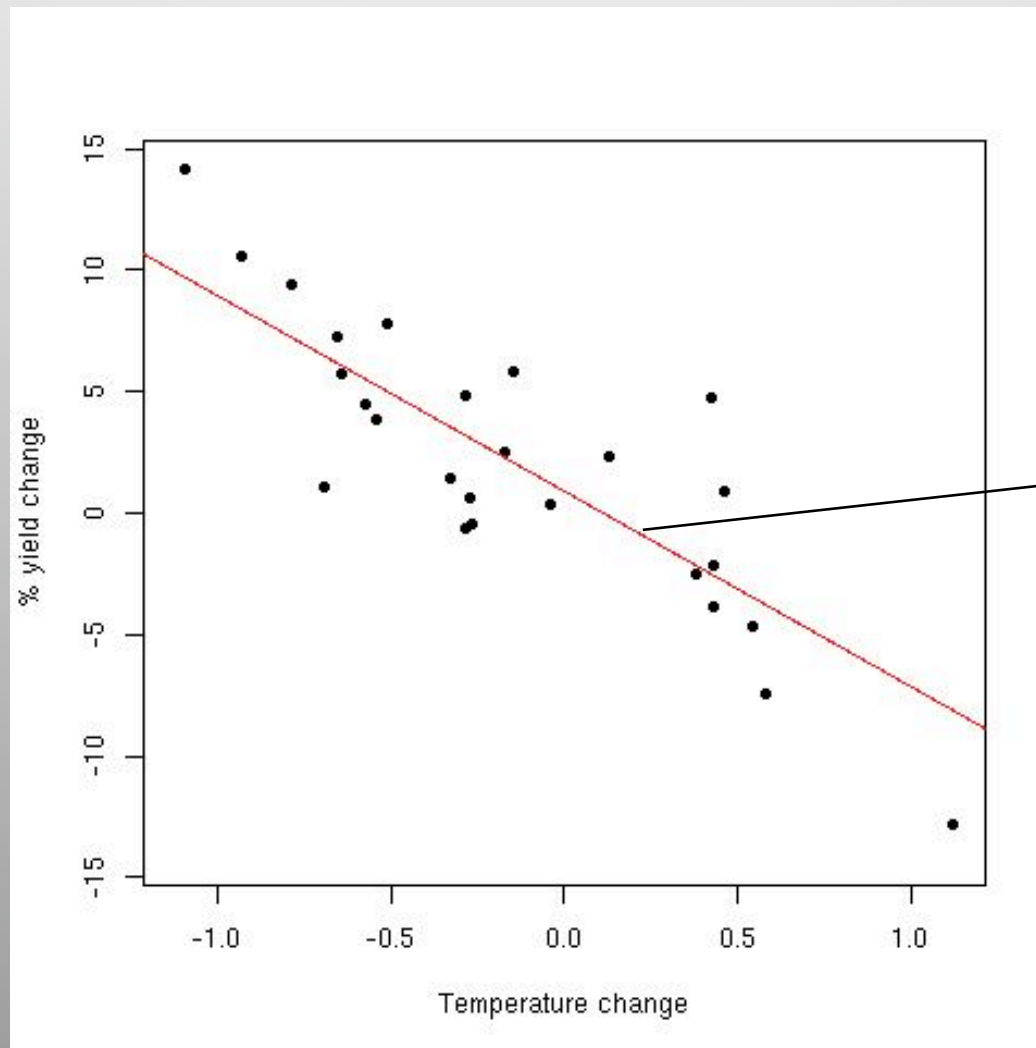
Uncertainties in crop response to climate variability
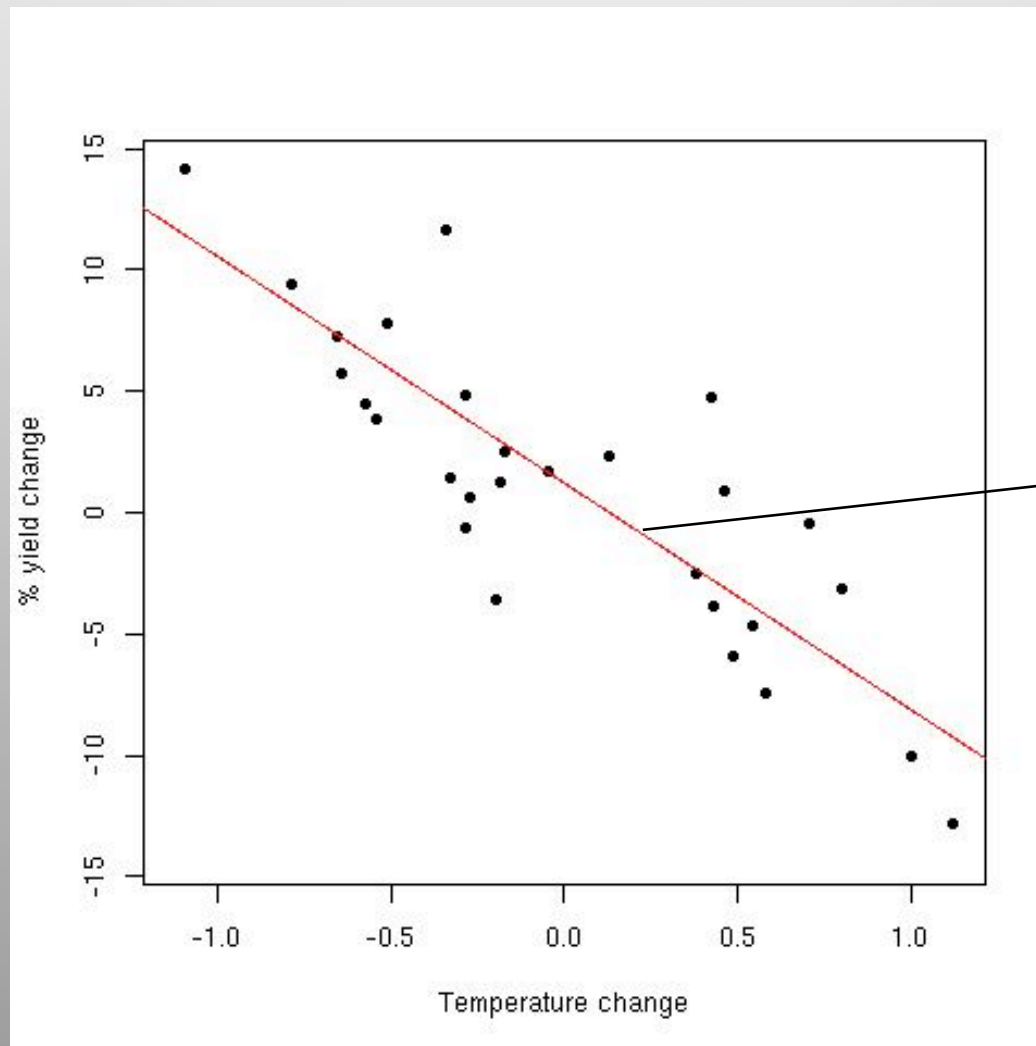
Uncertainties in crop response to climate variability

Uncertainties in crop response to climate variability

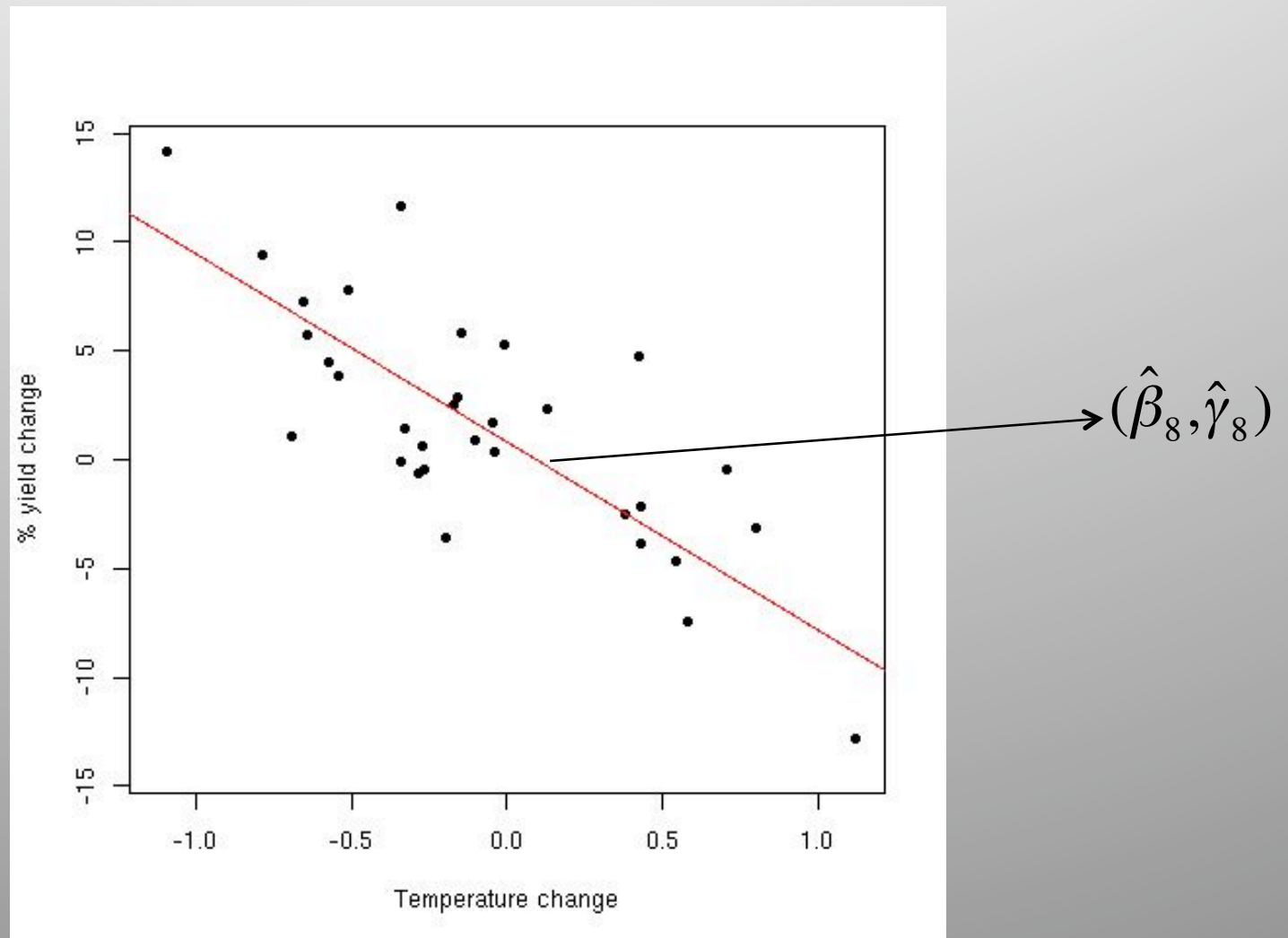# Uncertainties in crop response to climate variability

Uncertainties in crop response to climate variability
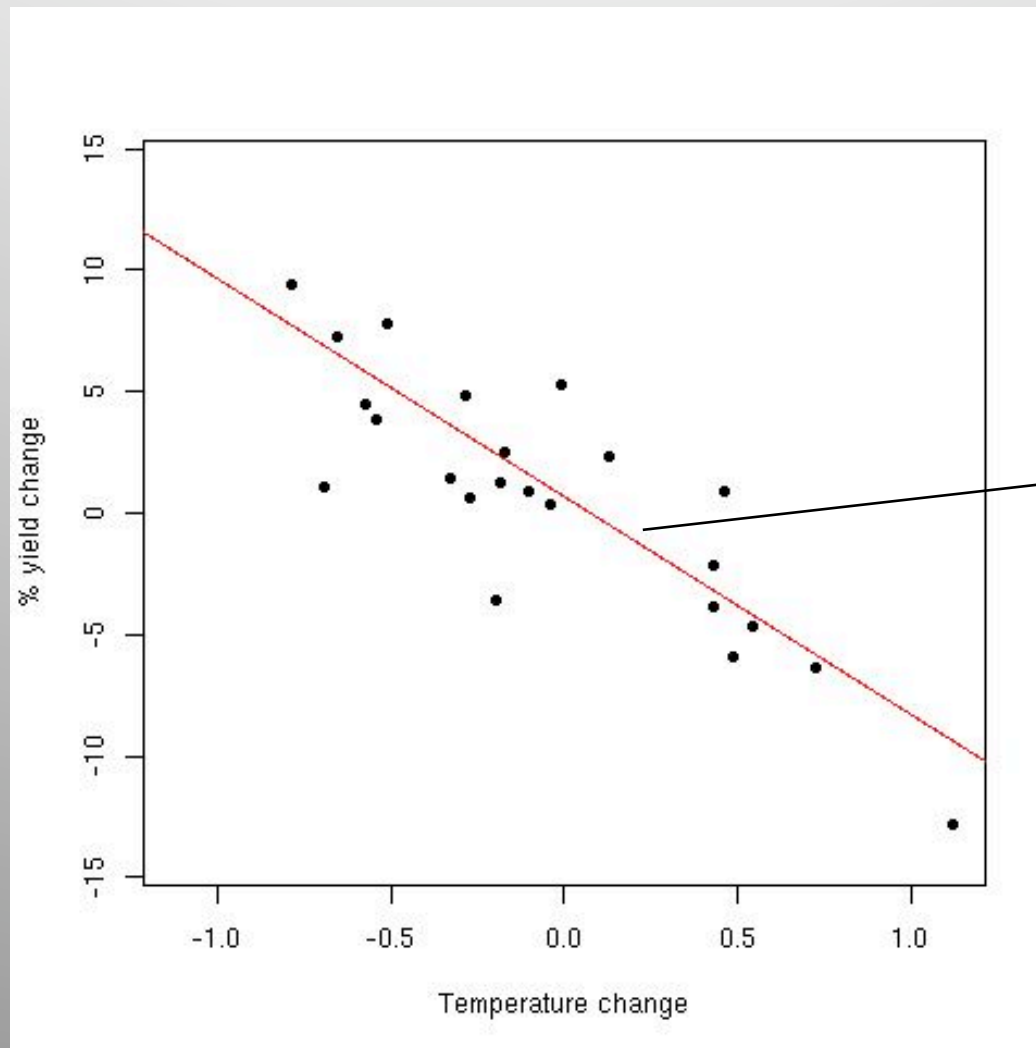
Uncertainties in crop response to climate variability

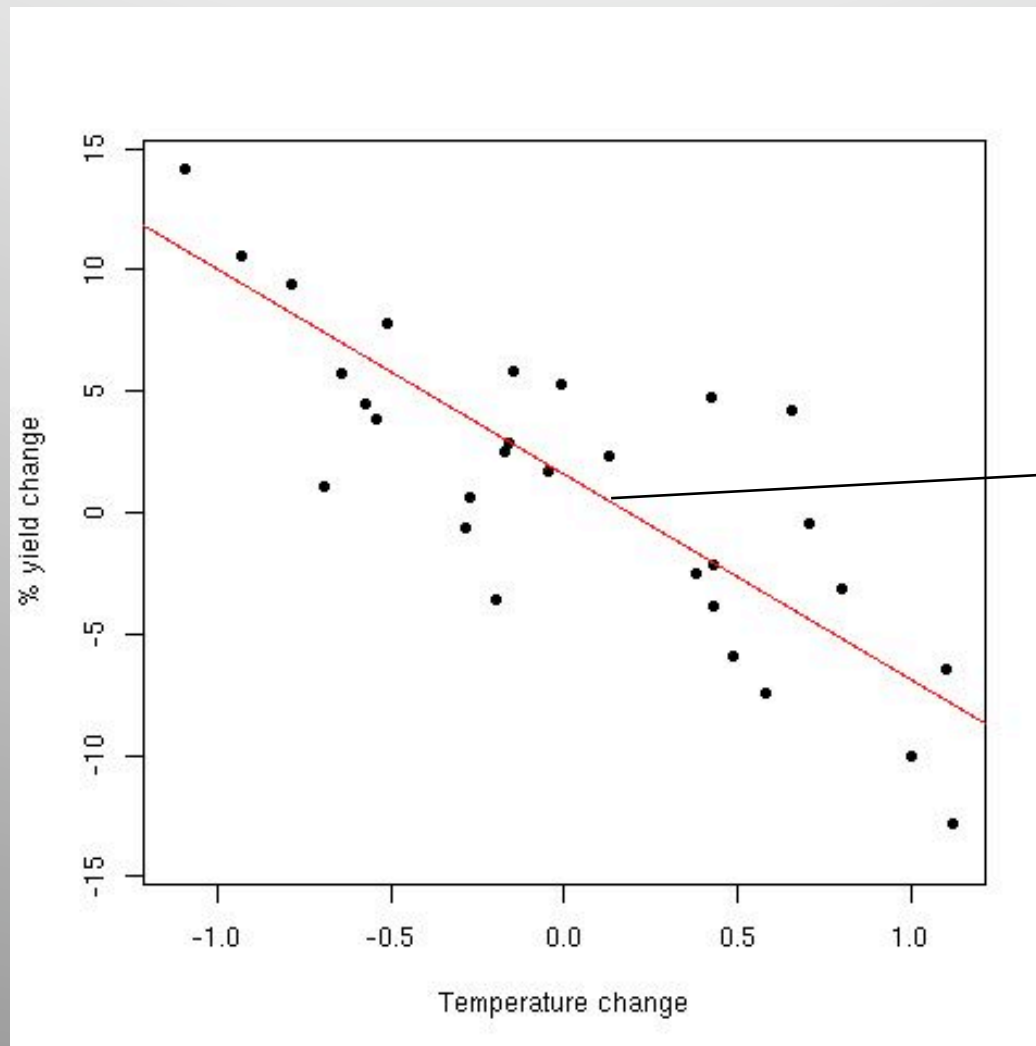If we didn't care about climate change uncertainty but we cared about crop response uncertainty:
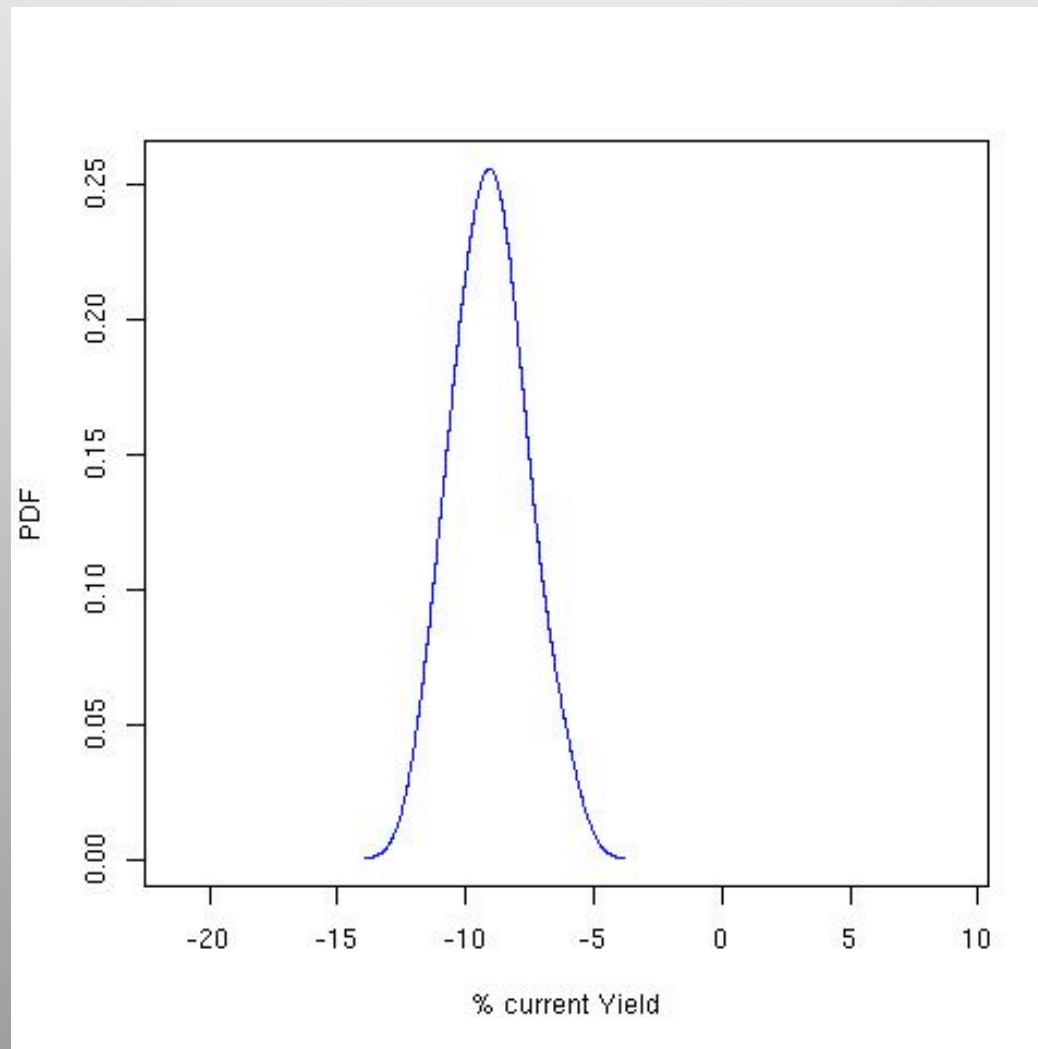
$$\Delta \hat{Y}_i = \hat{\beta}_i \Delta T^* + \hat{\gamma}_i \Delta P^*$$

Where

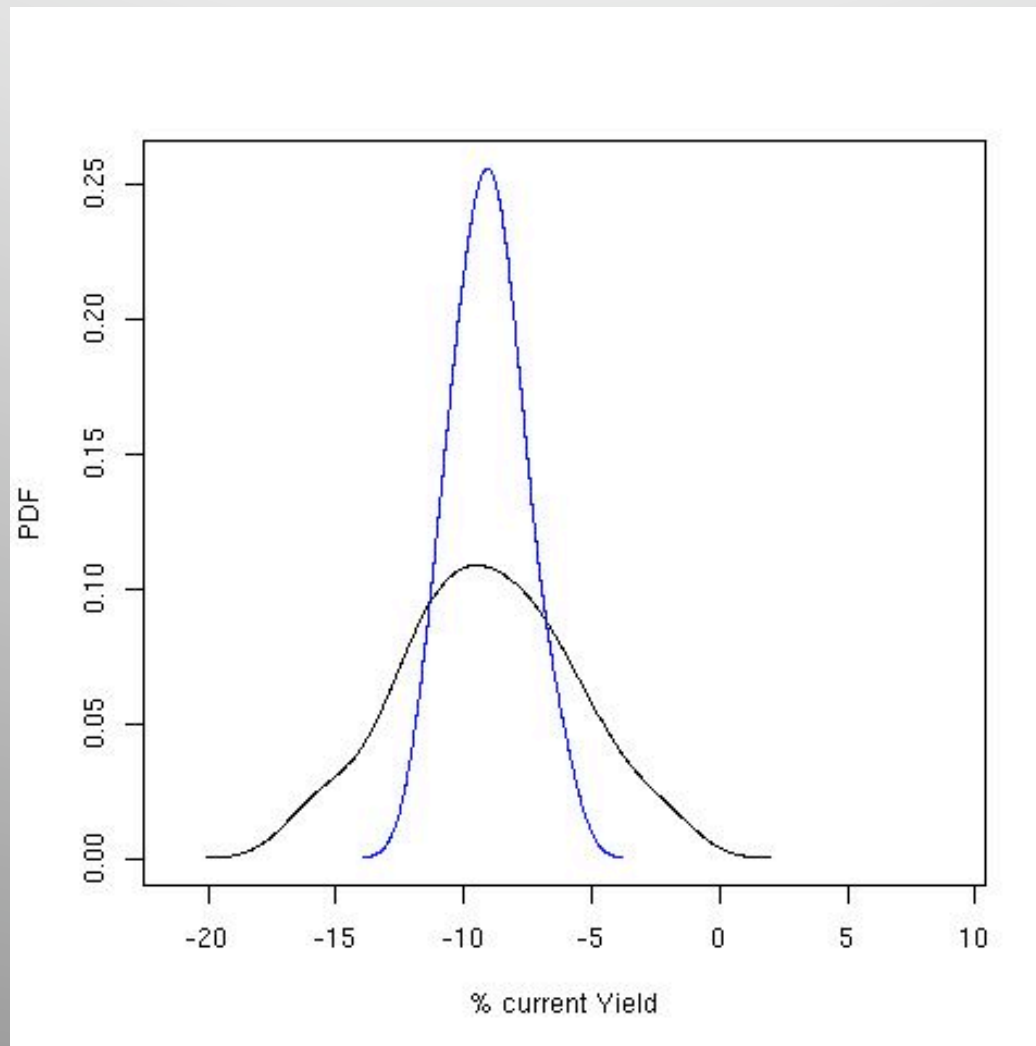$$\Delta T^*, \Delta P^*$$
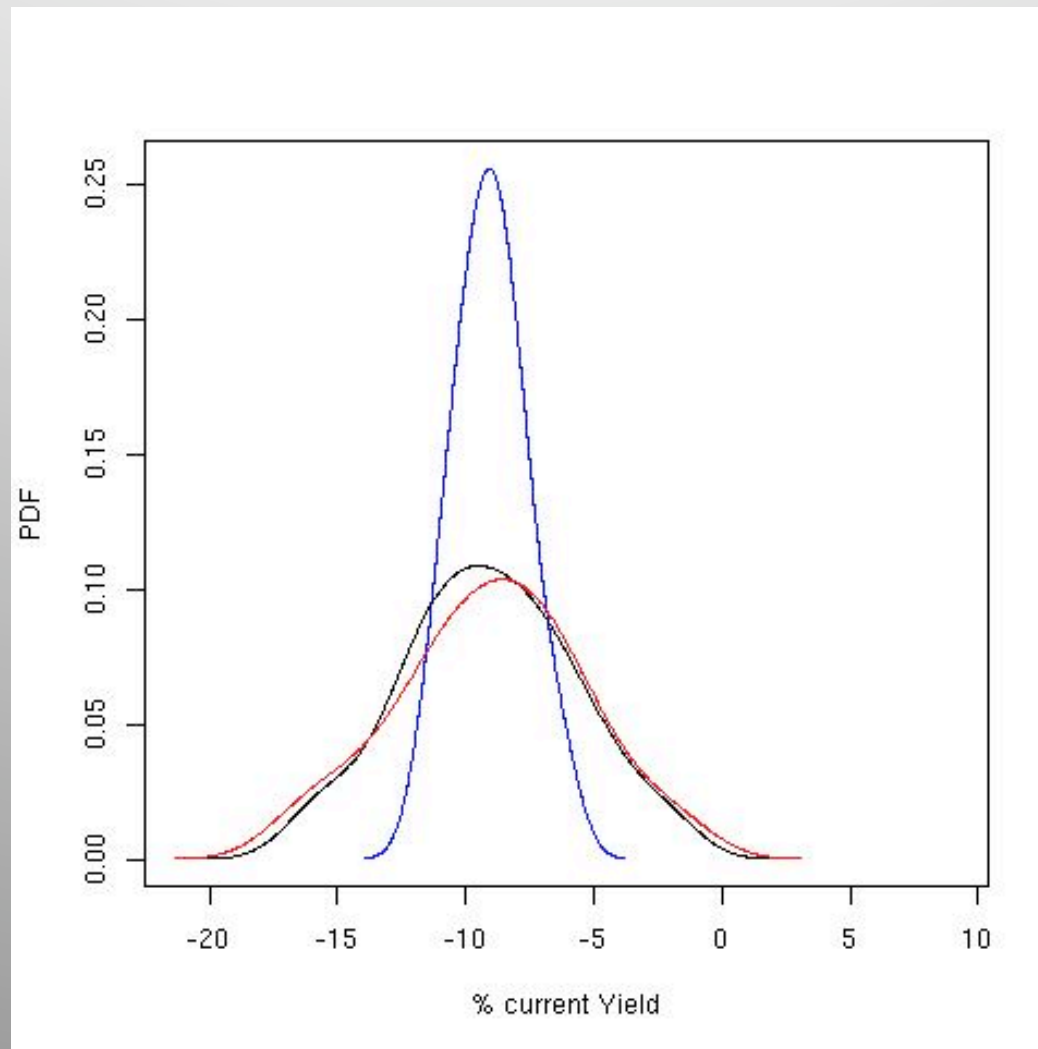
Are the posterior mean projections

Yield changes in the face of certain climate change but uncertain crop response

Yield changes in the face of certain climate change but uncertain crop response or viceversa

Yield changes in the face of uncertain climate change and uncertain crop response

Conclusions

Many sectors can take advantage of short term projections.
Even better if projections become predictions, i.e. if they become more precise.

A probabilistic format is a natural way of delivering this information
It may be a full PDF or samples from it or quantiles.

The set up is conducive to a Bayesian approach, with possibly prior information, data updating our believes, and a flow of additional information coming in over time that may help reshape the forecast

There is a range of possible "deliverable" from straightforward temperature and precipitation average projections to expected patterns of temperature and precipitation connected to low frequency indices, whose predictability may be better understood.