Estimating the Role of Natural Variability in Climate Change Using Observations

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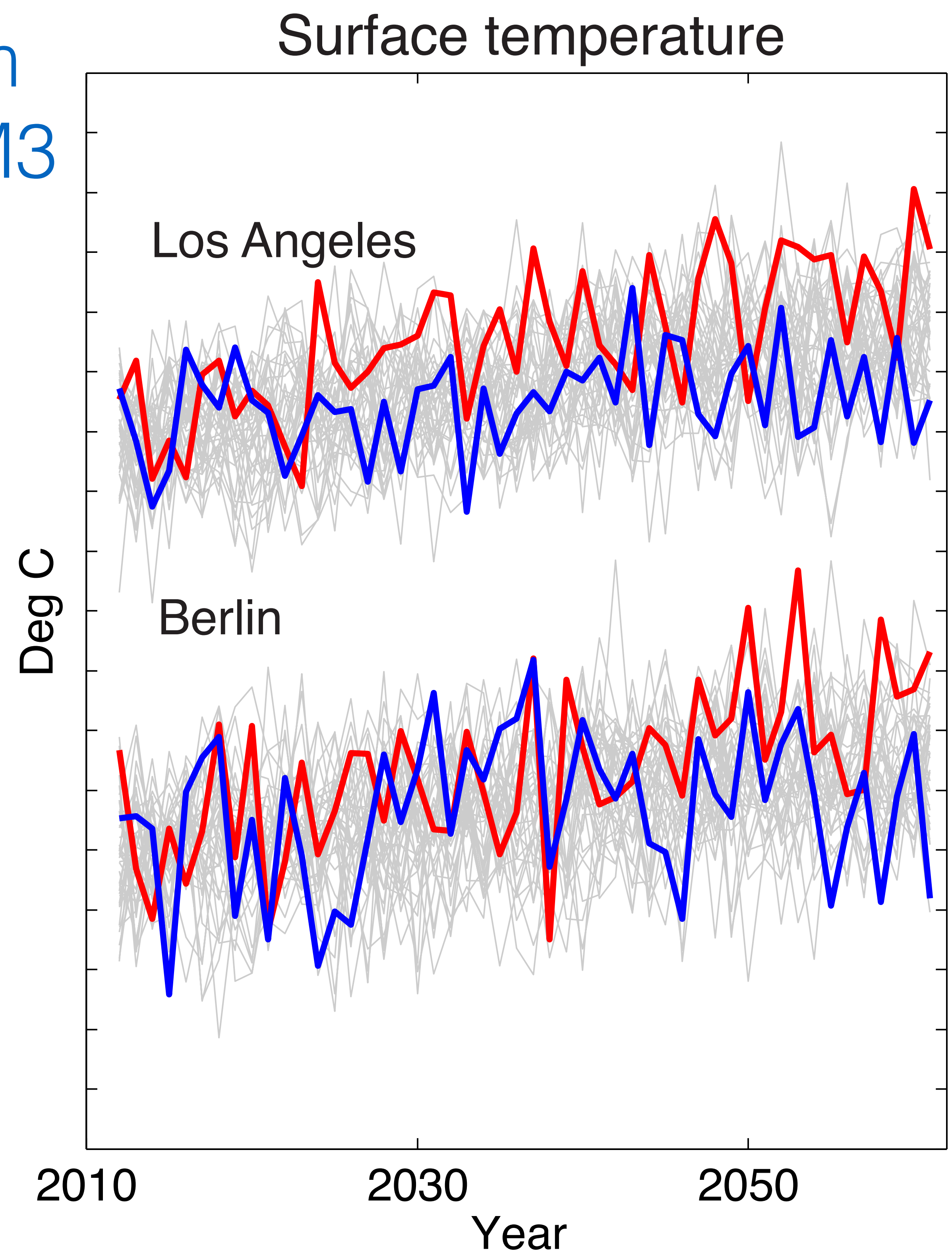
results drawing from:
- Thompson et al. (submitted to Journal of Climate)

see www.atmos.colostate.edu/~davet

Time series of near surface temperature from the NCAR CCSM3 40-member ensemble.

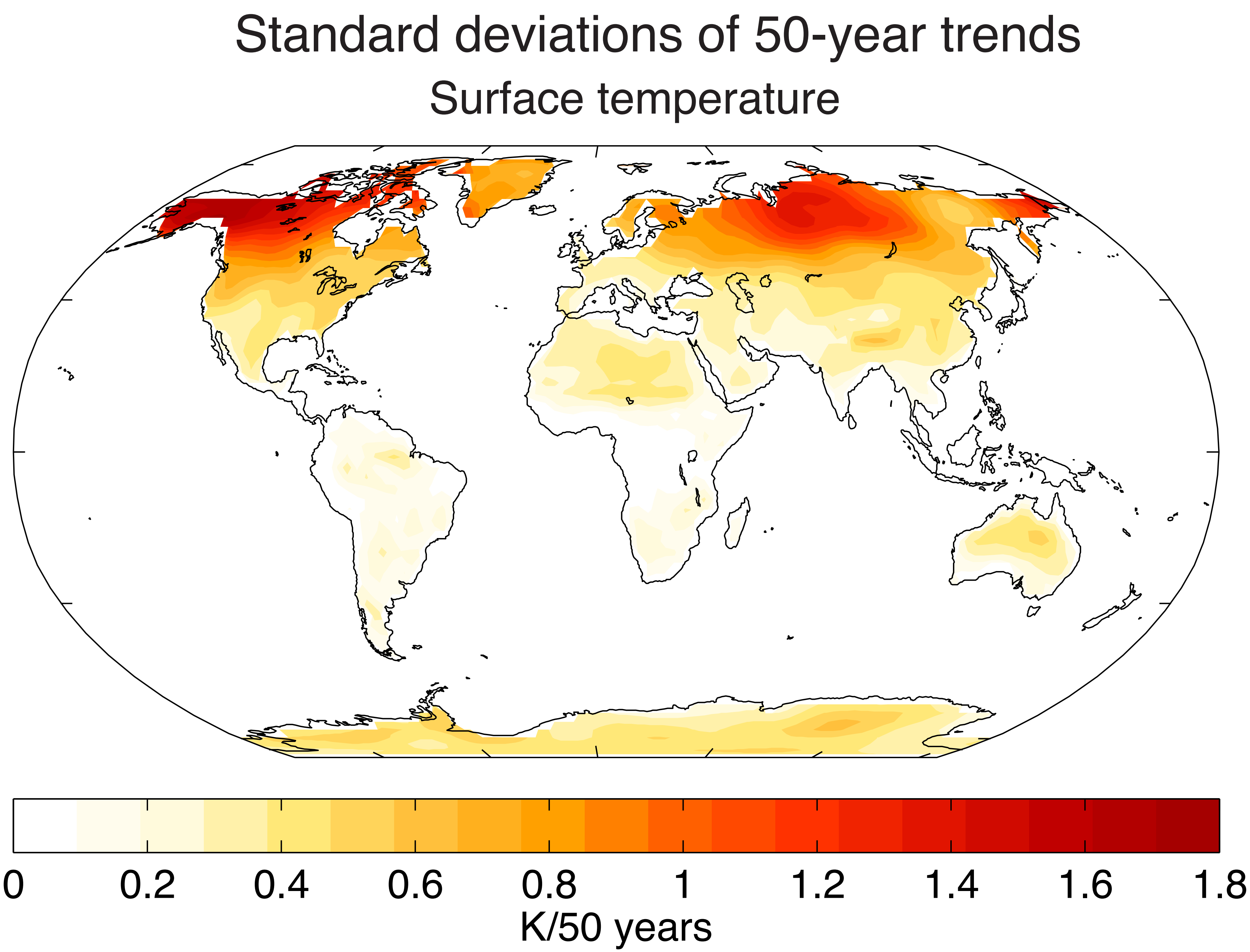


largest trend

smallest trend

Ticks at 1 deg.

See also Deser et al. 2012



Range of trends from all 40 ensemble members during October-March.

- What determines the range of trends indicated by the large ensemble?
- Can the range in climate trends be accurately estimated from a *control simulation*?
- Can the range in the trends be accurately estimated from *observations*?

An analytic expression for the margins of error in a Gaussian process.

Consider a time series ***x(t)*** with mean zero and linear least-squares trend ***b***.

The confidence interval on the trend in *x(t)* can be expressed as:

$$CI = b \pm e$$

Where ***e*** is the margin of error on the trend.

If the distribution of the deviations in *x(t)* about its linear trend is Gaussian, then the margin of error on the trend in *x(t)* is:

$$e = t_c s_b$$

desired confidence level

standard error of the trend.

If the distribution of the deviations in *x(t)* about its linear trend is Gaussian, then the margin of error on the trend in *x(t)* is:

$$e = t_c s_b$$

desired confidence level (t_c)

standard error of the trend. (s_b)

$$s_b = \frac{n_t s_e}{\sqrt{\sum_{i=1}^{n_t} (i - \bar{i})^2}}$$

After some algebra…

standard deviation of the residuals

length of the record

$$e = t_c \cdot n_t \cdot \sigma \cdot \gamma(n_t, r_1) \cdot g(n_t)$$

scaling factor to account for autocorrelation

arises from variance of the time axis

$$\gamma(n_t, r_1) \equiv \left(\frac{[n_t - 2]}{\left[n_t \left(\frac{1 - r_1}{1 + r_1} \right) - 2 \right]} \right)^{1/2}$$

$$g(n_t) \equiv \sqrt{\frac{12}{n_t^{\,3} - n_t}}$$

The margin of error on a trend in a Gaussian process is a function of three statistics:

1) the standard deviation of the internal (unforced) variability.
2) the lag-one autocorrelation of the internal (unforced) variability.
3) the number of time steps in the time series.

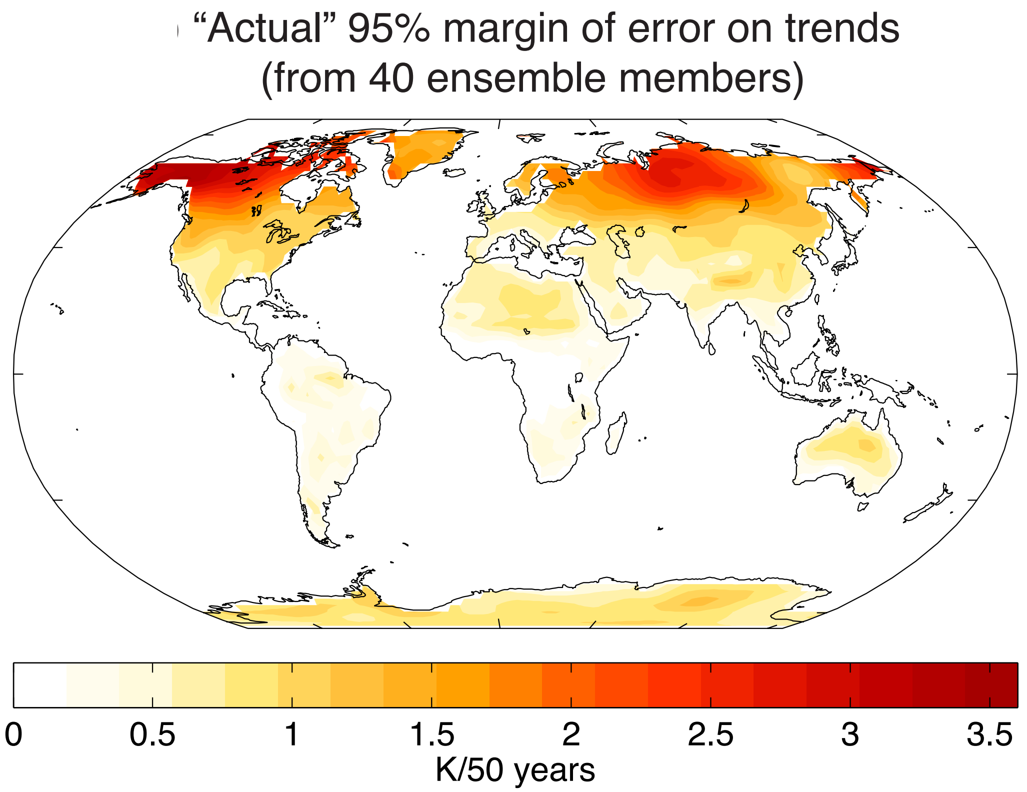
If the residuals are serially uncorrelated and the trend is 50 time steps, then:

$$e_{95\%} \sim \sigma \ \ (\text{for} \ \ n_t = 50 \ \text{and} \ r_1 \sim 0 \ )$$

95% margin of error on 50 year trend

interannual standard deviation

… testing the analytic model in the NCAR CCSM3 large ensemble

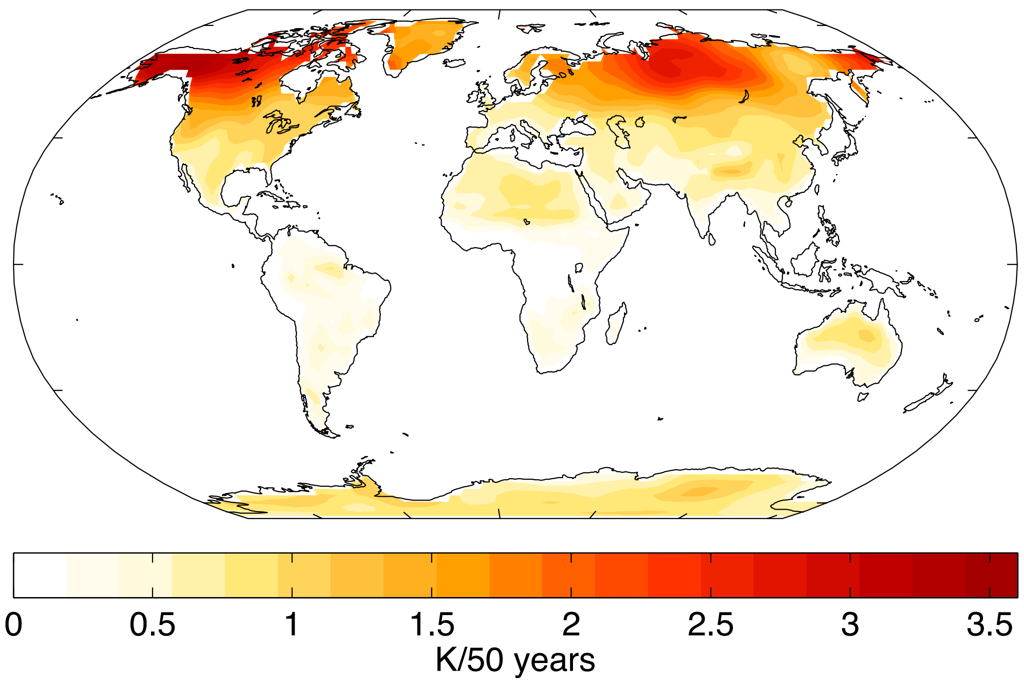


50 year trends in Oct-March surface temperature

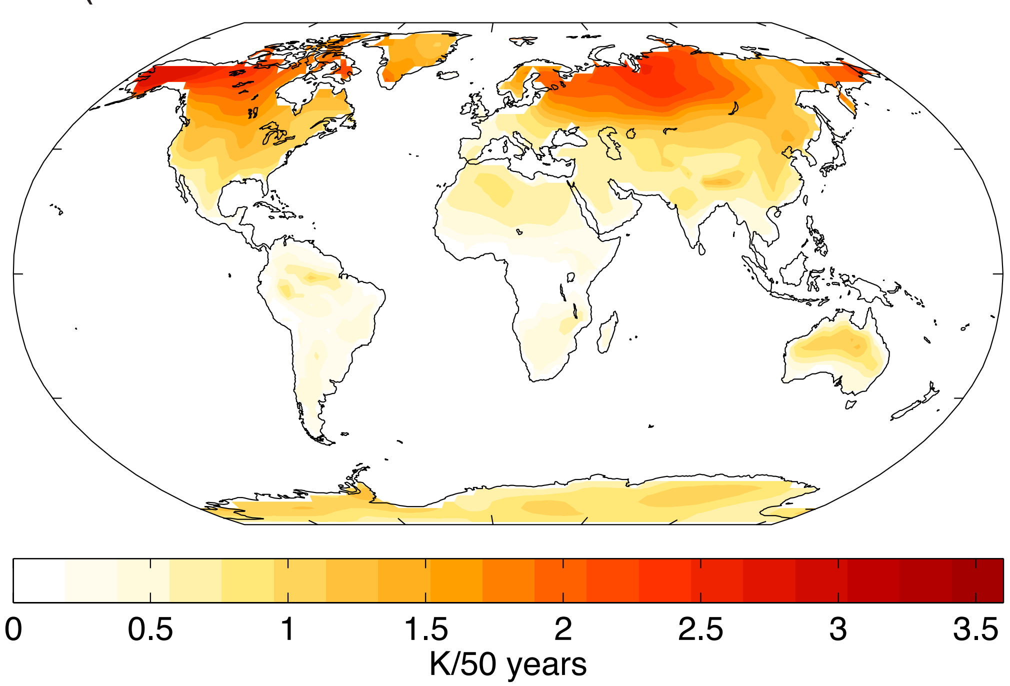
From Thompson et al. 2015

… testing the analytic model in the NCAR CCSM3 large ensemble

“Actual” 95% margin of error on trends
(from 40 ensemble members)



“Predicted” 95% margin of error
(from interannual standard deviation of control run)



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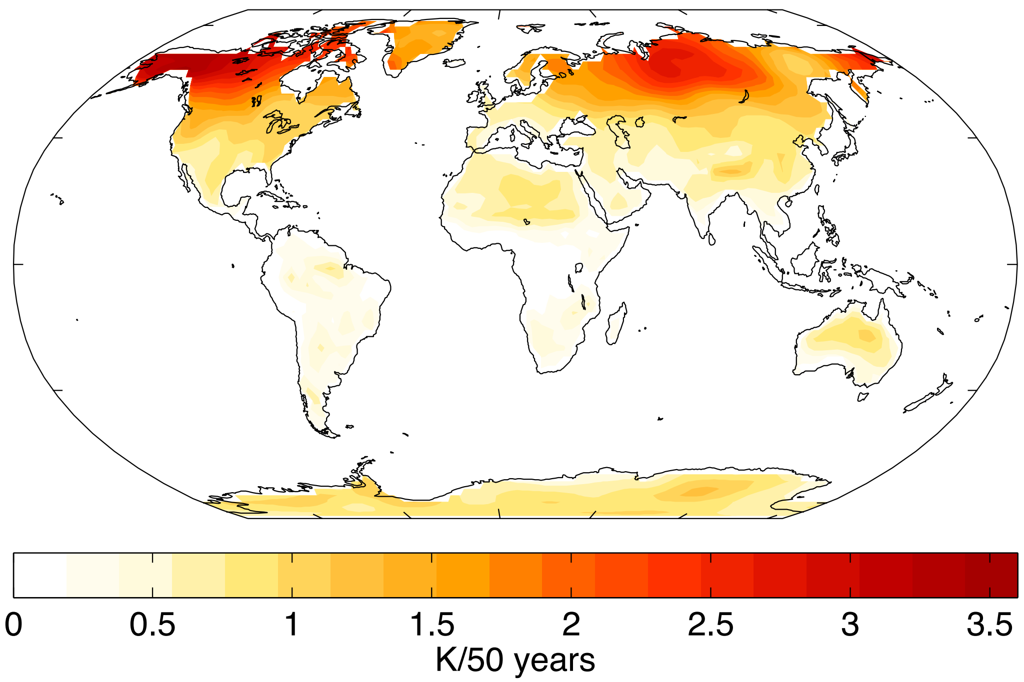
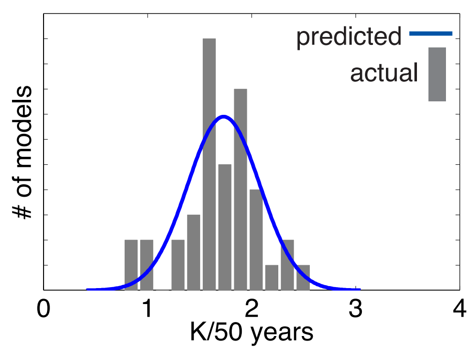
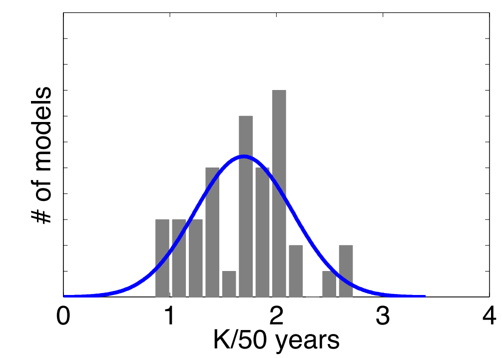


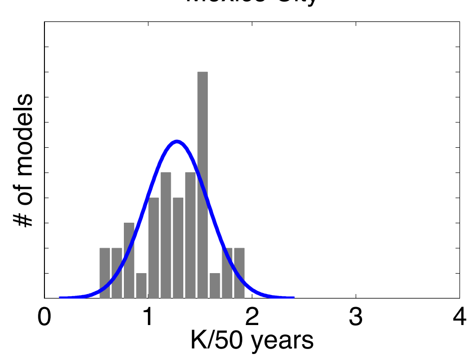
Los Angeles



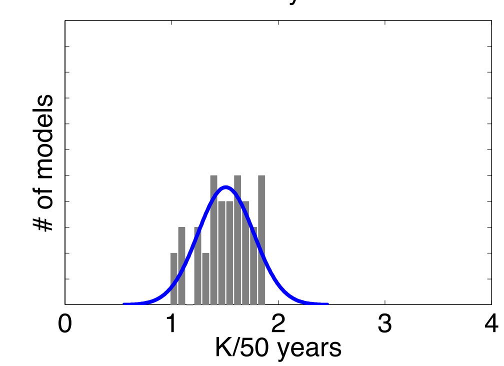
Berlin



Mexico City



Tokyo



“Predicted” 95% margin of error
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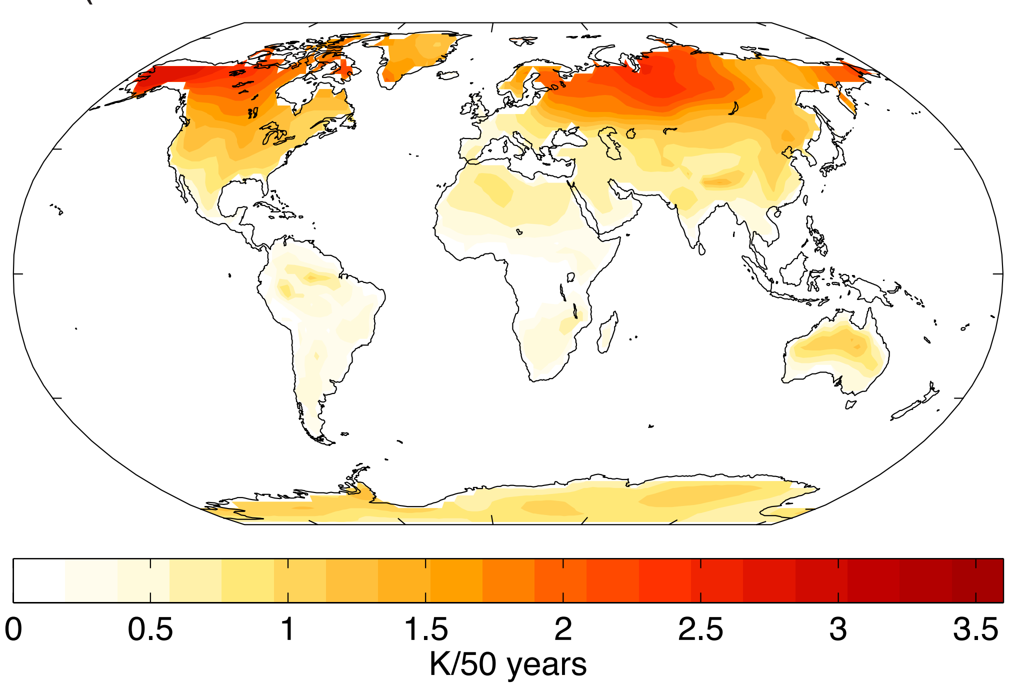
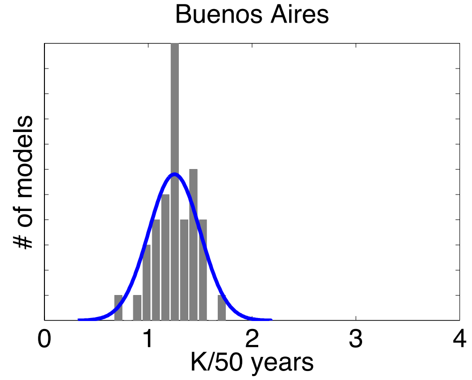
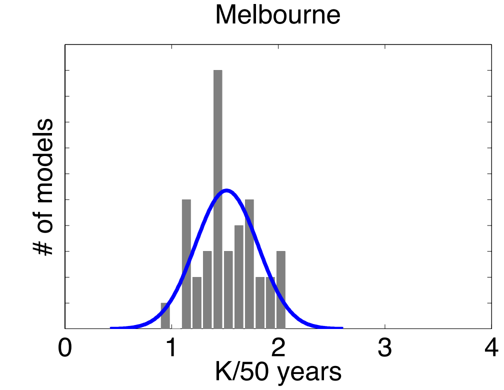


Buenos Aires

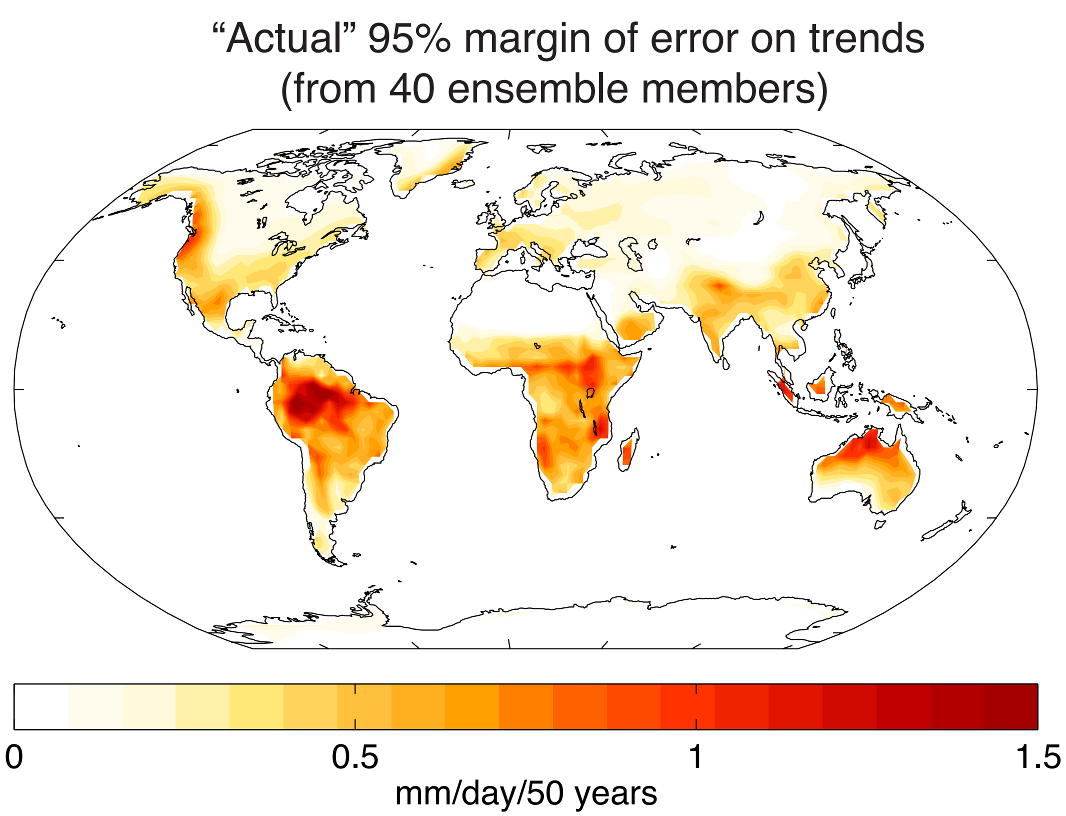


Melbourne



50 year trends in Oct-March surface temperature

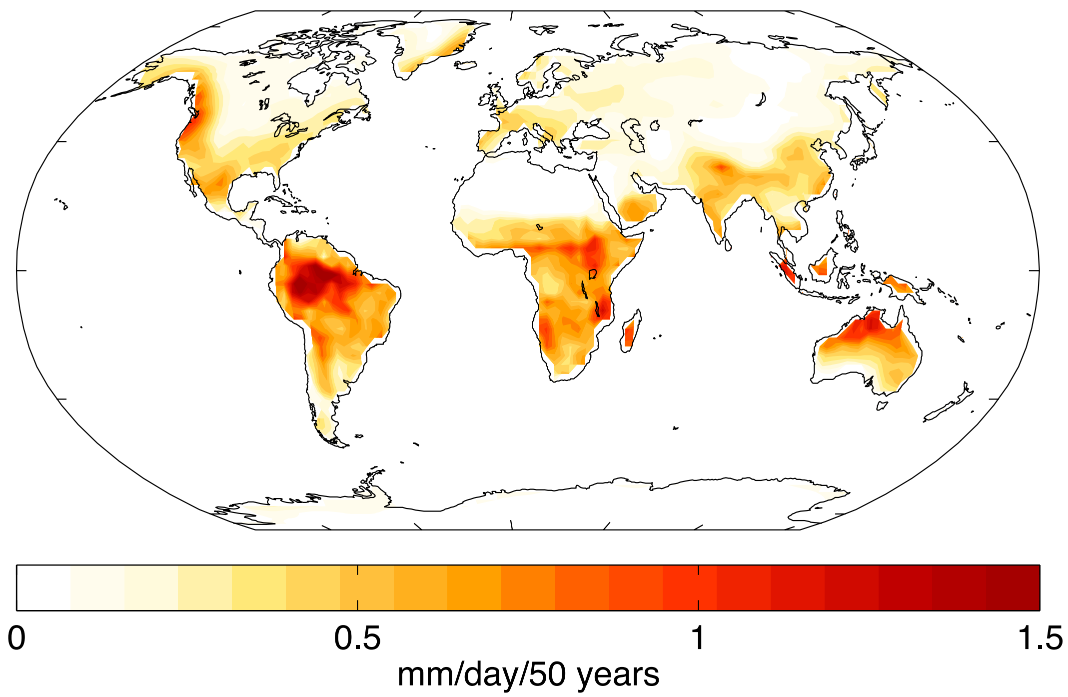
… testing the analytic model in the NCAR CCSM3 large ensemble



50 year trends in Oct-March precipitation *From Thompson et al. 2015*

… testing the analytic model in the NCAR CCSM3 large ensemble

“Actual” 95% margin of error on trends
(from 40 ensemble members)



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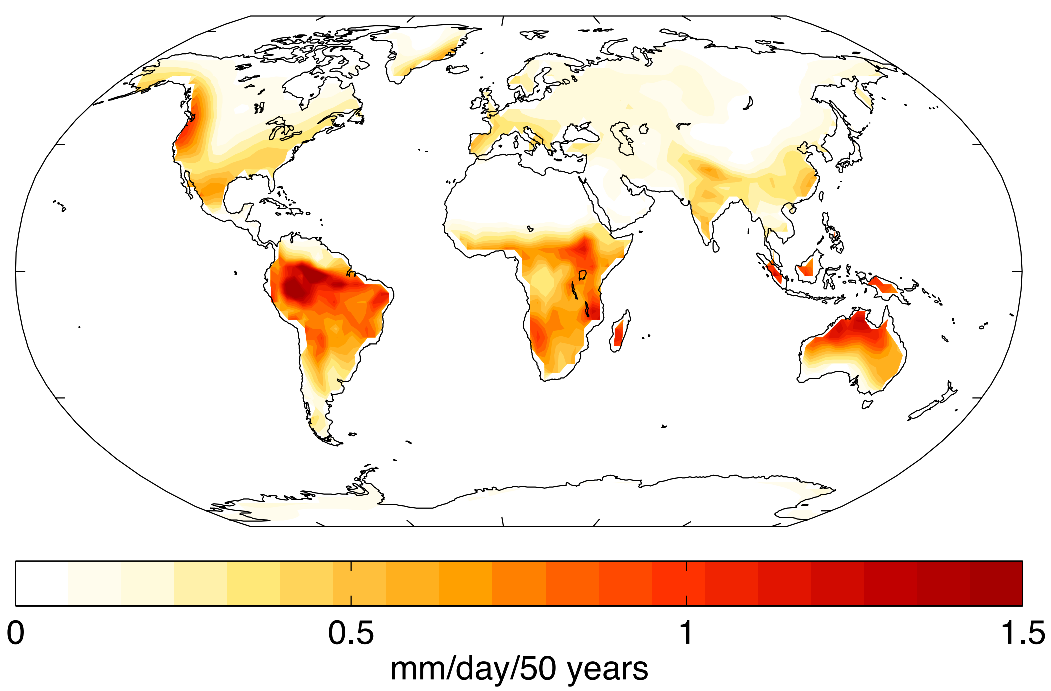
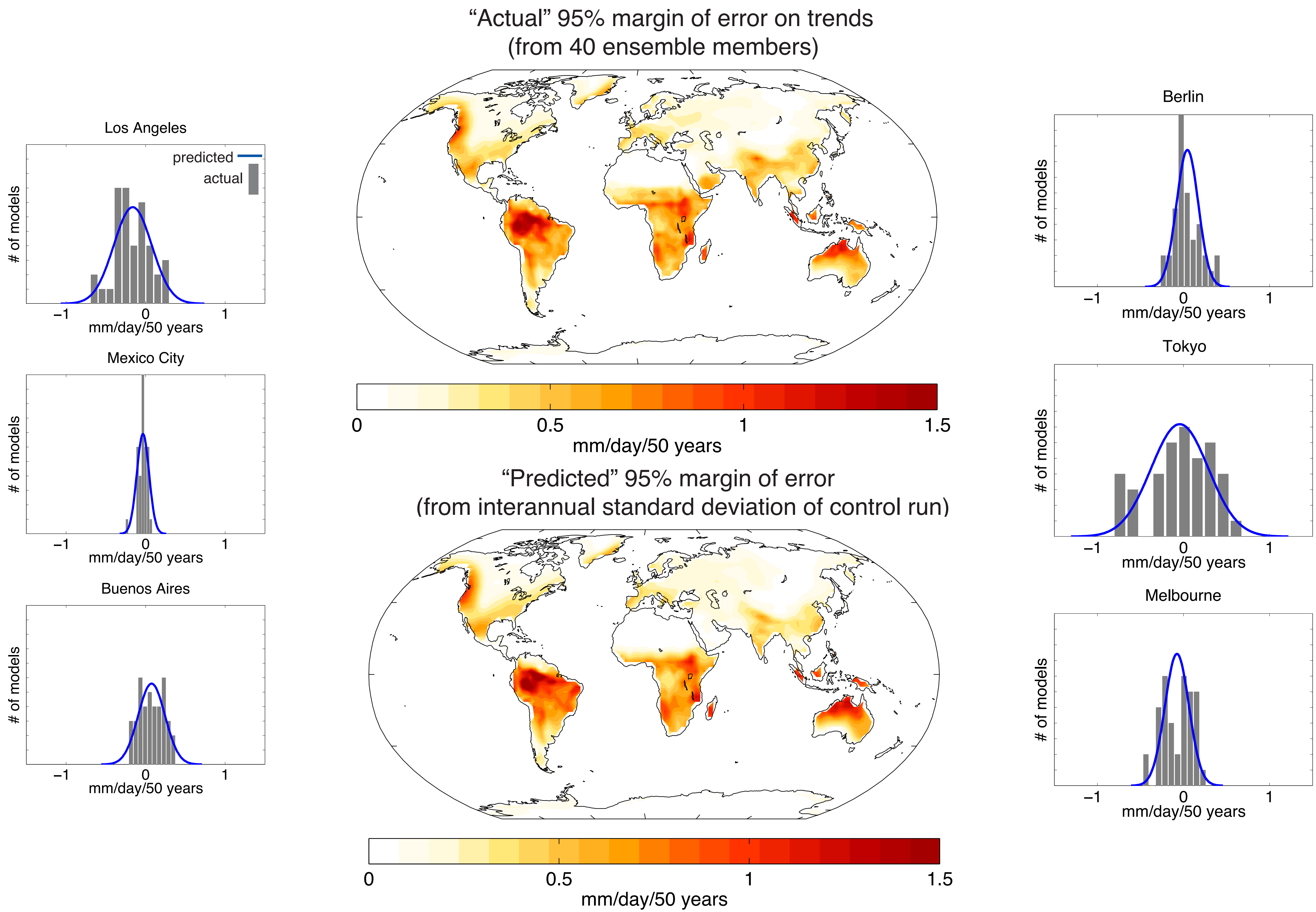


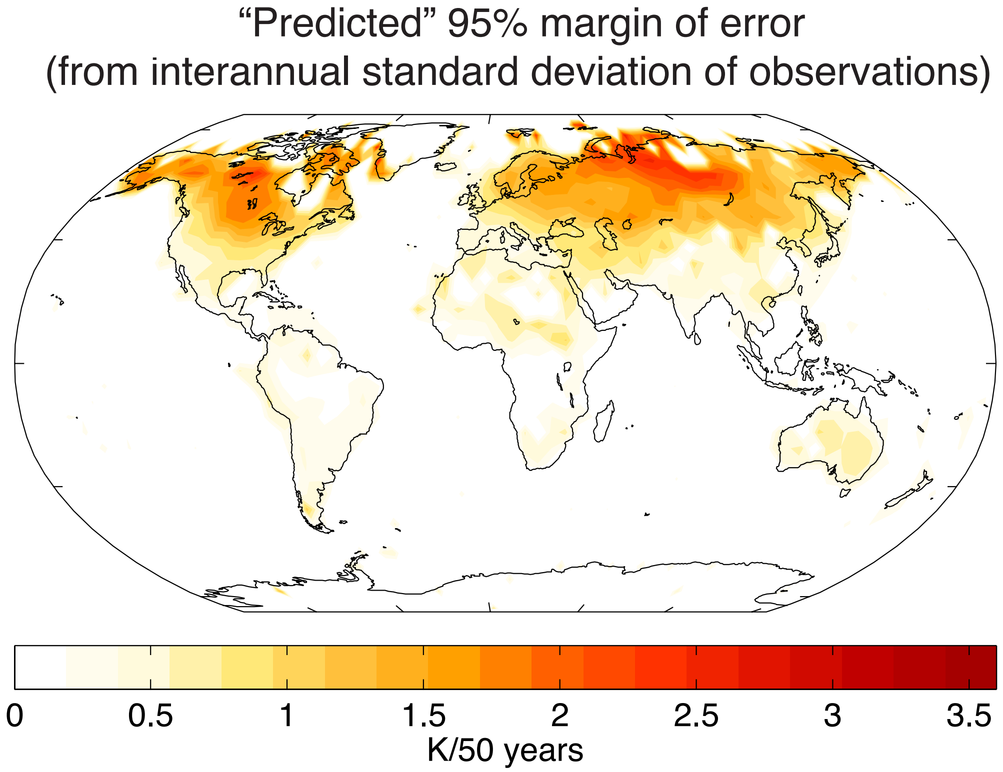
50 year trends in Oct-March precipitation

… testing the analytic model in the NCAR CCSM3 large ensemble



50 year trends in Oct-March precipitation

… applying the analytic model to observations

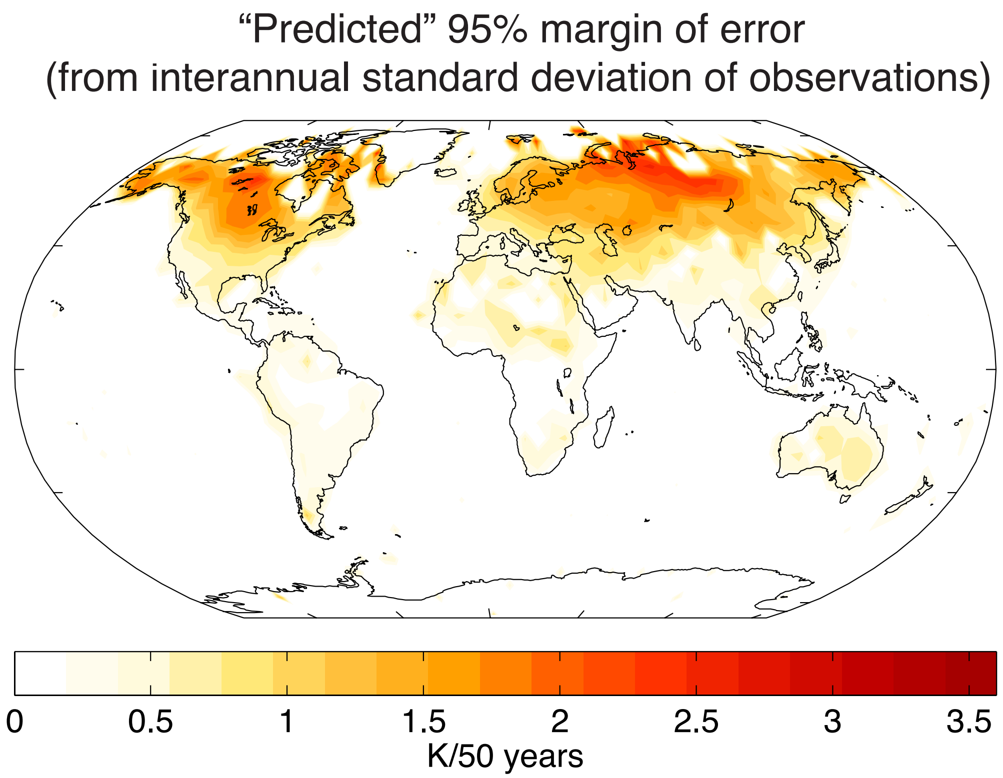


Observations from CRU

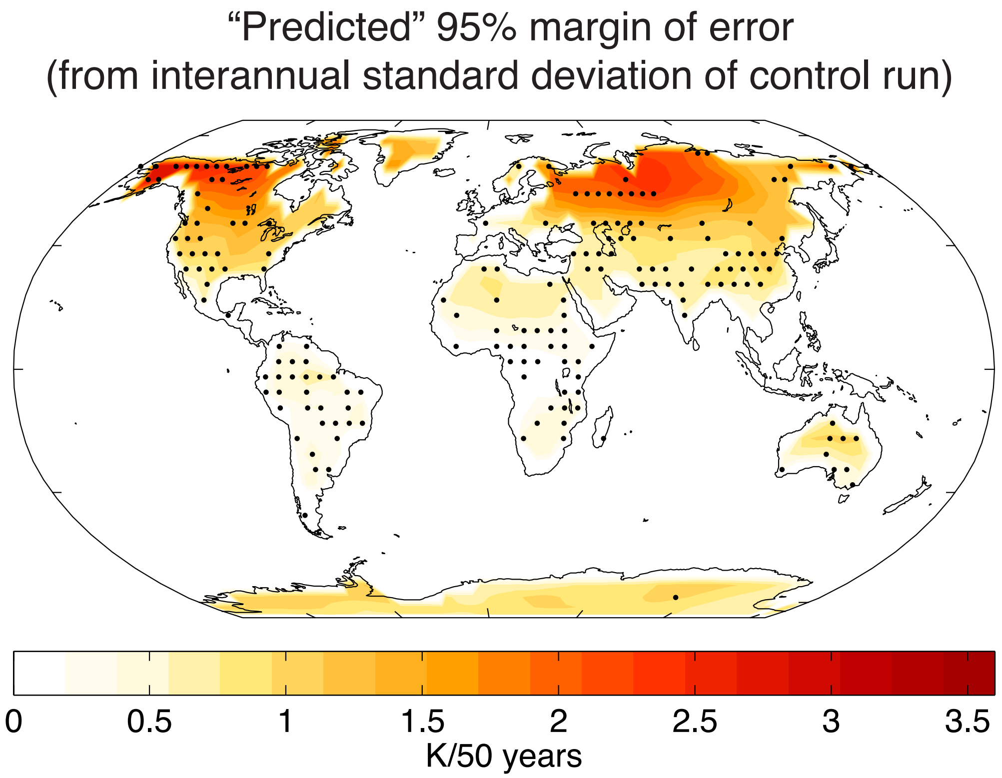
From Thompson et al. 2015

Predicted uncertainty in Oct-March surface temperature trends

… applying the analytic model to observations



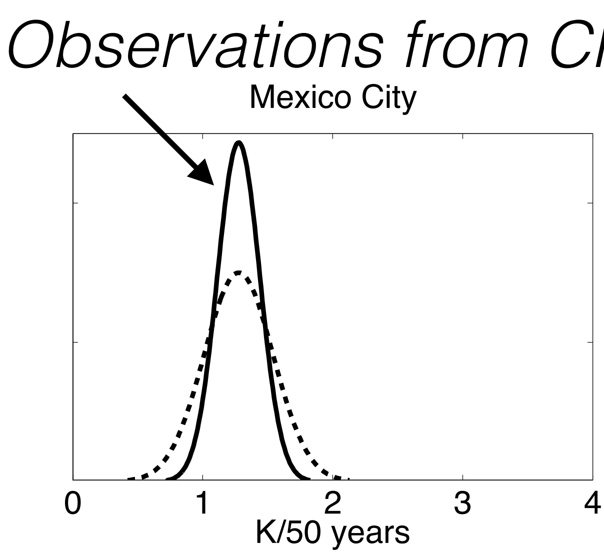
Observations from CRU



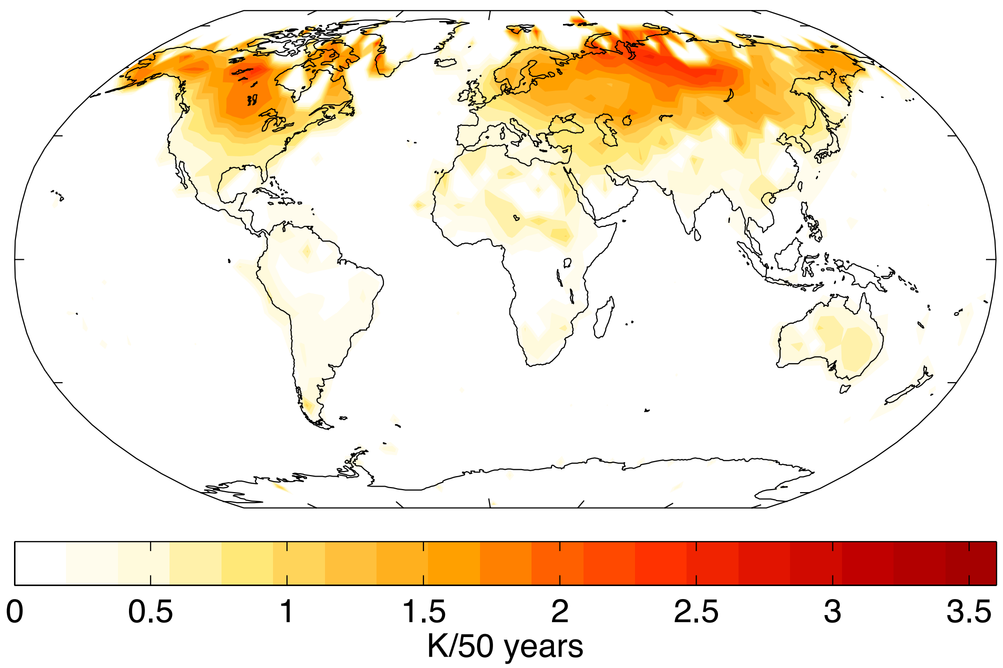
Control simulation

Predicted uncertainty in Oct-March surface temperature trends

… applying the analytic model to observations



“Predicted” 95% margin of error
(from interannual standard deviation of observations)



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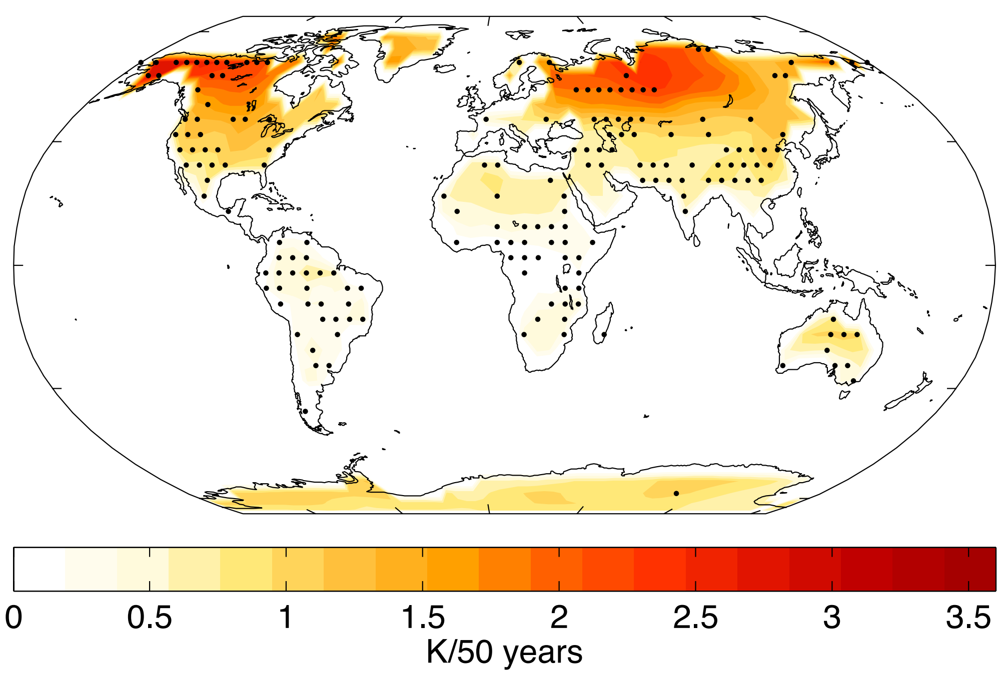

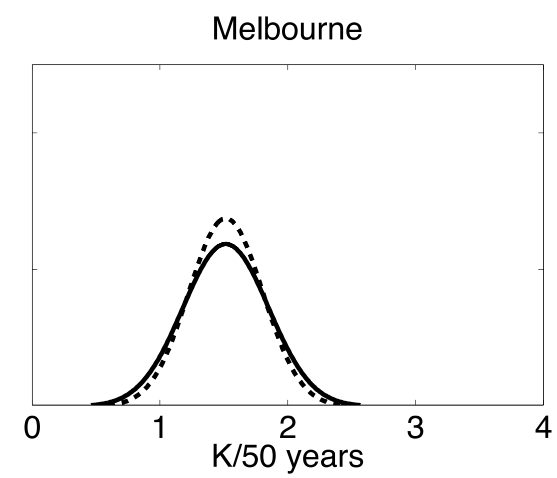

Predicted uncertainty in Oct-March surface temperature trends

… applying the analytic model to observations

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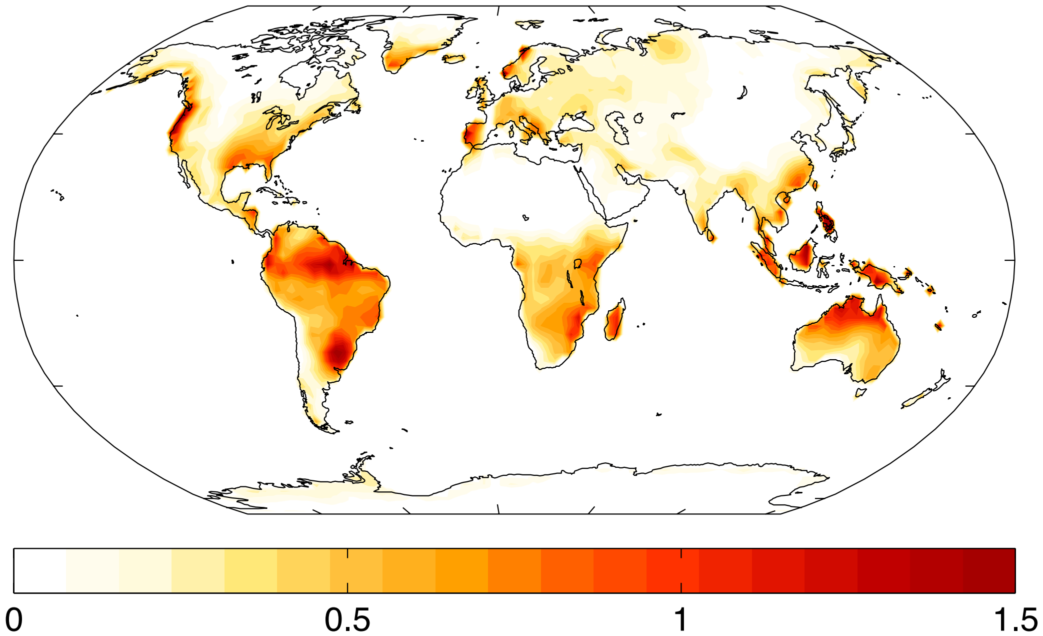

Observations from GPCP

From Thompson et al. 2015

Predicted uncertainty in Oct-March precipitation trends

… applying the analytic model to observations

“Predicted” 95% margin of error
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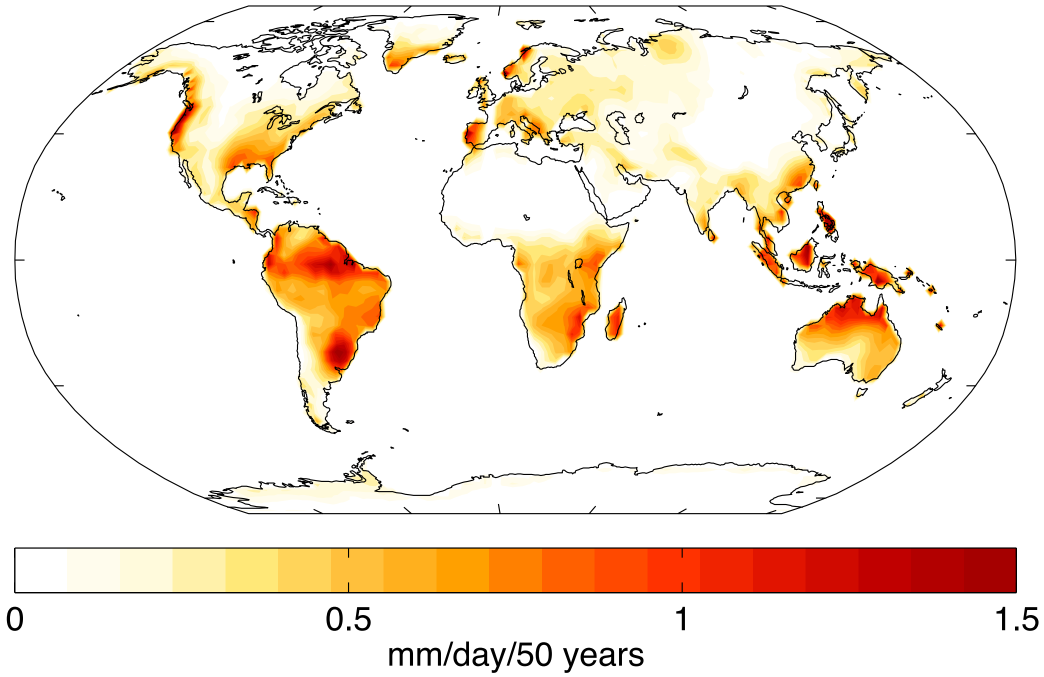

Observations from GPCP

“Predicted” 95% margin of error
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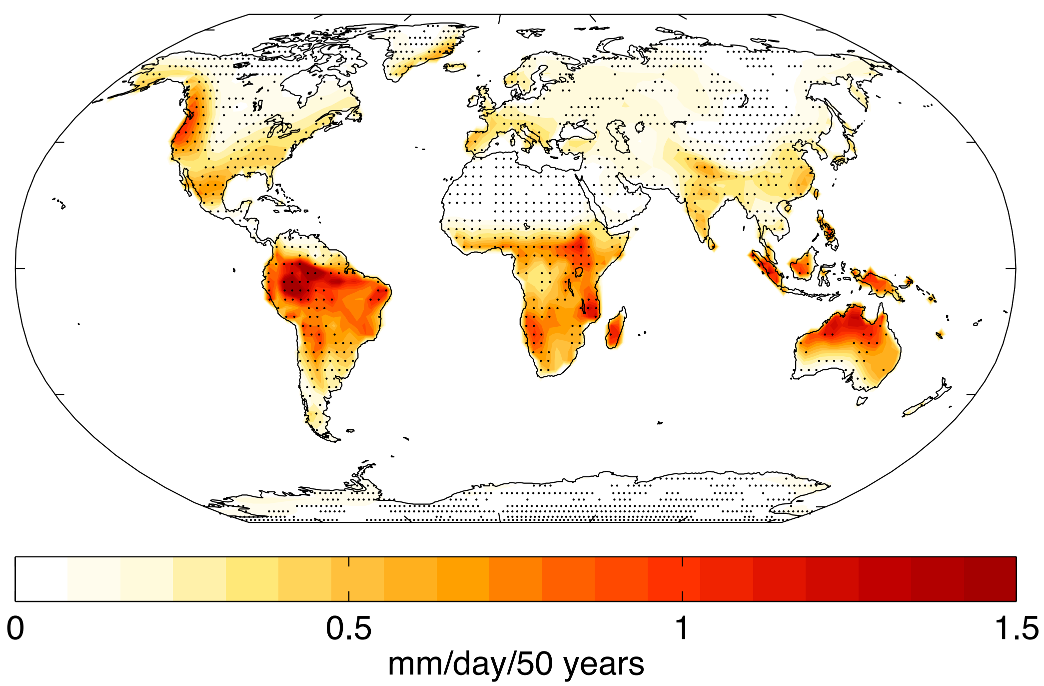


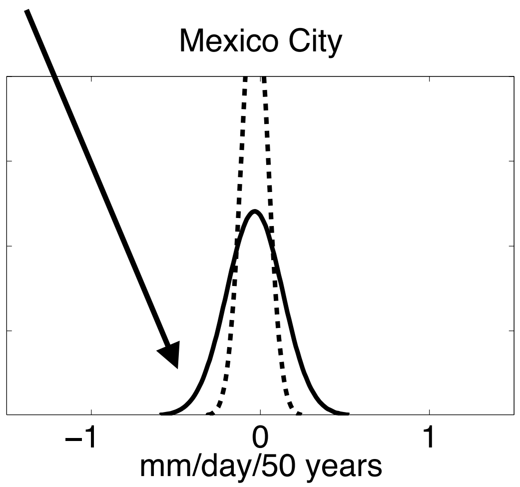
Control simulation

Predicted uncertainty in Oct-March precipitation trends

… applying the analytic model to observations

Observations from GPCP

Mexico City



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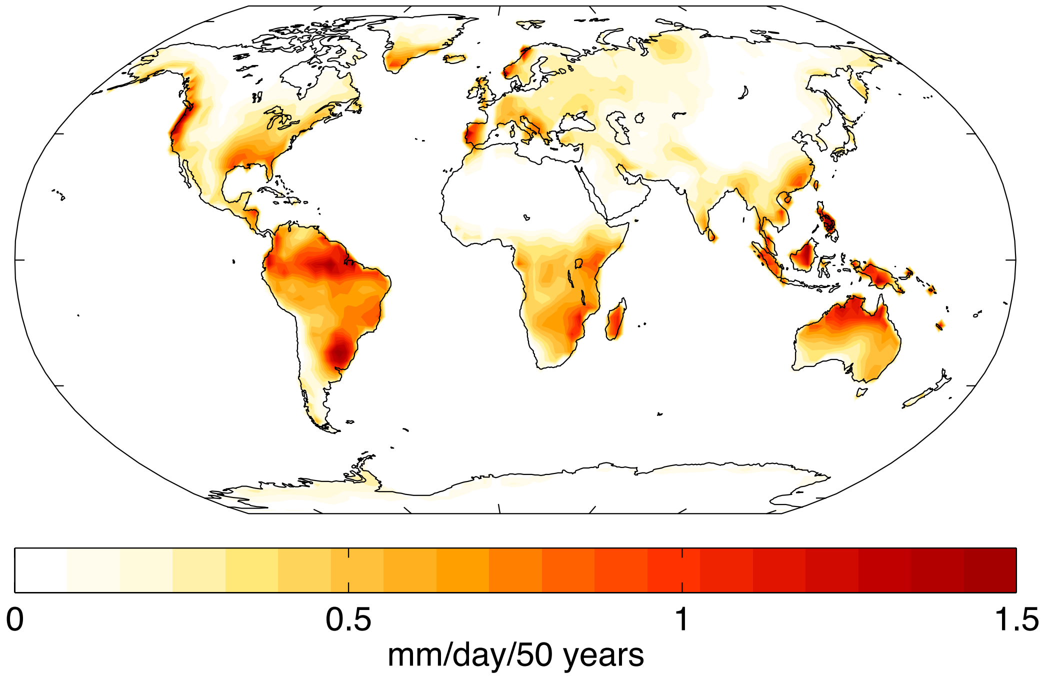

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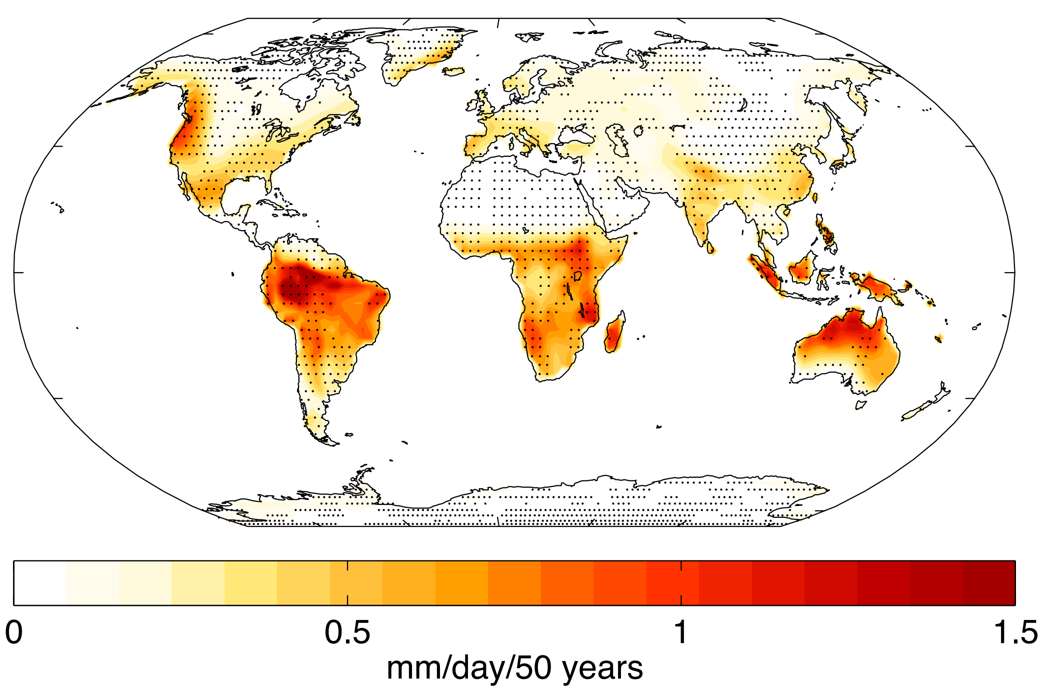
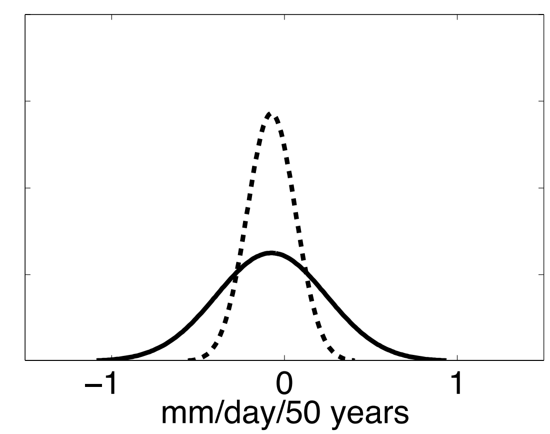


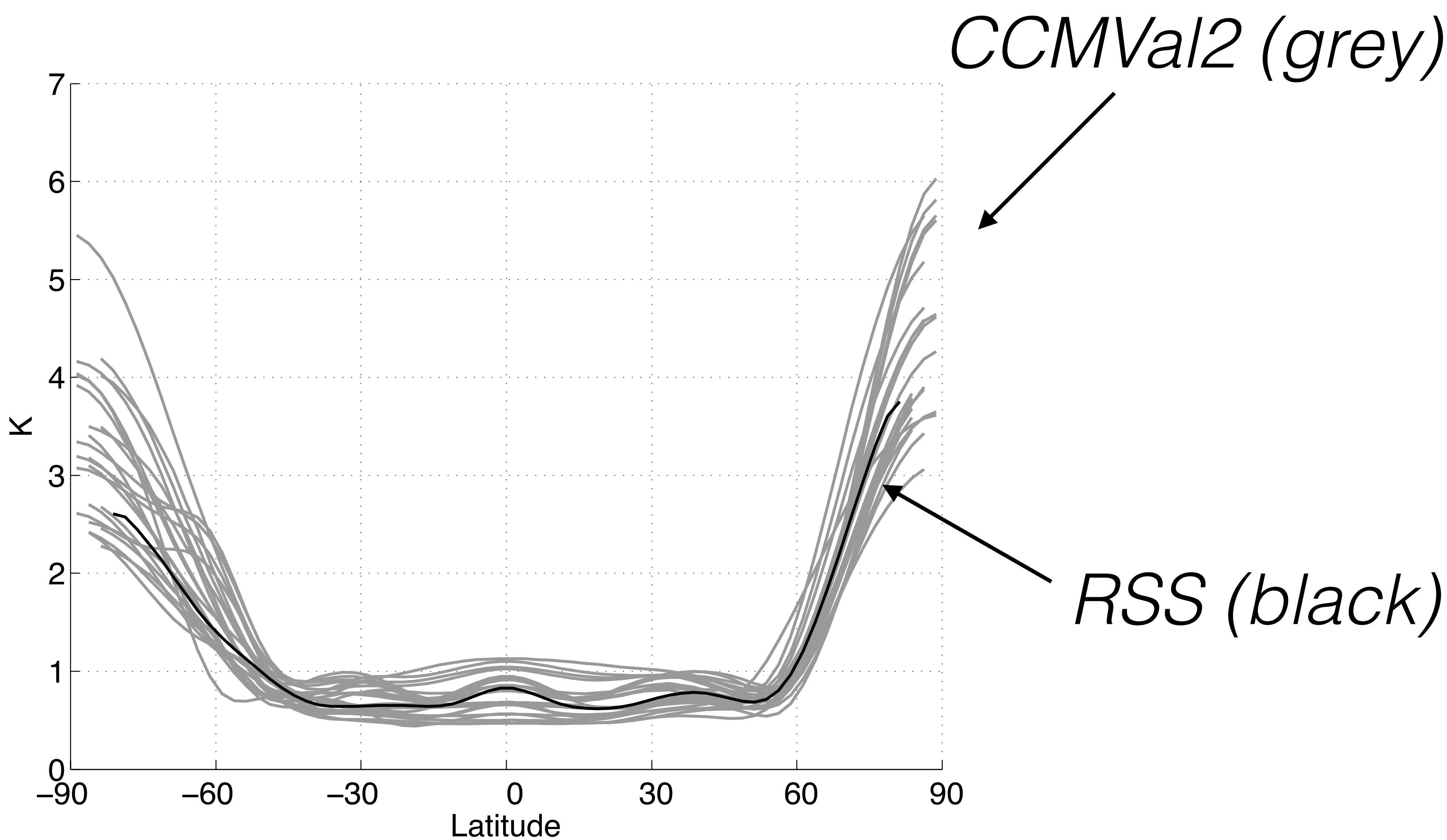
Melbourne



Predicted uncertainty in Oct-March precipitation trends

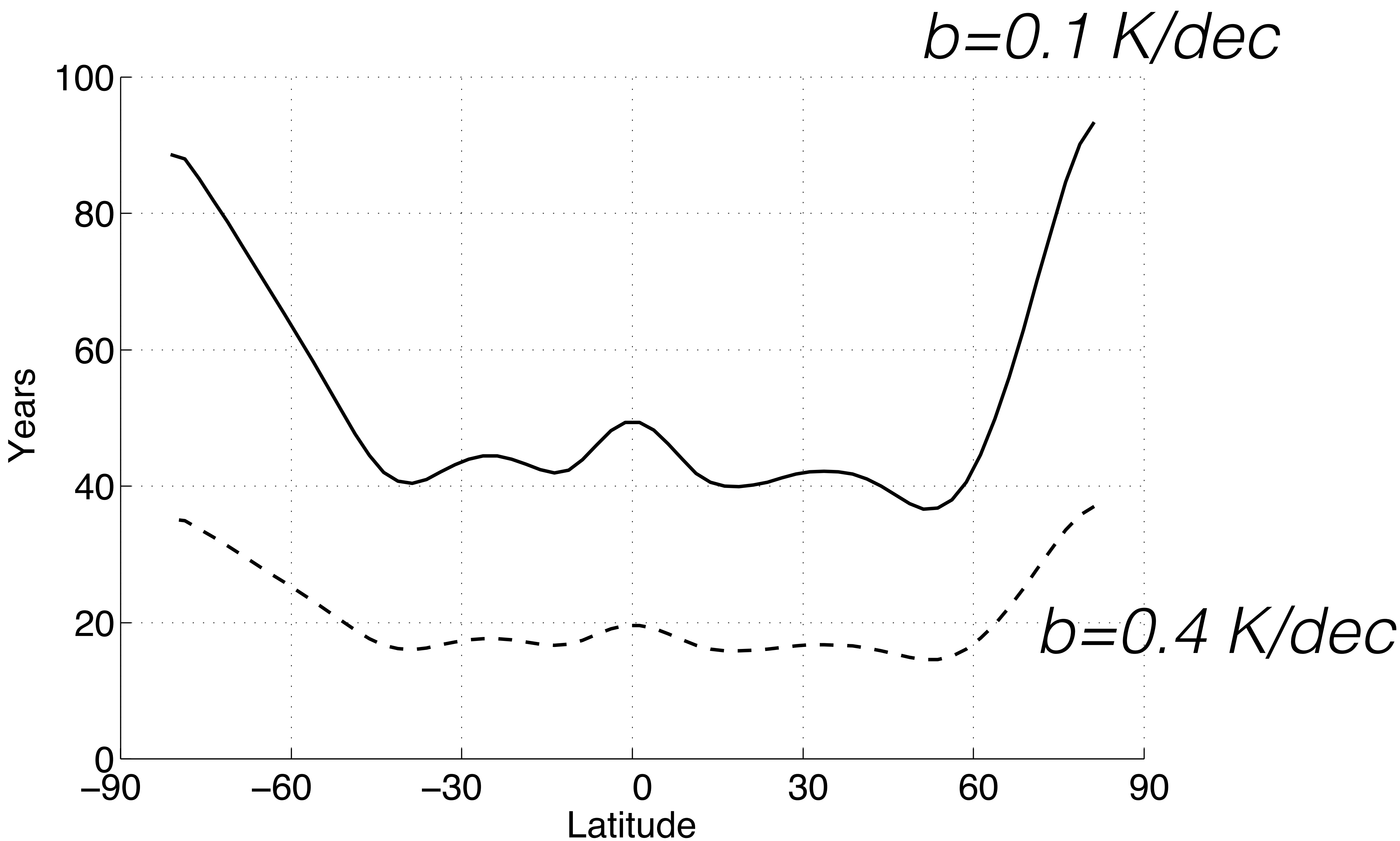
Regarding stratospheric trends:

1) The "natural variability" in the CCMVal2 simulations varies widely from model to model



Month-to-month std of detrended zonal mean TLS

2) The time of emergence is shortest in tropics



"Time of emergence" derived from RSS TLS annual-mean data

"Time of emergence" is defined as time step when *trend=e*

The analytic model provides a zeroth order estimate of the uncertainty in future trends in any *Gaussian* process with *stationary* variance.

e.g., the atmospheric circulation at middle latitudes, precipitation averaged over a specific watershed, surface temperature averaged over a broad agricultural region, ***stratospheric temperature.***

Large-ensembles provide seemingly little information on the role of internal variability in future climate that can not be inferred from a relatively short, unforced climate simulation.

(Multiple ensembles are required to estimate the forced response)

Arguably… the role of internal variability in future climate change is best estimated not from a climate model (which inevitably exhibits biases), but from the statistics of the observed climate.

(Decadal variability accounts for a relatively small fraction of the standard deviation on regional scales).

results drawing from:

- Thompson et al. (submitted to Journal of Climate)

see www.atmos.colostate.edu/~davet

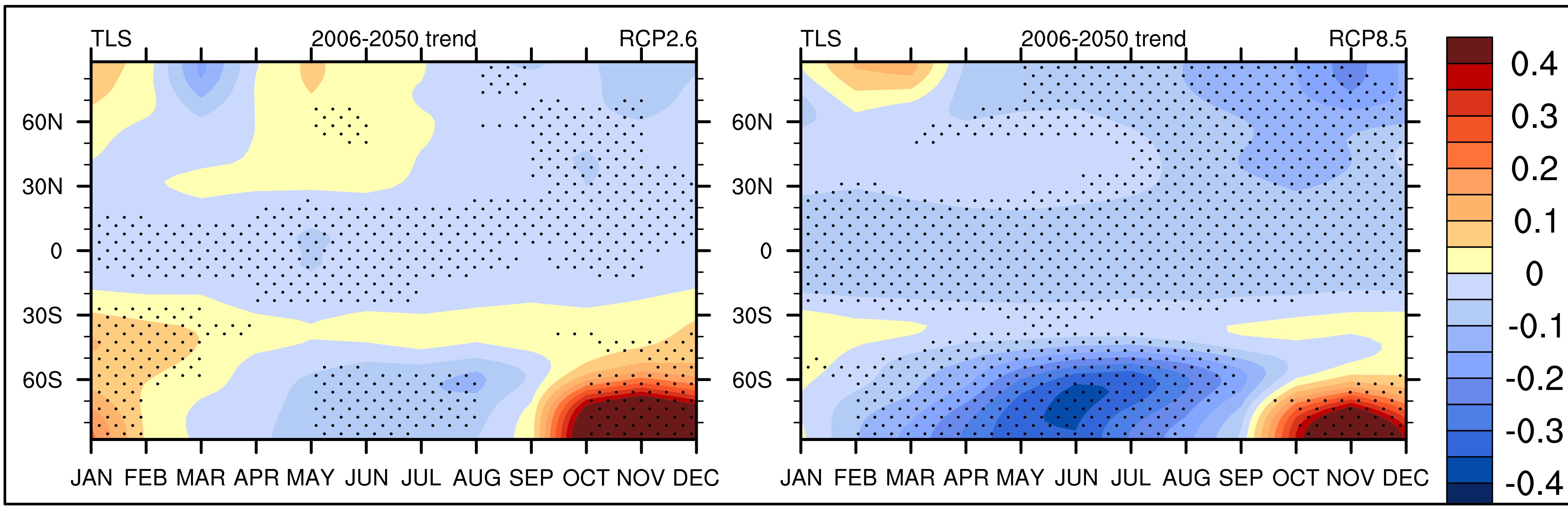
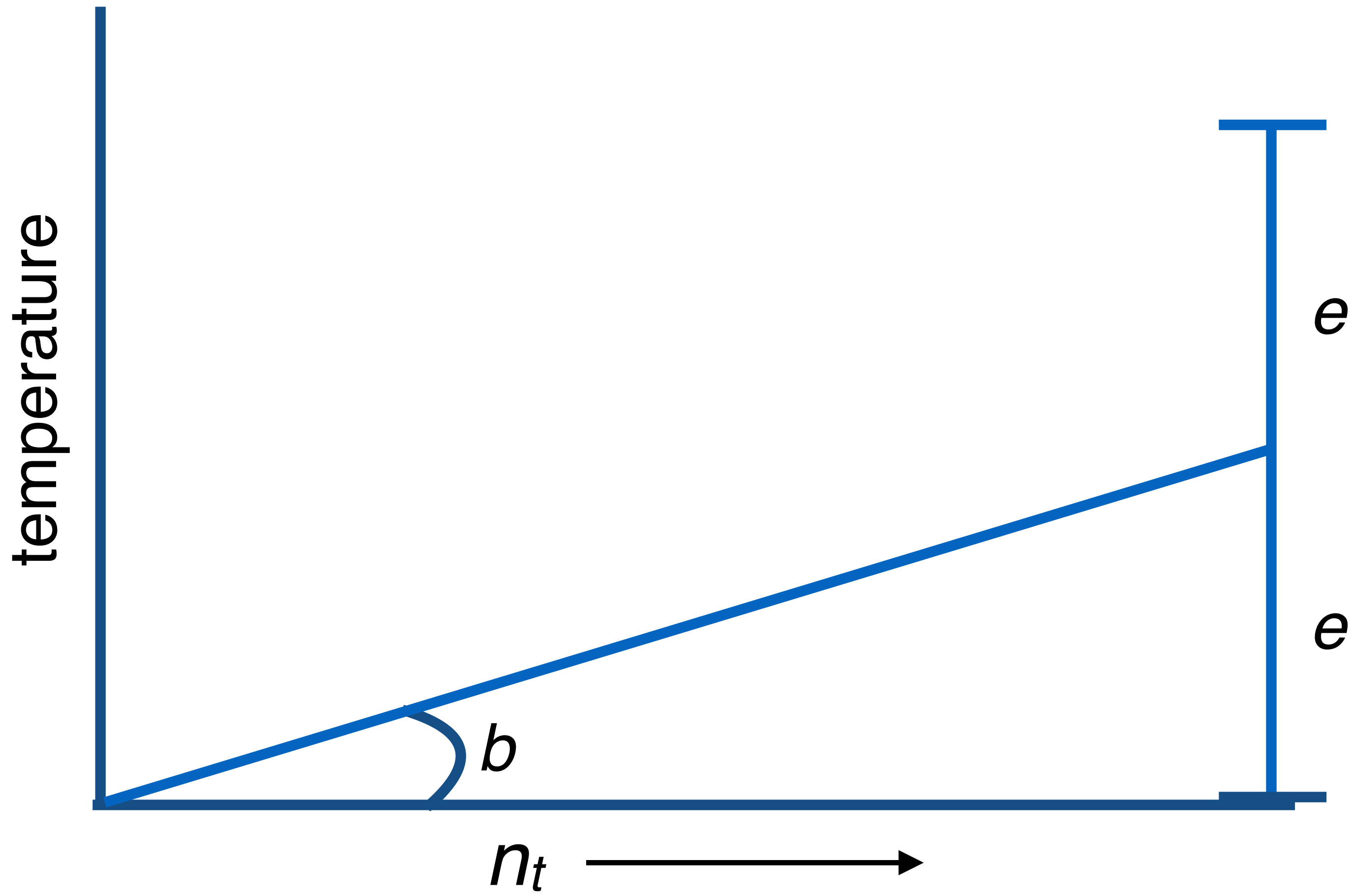


Figure 4-6. CMIP5 multi-model mean zonal mean lower stratospheric temperature trends (K per decade) over the period 2006–2050 under the low emissions scenario, RCP2.6 (*left*) and the high emissions scenario, RCP8.5 (*right*). Multi-model mean trends significant at the 5% level are stippled.

Time of emergence / when is a trend significant?

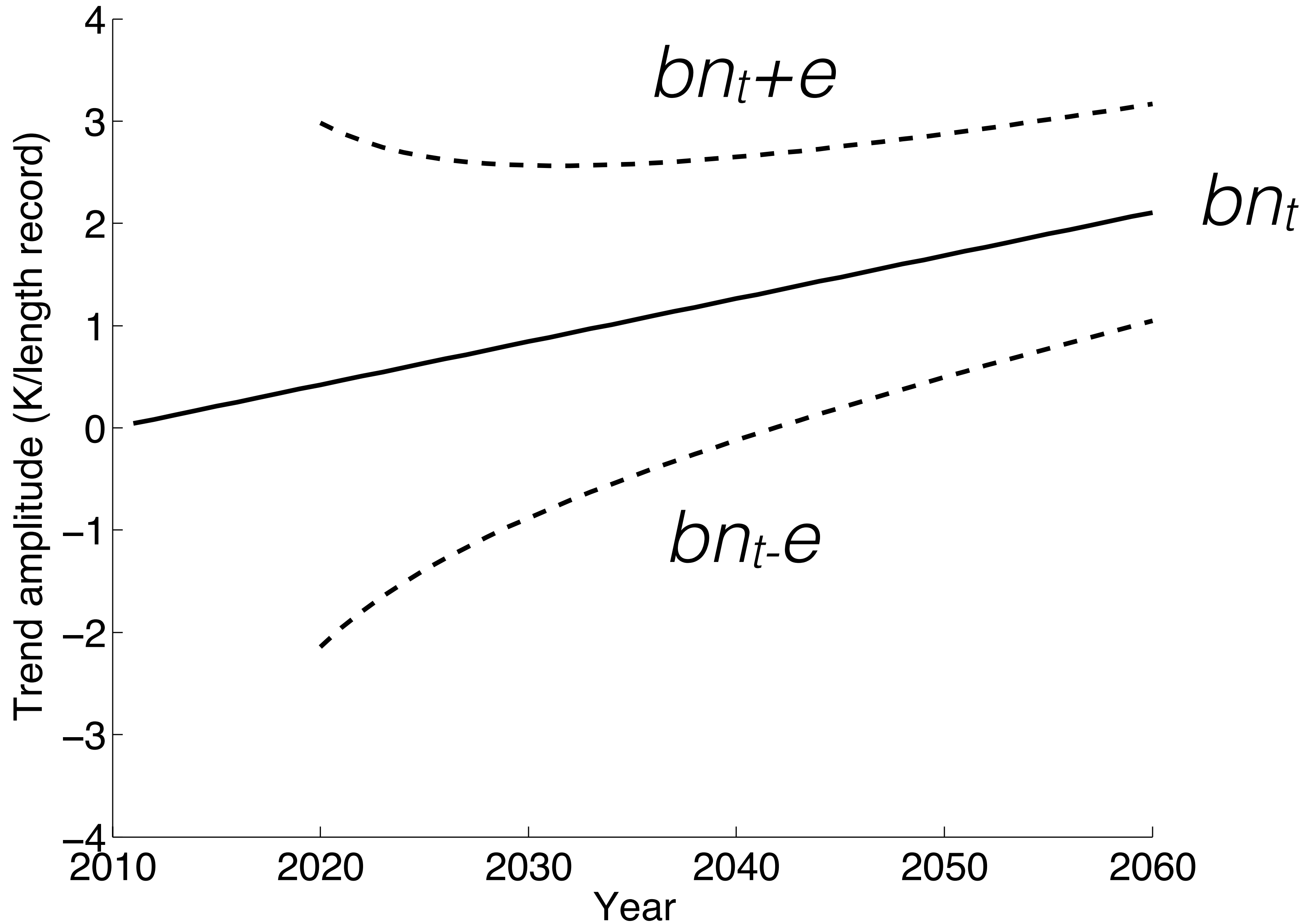


set $e=bn_t$ and solve for n_t

for seasonal-mean data and $n_t > \sim 10$:

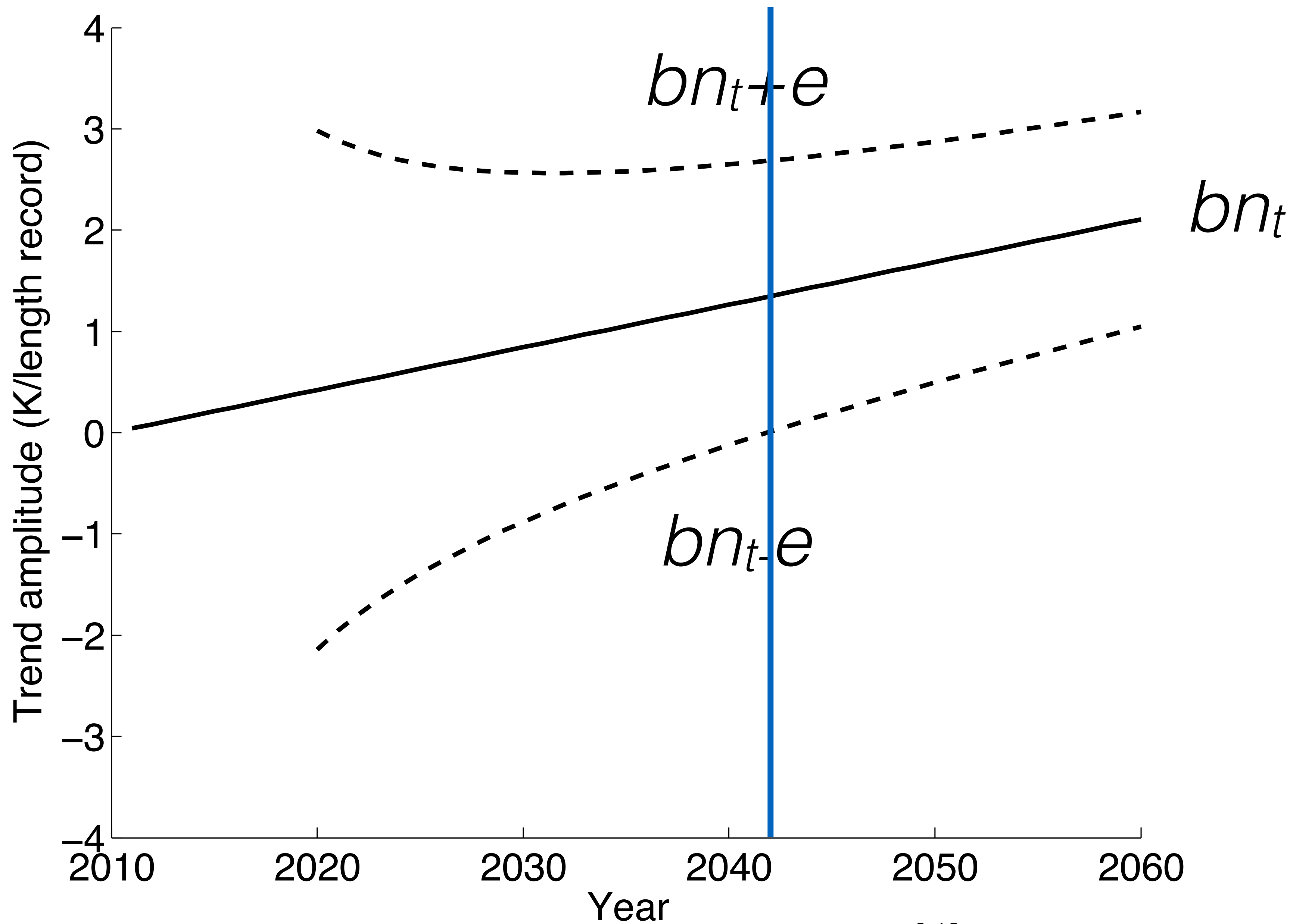
$$n_t = 12^{1/3}\left(\frac{t_c\sigma}{b}\right)^{2/3}$$

Chicago wintertime



- bn_t is the ensemble mean trend (the forced response)
- e is the uncertainty predicted by control

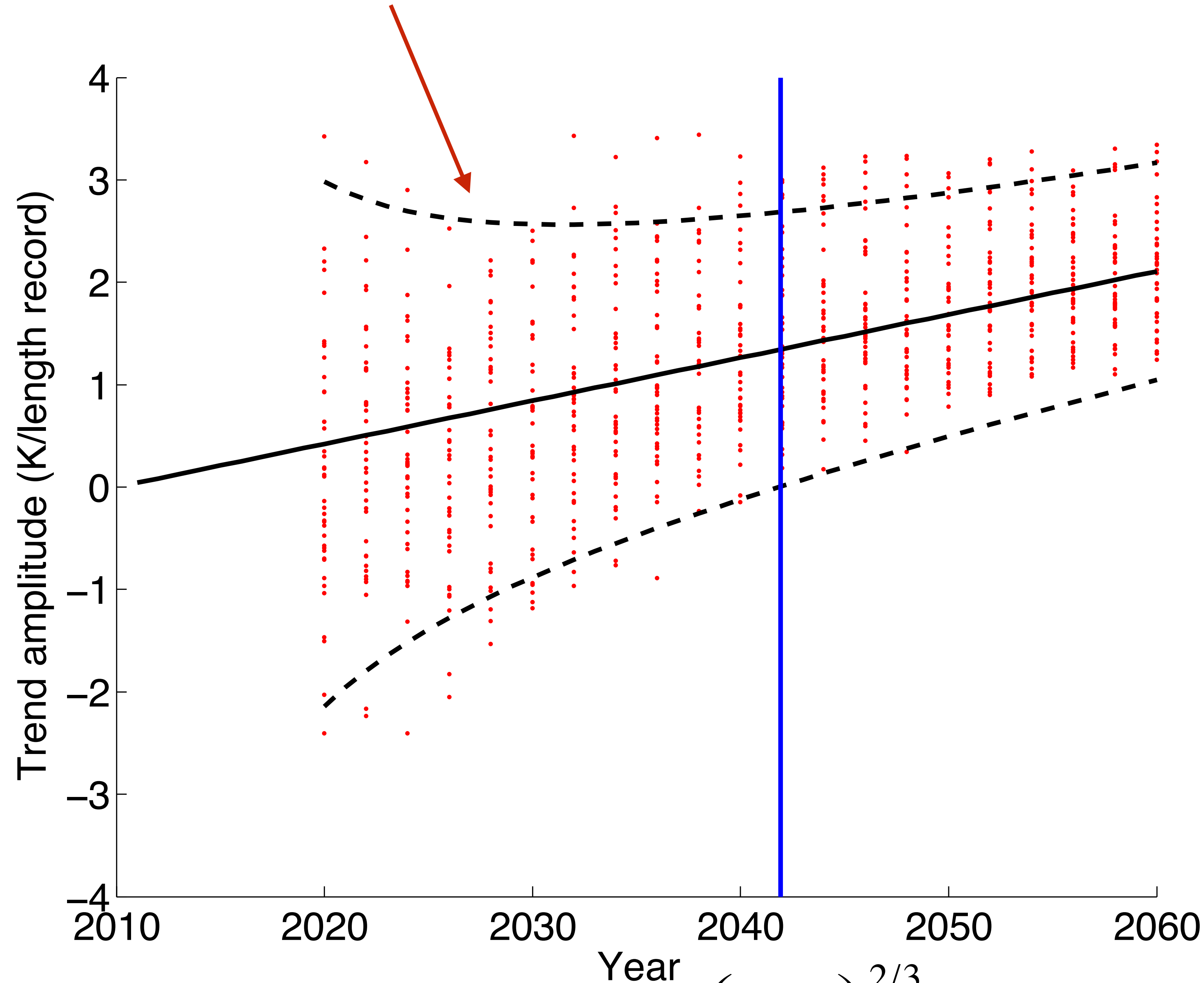
Chicago wintertime



$$n_t = 12^{1/3}\left(\frac{t_c\sigma}{b}\right)^{2/3}$$

n_t denotes the time step when 95% of the ensemble members (i.e., realizations of the real world) exceed a trend of 0.

trends from individual ensemble members



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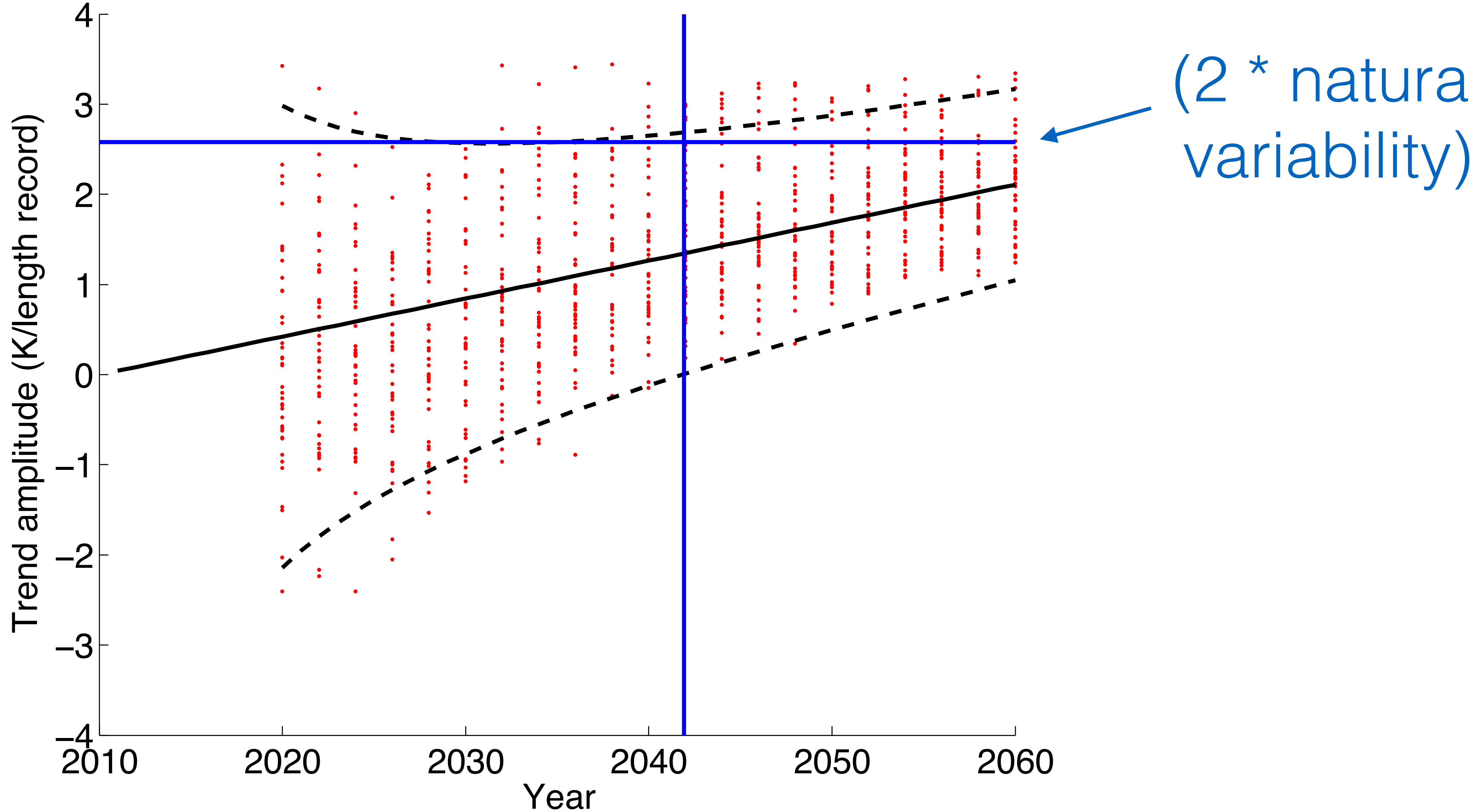
n_t denotes the time step when 95% of the ensemble members (i.e., realizations of the real world) exceed a trend of 0.

Comparison with the time of emergence



the "time of emergence" given by an individual ensemble member does not:

1) correspond to the time step when the forced signal is significant
2) account for the uncertainty in the trend due to natural variability