Climate models and uncertainty

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Sources of near-term forecast uncertainty

- “Internal” (natural weather/climate) variability *(last lecture)*
- Scenario (emissions, other “external forcing”) uncertainty
- Model error (model simulations of the above will differ)

Other sources of uncertainty (Hawkins and Sutton)

Suggests that relative importance of sources of uncertainty varies due to

1) forecast lead time
2) region (size)

[My opinion is that they underestimate impact of internal variability and model error, especially for precipitation]

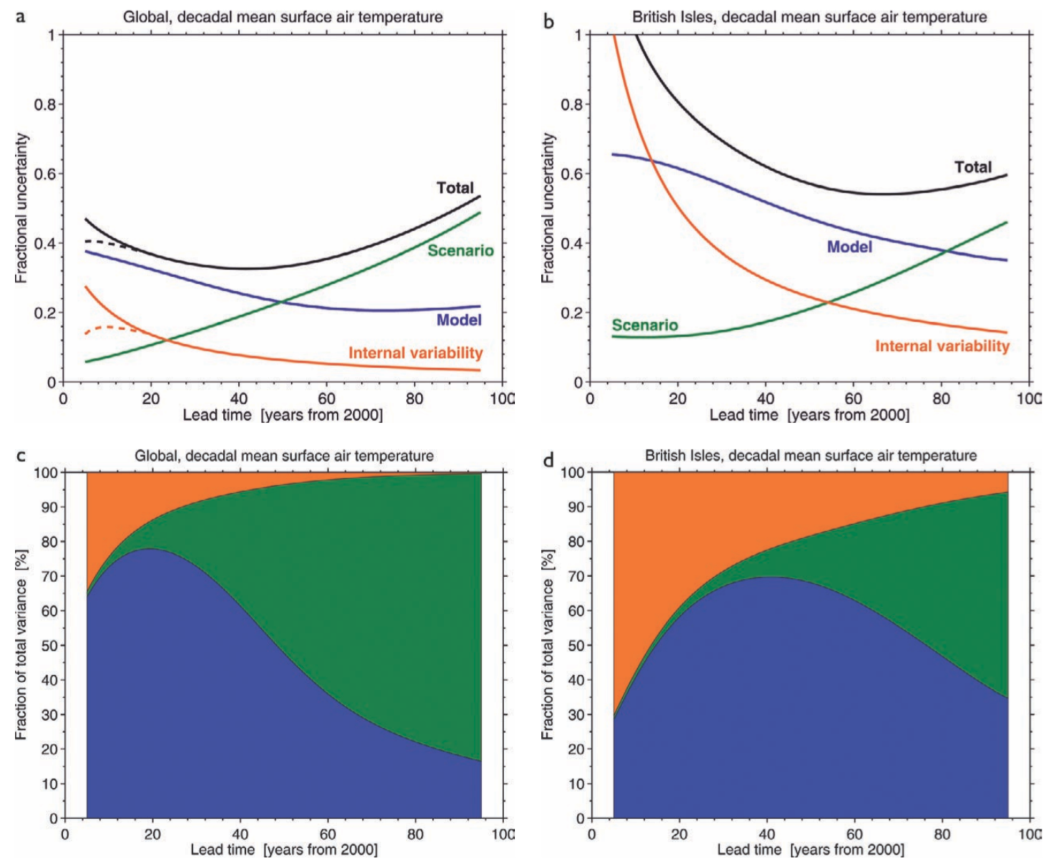


FIG. 4. The relative importance of each source of uncertainty in decadal mean surface temperature projections is shown by the fractional uncertainty (the 90% confidence level divided by the mean prediction) for (a) the global mean, relative to the warming from the 1971–2000 mean, and (b) the British Isles mean, relative to the warming from the 1971–2000 mean. The importance of model uncertainty is clearly visible for all policy-relevant timescales. Internal variability grows in importance for the smaller region. Scenario uncertainty only becomes important at multidecadal lead times. The dashed lines in (a) indicate reductions in internal variability, and hence total uncertainty, that may be possible through proper initialization of the predictions through assimilation of ocean observations (Smith et al. 2007). The fraction of total variance in decadal mean surface air temperature predictions explained by the three components of total uncertainty is shown for (c) a global mean and (d) a British Isles mean. Green regions represent scenario uncertainty, blue regions represent model uncertainty, and orange regions represent the internal variability component. As the size of the region is reduced, the relative importance of internal variability increases.

Regional sources of uncertainty (Hawkins and Sutton)

Similar to previous slide but gives more of a regional picture

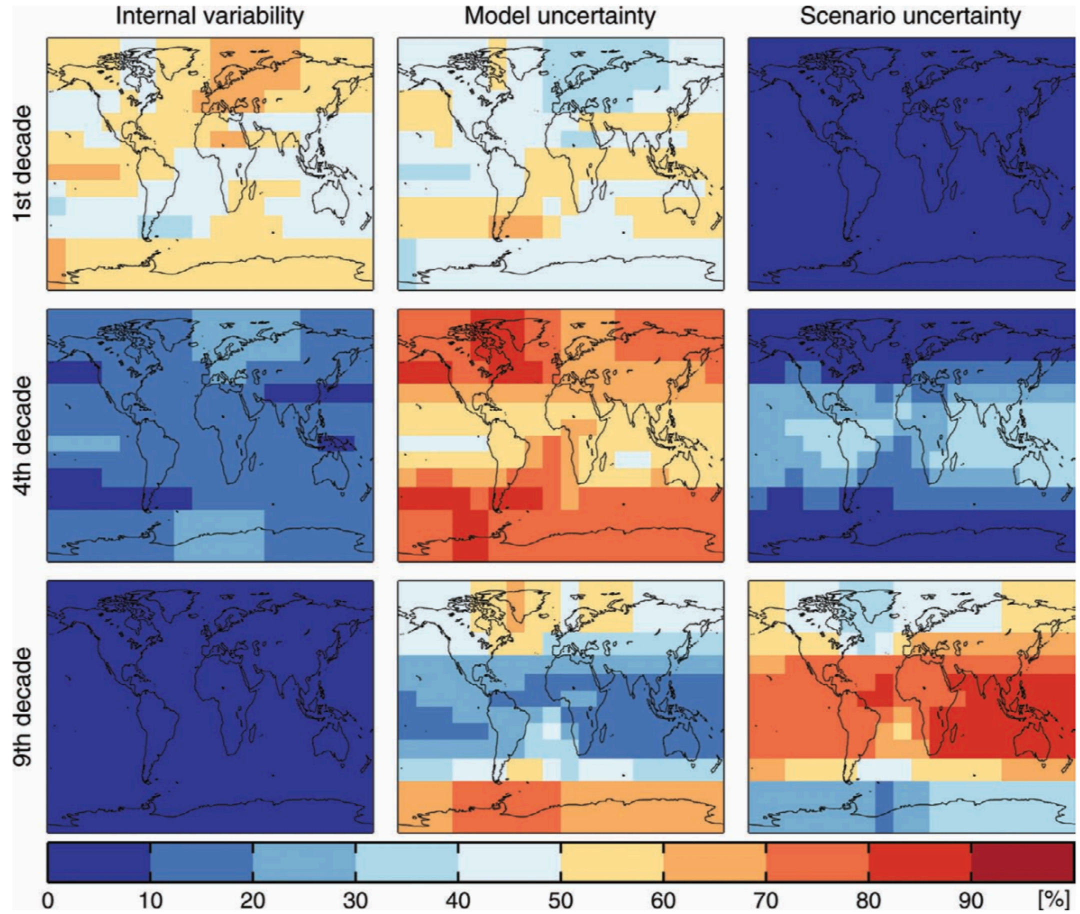


Fig. 6. Maps of the sources of uncertainty for decadal mean surface temperature for various lead times give information on where any reduction in uncertainty will have the most benefit. The columns show the total variance explained by (left) internal variability, (middle) model uncertainty, and (right) scenario uncertainty for predictions of the (top) first, (middle) fourth, and (bottom) ninth decade. It should be noted that (i) even on regional scales, the uncertainty due to internal variability is only a significant component for lead times up to a decade or two, (ii) the largest differences between models occur at high latitudes where climate feedbacks are particularly important, and (iii) even by the end of the century, the emissions scenario is less important than model uncertainty for the high latitudes but dominates in the tropics.

Discussion questions

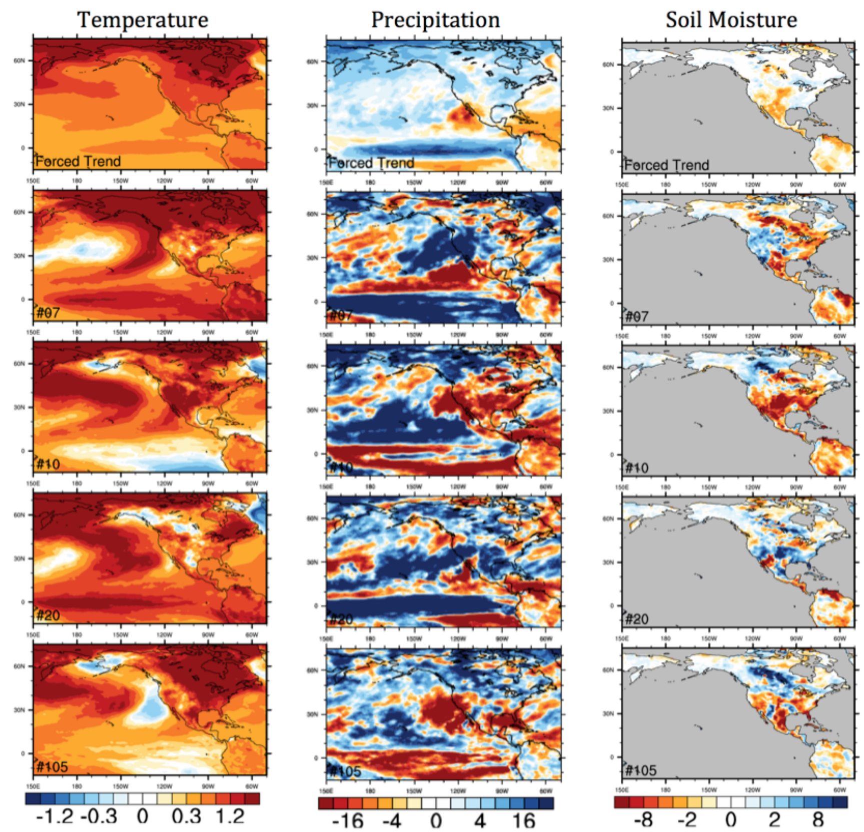
- How might adaptation policy based on near-term climate forecasts deal with uncertainty?
- Consider that the impact of forecast uncertainty could depend on:
  - forecast variables (e.g., max and min temperature, precipitation)
  - regions (e.g., southwest U.S. vs. Great Plains)
  - seasons
  - forecast lead times (e.g., 5, 10, 20 yrs, or longer)

Discussion questions

- How might this uncertainty affect the politics of formulating a response (either prevention or adaptation) to anthropogenic change? Should it? Why or why not?

Homework question

- Produce a communication strategy for the pictured climate forecast ensemble covering the next 20 years for the U.S. [Recall that the top row is the ensemble mean.]
- Consider how different audiences (policymakers, general public, land/water managers) may respond, especially to a discussion of uncertainty.



Sort of a counterfactual question:

What would we be saying now about climate change if we didn't have global coupled climate models?

(Why) do we need climate models?

- "If we had observations of the future, we obviously would trust them more than models, but unfortunately observations of the future are not available at this time" (Knutson and Tuleya 2005)

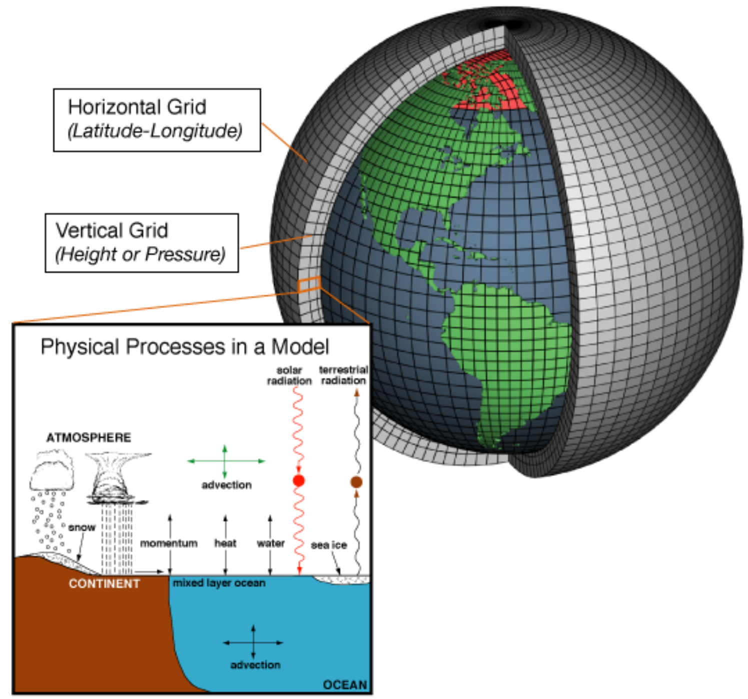
- Simple "single column" models yielded similar warming predictions decades ago as much more complex modern models do today
  - Not so helpful in showing how other aspects of the climate would change, though

- Problem: Difficulty in understanding why a simulation produces its results based on our understanding of the underlying theory

- Climate is an emergent phenomenon in a climate model!
  - That is, we construct a model of physical/thermodynamic processes, and the climate is an outcome

Components in a climate model

- Well-accepted physical laws (conservation of mass, energy etc.)
- Approximations to well-understood physics (have theory, but hard to solve with computer resources), but only on model grid
- Empirical *parameterizations* of unresolved processes (don't have theory), eg, cloud droplet formation, convection, turbulence, radiation. No single "right" answer!
  - Example: *cloud fraction* within grid cell based on temperature, humidity
- Estimates of important "forcing" sources (solar, volcanic, aerosols, green house gases)



Why are models tuned?

- Models are combinations of well known physical laws and less well determined parameterizations
- Parameterizations are often determined in isolation, not in combination with other variables and parameterizations
- Using the "best" value for each parameterization would produce a terrible model!
    - And introducing a "better" parameterization could make the model worse in some or many measures
- "Tuning consists of choosing parameter values [to minimize] some deviation of the model output from selected observations or theory…"
- Minimum requirement: energy into earth system = energy out ("top of atmosphere" balance)
    - THIS IS HARDER THAN IT SOUNDS but it is essential

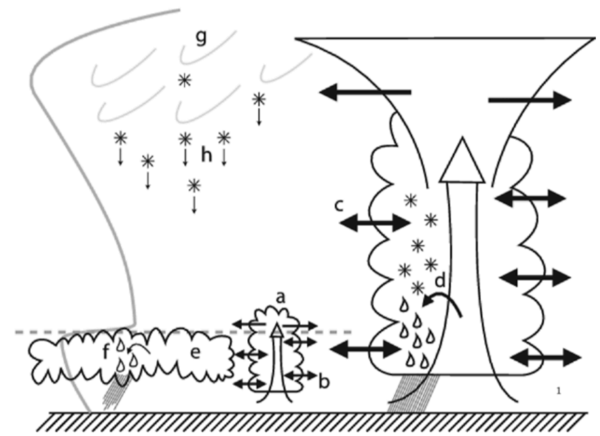


Fig. 1. Example of tuning approach for the ECHAM model (after Mauritsen et al. 2012). The figure illustrates the major uncertain climate-related cloud processes frequently used to tune the climate of the ECHAM model. Stratiform liquid and ice clouds and shallow and deep convective clouds are represented. The gray curve to the left represents tropospheric temperatures, and the dashed line is the top of the boundary layer. Parameters are (a) convective cloud mass flux above the level of nonbuoyancy, (b) shallow convective cloud lateral entrainment rate, (c) deep convective cloud lateral entrainment rate, (d) convective cloud water conversion rate to rain, (e) liquid cloud homogeneity, (f) liquid cloud water conversion rate to rain, (g) ice cloud homogeneity, and (h) ice particle fall velocity.

How are models tuned?

- Tune individual parameterizations, then components (eg, atmosphere, ocean), then climate system
- Adjust parameters
    - Particularly for clouds (microphysics/fraction/convection) and surface (albedo/soil & vegetation/friction)
- Compare various measures ("metrics") of the climate system in the model to what is observed in nature
    - Would like to do this objectively (see reading) but impractical to thoroughly investigate all parameter choices (not enough computer time!)
- Repeat
- Problem: some measures will improve but others will get *worse*
    - For example: average of a variable could get better but its variability would not

How are models tuned? (cont)

- Also: we don't want to tune to something we're trying to model!
  - Would like to avoid confirmation bias – such as for global mean temperature for the 20th century!
- And: we don't want to tune too carefully ("overtune")
  - Natural internal variability should yield differences from (uncertain) observations even for global mean temperature
- Concern is uncertainty about "equilibrium climate sensitivity" (how much warming for CO2 increase should we get)

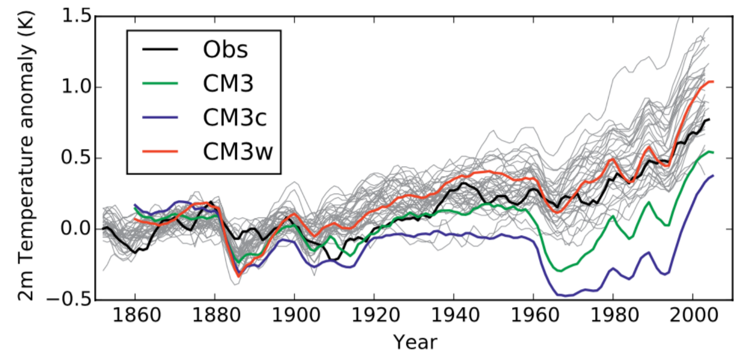


FIG. 3. Simulations of the twentieth-century temperature with the CMIP5 model ensemble (gray curves). Each curve corresponds to a 5-yr running mean of the anomaly of the global-mean temperature at 2 m above surface. The anomaly is computed using as a reference period years 1850–99. The black curve corresponds to the version 4 of the Hadley Centre/Climatic Research Unit (HadCRUT) observations. The colored curves correspond to three configurations of the GFDL CM3 model. CM3 denotes the CMIP5 model, while CM3c and CM3w denote alternate configurations with large and smaller, respectively, cooling from cloud aerosol interactions.

Read Stephens article: “Climate of Compete Certainty”

Stephens claims:

- Models and algorithms can be used to ***minimize*** uncertainty
- Claiming certainty on climate change will only backfire
  - "Claiming total certainty about the science traduces the spirit of science and creates openings for doubt whenever a climate claim proves wrong"

For remainder of class, we'll discuss this position.

Some questions to consider:

- Is this a fair argument? Does climate change get presented as "certain"? Can you think of examples where it does or does not?
- Can we reduce uncertainty? [Hawkins & Sutton think so.] If so, how much?
- If not, how much uncertainty can we tolerate? How certain do we need to be to take specific actions?
- How do we characterize uncertainty, in science and in the public? How do we communicate this to the public and policy makers?