Theme 1: Detection and Attribution Problem and State of the Art

Chair: R. Smith, Rapporteur: A. Braverman

Paul Kushner: Introduction to workshop

Remarks regarding this theme:

- DA is one of the primary methods by which one combines models and observations to better understand the climate system.
- Problem of climate change detection and attribution (DA): To quantify probability that climate signal, distinct from natural climate variability, can be detected in observed climate data, and attributed to external forcings.
- Problem of DA climate impacts: To quantify probabilityiy that impact signal, distinct from what would be happend otherwise, can be detected in observred data, and attributed to climate variations as well as other drivers, and perhaps attributed specifically to anthropogenic climate change.
- Intrinsicly statistical problems at intersection of many disciplines. Overarching goal of the week is to advance framework
- Ingredients: (i) observations, (ii) climate model inputs, (iii) statistical methods to relate (i) and (ii). (iii) is the focus of this week.
- DA is an "operational" endeavor: done routinely and thus some compromises are necessary.

Ben Santer: Identifying a "discernible human influence" on global climate: a personal perspective on the application of the Hasselmann fingerprint method

- Hasselmann method is what Ben has used over the course of his career.
- IPCC assessment reports have been coming to stronger and more definive statements on human influence on climate. Four lines of evidence for IPCC conclusions: 1) basic physics (energy balance), 2) circumstantial evidence (qualitative), 3) paleoclimate evidence using proxy indicators (temperature reconstructions), 4) fingerprint evidence: rigorous statistical comparisons.
- What is climate fingerprinting? Basic premise: different external influences have characteristic signatures that are visible when you look at spatio-temporal patterns of change. *Fingerprint = relationship between model-predicted response to climate change (in model output) and observations, particularly with respect to spatial and temporal patterns.* Example using PCM (Parallel Climate Model) at atmospheric temperature: when adding greenhouse gases as forcing, you are increasing the ability of the atmosphere to hold in heat in the troposphere. This shows up in the fingerprint. Now look at observations (weather balloons): qualitatively appears consistent with the greenhouse gas fingerprint. Not consistent with solar radiance increase fingerprint. Early critisism of IPCC conclusions included fact that only looked at surface temperature. By now, this influence has been seen in many aspects (variables) of the climate system.
- What is the Hasselmann fingerprinting method? One can borrow from signal processing to detect climate signal in a noisy background: Hasselmann (1979). Not optimal to look in the direction of maximum signal, but of maximum signal to noise ratio. Decompose control run data into EOF and amplitude time series; project the fingerprint (leading EOF) on control EOFs (see slides 15,16). Is this finger print statistically identifiable in the observations? Control run with no change in external forcing gives rise to a null distribution. Assumption: spatial structure of $f(x)$ is stable over time. Aim of optimal fingerprinting: enhance S/N. Include spatial and temporal patterns. EOF's used to

reduce spatial dimension down to one(?) number; look at how that number changes over time. Tie varying observed patterns and time varying control run patterns both projected onto model fingerprint -¿ signal and noise time series -¿ S/N ratios. Slide 23 shows benefits of optimization (panels change by number of EOF's used (m= truncation length)).

- Fingerprinting with atmospheric temperature (several levels) changes. Example with CMIP5 simulation output and ensembles of observations. Measurements are from MSU from NOAA polar orbiting satellites over past 33 years. See slide 26 for initial comparison. Model is smoother than observations because model is an average of number of model runs. Largest warming in the arctic. Alabama and RSS data sets constructed from the same DN data, but Alabama shows more arctic warming (ironic, isn't it?). Slide 26: dominant noise modes of top 5 CMIP5 models control run output (upper-left, upper-right, and lower-left) show small scale variations where as the multi-model fingerprint of the 11 CMIP5 models (lower-right; forced with greenhouse gases) shows larger scale features. Slide 28 shows observations and model simulations projected onto the fingerprint. Fingerprint is robust feature in the observations both from Alabama and RSS. That result is not a consequence of large-scale averaging. See slide 29.

- Do models systematically underestimate natural (internal) variability? Can't get this from observations because the record is too short. Look at model and observed SST variability. Some have contended that the models underestimate this variability. Use band-pass and high-pass filtering to assess relationships between temporal variability on short and long time-scales. See slide 39.

- Conclusions:
  - Fingerprints identified in a number of variables. Moved beyond just looking at temperature. Story told by this analysis is consistent across different variables and types of analysis. Skeptics often allege otherwise.
  - Predictions made in 2007 about DA: 1) we will have some form of "operational" capability, 2) routinely use multi-model ensembles, 3) structural uncertainties in observations will become integral part of DA. 4) we will have formally identified anthropogenic fingerprints, 5) Fingerprinting will be feasible with shorter observational records (satellites).
  - Are we there yet? (Rhetorical question)

- No questions/discussion due to time constraints.

David Lobell: Impacts of climate change on agriculture

- Focussed on present and future rather than past- no community of skeptics to debate.

- Challenges of DA in agriculture. Detection process of demonstrating that climate or a system has changed in some defined statistical sense (Hegerl). Key is having a clear baseline or counterfactual (e.g., a control run). What does it mean to detect a change in agriculture? Relative to a flat line? Relative to some counterfactual- what counterfactual? Tend to view detection as either trivial or impossible in agriculture. Attribution is the process of evaluatiing the relative contributions of multiple causal factor to a change or event. Key is having a clear fingerprint of each potential external forcing or driver. Attribution: lots of things are changing at the same time (fertilizers, CO2, seeds, etc.) In traditional attribution, we need fingerprints for all these things, but we have limited knowledge of (i) the spatial and temporal distribution of these factors and (ii) the quantitative effect of each factor on interactions and yields. For example, maize yields (slide 7). Is upward trends in yields in US relative to China and Italy due to increased temperatures in the latter two locations, or is it due to failure of the latter two to adopt genetically modified crops (slide 8)? Attribution is tricky.

- Review of studies on impacts of climate trends in agriculture. DA people tend to underestimate the difficulty of getting the fingerprints for these types of effects. Instead, historically, use process-based knowledge of climate effects on yields to model the influence of climate trends on yields. Then, the problem is a two-stage one: climate change analysis is the business of climate DA; concentrate on attribution question in the second stage. Nearly all of what's done up to now is in this second category. Crop models: how good is our process understanding? Pretty good a small scales where there is process understanding is good (site-level). Empirical approaches help integrate process understanding and observations. Some key things to happen in the next five years: Datasets rapidly improving, studies emerging to integrate empirical and process models, multi-model comparisons (AgMIP) coming. Examples of a number of different studies. Supit et al. (2010), for example, radiation (solar dimming) is included as a forcing in the underlying climate model. This is a very important assumption that affects the crop model output: "multi-step analysis done in the authors' heads". Slide 18: summary of lit review breaking down studies according to results, assumptions, and methodologies. Summary of state-of-the-art, but remember: these methods assume "fixed management" and do not typically include direct effects of CO2 or ozone.

- Options for moving forward. See slide 20. Get everyone on the same page: 1) crop modeling community needs to get up to speed on using the same variables and scales of climate models. 2) climate modeling community should focus on variable that crop community identified as important (also focus on locations and time that are important to agriculture). Need to expand the view: what is the food system sensitive to, not just what yields are sensitive to. Also, look multivariate (extremes in multiple variable simultaneously). 3) Tighter link between climate model control runs with different forcings and their consequences for crop models. Customize the strategy specifically for impacts on agricultural variables. Francis Zwiers: scale mismatch between climate models and crop models- is this an issue? Has fueled interest in downscaling climate models. Lobell is skeptical about utility of downscaling. Better to aggregate up and work there. Ben Shaby: can we fold in vegetation models into climate models? Lobell: this is one way to go and is being done in some places. Can look at feedbacks that way. 4) The "full Monty"- do the full-up DA for different drivers in agriculture starting with forcing in climate models. See slide 27 for a nice summary of these options.

- Discussion/questions. Ben Santer: tell us about AgMIP. Right now in the phase of executing the first round of experiments. Maize and wheat crops used, 15 or 20 models being studied. Only process models being used now. Same issues of multi-model ensembles (e.g., independence of ensemble members). Can't really be evaluated against field-level observations; models not designed for that. Can evaluate at aggregated scales though. Tim Delsole: what forcings to look at? Extreme rainfall and temperature (the usual suspect). Soil moisture to, but related to the other two. SMAP (Soil Moisture Active Passive) NASA mission is coming and should offer a new observational data set. Ben Armstrong: have you thought through how you might incorporate adaptation into your models? Answer: can control "management" in the models. Also can look at how stationary model coefficients are over time, but this would sweep in everything that changes (CO2) as well as adaptation.