Toward a probabilistic climate emulator for integrated assessment impacts research

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December 13, 2013

Plan of Talk

Why Emulation?

Space

- The spatial scales at which climate impacts manifest themselves is typically much finer than the global or regional scale "damage functions" in aggregate IAMs such as DICE/RICE or FUND.
- Long history of simple 1-D models can be used to project global mean temperature change
- BUT, we lack computationally efficient methods for generating the corresponding changes in climate variables at the fine spatial scales at which impacts occur
- Such a "synthetic GCM" can be coupled with emerging empirical estimates of the relationships between climate variables and key impact endpoints in order to generate shocks to human and natural systems that can then be fed into IAMs

Probability

- Currently the only way to obtain the changes in climate variables at fine spatial scales that correspond to given amounts of global mean temperature change is to simulate GCMs
- Any downstream impact studies that use GCM outputs become "locked-in" to the particular GCM x scenario combinations used to produce the fields of climate variables
- Probabilities over scenarios do not exist
- An emulator which captures the statistically captures the envelope of the response of *all* GCMs to a given amount of warming allows us to construct the spatial contours of the probabilities of local changes conditional on global change

Overview of the Procedure

1. Assemble temperature and precipitation fields from 17 different GCMs for A1B, A2, and B1 scenarios from 1980 to 2099 from the CMIP3 archive, remap to a T42 grid
2. Construct patterns of change in decadal seasonal mean temperature and precipitation at each grid cell as local linear functions of global mean temperature change
3. Estimate GCMs' internal variability from their 20th century historical runs (20C3M), use the result to scale the residuals from the pattern in (2)
4. Construct a dataset of the residuals that correspond to the global mean temperature change of interest (e.g., 2°C warming)
5. Fit a spatial covariance function to the dataset
6. Sample from the fitted covariance function to produce a large number of distinct but spatially consistent realizations of local errors from the overall pattern
7. Add these errors back to the pattern, use the resulting datasets for assessment of climate risks!

Details

- For variable v, grid cell i, season s, GCM m and decade t, compute the pattern response of variables $\Delta Y^v_{i,s,m,t}$ to global mean temperature $\Delta T_{m,t}$:

$$\Delta Y^v_{i,s,m,t} = \beta^v_{i,s} \Delta T_{m,t} + \varepsilon^v_{i,s,m,t}$$

  where β^v_i is the pattern.
- Scale residuals by GCMs' internal variability, $\hat{\sigma}^v_{i,m}$: $\tilde{\varepsilon}^v_{i,s,m,t} = \varepsilon^v_{i,s,m,t} / \hat{\sigma}^v_{i,m}$
- Sample scaled residuals corresponding to a target global mean temperature change, ΔT^*: $z^v_{i,s}(\Delta T^*)$
- Fit a spatial covariance function to $\mathbf{z}^v$: for grid coordinates $\mathbf{x}$

$$\mathbf{z}^v = \Psi^v(\mathbf{x}, \boldsymbol{\theta}) + \mathbf{u}^v$$

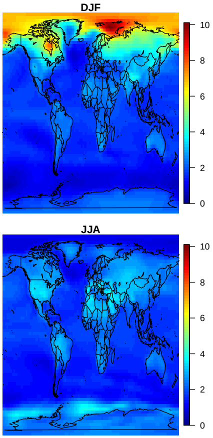
  where Ψ is a vector of fixed basis functions defined over the distances between grid cells, weighted by coefficients $\boldsymbol{\theta}$ that are modeled with a Gaussian Markov random field (GMRF)[1]
- Use $\hat{\Psi}^v$ to generate 10,000 realizations of the spatial field of residuals, add the result to the pattern

$$\Delta \hat{Y}^v_{i,s}(\Delta T^*) = \hat{\beta}^v_{i,s} \Delta T^* + \hat{z}^v_{i,s}(\Delta T^*)$$

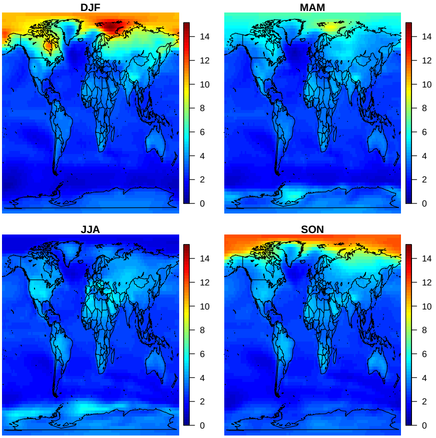
[1] Nychka, D. W., Bandyopadhyay, S., Hammerling, D., Lindgren, F., and Sain, S. R. (2013). A multi-resolution gaussian process model for the analysis of large spatial data sets, typescript.

Temperature Patterns

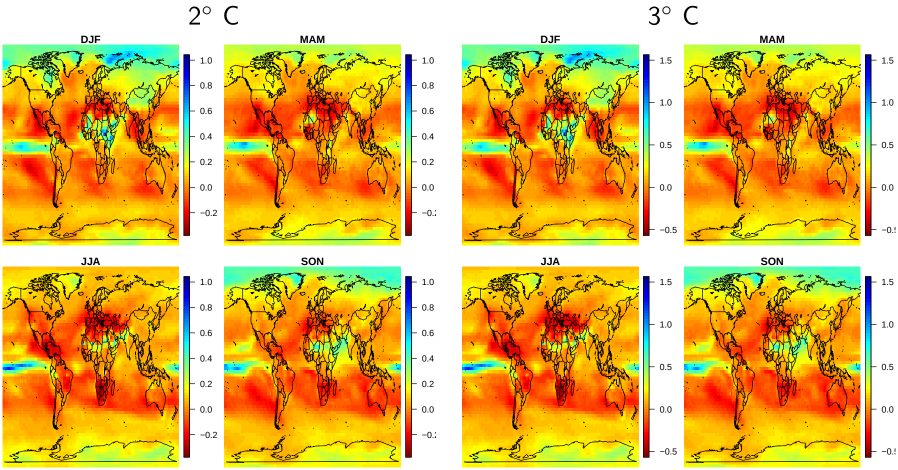
2° C



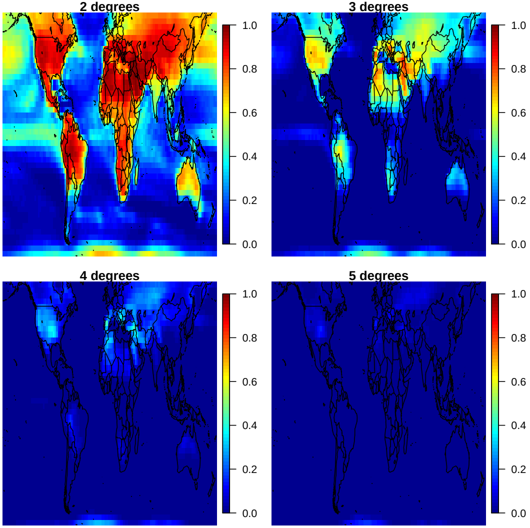
3° C



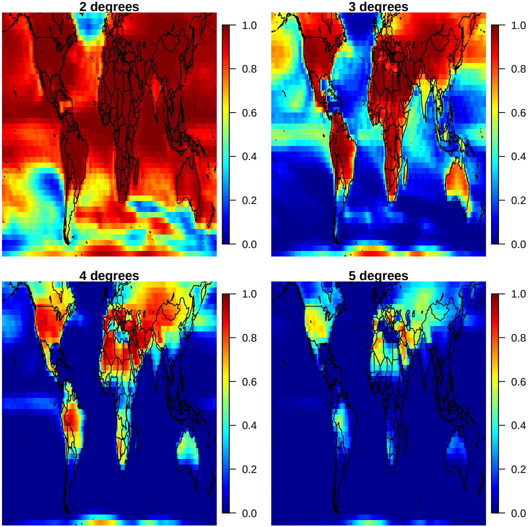
Precipitation Patterns



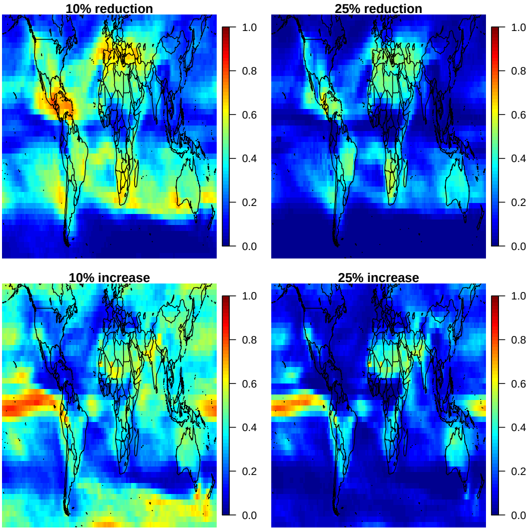
JJA Temperature Exceedance Probabilities: 2° warming



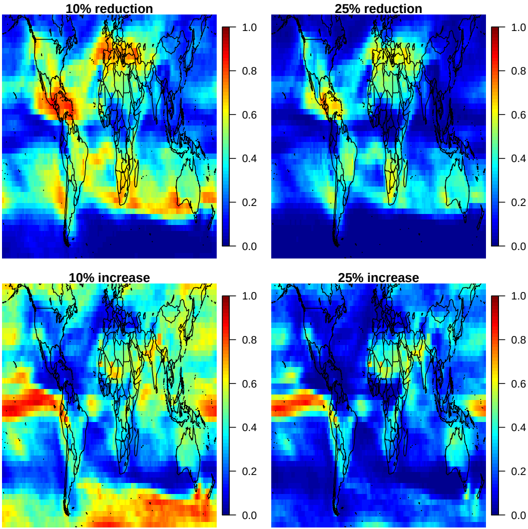
JJA Temperature Exceedance Probabilities: 3° warming



JJA Precipitation Change Probabilities: 2° warming



JJA Precipitation Change Probabilities: 3° warming



Next Steps

1. Do all this over for CMIP5 archive!
2. A key shortcoming of this work is the assumption of *independence* between temperature and precipitation. A top priority is to extend the the GMRF lattice kriging technique to account for spatio-temporal cross-correlations among the variable residuals $z_{i,s}^{\text{Temperature}}(\Delta T^*)$, $z_{i,s}^{\text{Precipitation}}(\Delta T^*)$. But doing this in a capmutationally efficient manner will involve some serious applied stats research.
3. Extend to additional variables
4. Broaden the focus from seasonal means to higher moments of the distributions of variables (Monier and Sue Wing, in progress)