Improving climate projections using “intelligent” ensembles

Noël C. Baker and Patrick C. Taylor
NASA Postdoctoral Program

Presented at the AGU Joint Assembly in Montréal, Canada
May 5, 2015
CMIP5: group of ~45 models

Models are averaged together to make climate predictions

Predicted temperature changes

IPCC AR5 Ch.12
But models can have a large spread in predictions, and individual models can perform very differently from observations.
The traditional **Multi-Model Ensemble Approach** uses the model mean to provide an improved “best estimate” forecast.
The multi-model ensemble generally performs better than individual models

Example: $I^2$ performance index (Reichler and Kim 2008)

Calculates aggregated model errors relative to NCEP/NCAR reanalyses for multiple climate variables
The multi-model ensemble generally performs better than individual models

Example: \( I^2 \) performance index (Reichler and Kim 2008)

Calculates aggregated model errors relative to NCEP/NCAR reanalyses for multiple climate variables

“Observations” (reanalysis)

Better performance: Less error
Some models perform better than others:

Can we use knowledge of model performance for a better way to combine model output?
The “intelligent ensemble” approach
for creating multi-model ensemble projections
Project goal:
determine future climate state using observed current climate and an ensemble of models

\[ f(x_{\text{obs}}) = \Delta x \]

Observed climate
Future climate state
Previous work has explored model performance and some unequal-weighting metrics

Several examples:

- Use only subsets of models (USGCRP 2009)
- Create mean-state metrics using model skill (Giorgi and Mearns 2002, 2003; Reichler and Kim 2008)
- Constrain model projections using mean-state CERES data (Tett et al. 2013)
- Weight using regression between observed and future trends (Boe et al. 2009)
- Apply bias correction for present-day to future trends (Baker and Huang 2012)

“The community would benefit from a larger set of proposed methods and metrics” (Knutti 2010)
This project tests new climate model performance metrics

Radiation budget quantities:

- Top-of-atmosphere (TOA) longwave (LW) and shortwave (SW) radiation fluxes
- Surface LW and SW radiation fluxes
- Surface temperature

New process-oriented metrics:

\[ \frac{\Delta \text{TOA Radiation flux}}{\Delta \text{Surface temperature}} \]

Statistical tests:

- F-test for equal variances
- Kolmogorov-Smirnov test for distribution similarity
- Earth Mover’s Distance (EMD): test for area of distribution overlap
- Local Variance: test variance of first difference time series (Baker and Taylor 2015)
Model data:

35 CMIP5 models
http://pcmdi9.llnl.gov/

- ‘Pre-Industrial Control’ simulations (monthly mean, 100 years) to create metric weights
- ‘RCP 8.5’ future simulations (monthly mean, 2081-2100 minus 2011-2030 to produce 21st-century trends)

Observational datasets:

NASA CERES EBAF-TOA and surface monthly global-mean
http://ceres.larc.nasa.gov/

NASA GISS Surface Temperature Analysis (GISTEMP)
http://data.giss.nasa.gov/gistemp/
Step 1: Test model quality with selected metrics

- OLR all-sky variance test
- OLR all-sky K-S test
- OLR all-sky local variance test
- OLR all-sky EMD value
- OLR cloudy-sky variance test
- OLR cloudy-sky K-S test
- OLR cloudy-sky local variance test
- OLR cloudy-sky EMD value
- OLR clear-sky variance test
- OLR clear-sky K-S test
- OLR clear-sky local variance test
- OLR clear-sky EMD value
- SW all-sky variance test
- SW all-sky K-S test
- SW all-sky local variance test
- SW all-sky EMD value
- SW cloudy-sky variance test
- SW cloudy-sky K-S test
- SW cloudy-sky local variance test
- SW cloudy-sky EMD value
- SW clear-sky variance test
- SW clear-sky K-S test
- SW clear-sky local variance test
- SW clear-sky EMD value
- Surface temperature variance test
- Surface temperature K-S test
- Surface temperature local variance test
- Surface temperature EMD value
- OLR/Ts variance test
- OLR(cloudy-sky)/Ts variance test
- OLR/Ts K-S test
- OLR(cloudy-sky)/Ts K-S test
- OLR Ts regression means test
- OLR(cloudy-sky) Ts regression means test
- SW/Ts variance test
- SW(cloudy-sky)/Ts variance test
- SW/Ts K-S test
- SW(cloudy-sky)/Ts K-S test
- SW Ts regression means test
- SW(cloudy-sky) Ts regression means test
- Metric mean

Model mean
Step 2: Using skill-subset of models, apply “perfect model” approach (Räisänen and Palmer 2001)

Create set of potential “Earths” each with a continuous time series of observations
Model mean $I^2$ performance index
Metric performance and consistency is correlated:

Metrics which best reduce error in future projections behave similarly across model ensemble.
Step 3: Using best-performing metrics, create new “intelligent ensemble” projections

Use metric values as model weights to create unequal-weighted mean projections
Results: new 21st-century projections (surface temperature)
Results: new 21st-century projections (precipitation)
Results: new 21st-century projections (surface downward SW radiation)

"Intelligent" ensemble mean surface shortwave radiation trend (W/m²)

Difference between "Intelligent" and Equal-weight ensemble means (W/m²)
Results: new 21st-century projections (TOA LW radiation)

"Intelligent" ensemble mean outgoing longwave radiation trend (W/m²)

Difference between "Intelligent" and Equal-weight ensemble means (W/m²)
Results: new 21st-century projections (TOA SW radiation)

"Intelligent" ensemble mean reflected shortwave radiation trend (W/m²)

Difference between "Intelligent" and Equal-weight ensemble means (W/m²)
Results: new 21st-century projections (regional-mean weights)
Results: new 21st-century projections (regional-mean weights)

"Intelligent" ensemble mean precipitation trend (cm/year)

Difference between "Intelligent" and Equal-weight ensemble means (cm/year)
Results: new 21st-century projections (regional-mean weights)

"Intelligent" ensemble mean surface shortwave radiation trend (W/m²)

Difference between "Intelligent" and Equal-weight ensemble means (W/m²)
USDA Farm Resource Regions (1° resolution)
Results: new 21st-century projections

"Intelligent" ensemble mean temperature trend (°C)

US mean temperature increase: 3.9 °C

- Basin and Range: 3.9 °C
- Fruitful Rim: 3.4 °C
- Prairie Gateway: 3.8 °C
- Northern Great Plains: 4.1 °C
- Heartland: 4.1 °C
- Northern Crescent: 4.3 °C
- Eastern Uplands: 3.8 °C
- Southern Seaboard: 3.5 °C
- Mississippi Portal: 3.6 °C
Results: new 21st-century projections

"Intelligent" ensemble mean precipitation trend (cm/year)

US mean precipitation increase: 3.4 cm/year

- Basin and Range: 0.6 cm/year
- Fruitful Rim: 0.8 cm/year
- Prairie Gateway: -1.8 cm/year
- Northern Great Plains: 2.7 cm/year
- Heartland: 7.2 cm/year
- Northern Crescent: 9.1 cm/year
- Eastern Uplands: 6.8 cm/year
- Southern Seaboard: 6.8 cm/year
- Mississippi Portal: 5.4 cm/year
Results: new 21\textsuperscript{st}-century projections

"Intelligent" ensemble mean surface shortwave radiation trend (W/m\textsuperscript{2})

US mean decrease in surface solar radiation: -.33 Watts/m\textsuperscript{2}

Basin and Range: -2.4 Watts/m\textsuperscript{2}
Fruitful Rim: -0.5 Watts/m\textsuperscript{2}
Prairie Gateway: 0.7 Watts/m\textsuperscript{2}
Northern Great Plains: -1.9 Watts/m\textsuperscript{2}
Heartland: 0.7 Watts/m\textsuperscript{2}
Northern Crescent: -0.1 Watts/m\textsuperscript{2}
Eastern Uplands: 2.7 Watts/m\textsuperscript{2}
Southern Seaboard: 2.5 Watts/m\textsuperscript{2}
Mississippi Portal: 2.6 Watts/m\textsuperscript{2}