25th Conference on Climate Variability and Change, 7 January 2013, Austin, Texas

# Evaluation of the Surface Climate Fields in the NARCCAP Hindcast Experiment

**Jinwon Kim[1], Duane E. Waliser[1,2], Chris A. Mattmann[1,2], Linda O. Mearns[3], Cameron E. Goodale[2], Andrew F. Hart[2], Daniel J. Crichton[2], and Seth McGinnis[3]**

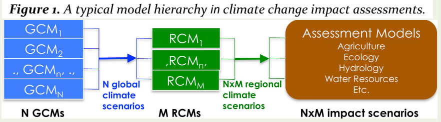
[1]JIFRESSE, University of California Los Angeles; [2]Jet Propulsion Laboratory, California Institute of Technology; [3]National Center for Atmospheric Research

*For more information, please contact: jkim@atmos.ucla.edu, duane.waliser@jpl.nasa.gov, chris.a.mattmann@jpl.nasa.gov, and lindam@ncar.ucar.edu; Also visit http://rcmes.jpl.nasa.gov*

## Introduction

- Climate model projections play a crucial role in developing plans to mitigate and adapt to climate variations and change for sustainable developments.
- Assessing model performance is an important step in linking climate simulation quality to projection uncertainty and then to climate change impacts assessments.

*Figure 1. A typical model hierarchy in climate change impact assessments.*



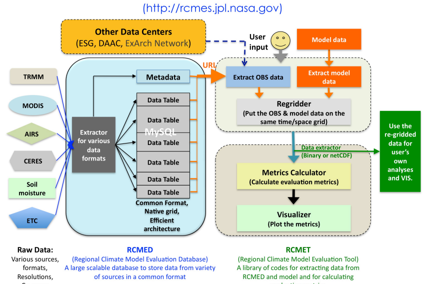
- Uncertainties propagate according to model hierarchy
- Bias correction & multi-model ensemble construction.

- This study evaluates three variables – *precipitation*, *surface air temperature*, and *surface insolation* – that are *key variables in the surface climate and crucial inputs for a number of impact assessment models*.

## Regional Climate Model Evaluation System (http://rcmes.jpl.nasa.gov)

*Figure 2. An outline of the JPL Regional Climate Model Evaluation System.*

RCMES2.0
(http://rcmes.jpl.nasa.gov)



- Easy access to suitable reference datasets can facilitate model evaluation tasks.
- The Regional Climate Model Evaluation System (RCMES) targets to enable researchers to access a large volume of data in various sites, especially NASA remote sensing and assimilation products.
- The system is efficient, user friendly, flexible, and expandable to accommodate additional observational data and to calculate various model evaluation metrics.

## Experiment

- Climatology of the three variables from multiple RCMs in the NARCCAP hindcast experiment is evaluated over the conterminous US region.

*Figure3. The conterminous US region and sub-regions for RCM evaluation.*

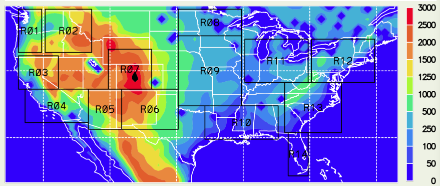


*Table 1. The RCMs, variables, and evaluation periods in this study.*

| Model | Precipitation | T2m | Insolation |
|---|---|---|---|
| CRCM | 1980-2003 | 1980-2003 | 1984-2003 |
| ECP2 | 1980-2003 | 1980-2003 | 1984-2003 |
| HRM3 | 1980-2003 | 1980-2003 | 1984-2003 |
| MM5 | 1980-2003 | 1980-2003 | N/A |
| WRF | 1980-2003 | 1980-2003 | 1984-2003 |
| *REF Data* | CRU3.1 | CRU3.1 | CERES |

## Surface Air Temperatures

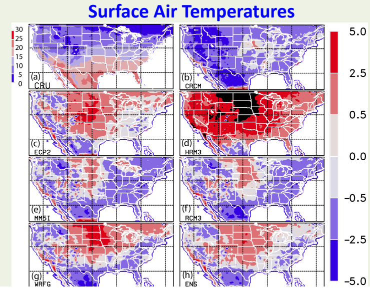
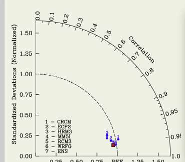


*Figure 4. The CRU climatology and the corresponding model T2 biases.*

- Details vary, but models show common biases:
  - Warm biases in the Great Plains/CA Central Valley
  - Cold biases in the Atlantic & Gulf of Mexico coasts, western mountainous regions
- Biases in the mountainous WUS vary for terrain heights.



- All RCMs well simulates the spatial variability of the surface air temperature over the land surface.
  - The correlation coefficients of 0.95 - 0.99 with the CRU analysis.
  - The normalized STD DEV of 0.9 - 1.05.
- The simple *multi-model ensemble* (*ENS*) yields the *highest correlation coefficient* and the *smallest RMSE*.

*Figure 5. Evaluation of the overland temperature variability.*

## Precipitation

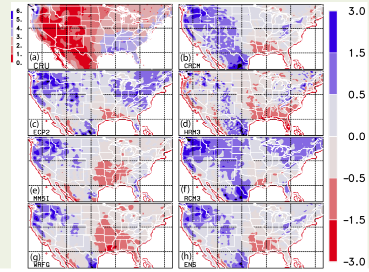
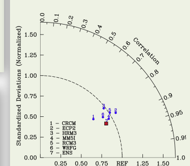


*Figure 6. The CRU climatology and the corresponding model PR biases.*

- Precipitation biases also show common features:
  - Wet biases over the Pacific NW region in all RCMs
  - Dry biases over the Gulf coast region in all models.



- All RCMs also simulates the spatial variability of the over-land precipitation reasonably.
  - The correlation coefficients of 0.75 - 0.95 with the CRU analysis.
  - The normalized standard deviations of 0.75 - 1.15.
  - Skill varies more for the magnitude than the pattern.
- The simple *multi-model ensemble* (*ENS*) yields the best performance like for T2.

*Figure 7. Evaluation of the overland precipitation variability.*

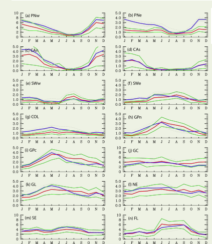


***Figure 8.*** *Precipitation annual cycle in the 14 sub-regions.*

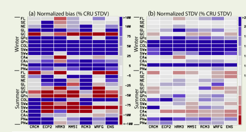


***Figure 9.*** *Evaluation of the simulated interannual variability in terms of the bias, normalized by the interannual variability of the CRU data, & correlation coeffs.*

- *Figure 8 – Annual cycle*
- The model ensemble (blue) is generally within ±1σ from the observed mean (red) except for the inland Pacific NW, Colorado, and the northern Great Planes region.
- Model performance in simulating the annual cycle varies widely among RCMs.
  - Wet biases in PNw, CAn, CAs
  - Dry biases in the Gulf coast region
- *Figure 9 – Summer (JJA) and winter (DJF) precipitation biases & interannual var.*
- Model performance varies according to season and region
- The systematic bias in the interannual variability of the summer precipitation is underestimations in the California region and overestimations in the PNW, Colorado, and Great Lakes regions.

## Surface Insolation

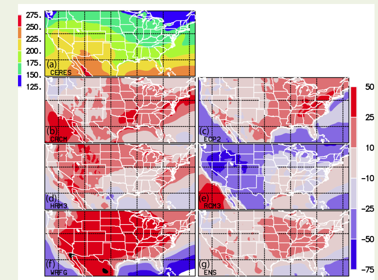
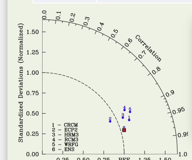


*Figure 10. Same as Figure 6, but surface insolation.*

- All but RCM3 show positive biases over the land surface
- The biases vary regionally
  - All RCMs show smaller (larger) positive (negative) biases in the western half of the conterminous US than in the eastern half.
- The surface insolation biases are negatively correlated with precipitation biases in Figure 6 (Table 2).
  - This implies that precipitation- and insolation biases are related, likely via model clouds.
  - The insolation bias is not either closely or systematically correlated with the surface air temperature biases.

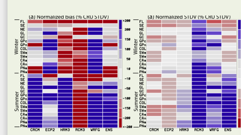
*Table 2. The land-mean precipitation and insolation biases and the spatial correlation coefficients between the two bias fields.*

| Model | Land-mean PR bias | Land-mean S↓ bias | Corr. Coeff. |
|---|---|---|---|
| CRCM | 0.33 | 10.2 | -0.47 |
| ECP2 | 0.41 | 9.0 | -0.28 |
| HRM3 | 0.54 | 10.6 | -0.30 |
| RCM3 | 0.54 | -29.9 | -0.50 |
| WRFG | -0.08 | 30.4 | -0.18 |
| *ENS* | 0.25 | 4.92 | -0.62 |



- The RCM skill in simulating the spatial variability of the surface insolation is collectively somewhat higher than that for precipitation but lower than for surface air temperature.
- Like for T2 and precipitation, the simple *multi-model ensemble* (*ENS*) yields the best skill like for the surface air temperature.

*Figure 11. Evaluation of the insolation variability.*



- RCMs, especially ENS, generally show higher performance in simulating the insolation interannual variability for summer than winter.
- Inter-RCM variation in the skill is larger than for precipitation or temperature.

***Figure 12.*** *Evaluation of the simulated interannual variability in terms of the biases, normalized by the interannual variability of the CERES data, & correl'n coeffs.*

## Conclusions and Discussions

- Precipitation, surface air temperature, and surface insolation in the NARCCAP hindcast experiment are evaluated using RCMES.
- The model biases show well-defined regional and seasonal structures despite large differences between models.
- These systematic variations must be considered in bias correction and constructing multi-model ensembles for assessment studies.
- Biases in precipitation and surface insolation are negatively correlated with each other, likely via model clouds.

## Acknowledgements

This study was supported by American Recovery and Reinvestment Act (ARRA), NASA NCA (ID 11-NCA11-0028), NASA AIST (ID 87-17895-11), ExArch (ID 1125798), and NSF EaSM (ID 2011-67004-30224). The NARCCAP project is funded by NSF, the U.S. DOE, and the U.S. EPA. The contribution from D. Waliser, C. Mattmann, C. Goodale, A. Hart, P. Zimdars, and D. Crichton to this study was performed on behalf of the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration.

- Publications:
  - Crichton, D.J., C.A. Mattmann, L. Cinquini, A. Braverman, D.E. Waliser, M. Gunson, A. Hart, C. Goodale, P.W. Lean, and J. Kim, 2012: Software and Architecture for Sharing Satellite Observations with the Climate Modeling Community. *IEEE Software*, **29**, 63-71.
  - Whitehall, K., C. Mattmann, D. Waliser, J. Kim, C. Goodale, A. Hart, P. Ramirez, P. Zimdars, D. Crichton, G. Jenkins, C. Jones, G. Asrar, and B. Hewitson, 2012: Building model evaluation and decision support capacity for CORDEX. *WMO Bulletin*, **61**, 29-34.
  - Kim, J., D. Waliser, C. Mattmann, L. Mearns, C. Goodale, A. Hart, D. Crichton, and S. McGinnis, 2012: Evaluations of the surface air temperature, precipitation, and insolation over the conterminous U.S. in the NARCCAP multi-RCM hindcast experiment using RCMES. *J. Climate,* under revision.