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Simulating Extreme Precipitation in the Lake Champlain Basin using a Regional Climate Model: Limitations and Uncertainties

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1. Introduction

- The amount of extreme precipitation (EP; heaviest 1% of all daily precipitation events) has recently increased over the Northeast[1,2], as well as EP event frequency and intensity[2].

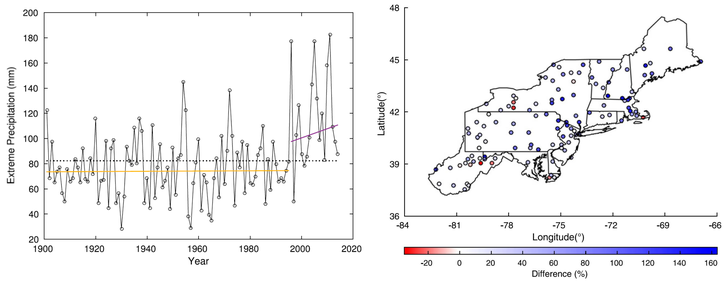

Figure 1: Time series of Northeast annual EP (mm) from 1901–2014 (left) and percentage change in annual EP between the periods 1996–2014 and 1901–95 relative to 1901–95 (right)[1].

- Extreme events have caused infrastructure damage and reduced water quality in the Lake Champlain Basin (LCB)[3].
- Regional climate models (RCMs) are useful tools to downscale GCM outputs to finer scales for impact studies and improve the representation of physical processes[4].
- Research Question: How well can a RCM simulate mean and extreme temperature and precipitation in the LCB?

2. Data and Methods

- The Weather Research and Forecasting model (WRF), a mesoscale numerical weather prediction system[5], is applied to downscale the ERA-Interim reanalysis[6].
- A one-way, three-domain (36, 12, and 4 km) nested model configuration is used, with the inner-most domain covering the LCB (Figure 2).

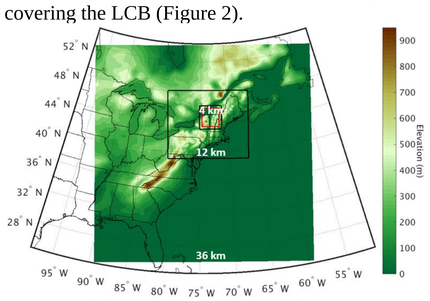

Figure 2: Three nested domains (D1: 36 km, D2: 12 km, D3: 4 km) and elevations.

- We tested five sets of physics configurations in WRF (Figure 3) over a 15-year period (1980–1984, 1995–1999, 2010–2014). Each set is a combination of four physics categories, with two options for each category: 1) radiation (3: CAM; 4: RRTMG), 2) cumulus (1: Kain-Fritsch; 14: New SAS), 3) microphysics (6: WSM6; 8: Thompson), and 4) planetary boundary layer (1: MYJ; 2: YSU)[5].
- Model evaluation was conducted with an observational dataset, Daymet[7], and several metrics including spatial bias, seasonal cycle, Taylor diagram, and PDF-based skill score.

		CKWY	RKWY	RNWY	RNTY	RNWM
Radiation	ra_lw_physics	3	4	4	4	4
	ra_sw_physics	3	4	4	4	4
Cumulus	cu_physics	1	1	14	14	14
Microphysics	mp_physics	6	6	6	8	6
Planetary boundary layer	bl_pbl_physics	1	1	1	1	1
	sf_sfclay_physics	1	1	1	1	2
						2

Figure 3: Physics parameterizations of five WRF model experiments.

3. Temperature Evaluation

- All simulations have consistent cold biases, with the largest cold bias in CKWY (-2.6 °C) and smallest bias in RNWM (-0.5 °C).
- The relative importance of the four physics options in simulating mean temperature, from highest to lowest, is radiation, microphysics, planetary boundary layer, and cumulus.

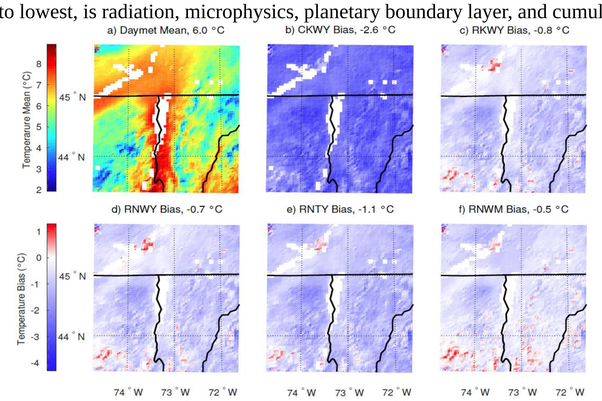

Figure 4: Mean temperature (℃) in the Daymet observations (a) and bias in mean temperature by the five WRF simulations (b–f) as compared to Daymet over the 15-year period.

- Simulated monthly temperatures are characterized by positive bias in warm season and negative bias in cold season. For instance, RNWM produces a -0.5 °C bias (annually averaged relative to Daymet), which is comprised of a -2 °C underestimation in cold season and +1.1 °C overestimation in warm season.

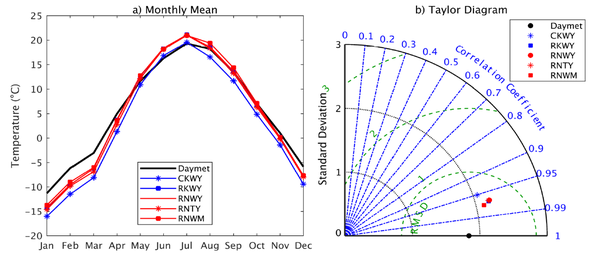

Figure 5: a) Monthly mean temperature (℃) over the 15-year period for Daymet and the five WRF simulations, and b) Taylor diagram for monthly temperature anomalies.

- The simulations are similarly skillful in capturing daily mean temperature, however, they do not perform as well in reproducing extreme hot and cold temperatures.

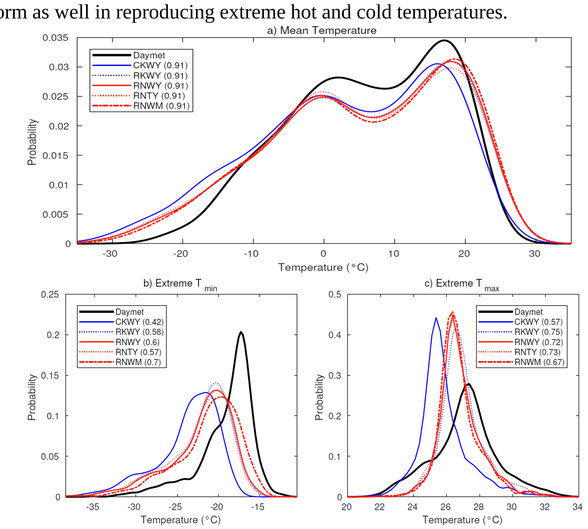

Figure 6: Probability density functions of daily mean temperature (a), extreme daily minimum temperature (b, 90th percentile days), and extreme daily maximum temperature (c, 90th percentile days). The numbers in parentheses represent the PDF-based skill scores as compared to Daymet.

4. Precipitation Evaluation

- WRF experiments produce regional wet biases ranging between 0.3–0.7 mm day^{-1} (10–22%).
- Radiation, cumulus, and microphysics are important physics options in capturing mean precipitation, while planetary boundary layer plays a minor role in simulated precipitation.

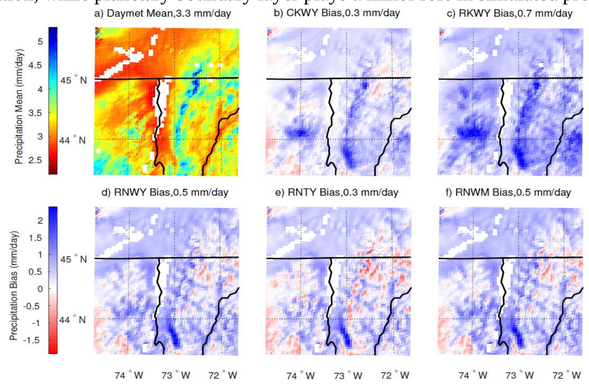

Figure 7: Mean precipitation (mm day^{-1}) in the Daymet observations (a) and bias in mean precipitation by the five WRF simulations (b–f) as compared to Daymet over the 15-year period.

- WRF simulations overestimate precipitation in most months, but preserve the general shape of the Daymet seasonal cycle.

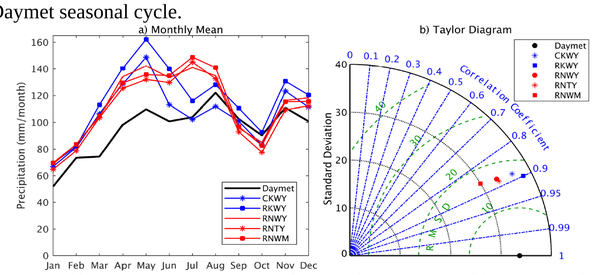

Figure 8: a) Monthly mean precipitation (mm month^{-1}) over the 15-year period for Daymet and the five WRF simulations, and b) Taylor diagram for monthly precipitation anomalies.

- All simulations have similar capabilities in reproducing precipitation in wet days (>1 mm), but show very distinct skills in capturing extreme precipitation (90th percentile wet days).

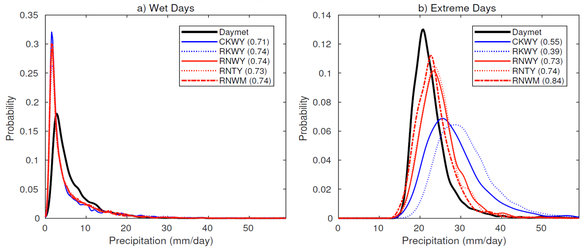

Figure 9: Probability density functions of daily precipitation in wet days (a, >1 mm day^{-1}) and extreme days (b, 90th percentile wet days). The numbers in parentheses represent the PDF-based skill scores as compared to Daymet.

5. Conclusions

- WRF simulations run over the LCB generally produce cold and wet biases, and each set of physics configuration plays a different role in determining temperature and precipitation.
- WRF is more capable in capturing mean climate and temperature than extreme climate and precipitation.
- RNWM configuration (i.e. RRTMG-New SAS-WSM6-MYJ) has the overall best performance in reproducing temperature and precipitation, especially extreme precipitation.

Acknowledgement

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References

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