Rainfall characteristics in CMIP models

Angeline Pendergrass
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Why improve precipitation in climate models?

• To accurately simulate atmospheric circulation and coupled climate system interactions affected by fluxes of water and energy, which affect the ocean, land surface, biosphere, and cryosphere

• Precipitation is a primary manifestation of climate influencing the natural and human-managed environment, and people, and so it should be a key variable in climate models

• Many impacts of climate change are driven by precipitation, and users are increasingly trying to extract information about future precipitation from climate model projections – often indirectly (via downscaling, bias correction, ...)

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- Many impacts of climate change are driven by precipitation, and users are increasingly trying to extract information about future precipitation from climate model projections – often indirectly (via downscaling, bias correction, ...).

- Nonetheless, we often hear that precipitation isn’t that good in climate models.
Outline

• Precipitation in CMIP5 models
  • The distribution of precipitation
  • Re-confirming light rain bias
  • Unevenness of contributions from heavy precipitation

• Evaluating precipitation in CMIP models (ongoing work)

• Thoughts about future work and efforts
CMIP5 daily precipitation distribution

Rain frequency

Pendergrass and Hartmann (2014) *J Clim*
CMIP5 daily precipitation distribution

Rain frequency

Rain amount

Pendergrass and Hartmann (2014) *J Clim*
Observed daily precipitation distribution

Rain frequency

Rain amount

Pendergrass and Deser (2017) *J Clim*
CMIP5 rain amount distributions: Global

- Distribution calculated at each grid point, then globally averaged
- Compared against GPCP 1dd coarsened to model grid

Pendergrass and Hartmann (2014) *J Clim*
Observed zonal mean rain amount distribution

Specifically, the rain amount width is the ratio of the two rain rates where a line of constant rain amount intersects the rain amount distribution: it is expressed nondimensionally as the ratio of the greater to the lesser of these rain rates. We have chosen a width such that 10% of the total precipitation occurs in this portion of the rain amount distribution, as illustrated in Fig. 2a for the global annual mean. In the event that the rain amount distribution crosses the line of constant rain amount more than twice, the first rain rate it intersects on each side of the rain amount peak is chosen. The choice of 10% as a target fraction is arbitrary; we also tried 50%, which resulted in a change in magnitude but did not affect the geographical patterns or seasonal dependence. The rain amount width describes the range of rain rates where the most rain falls. The width of the global mean rain amount distribution is 2.2, indicating that 10% of the total precipitation falls between 9 and 30 mm day$^{-1}$.

We expect that the rain amount peak, rain frequency peak, and rain amount width will depend quantitatively but not qualitatively on the spatial and temporal resolution of the precipitation data from which they are computed. However, they do not depend systematically on the bin width, although the bin width does determine how accurate the metrics are (smaller bin widths provide finer granularity of the metrics, although they also require more sampling). We provide quantitative values of all three metrics, cognizant that they are specific to the spatial and temporal resolution of the particular datasets we examine.

4. The climatological distribution of rain in GPCP

a. The zonal-mean distribution of rain

We decompose the global mean rain amount distribution from GPCP into contributions from different latitudes in Fig. 3a. Note that the latitude axis is cosine weighted, proportional to the areal contribution of each latitude band. The peak of the rain amount distribution at each latitude is delineated by the thin black curve. Integration of the rain amount distribution at each...
CMIP5 rain amount distributions: Zonal mean
Zonal mean rain amount distributions

consistent with its higher frequency of light rain days, which play little role in the rain amount distribution width. It also shares more characteristics with TRMM than GPCP, including reaching minima rather than maxima in dry zones and reaching maxima rather than minima near the midlatitude storm tracks.

7. Discussion

As we have just shown, CESM1 has a much higher frequency of light rain than either GPCP or TRMM and correspondingly lower values of rain frequency peak, especially over the subtropical oceans. While we know that climate models disagree about some of the physical processes controlling stratocumulus clouds in the eastern side of the subtropical ocean basins (e.g., Fasullo and Trenberth 2012; Medeiros et al. 2012; Sherwood et al. 2014), we also know that the satellite measurements incorporated into GPCP and TRMM are not sensitive enough to light precipitation below about 1 mm day $^{-1}$ (Behrangi et al. 2012, 2014), which are especially important for obtaining the correct rain frequency distribution (Huffman et al. 2001, 2007). Other datasets such as CloudSat radar and CALIPSO lidar measurements accurately represent the frequency of occurrence of rain, including very light rain (e.g., Lebsock and L’Ecuyer 2011), but cannot accurately estimate the rain rate for moderate to heavy precipitation. They also have insufficient sampling to form the basis for high spatial and temporal resolution gridded datasets like GPCP and TRMM. Even considering the frequency of light precipitation observed by CloudSat, it is still likely that climate models overestimate the frequency of light rainfall (Stephens et al. 2010). However, more and improved observations of light precipitation are needed to better understand this discrepancy. The new Global

FIG. 15. Comparison between climatological zonal annual-mean distributions of (top) rain amount (mm day $^{-1}$) and (bottom) rain frequency (%) for (a),(d) GPCP 1DD, (b),(e) TRMM 3B42 (coarsened to 1° resolution), and (c),(f) CESM1.
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Zonal mean rain frequency distributions

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Light rain bias persists in CESM1 compared to CloudSat

- CloudSat captures light rain frequency more accurately than measurements going into GPCP, TRMM, and GPM
- Satellite simulators for precipitation enable apples-to-apples comparison
- Extends work on cloud satellite simulators – could be scaled across models, and to GPM

Kay et al (2018) JGR
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Kay et al (2018) JGR
Unevenness of precipitation

One year of daily precip

Sort wettest to dryest

Cumulatively sum

Normalize by total precip

Pendergrass and Knutti (2018) *GRL*
Unevenness of precipitation in observations and CMIP5 models

Models underestimate unevenness, even when resolution is accounted for

Pendergrass and Knutti (2018) GRL
Assessing simulation of precipitation in Earth System Models

- Inspired by the lack of objective and systematic benchmarking of simulated precipitation
- Date/venue: July 1-2, 2019 in Rockville, MD

- Identify targets for improvement
  Team of experts identifies useful measures for gauging how well models simulate precipitation

- Develop capability to gauge model quality
  Baseline metrics incorporated into a model evaluation capability and used to assess current models

- Improve simulated Precipitation
  Modelers provided with metrics capability to serve as a target for improving newer model versions

Renu Joseph (DOE), Angie Pendergrass (NCAR), Peter Gleckler (LLNL), Christian Jakob (Monash Uni), Ruby Leung (PNNL)

https://climatemodeling.science.energy.gov/news/doe-host-precipitation-metrics-workshop
Baseline metrics

Scope of phase 1: CMIP6 DECK + Historical simulations with standard output
- piControl
- AMIP
- 1pctCO2, abrupt4xCO2
- Historical
- Data: monthly, daily, and 3h mean precip, monthly prsn
Baseline metrics: Tiers

Spatial distribution of mean state
- RMS error / MAE of mean state
- Pattern correlation
- Monthly mean snow amount

Seasonal cycle
- Amplitude+phase of seasonal cycle (first two harmonics)
- or: Monthly score (RMS error?) following iLAMB
- Monthly mean snow amount

Variability across timescales
- Standard deviation at different timescales
  - Daily, weekly / synoptic, intraseasonal, interannual, ENSO
  - Absolute and relative
  - Seasonal breakdown
- Diurnal cycle – phase and amplitude

Intensity / frequency distributions
- Simple Daily Intensity Index (SDII)
- Unevenness (number of days for half of annual precip)
- Mean and variance of daily precip
  - Cutoff precip rate
  - Power law scale
- Perkins score (goodness of fit) - various moments
- Fraction of precipitating days

Extremes
- Rx1day
- Rx5day
- 20-y return values (from GEV)
- Rx3h
- Seasonal breakdown

Drought (lack of precip)
- Frequency of SPI spells below a threshold
- Consecutive Dry Days
Baseline metrics: CMIP6 evaluation

• Baseline metrics will be incorporated into the PCMDI Metrics Package (PMP) and run on simulations in the CMIP archive, as well as a suite of observational datasets (likely FROGS, Roca et al., 2019)

• An initial study and report will use the baseline metrics to evaluate CMIP6 DECK and Historical simulations
  • And also compare them against previous generations (CMIP3 and 5) to evaluate change over time

• Simultaneously, an effort on Exploratory Metrics is including more process-oriented diagnostics
Future studies to address biases in CMIP models

• Working with observations
  • Understanding differences among observational datasets for moments beyond mean precipitation – its intensity distribution, and variability across timescales
  • Developing a gridded observational dataset focused on the higher moments
  • Quantifying uncertainty

• Intriguing process-oriented model development approach: Stochastic parameterization

• Focused effort on improving precipitation for the next generation of climate models, using the precipitation benchmarking as a guide
Stochastic parameterizations can improve monsoon precip.

Strømmen et al., (2017) Climate Dynamics
Questions / Comments?

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Precipitation variability: Power spectral density change from present to RCP8.5

CMIP5
Precipitation variability: Power spectral density change from present to RCP8.5

CMIP5

CESM1
Precipitation variability: Power spectral density change from present to RCP8.5

How much precipitation change is a simple projection of increased moisture onto variability that is mostly white? (Perhaps a lot)

Is this realistic?

Pendergrass et al (2017) Scientific Reports
Beyond the baseline: Exploratory metrics

• Standard metrics decomposed into their components contributing to model biases
• Metrics relating model biases to processes or phenomena to inform model development
• Relationships that connect model biases to their regional-to-global implications
• Emergent relationships that connect model biases to model responses to perturbations
• Use-inspired metrics connected with impacts
## Exploratory metrics: Hierarchy

<table>
<thead>
<tr>
<th>Space and time scales</th>
<th>Phenomena and impacts</th>
<th>Relationships and processes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean state</td>
<td></td>
<td>Relationships between variables such as:</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- P-moisture</td>
</tr>
<tr>
<td>Seasonal cycle</td>
<td>Monsoon regional features (e.g., monsoon depression, Meiyu rainfall jump), precipitation in Mediterranean climate</td>
<td>- P-T</td>
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<tr>
<td></td>
<td></td>
<td>- P-omega</td>
</tr>
<tr>
<td>Synoptic</td>
<td>Frontal, extratropical cyclones, atmospheric rivers</td>
<td>- P-MSE</td>
</tr>
<tr>
<td>Sub-daily</td>
<td>Orographic precipitation, mesoscale convective systems</td>
<td>- P-entrainment/trigger</td>
</tr>
<tr>
<td>PDF</td>
<td>Intensity-duration-frequency curve</td>
<td>Teleconnection relationships such as:</td>
</tr>
<tr>
<td>Extremes</td>
<td>Tropical cyclones, severe convective storms, compound extremes, composites of top 10 events</td>
<td>- Influence of ENSO-PNA on P</td>
</tr>
<tr>
<td>Tropical variability</td>
<td></td>
<td>- MJO-TC connection and impacts on P</td>
</tr>
<tr>
<td>Mid-to-high latitude variability</td>
<td></td>
<td>- MJO-AR connection and impacts on P</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent relationships to constrain projected changes in P</td>
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CMIP5 rain frequency distributions: Zonal mean