Use of Climate Model Data for Assessing the Effects of Climate Change on Water Resources: Uncertainties and Bias Correction

Part 2: Climate Model Data for Driving Surface Hydrology Simulations

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Summary of Sections 1 & 2

- Recent research activities have confirmed that *the increase in the global-mean surface temperature in the 20th century is caused by the combinations of natural variability and the anthropogenic forcing by the emissions of GHG from industrial activities.*

- Developing plans to adapt to and mitigate the impact of climate change on regional sectors need *climate data for future periods*.

- Future climate data projected by climate models contain uncertainties primarily from
  1. *Projecting human activities that emit GHGs*
  2. *Incompleteness of climate model formulations*

- The uncertainty due to future industrial activities is very difficult to estimate.
  - IPCC introduced multiple future emissions scenarios as a guide for AOGCM experiments.

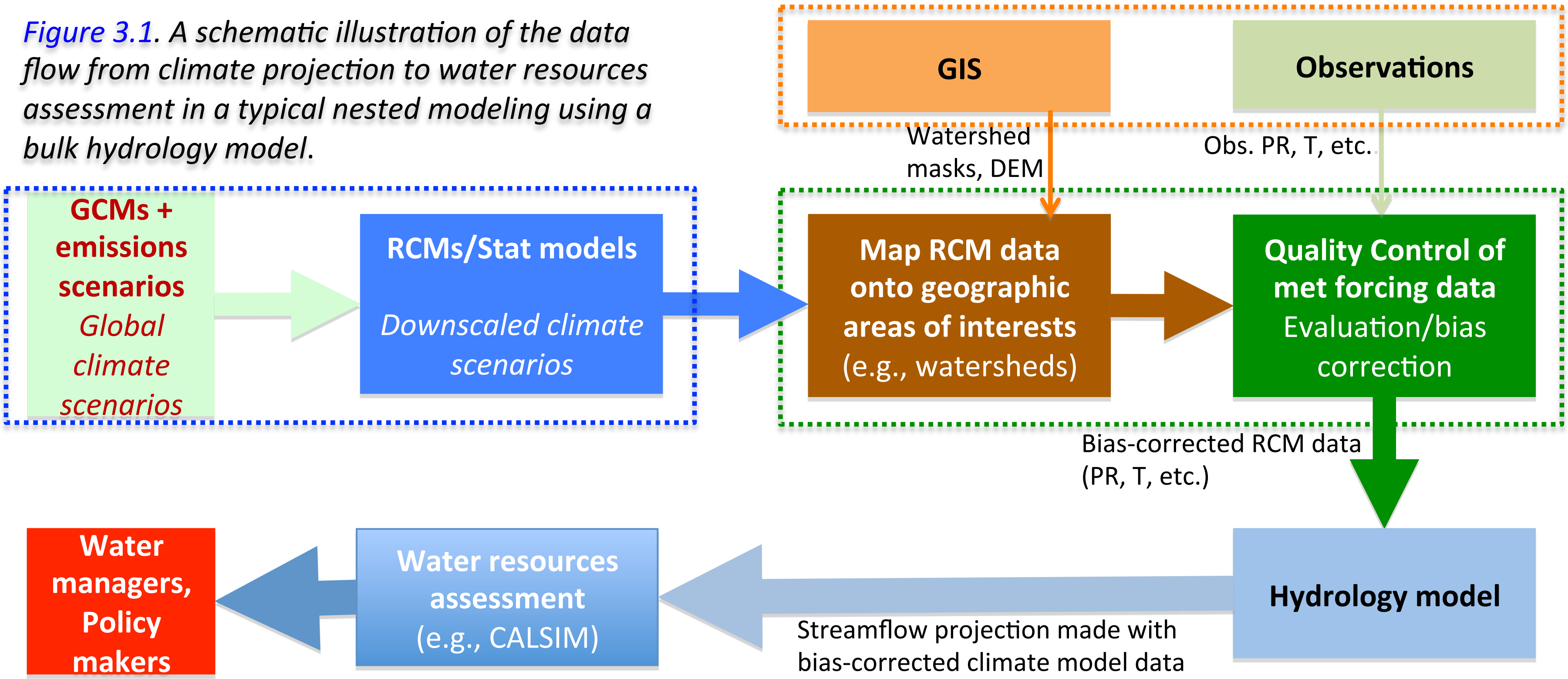
- The biases due to model formulations may be quantified in controlled experiments.
  - The climate model related uncertainties may be dealt with via bias correction, multi-model ensemble or both, based on rigorous model evaluation.

Section 3. Uncertainties in forcing data

Assessment model hierarchy

- Assessments of future water resources are generally based on a nested modeling system illustrated in *Figure 3.1*:
  - GCMs -> RCMs/Statistical models generate future regional climate scenarios.
  - *The projected data are processed to assess biases and apply correction schemes*
  - *The bias-corrected climate data drive hydrology models to calculate reservoir inflows.*
  - The reservoir inflow scenarios are used to run water resources assessment models.
  - The water resources scenarios are used to develop management plans.

Figure 3.1. A schematic illustration of the data flow from climate projection to water resources assessment in a typical nested modeling using a bulk hydrology model.



Section 3. Uncertainties in forcing data
Met data preparation

- Transferring the gridded climate model data onto a watershed is the first step in assessing water resources using a bulk hydrology model that runs on watershed-mean met data (*Figure 3.2*)
  1. Overlay model grid over the watershed area.
  2. Calculate the percentage of each grid box contained within the watershed area. This is the weighting factor for calculating the area-mean meteorological data.
  3. Using the weights, the watershed-mean value of a variable *P* is calculated as: $\overline{P} = \left(w_{ij}P_{i,j}\right) / \sum w_{ij}$

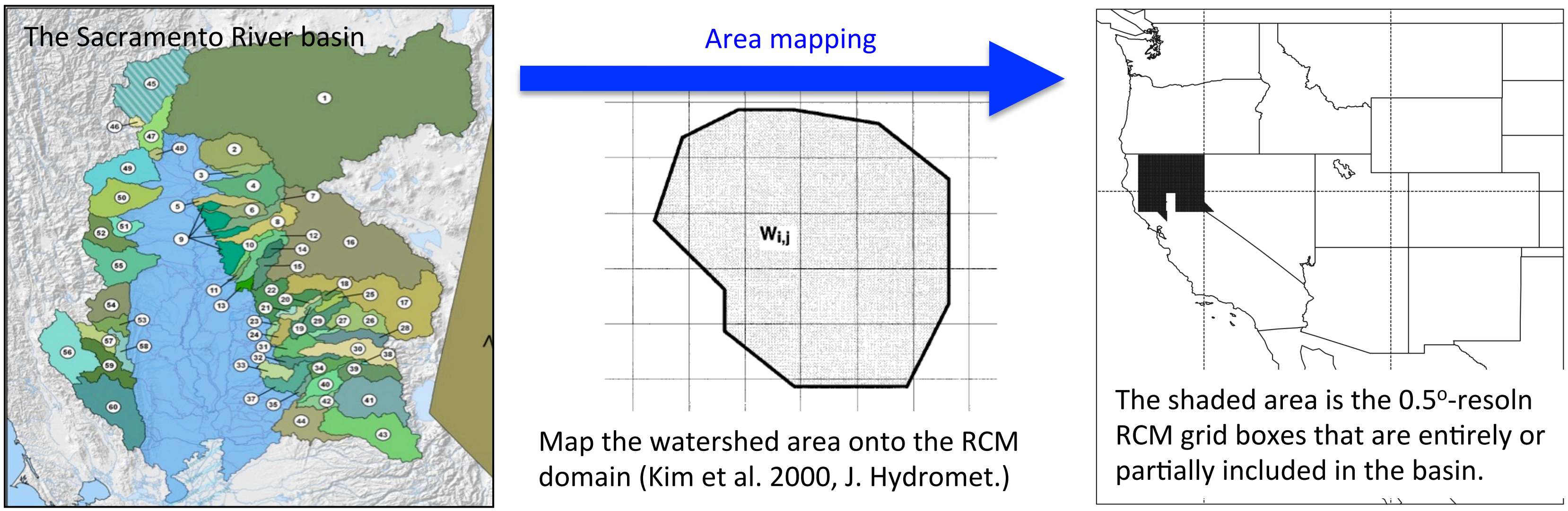


Figure 3.2. Calculation of area-mean data for an irregularly-shaped watershed from gridded climate model data.

- Next Steps:
  1. Prepare a watershed-mean time series from multiple regional climate models in the North American Regional Climate Change and Assessment Project (NARCCAP) hindcast.
  2. Evaluation of the simulated watershed-mean time series
  3. Bias correction of the forcing time series.

Evaluation of the basin-mean time series and their climatology

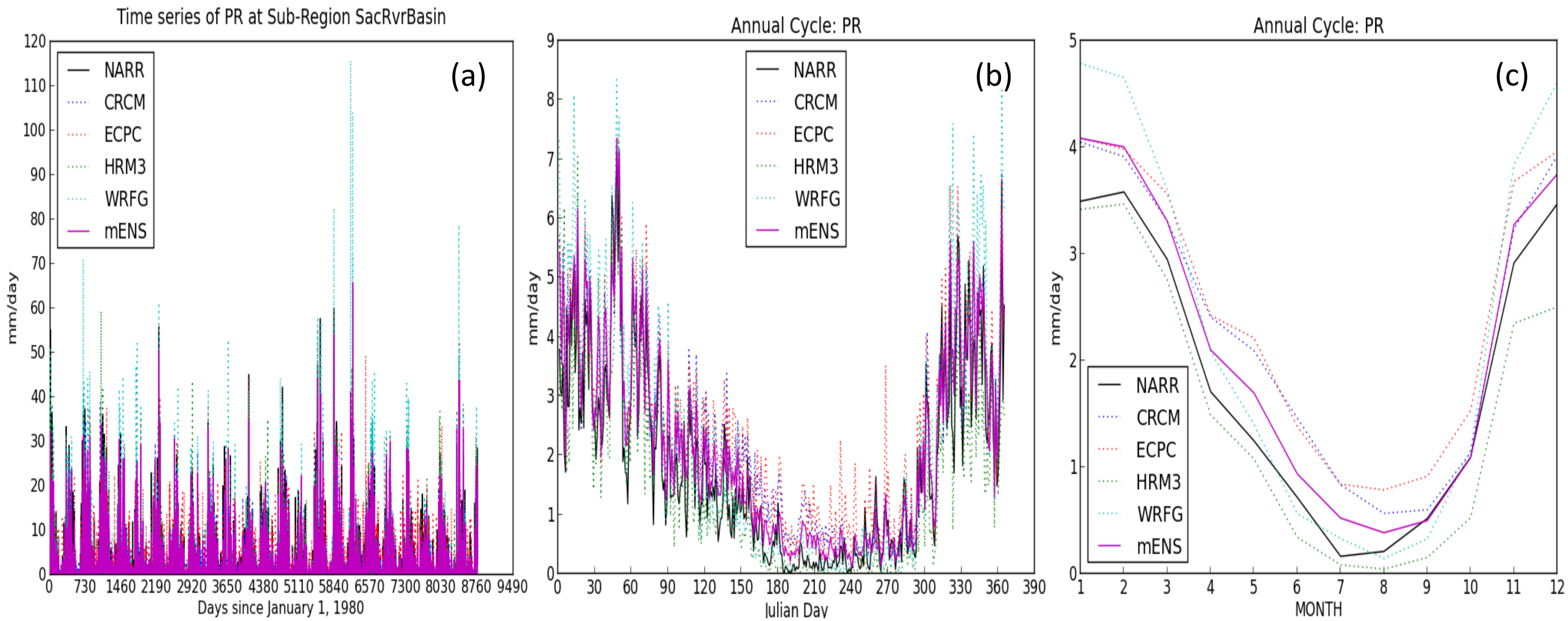


Figure 3.3. (a) Daily precipitation time series for 1990-2003 and annual cycle in (b) daily climatology and (c) monthly climatology.

- By projecting the model data onto the watershed area, the watershed-mean daily precipitation time series are constructed for the reference (NARR) and model data including model ensemble (*Fig. 3.3a*).

- The daily time series are further processed to construct annual cycle in terms of daily (Fig. 3.3b) and monthly (*Fig. 3.3c*) means – quick examination of model errors in climatology. These are useful for quick visual inspection of the model data against the reference data.
  - *Fig. 3.3b* and *3.3c* show that all models depict the observed annual cycle but contain biases
  - The model errors in simulating the annual cycle vary according to months/seasons.
  - The percentage error is largest during dry summer months

Section 3. Uncertainties in forcing data

PDF, cPEF and Quantile plots

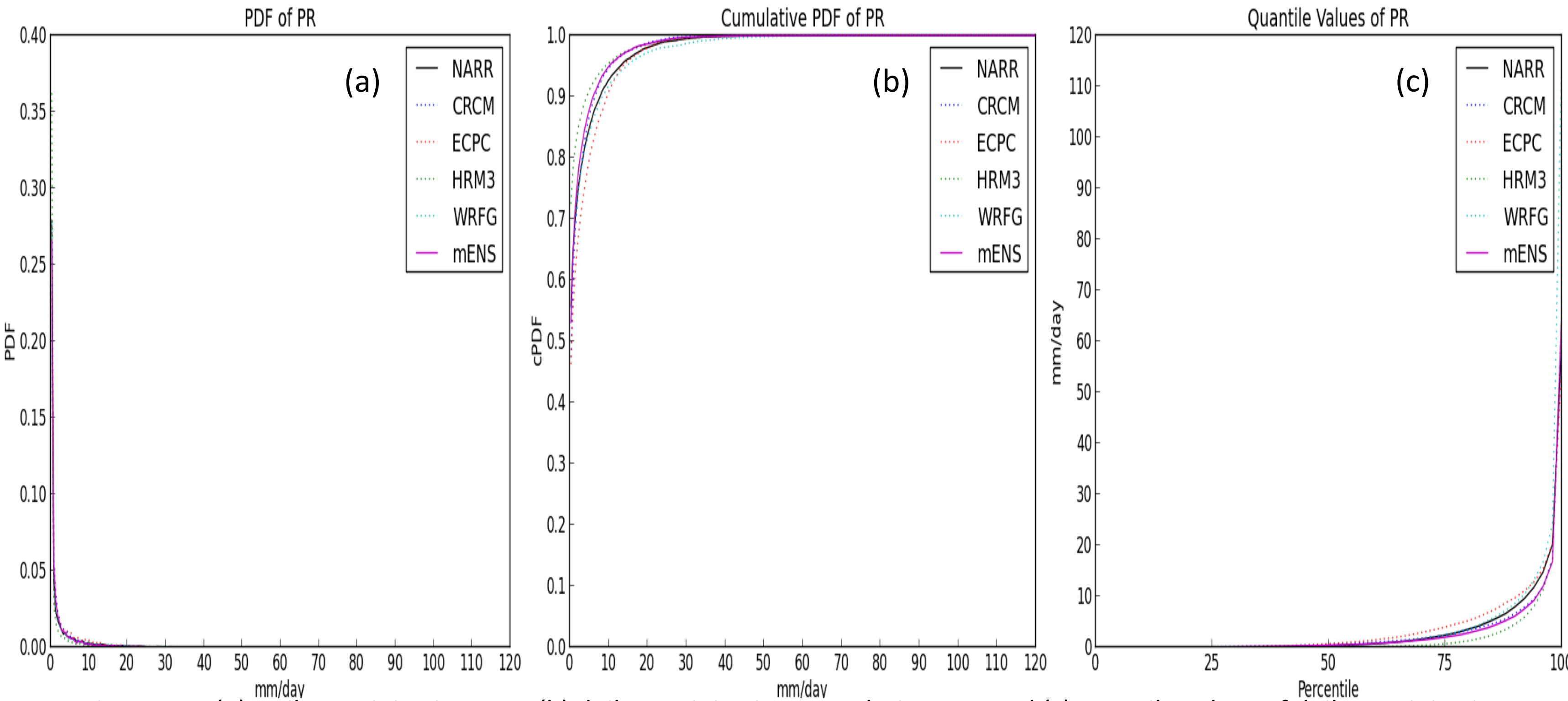


Figure 3.4. (a) Daily precipitation PDF, (b) daily precipitation Cumulative PDF and (c) quantile values of daily precipitation.

- Probability distribution functions of the observed and simulated precipitation are useful for examining the statistical characteristics of the simulated variables against the observation.
- This examples show that RCMs tend to overestimate both extremely light or heavy precipitation events (in the both tails of PDFs) compared to the NARR data.
- Quantile plot is often more useful than PDF or cPDF plots for depicting data distribution, especially for bias correction using quantile mapping methods.

Section 3. Uncertainties in forcing data

Evaluation of the raw time series

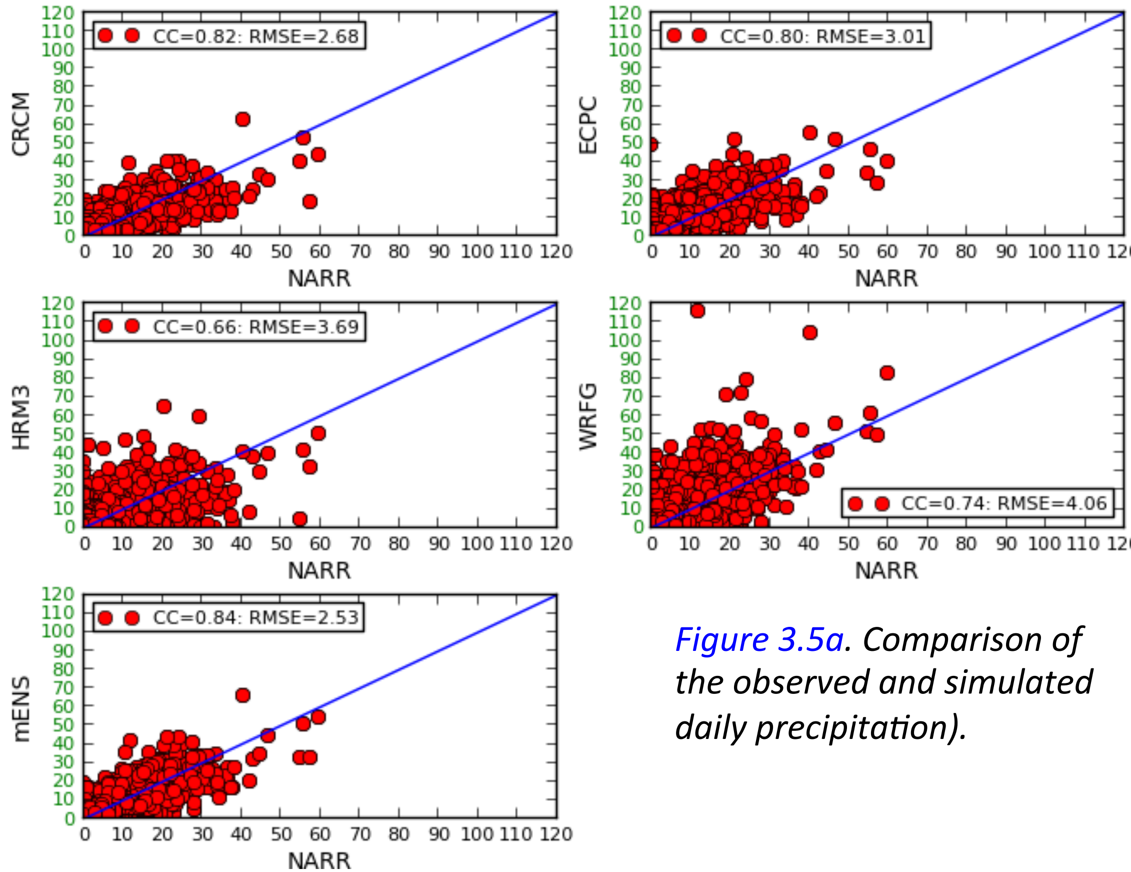


Figure 3.5a. Comparison of the observed and simulated daily precipitation).

- Scatter diagrams visualize the one-to-one correspondence between the reference and simulated data, a very intuitively way of comparing the model data with the reference data.

- The correlation coefficients and RMSE between the observed and model data provides a quantitative measure of the closeness of the simulated time series to the reference data.

Section 3. Uncertainties in forcing data

Evaluation of the temporal variability of multiple model time series

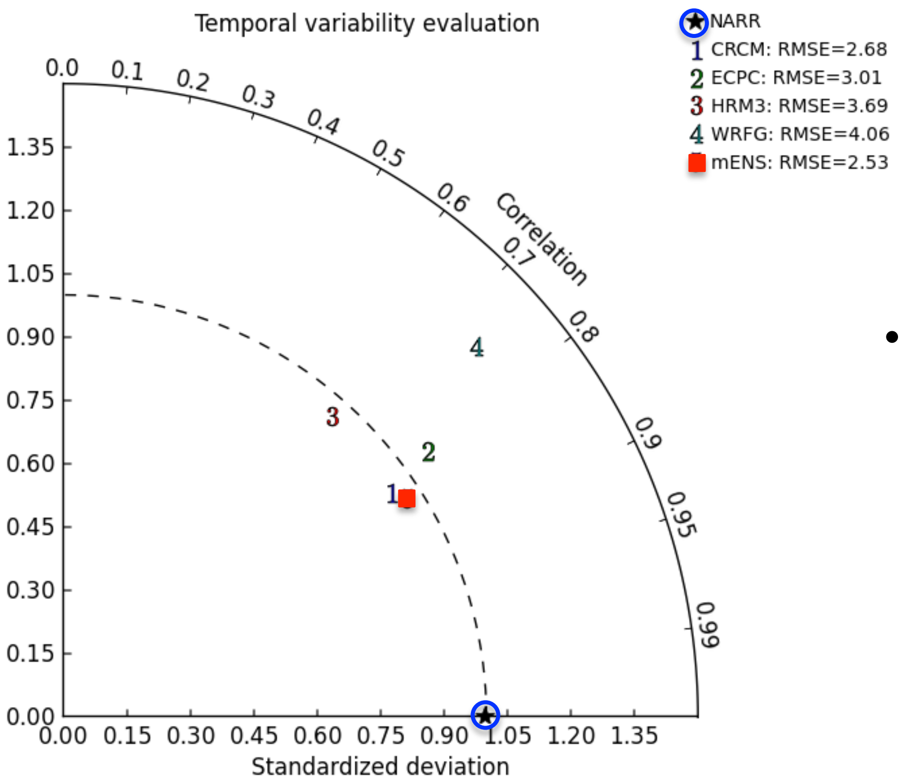


Figure 3.5b. Evaluation of the temporal variability of the simulated precipitation using a Taylor diagram (right).

- The temporal variability of the simulated time series and their equal-weight multi-model ensemble (*mENS*) is evaluated in terms of *standardized deviation* and *correlation coefficient* with the reference data (NARR).
- The resulting Taylor diagram shows that:
  - 3 out of 4 RCMs (*CRCM*, *ECPC*, *HRM3*) and *mENS* closely simulate the temporal standard deviation of the NARR precipitation data.
  - The multi-model ensemble yields the best correlation coefficient and the smallest *RMSE* (the distance between the reference point ('star' in Fig. 3.5b) and the model point corresponds to RMSE in a Taylor diagram constructed with standardized deviation and correlation coefficient).

Section 3. Uncertainties in forcing data
Bias Correction

- Evaluation of the simulated time series of the watershed-mean precipitation reveals the presence of biases of varying degree in the simulated data.

- In model hindcast experiments, these biases are regarded as model errors resulting from *incompleteness of model formulations*.
  - In reality, some of these model errors are due to the biases in the large-scale data used to drive these hindcast runs, however,
  - Errors in re-analysis data and their effects on the simulation errors are likely to be small compared to model errors.

- Used to drive hydrology model simulations, these model errors will be a major source of errors (or uncertainties) in the simulated surface hydrology data such as hydrograph and other hydrology parameters in the model.

Bias Correction

- Bias correction is performed in an attempt to alleviate the effects of the errors in (model) data on the downstream calculations which utilizes the (model) data as inputs.

- Bias correction *derives transfer functions in a control experiment to match certain statistical properties of the model data with the reference data*.
  - *Transfer functions (or correction factors) are derived for the present-day period in which observations are available.*
  - *Transfer functions (or correction factors) may be defined in a different form according to variables* (e.g. ratios between the control run data and the reference data for precipitation; differences between the control run data and the reference data for temperatures).

- *There exist multiple bias correction methods*
  - *Performance of various bias correction schemes must be throughtly examined.*

- *Limitations of bias correction approach*:
  - *Bias correction assumes that models' bias characteristics remain similar for different climate regimes. In reality, the model bias can vary according to climate state.*
  - *The quality of bias correction depends on the quality of reference data.*
  - *Bias correction is applied to correct a limited number of statistical properties.*

Section 3. Uncertainties in forcing data
Bias Correction: Annual Cycle Matching

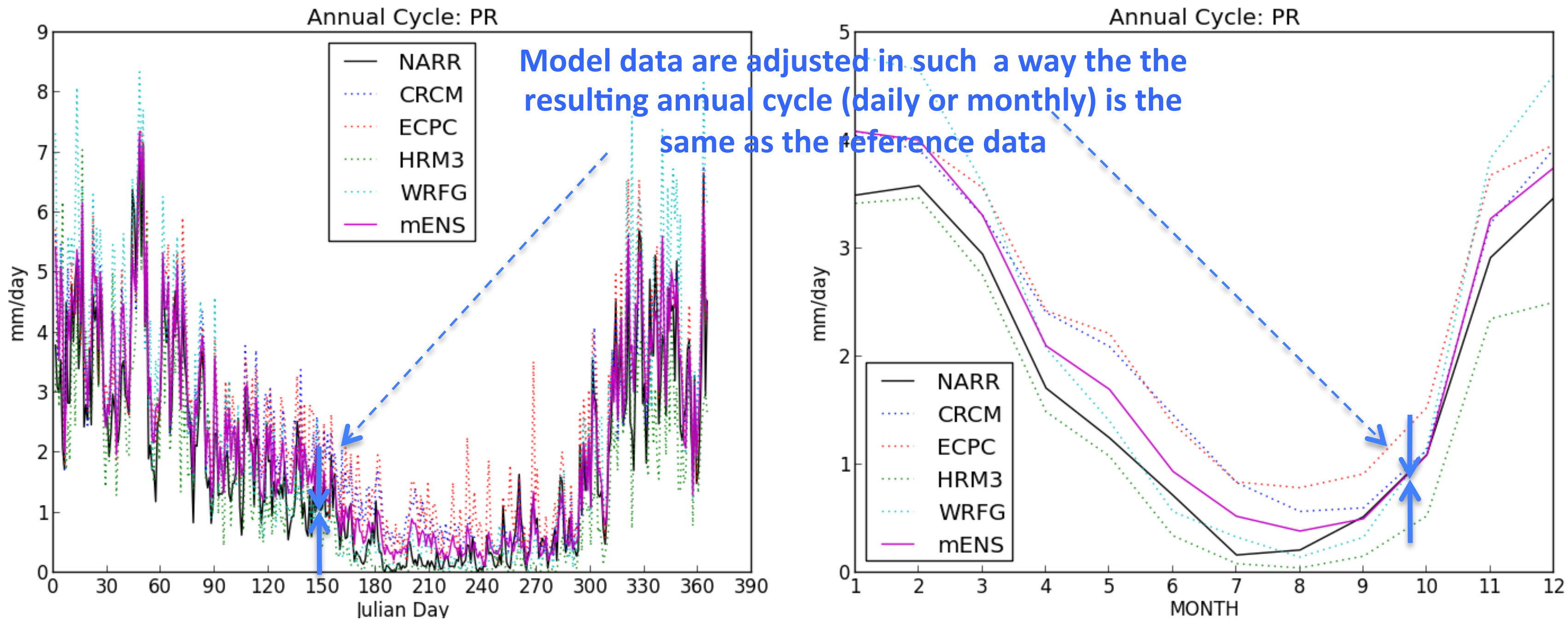


Figure 3.6. Annual cycle in terms of daily and monthly means. Same as Figure 3.3 (b) and (c).

- Annual cycle matching may be the earliest and simplest bias correction method.
  - Applied to either daily- or monthly climatology.
  - Correction factors obtained for each day or month from a hindcast period is applied to the same day or month in the simulated future time series.
  - For shorter evaluation periods and/or arid regions, monthly climatology matching is be preferred because the daily climatology generally suffer from the lack of samples.

- Annual cycle matching methods result in eliminating the biases in the mean values from the simulated data.

Quantile mapping

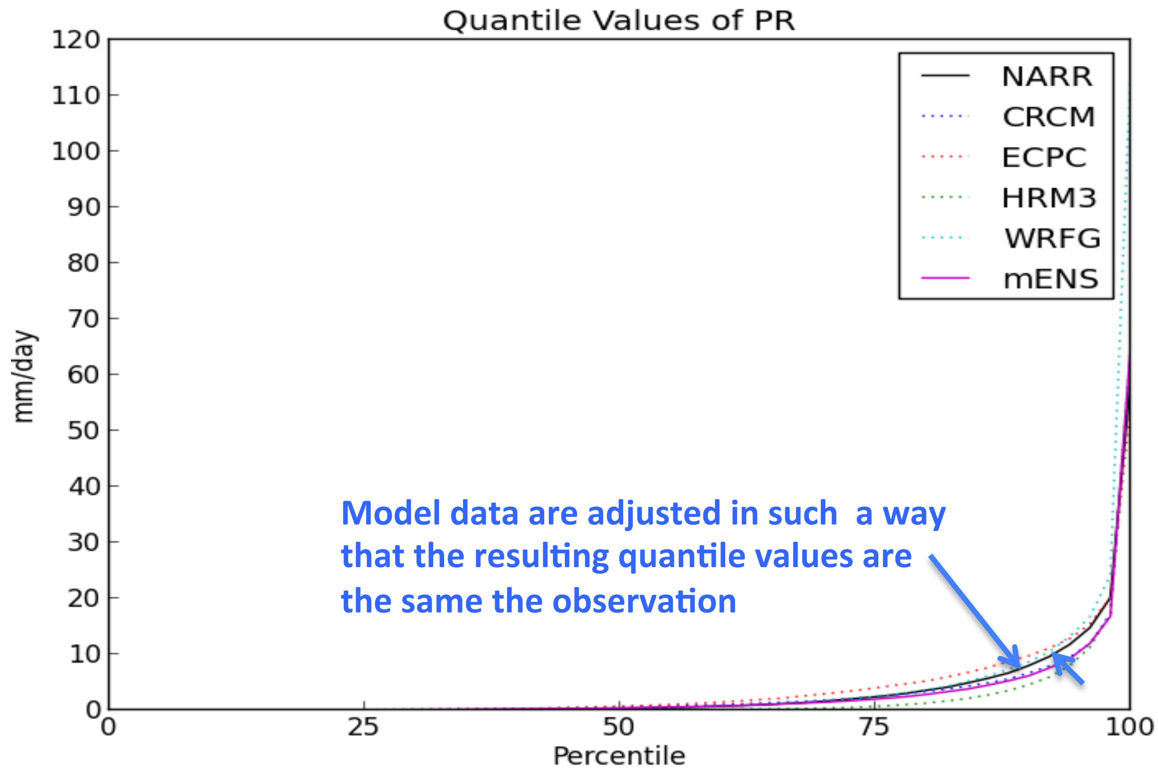


Figure 3.7. Daily precipitation quantile map (the same as Figure 3.4(c).

- Quantile mapping methods are based on matching quantile values between the PDFs of the simulated and reference data.
- Quantile mapping schemes match the frequency distribution of the simulated variables in addition to the climatological totals.
- Unlike the annual cycle mapping schemes, quantile mapping schemes alone do not explicitly improve seasonal cycle of the simulated variables.

Section 3. Uncertainties in forcing data
Quantile maps of bias-corrected precipitation timeseries

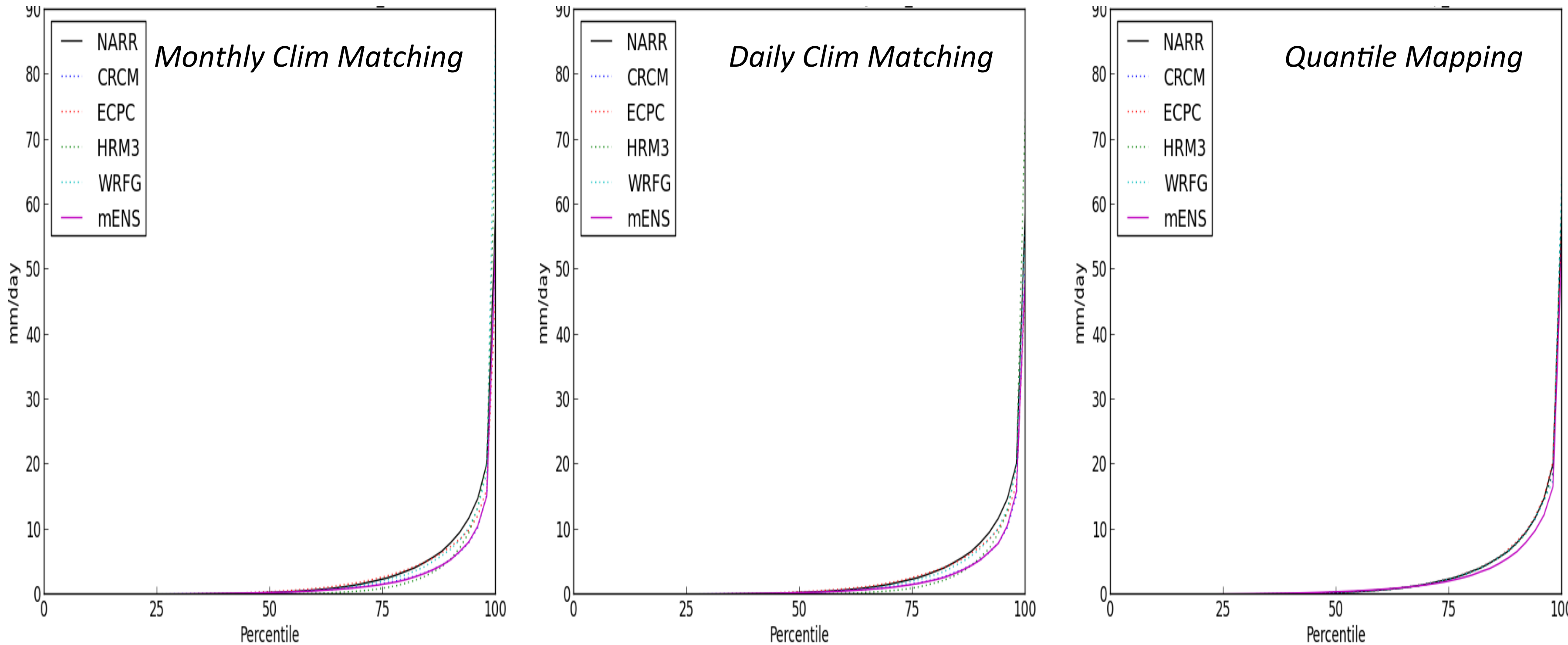


Figure 3.8. Quantile maps of bias corrected daily precipitation time series.

- Performance of bias correction schemes are examined.
  1. The quantile maps of the bias-corrected time series are still different from observation, but smaller than the raw data.
  2. The quantile matching method generates time series that exactly match the quantile map of the reference data; however
  3. The ensemble of quantile mapped time series does not exactly match the observation.

Section 3. Uncertainties in forcing data

Comparison of the bias-corrected model data and reference data

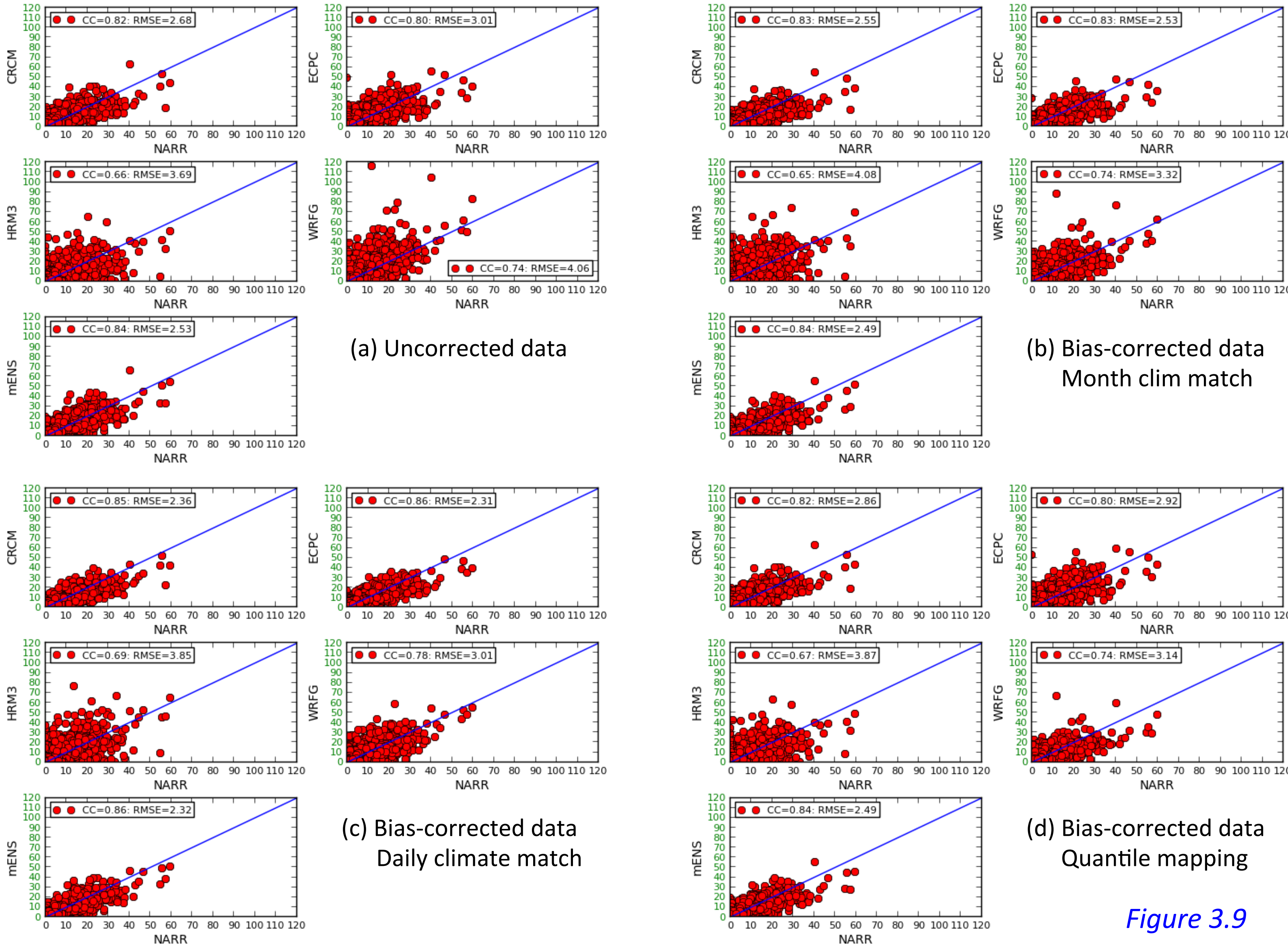


Figure 3.9

- Comparison of the (a) original and (b-d) bias corrected model data and the reference data (*Fig. 3.9*) shows that the effects of bias correction vary according to models.

Section 3. Uncertainties in the climate forcing data
Temporal variability evaluation: Uncorrected and Corrected data

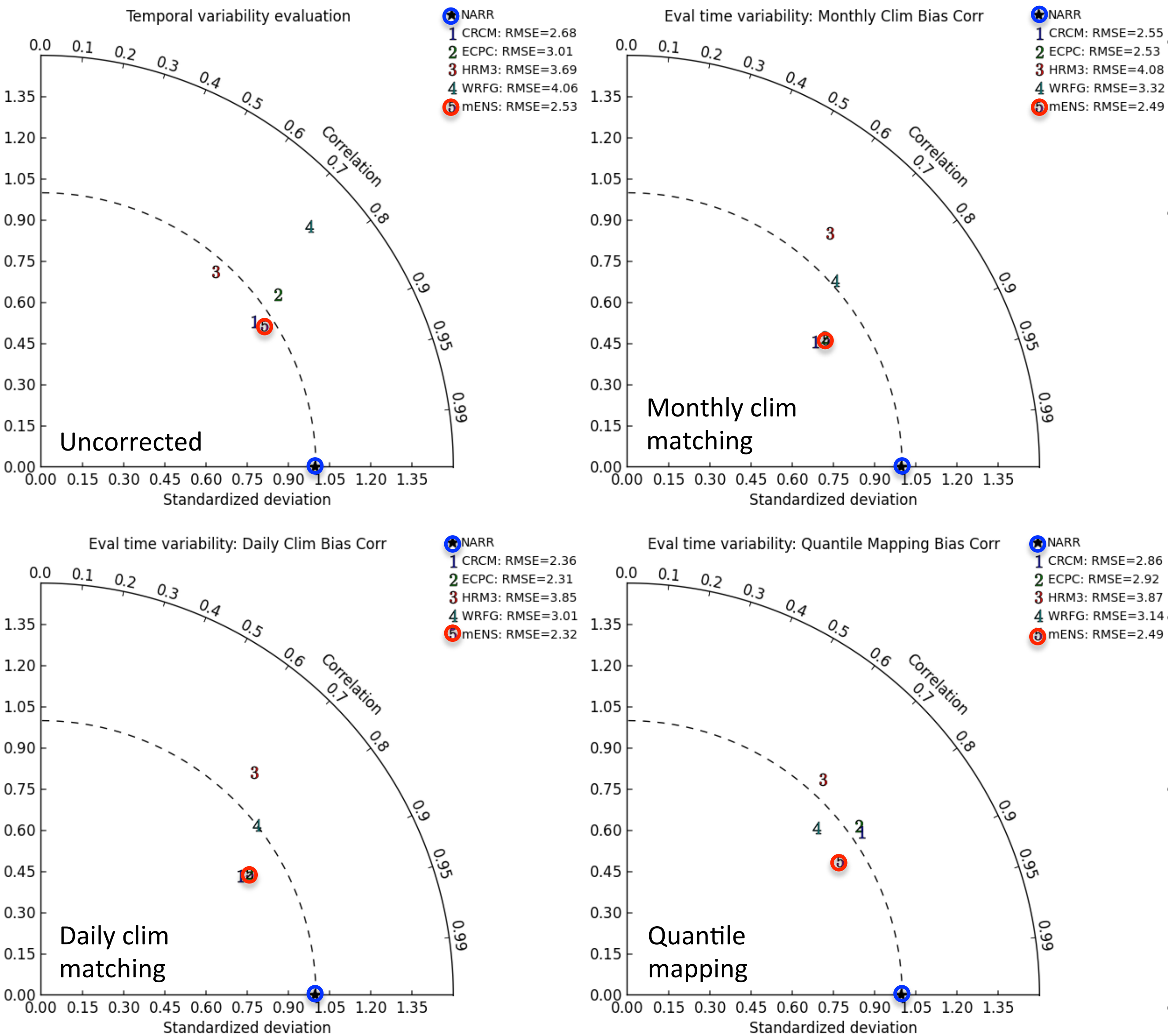


Figure 3.10. Evaluation of the temporal variability of the bias-corrected time series.

- Both annual-cycle matching methods reduce RMSE for 3 out of 4 models.
- The quantile mapping scheme reduces RMSE for two models (*ECPC* & *WRFG*) but increases the other two models (*CRCM* & *HRM3*).
  - All schemes increase RMSE for *HRM3*.
- All three schemes reduce the RMSE for the multi-model ensemble.
- The daily climatology matching reduces RMSE most among the three correction schemes.
- Bias correction tends to improve model data, but only by limited amounts.

Section 3. Uncertainties in the climate forcing data – continued
Application to gridded hydrology model

- Some recent hydrology models are developed to resolve surface area using a grid system (e.g., *VIC, CHYM*).
  - Distributed hydrology models based on regular grid nest requires meteorological input data at individual grid points (red circles in *Figure 3.11*).

- The procedure for generating the bias-corrected met forcing data for a bulk watershed can be applied to prepare bias-corrected input data for distributed hydrology models of *M* x *N* grids:

  1. Interpolate the observed and model meteorological data onto the hydrology model grid points.
  2. Apply the bias-correction procedures in the previous section to individual time series.
  3. Apply the bias-corrected meteorological forcing data to distributed hydrology model calculations.

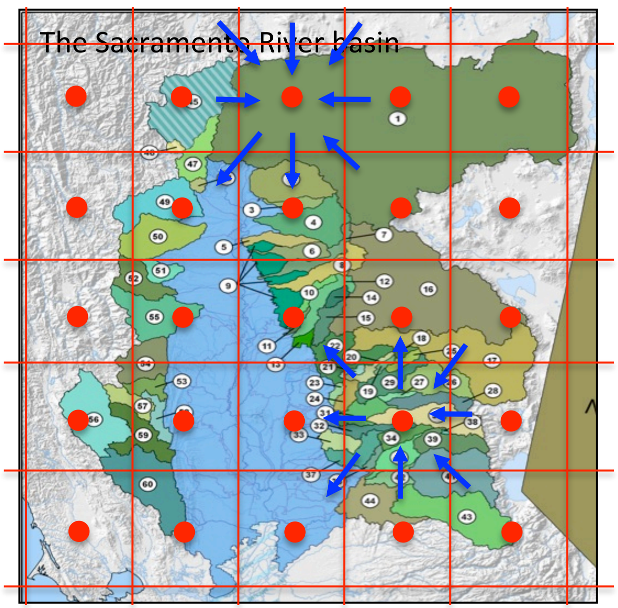


Figure 3.11. An example of grid-based distributed hydrology model over northern California including the Sacramento River basin.

Summary

- Bias correction of the meteorological input data for hydrology simulation is necessary to reduce the impact of model errors on simulating hydrologic properties.
  - In typical climate change impact assessments based on one-way nested modeling approach, upstream model errors are the sources of uncertainties in downstream model results.

- A number of bias correction methods are available
  - Each method deals with specific statistical properties of the targeted time series.

- In this example, three different methods are examined
  - Monthly and daily climatology matching schemes
  - Quantile mapping scheme

- Evaluation of the bias-corrected time series using these three schemes are evaluated.
  - All schemes generally improve the temporal variability of the uncorrected time series.
  - The efficiency of bias correction varies among models
  - Judging from the temporal variability, simple climatology-matching schemes perform as well as the quantile-mapping scheme.

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