PICSC Downscaling Workshop

Presentation on Statistical Downscaling

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Primary objective:
Mapping future seasonal mean rainfall changes
(the average of rain-producing weather events in a season)
Wet season: November-April
Dry season: May-Oct

Secondary objectives:
Estimating future changes in heavy rain events
Drought-related rainfall characteristics
Compounding effects: high temperatures and dry conditions

Background

Research team:
T.W. Giambelluca, H.F. Diaz, M. Takahashi, L. Kaiser, A. Frazier, R. Longman

First statistical downscaling (Timm and Diaz, 2009):
limited station data, single predictor information (south-north wind)
CMIP3 models (6 objectively selected models from the full ensemble)

Downscaling heavy rain events (Elison Timm et al. , 2011, 2013):
ENSO/PNA variability connection with heavy rain event frequency
future mean shifts in the ENSO/PNA states (same 6 CMIP3 models)
→ future changes in heavy rain frequency

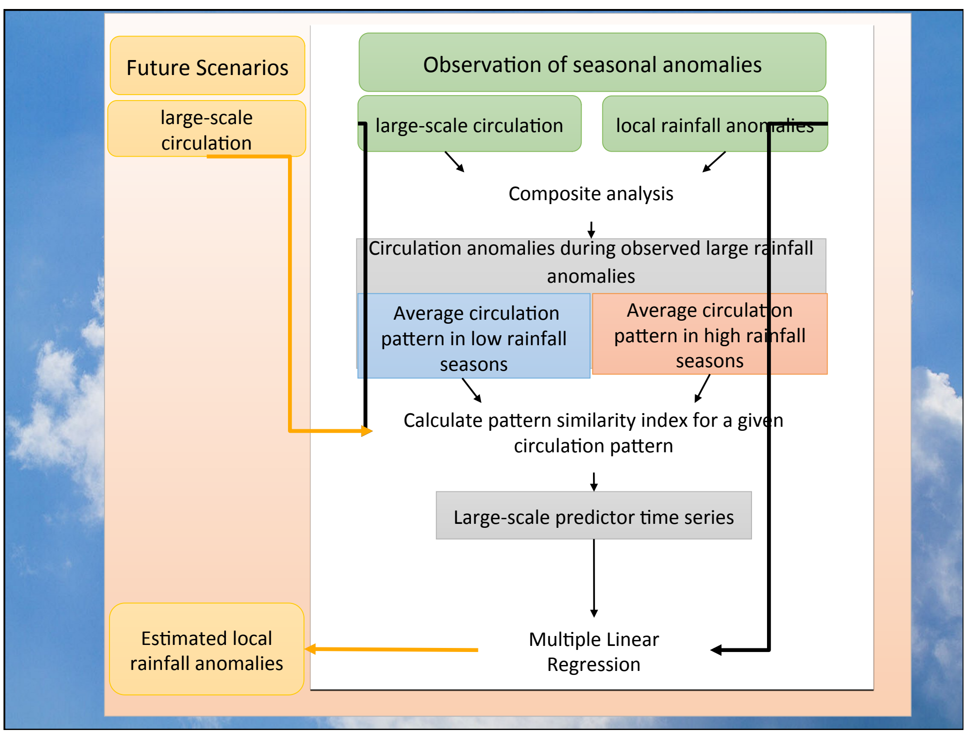
Refined heavy rain event analysis and downscaling:
downscaled directly daily weather statistics from the CMIP3 models

Updated seasonal downscaling and spatial maps:
more stations, CMIP5 ensemble (32 models), multiple predictors

Studied effects of kona lows on local rainfall

Statistical Downscaling Model

- **Boundary-type conditions:**
  - Local station network determines what spatial details can directly be resolved (spatial interpolation after downscaling)
  - Temporal sample space is limited to observations of 1978-2007:
  - → Observations represent positive phase of the
  - Pacific Decadal Oscillation more than the negative phase.
  - → bias the SD model parameters (?)
- **Spatial scale for projected rainfall scenarios:**
  - First interpolation (gridding): 0.5 minute resolution
  - Additional maps interpolated to 3km and 250m resolution
- **Time period:**
  - 2041-2070, 2071-2099, main target period
  - Time steps: annual time steps were used in the downscaling



Parameter fitting & cross-validation

All observations were used to find composite pattern. They are not part of the cross-validation.

Cross-validation:
Splitting the observations into two sub-sets:
(random, high/low rainfall)
One exclusively used for **parameter fitting**,
the other is reserved for **cross-validation metrics:**
Correlation, sign-test, bias-test

Observation of seasonal anomalies

large-scale circulation

local rainfall anomalies

Calculate pattern similarity index for a given circulation pattern

Large-scale predictor time series

Multiple Linear Regression

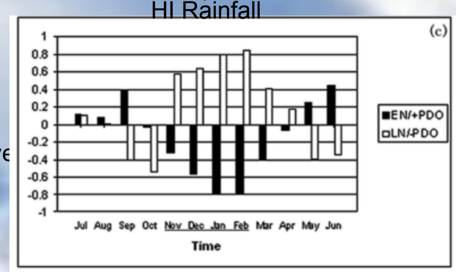
How are ENSO/PDO and other oceanic processes incorporated?

Their large-scale circulation anomalies are represented in the composite technique and the MLR

Future change projections:
anthropogenically forced shifts in their mean state
Ensemble mean projections remove most of the internal variability.

PDO (+) — PNA (+) — NINO3.4 (+)

HI Rainfall



Assumptions of stationary

Statistical relations found in the calibration itself remain constant in time
Results from cross-validation and associated uncertainties/confidence are representative in future
Consequences if stationarity breaks downs in future:
Underestimation/overestimation of rainfall anomalies
Even methodically possible change in sign
(physically this may not be possible, though)
Overestimated confidence in downscaled results.

How well are synoptic and smaller scale systems reflected in the model and output?

Trade wind regimes
well represented in their effects for windward rainfall
moderately represented for leeward rainfall impacts
Kona weather
any change in kona weather would likely be underestimated in their impacts on rainfall (in particular, leeward and dry sites during winter months)
Inversion layer
Intensity and frequency implicitly accounted for
Not resolved in the SD model: height shifts
Uncertain, due to non-linear effects on rainfall

How well are synoptic and smaller scale systems reflected in the model and output?

Convective pop-up

Summer convection, land-sea breeze rain events difficult to represent in the SD downscaling for seasonal mean rainfall

Little information on uncertainty and bias effects

Cyclones

Not taken into account in SD model,

uncertain if seasonal mean circulation could provide statistical information to account for cyclone changes indirectly

(but note the current El-Nino case: indirect cyclone impacts may be captured through the large-scale circulation)

Identification of parameter sensitivities

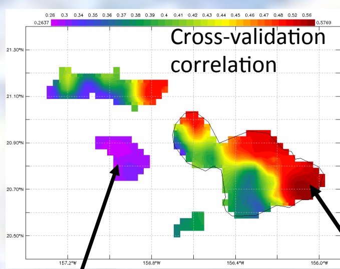
How is parameter sensitivity evaluated?

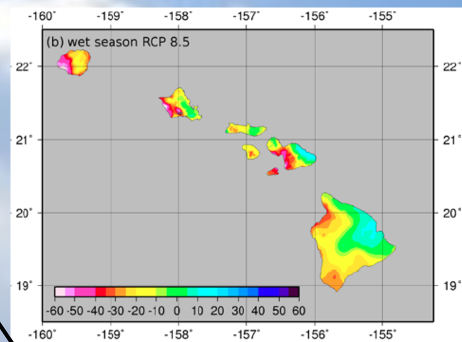
In the statistical downscaling model parameters are fitted to observations.

Monte-Carlo methods were used to test the fitted model parameters

Note: Our SD model does not include a parameterization of unresolved smaller scale systems such as trade-wind inversion, convective rain (in dependence on mean-states)

Primary sources of error





Low correlation score:
→ Statistical error is large
→ Other errors of secondary importance

Good cross-validation result:
Differences among emissions scenarios primary source of uncertainty

Effects of ensemble averages or lumping in representing potential future conditions

Ensemble average:

Reduces internal variability and individual GCM model uncertainty

Natural variability is suppressed
(ENSO, PDO and other modes of variability)

Any 30-year period in future may experience a PDO (+) or (-) phase superposed on the mean change.

→ Uncertain when to expect critical thresholds to be exceeded.

What are your challenges representing extremes?

Statistical method is adaptable
→ other target statistics than the average rainfall
(e.g. number of heavy rain events)
However, problem with extreme downscaling is:
- extremes are rare events => small sample to fit model parameters
- extreme weather events require daily model data from GCMs, i.e. weather variability
- GCMs weather variability less confident

Options: derive relationships between local short-duration extreme weather and large-scale monthly-mean circulation?

Which aspects of the model are the most confident?

Timescales:
- Statistical error grows with time (as the anomalies grow in amplitude)
- Linear assumption best justified for small changes 10%-20% (30%)
- → 30-50 year outlook (mid 21st century) highest confidence
- Wet season (winter months Nov-Apr)

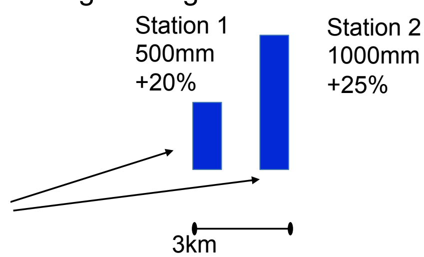
Spatial scale/location:
- The statistical model projects rainfall anomalies through a linear combination of a few spatial pattern:
- Higher confidence in the 'island-wide anomaly pattern associated with ENSO,PDO
- Dipole pattern: more confidence on the windward sides

→ highest confidence in windward sides of Big Island, Maui, Oahu

Which aspects of the model are the most confident?

Downscaled variables (products):

highest confidence in the sign
of the seasonal mean rainfall anomalies
confidence higher in percentage change than absolute values*



Present-day reference rainfall: Sharp gradients (e.g. cloud-elevation, or topographic shadowing /channeling effects)

Which aspects of the model are the most uncertain?

Timescales ('forecast horizon')

- Statistical error grows with time as the anomalies grow in amplitude
- Linear assumption best justified for small changes 10%-30%

→ end of 21st century lowest confidence in amplitudes

- Dry season
- Individual years or short-term averages (i.e. decadal averages)

Process time scales

- Extreme events on sub-seasonal time scale: hourly or daily high intensity rainfall**
- Synoptic events such as convection, tropical cyclones

Other issues, concerns, or ideas

Temperature downscaling progress:

First order 'bias-correction' scheme:

Take from dynamical downscaling the temperature change-elevation dependence

Take a GCM model air temperature anomaly for a given year at sea level (ambient warming over surrounding ocean scale with elevation-dependent factor.

Questions:

Would this type of information be useful?

Would it make a 'consistent' combination with SD downscaled rainfall scenarios?

Compounding effects: Temperature-enhanced water stress on plants during dry-spell?

Conceptual model:

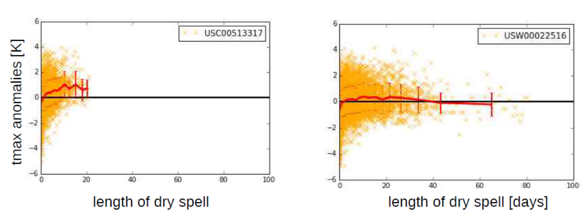
Decrease in seasonal rainfall

Increase in dry-spell length

Increase in daily maximum temp.

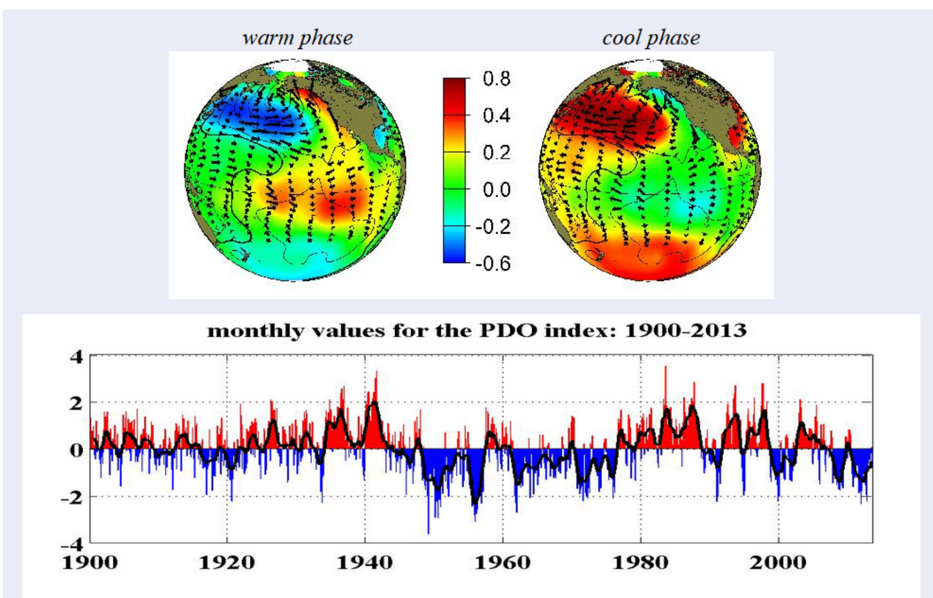
Enhanced water vapor deficit

Two example stations:
Dependence of tmax anomalies on dry spell length

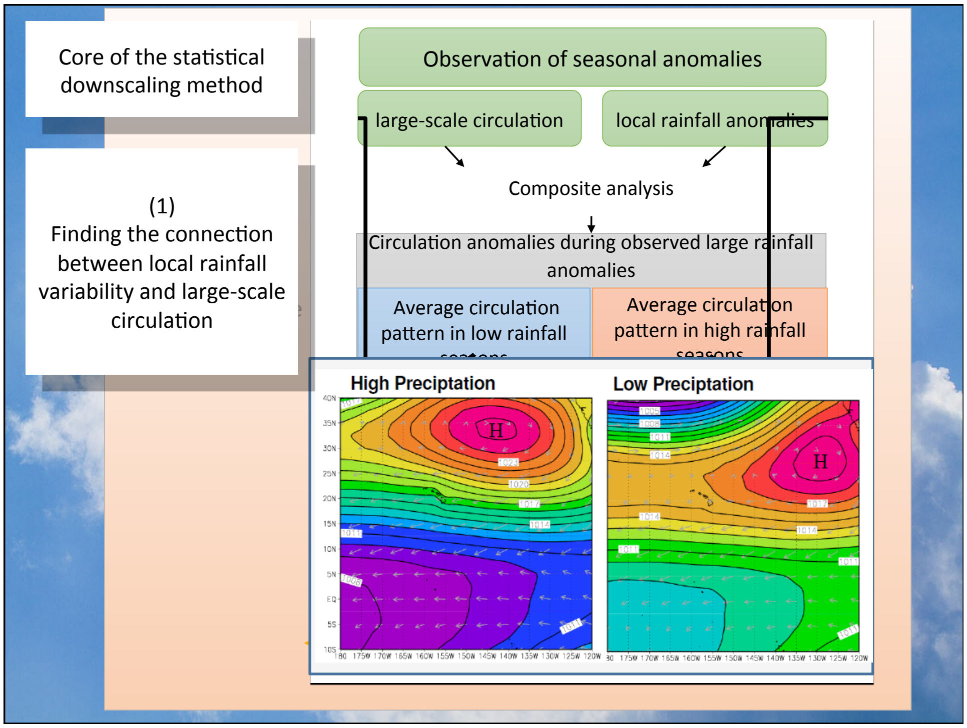


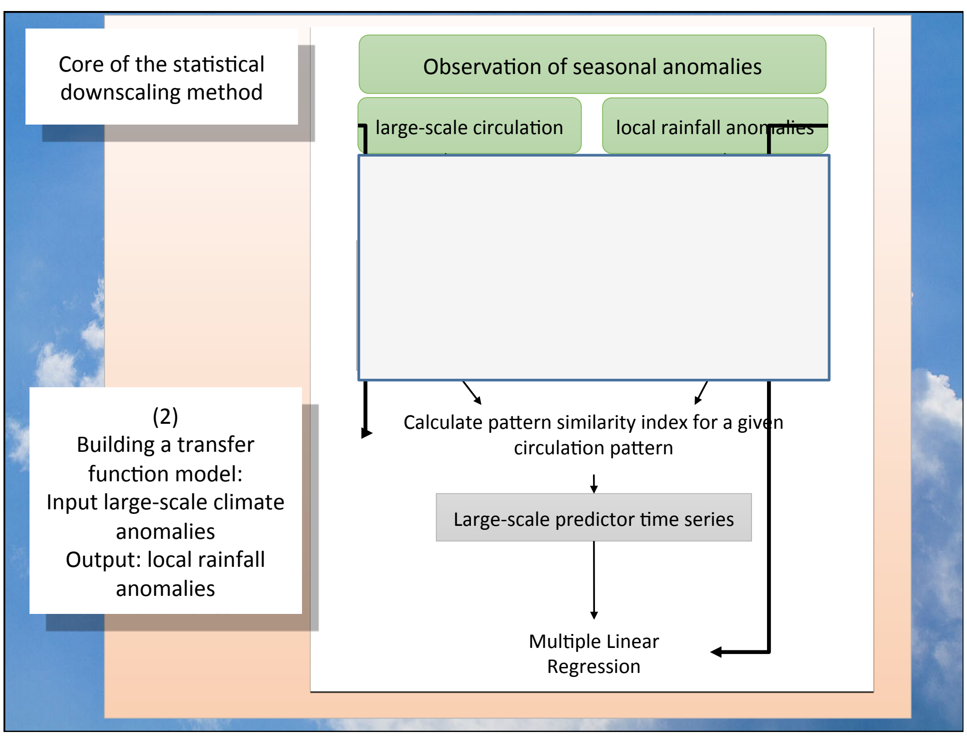
Appendix: Useful additional information for upcoming questions
In discussions or for one-on-one talks during breaks

Appendix: Pacific Decadal Oscillation (PDO)



Source: http://research.jisao.washington.edu/pdo/


Core of the statistical downscaling method
(1)
Finding the connection between local rainfall variability and large-scale circulation
Observation of seasonal anomalies
large-scale circulation
local rainfall anomalies
Composite analysis
Circulation anomalies during observed large rainfall anomalies
Average circulation pattern in low rainfall seasons
Average circulation pattern in high rainfall seasons
High Preciptation
Low Preciptation
H
H

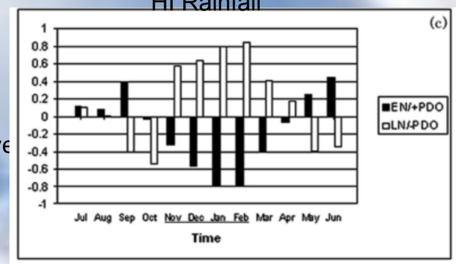

Core of the statistical downscaling method
Observation of seasonal anomalies
large-scale circulation
local rainfall anomalies
(2)
Building a transfer function model:
Input large-scale climate anomalies
Output: local rainfall anomalies
Calculate pattern similarity index for a given circulation pattern
Large-scale predictor time series
Multiple Linear Regression

How are ENSO/PDO and other oceanic processes incorporated?

Their large-scale circulation anomalies are represented in the composite technique and the MLR

PDO (+) — PNA (+) — NINO3.4 (+)

HI Rainfall



Future change projections:
anthropogenically forced shifts in their mean state
Ensemble mean projections remove most of the internal variability.

Appendix: Effects of ensemble averaging

- SLP example form Deser et al. 2014, *J. of Climate*

b) Winter Precip and SLP

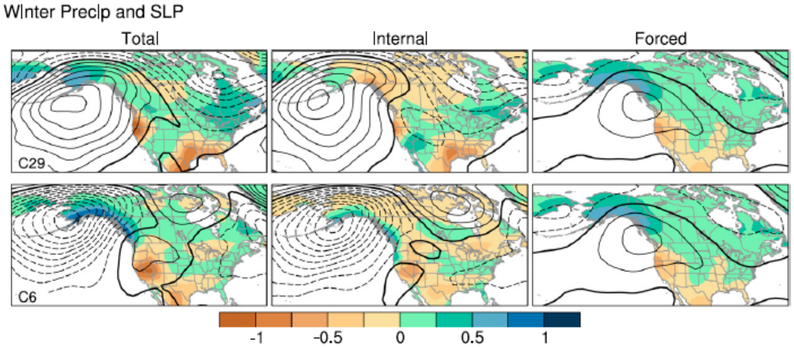
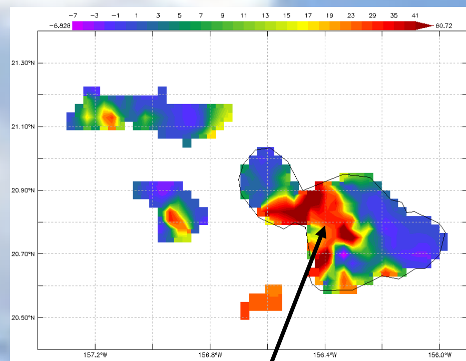


FIG. 10. (left) Total 2010–60 winter trends decomposed into (center) internal and (right) forced components for two contrasting CCSM3 ensemble members (runs 29 and 6) for (a) SAT [color shading; °C (51 yr)$^{-1}$] and SLP (contours) and (b) precipitation [color shading; mm day^{-1} (51 yr)$^{-1}$] and SLP (contours). SLP contour interval is 1 hPa (51 yr)$^{-1}$, with solid (dashed) contours for positive (negative) values; the zero contour is thickened.

Appendix: Taking into account multimodel ensemble and internal modes of variability

Example:
Taking 32 CMIP5 RCP8.5 scenarios(wet season) and using all individual years 2071-2099

We calculate the percentage of the multi-model and multi-year sample that indicates dryer conditions than in the lowest value in the present-day reference period.



Red: 30-40% of the modelled years are drier than the driest year of 1978-2007.

Appendix: What are your challenges representing extremes?

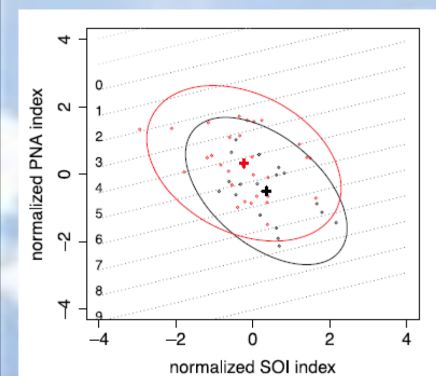


Figure 4. Phase-space presentation of the tropical and North Pacific atmospheric circulation in the SOI and PNAI subspace for the periods 1958–1976 and 1977–2005. Each

Example: Using ENSO and PNA as predictors
For the number of heavy rain events

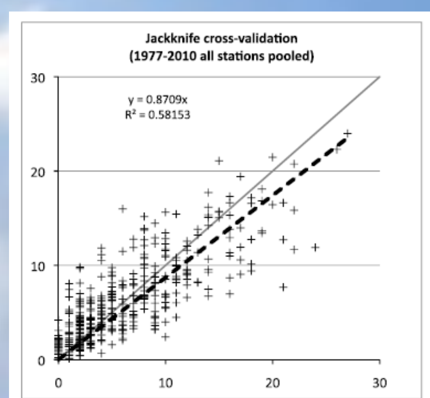


Figure 6. Scatter plot of the predicted values from the Jackknife validation (*y* axis) against the observed number of heavy rain events (*x* axis). All years (1977–2010) and all stations are plotted.

Example: Validating synoptic-weather pattern-based downscaled heavy rain events with observed heavy rain events during winter seasons

For the case of in-depth discussion representing extremes in mean statistics

Some considerations of the mean statistics.

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$$

$$\bar{X} = \frac{1}{n}\left(\sum_{i=1}^{m} X_i + \sum_{j=1}^{k} X_j\right) = \frac{1}{n}\left(m\bar{X}_{norm} + k\bar{X}_{extr}\right)$$

$$\frac{\bar{X}_{extr} - \bar{X}_{norm}}{\bar{X}_{norm}} \approx \frac{m}{k}$$

$$\frac{\bar{X}_{extr}}{\bar{X}_{norm}} \approx \frac{n}{k} \approx p(E)$$

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- Primary objective:
  - Estimating future seasonal mean rainfall changes: that is the average of rain-producing (and non-producing) weather events in a season.
  - Wet season: November-April
- Dry season: May-Oct
- Secondary objectives:
- Estimating future changes in heavy rain events, drought-related rainfall characteristics.

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