6th Workshop on Water Resources in Developing Countries: Hydroclimate Modeling, Information Tools andSimulation Techniques
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Bias adjustment of PERSIANN-CCS estimates using rain gauge observation

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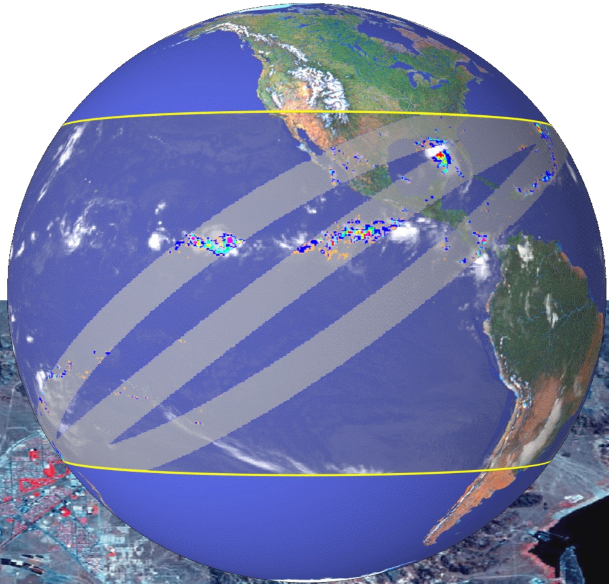
Integration of Satellite & Ground Measurements

Bias Adjustment of Satellite Estimation using Gauge Measurements



AGU PUBLICATIONS

JGR

Journal of Geophysical Research: Atmospheres

RESEARCH ARTICLE

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Bias adjustment of satellite-based precipitation estimation using gauge observations: A case study in Chile

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Key Points:
- Bias adjustment model based on historical satellite and point-wise gauge data
- High effectiveness in adjusting systematic bias of satellite-based precipitation estimation
- Can adjust satellite precipitation estimates into the future

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Abstract Satellite-based precipitation estimates (SPEs) are promising alternative precipitation data for climatic and hydrological applications, especially for regions where ground-based observations are limited. However, existing satellite-based rainfall estimations are subject to systematic biases. This study aims to adjust the biases in the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Cloud Classification System (PERSIANN-CCS) rainfall data over Chile, using gauge observations as reference. A novel bias adjustment framework, termed QM-GW, is proposed based on the nonparametric quantile mapping approach and a Gaussian weighting interpolation scheme. The PERSIANN-CCS precipitation estimates (daily, 0.04°×0.04°) over Chile are adjusted for the period of 2009–2014. The historical data (satellite and gauge) for 2009–2013 are used to calibrate the methodology; nonparametric cumulative distribution functions of satellite and gauge observations are estimated at every 1°×1° box region. One year (2014) of gauge data was used for validation. The results show that the biases of the PERSIANN-CCS precipitation data are effectively reduced. The spatial patterns of adjusted satellite rainfall show high consistency to the gauge observations, with reduced root-mean-square errors and mean biases. The systematic biases of the PERSIANN-CCS precipitation time series, at both monthly and daily scales, are removed. The extended validation also verifies that the proposed approach can be applied to adjust SPEs into the future, without further need for ground-based measurements. This study serves as a valuable reference for the bias adjustment of existing SPEs using gauge observations worldwide.

1. Introduction

Precipitation is one key input variable for hydrological process modeling and climatic studies of extreme events, such as floods and droughts. The quality of precipitation estimates can largely influence the inferred outcomes of these applications. It is widely recognized that the ground-based gauge can provide reliable precipitation measurements at gauge points. However, uncertainty from gauges increases when the precipi-

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Improve Satellite Precipitation Estimation Using Gauge Observation

Bias adjustment of PERSIANN-CCS Estimation Using Local Gauge Measurements: A Case Study over Chile

❖ ***Gauge Observation***

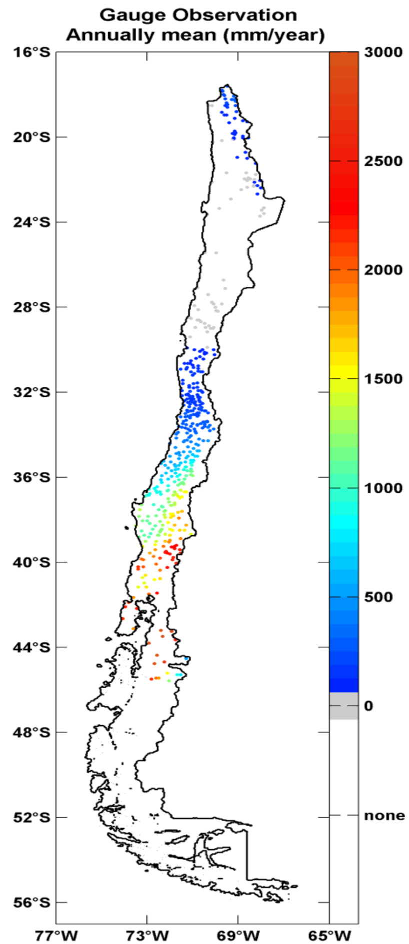
- ***456 gauges are selected***
- ***Data period: 2009-2013 (5 years)***
- ***Observations** (see **figures on the right)***

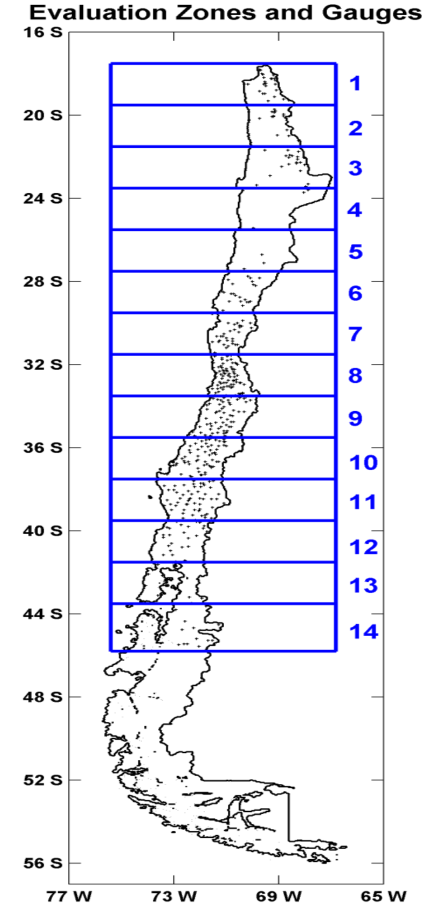
❖ ***PERSIANN-CCS***

- ***Match to the same time period for evaluation***

❖ ***Evaluation zones***

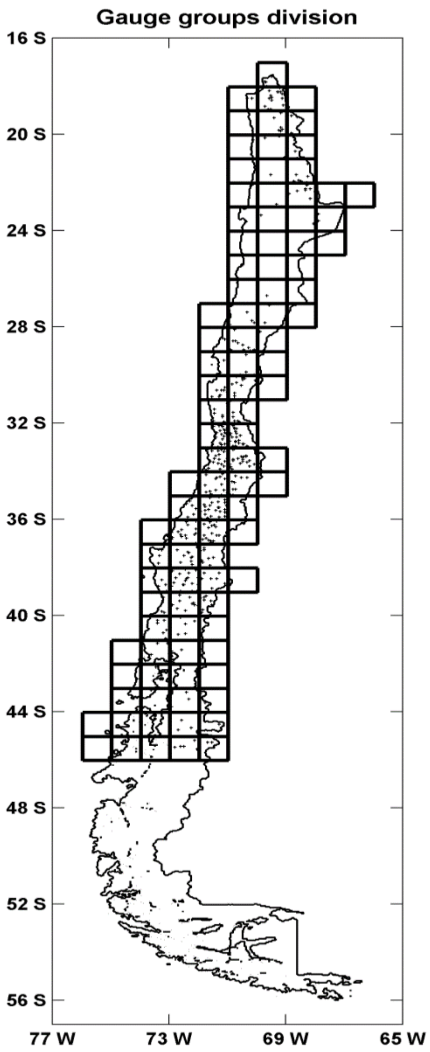
- ***14 zones are divided by every 2° latitudes over the adjusted region (shown as the right figure)***





Yang et al., JGR Atmosphere 2016

Bias Correction



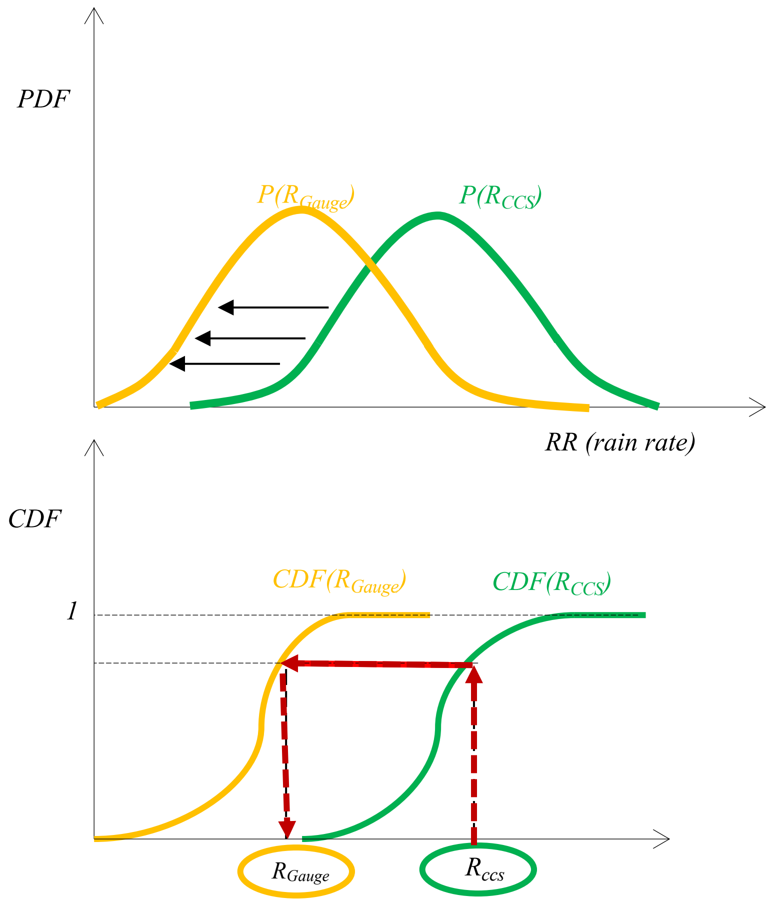
- ***Gauge Data***
  - ***Gauges are selected from 1° × 1° boxes (shown as the left figure)***
  - ***Gauge observations within each 1° × 1° box are assumed to have the same distribution over the same season***
- ***PERSIANN-CCS Bias correction***
  - ***Concurrent samples are taken from PERSIANN-CCS and gauge estimation at daily 0.04^o x0.04^o scales.***
  - ***For each 1^{o}x1^o grid box with gauge observations, CDFs of daily PERSIANN-CCS rainfall (@0.04^o) and gauge rainfall samples are calculated.***
  - ***For 1^{o}x1^o grids without gauge observation, concurrent samples of gauge & PERSIANN-CCS estimation from neighboring grid boxes are used to estimate CDFs .***

Step 1: Data Processing

- Process daily rainfall data based on the local time over the study area

Step II: Quantile Mapping of CCS to Gauge Estimation

Probability Matching of CCS to Gauge Rainfall Estimation



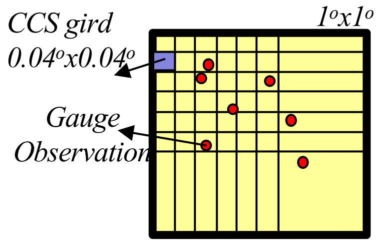
$$\int_0^{R_{ccs}^*} P(R_{ccs})dR = \int_0^{R_{Gauge}^*} P(R_{Gauge}^*)dR$$

R_{ccs}: Rain rate from CCS estimation
R_{Gauge}: Rain rate from gauge observation

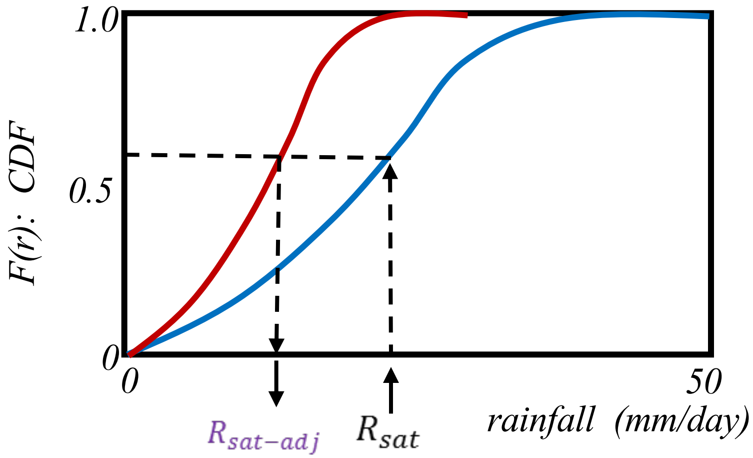
$$R_{ccs} \rightarrow R_{Gauge}$$

Quantile Mapping of CCS to Gauge Estimation

Estimate cumulative distribution of satellite and gauge rainfall estimation at 0.04°x0.04° under 1°x1° coverage



$$R_{sat-adj} = F_G^{-1}(F_{sat}(R_{sat}))$$



$F_{sat}(r)$: CDF of Satellite Estimation

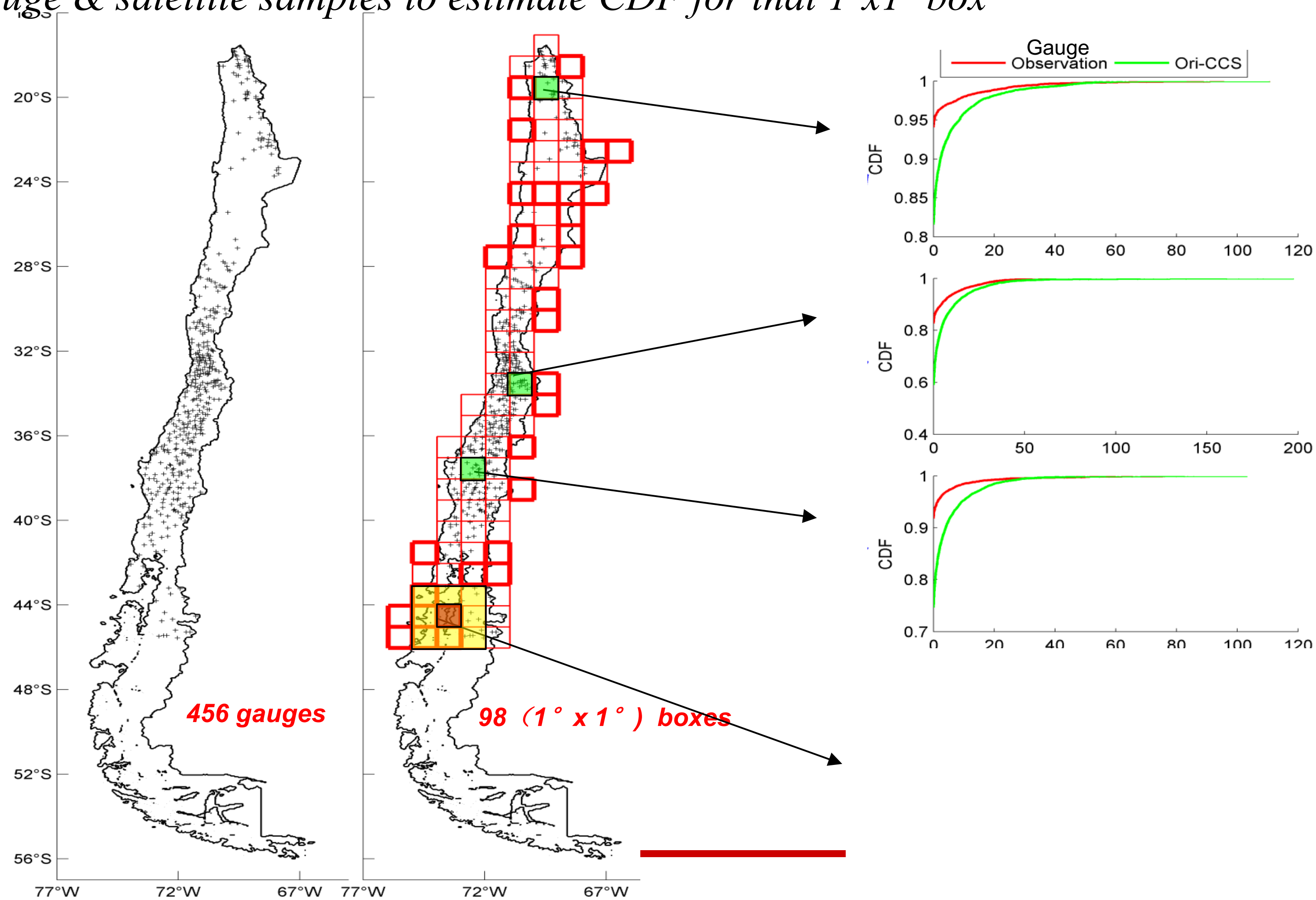
$F_G(r)$: CDF of Gauge Measurement

R_{sat}: Satellite Estimates

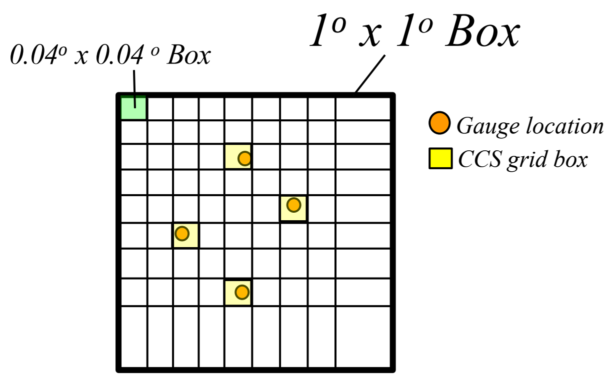
$R_{sat-adj}$: Adjusted Satellite Estimations

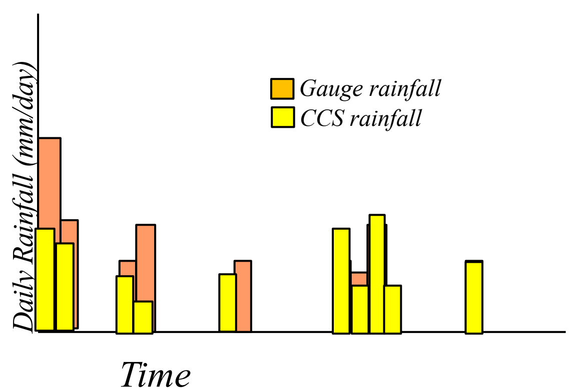
Step III: Calculate CDF curves of CCS and gauge observations

- *5-year of daily gauge and CCS estimations are collected*
- *Estimate the corresponding CDF curve for each 1ºx1º box for each season (or month)*
- *If gauge is not available for a 1ºx1º box, extend the box size to 3ºx3º or larger to collect gauge & satellite samples to estimate CDF for that 1ºx1º box*



CDF curves of CCS and gauge Estimates



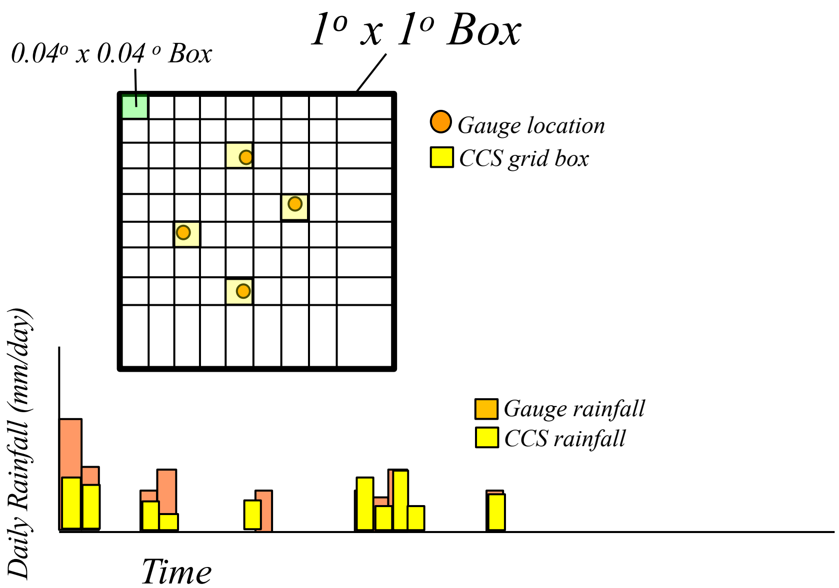


- Prepare daily gauge and CCS estimation
- Collect concurrent samples of CCS and gauge estimation at 0.04ºx0.04º gird box
- Sort the data (value from low to high)

Gauge (mm/day)	Satellite (mm/day)
0	0
0	0
…	…
0.5	0
1	1
3	2
4	5
10	8
…	…

Low → High

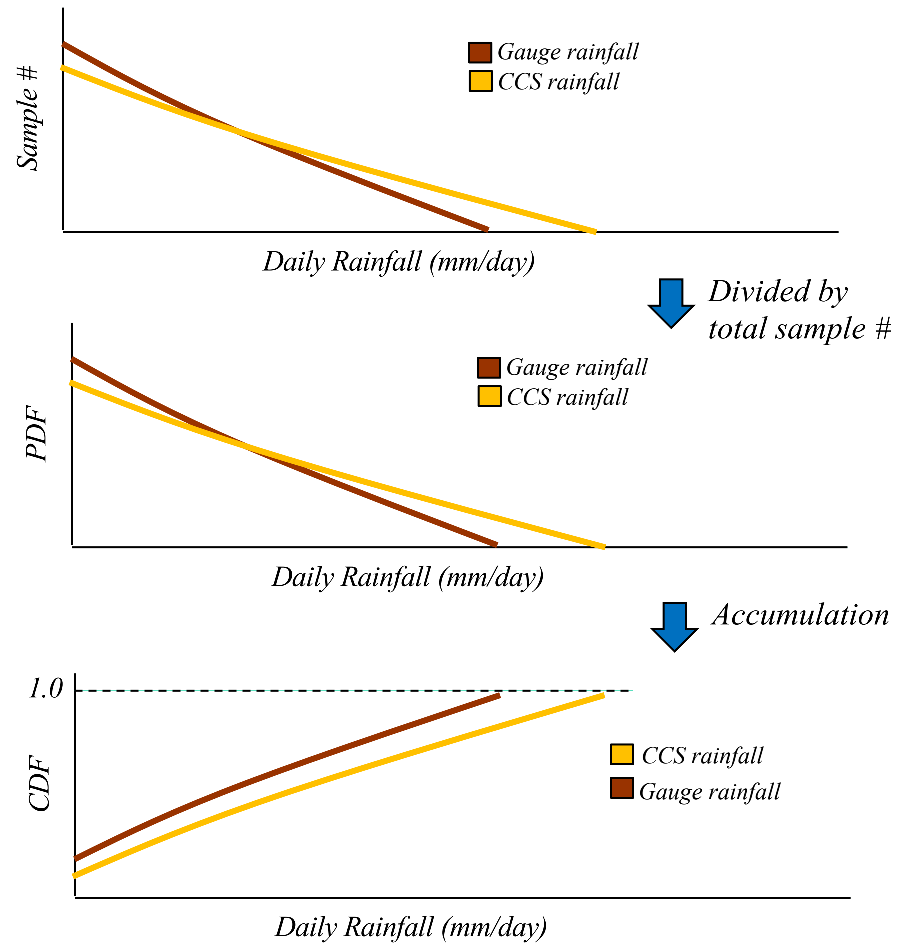
CDF curves of CCS and gauge observations



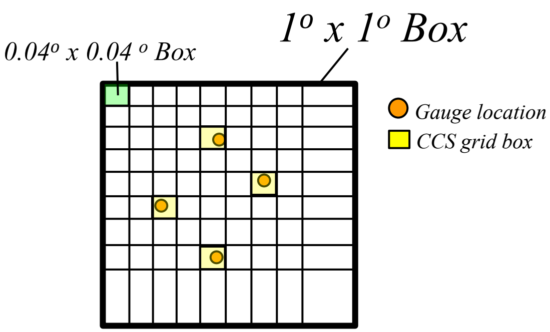
Gauge (mm/day)	Satellite (mm/day)
0	0
0	0
…	…
0.5	0
1	1
3	2
4	5
10	8
…	…

Low → High

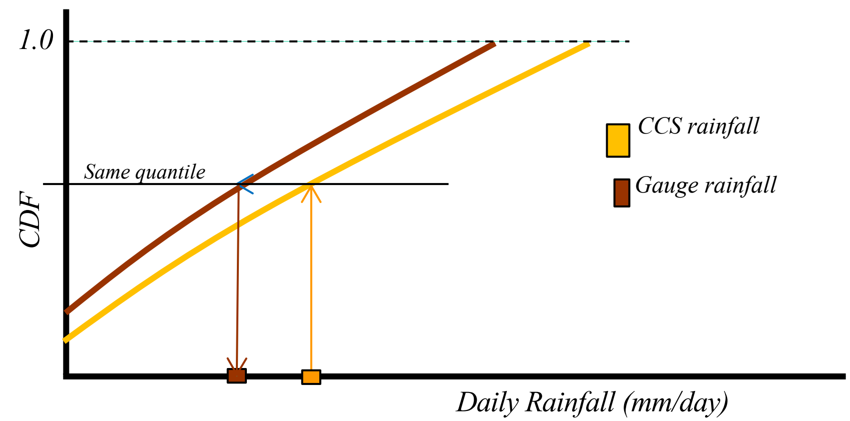
- Estimate CDF of CCS and gauge data at 1ºx1º coverage

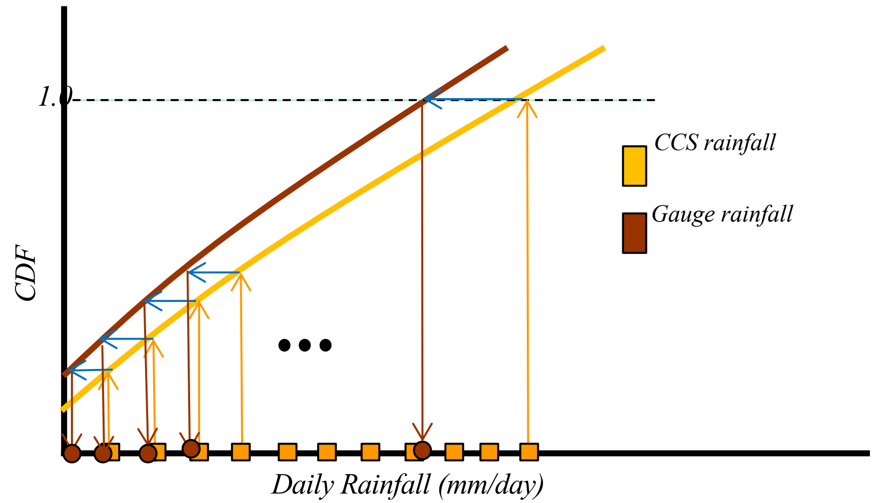


CDF curves of CCS and gauge observations



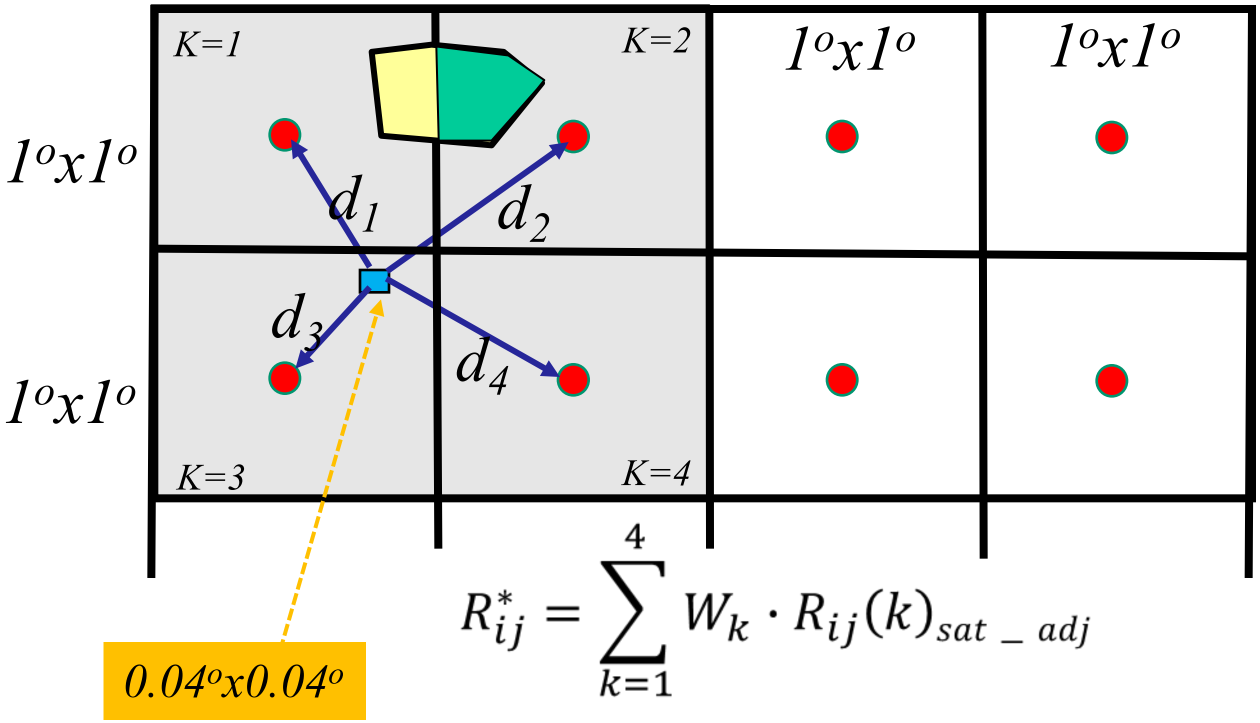
- Quantile mapping of CCS to gauge observation





Step IV: Gauge Adjusted CCS Rainfall at 0.04°x0.04°

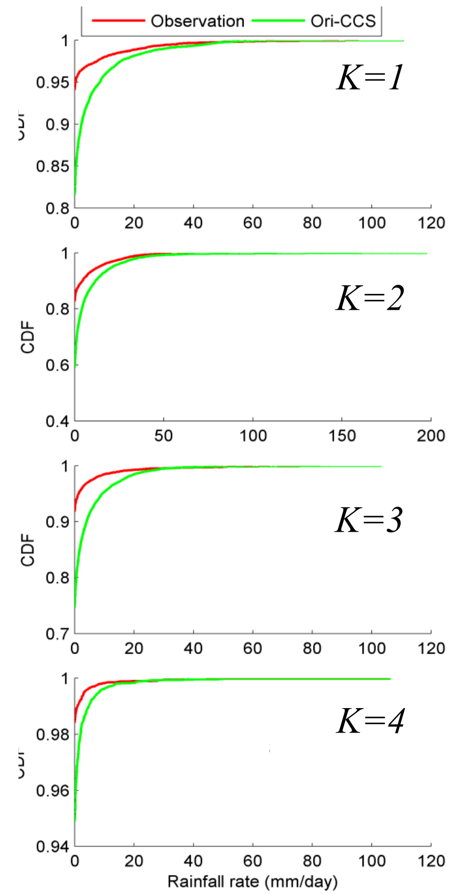
Use CDF curves from four neighbor 1°x1° boxes to smooth the gauge adjusted CCS estimation

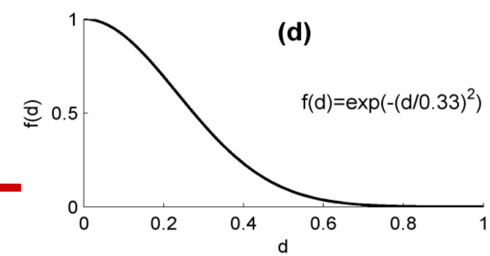


$$R^*_{ij} = \sum_{k=1}^{4} W_k \cdot R_{ij}(k)_{sat\_adj}$$

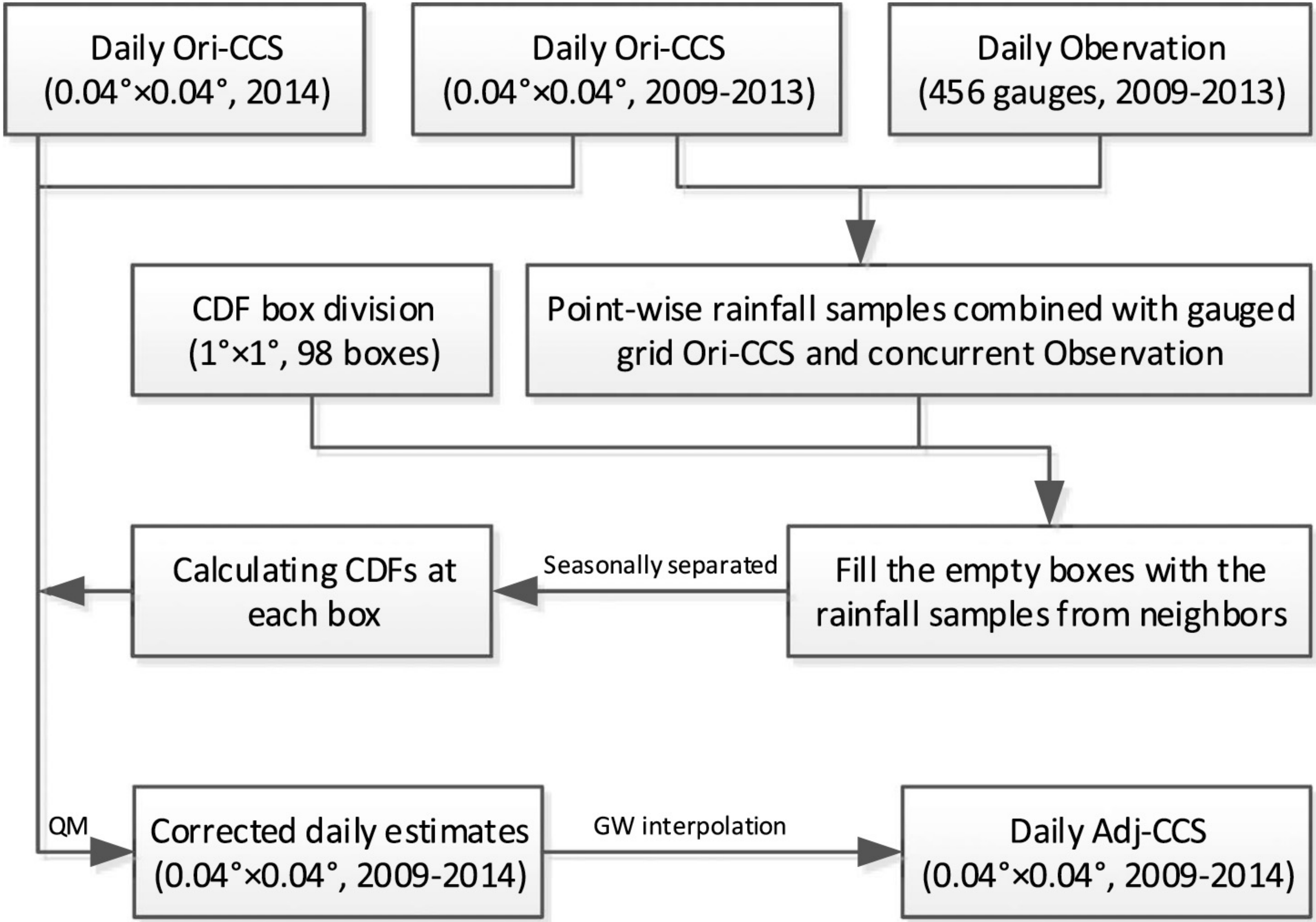
$$W_k = f(d_k) / \sum_{l=1}^{4} f(d_l)$$

$$f(d_l) = \exp\left(-\left(\frac{d_l}{0.33}\right)^2\right)$$

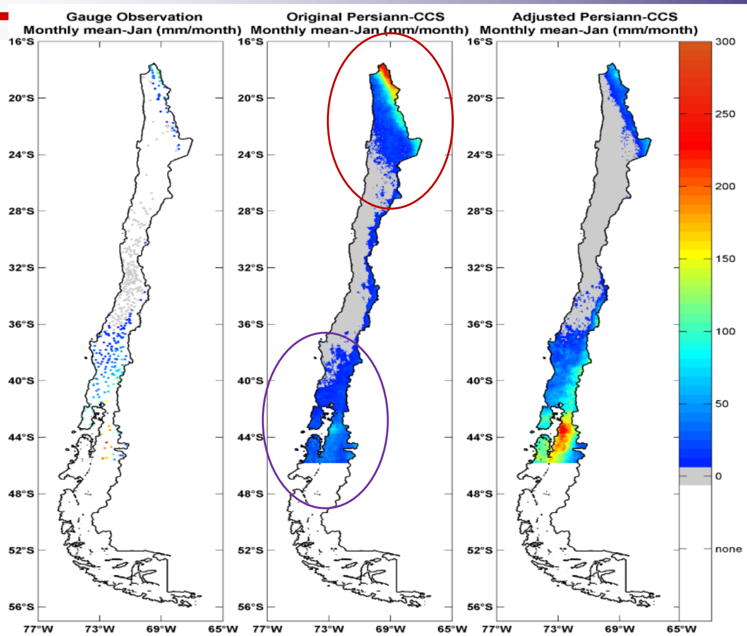




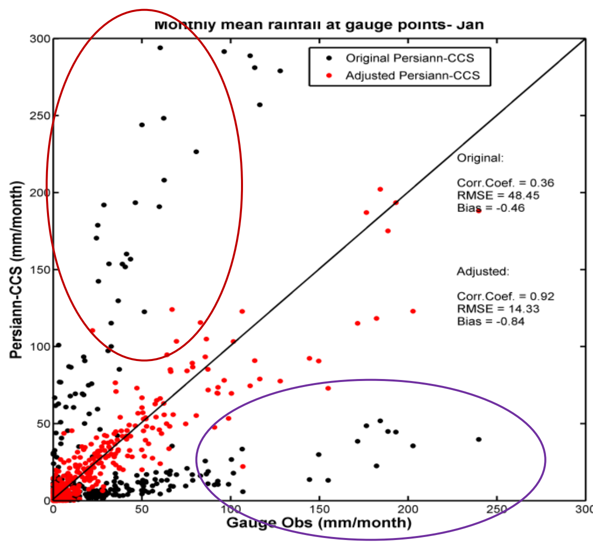
Flowchart for the adjustment of PERSIANN-CCS

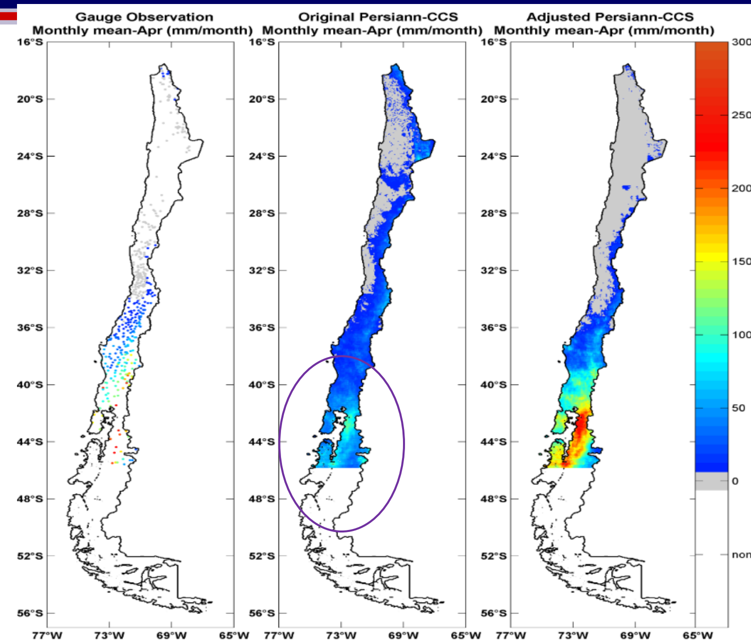


Bias Correction of Monthly Rainfall (5-year average)

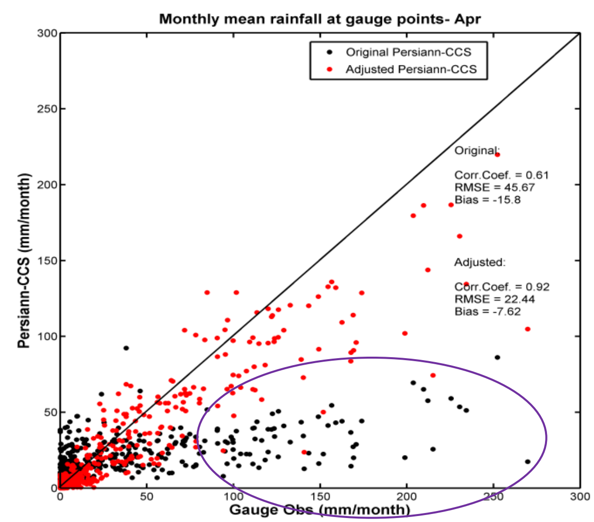


January

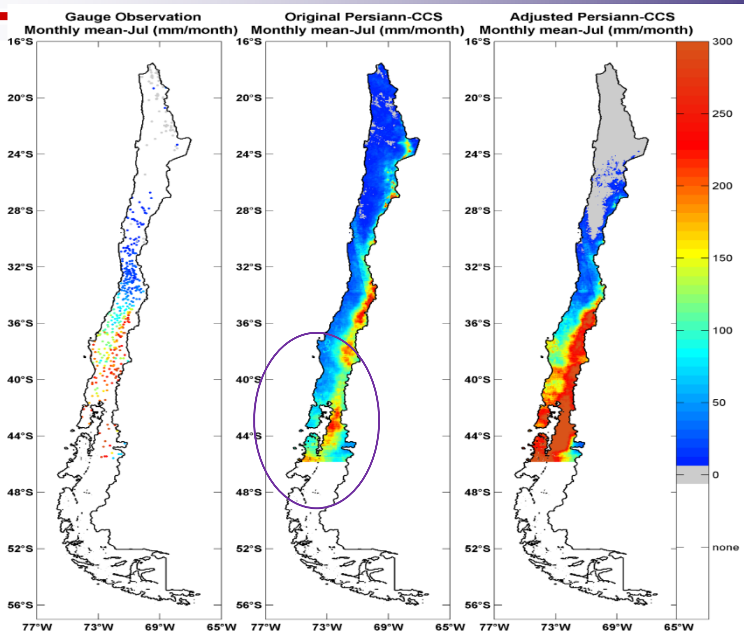




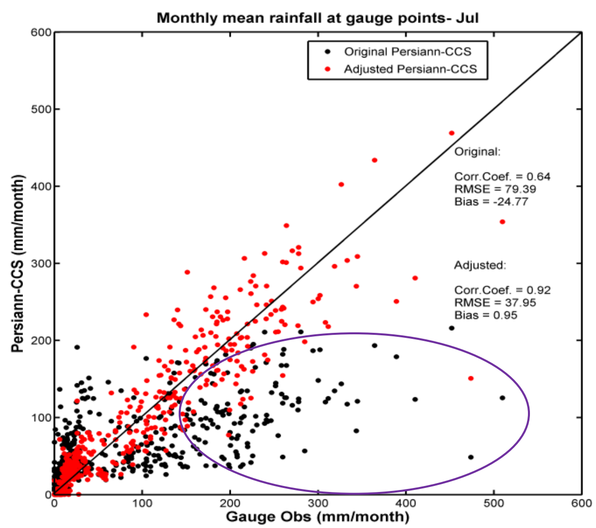
April

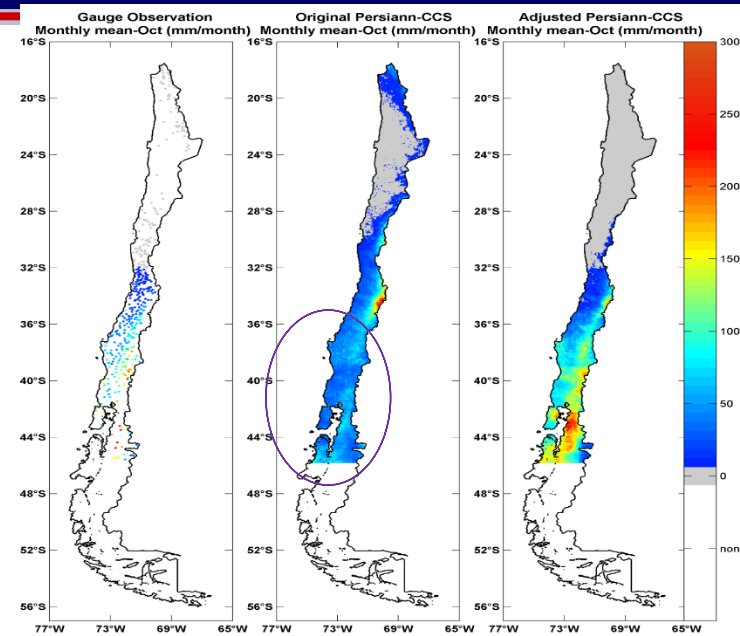


Bias Correction of Monthly Rainfall (5-year average)

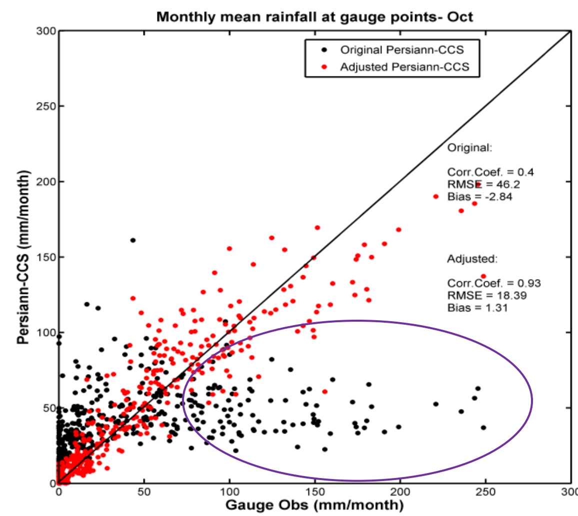


July

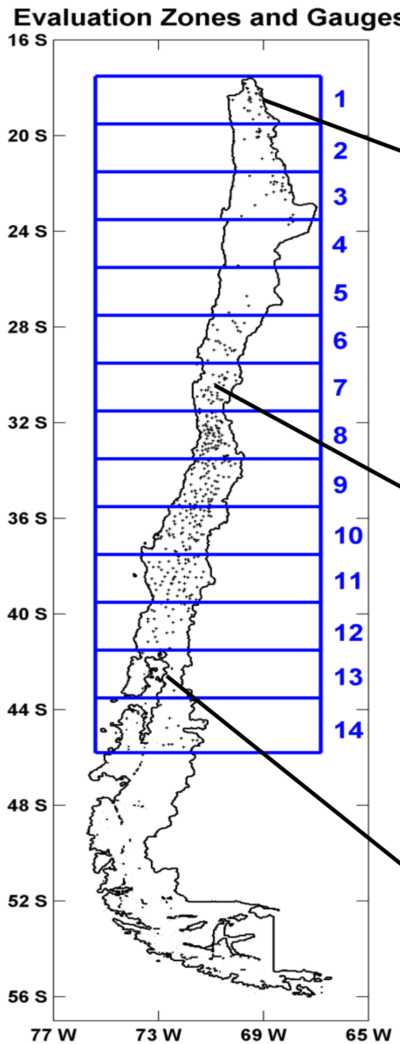


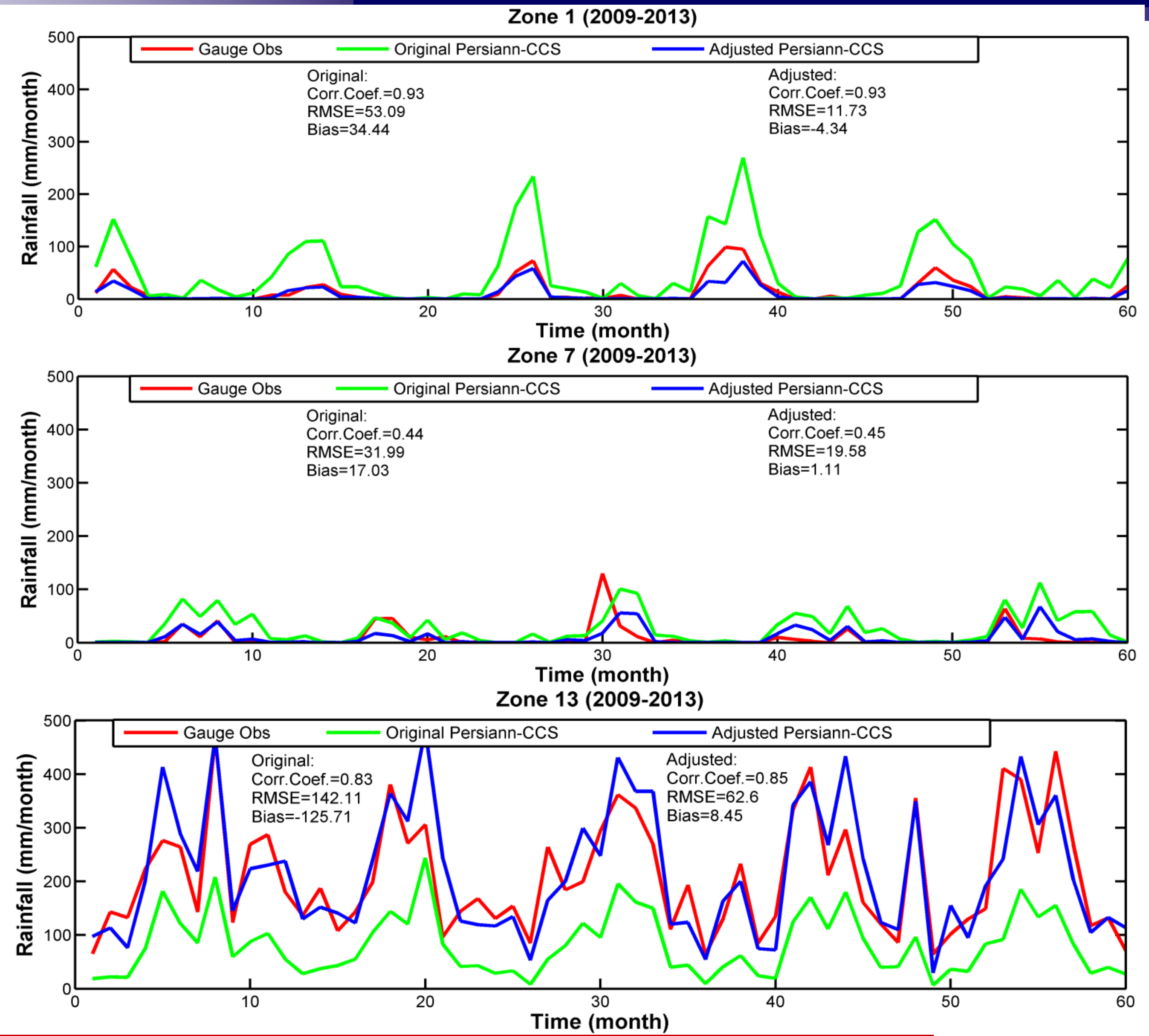


October

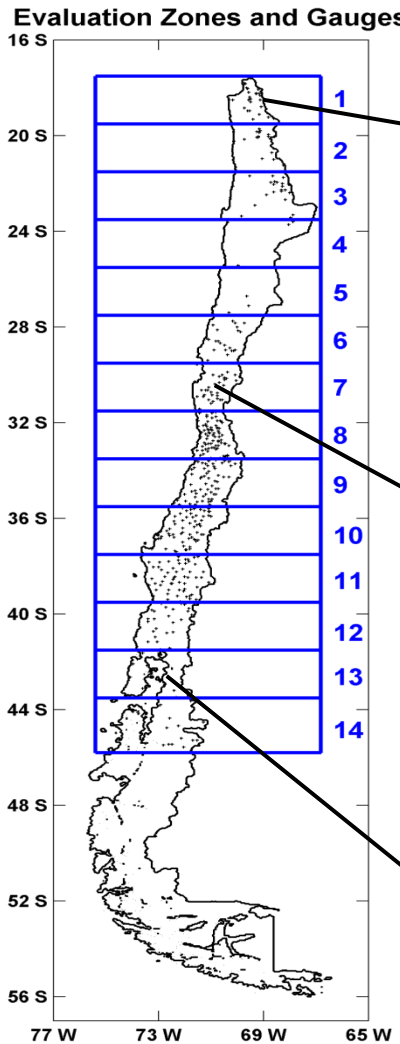


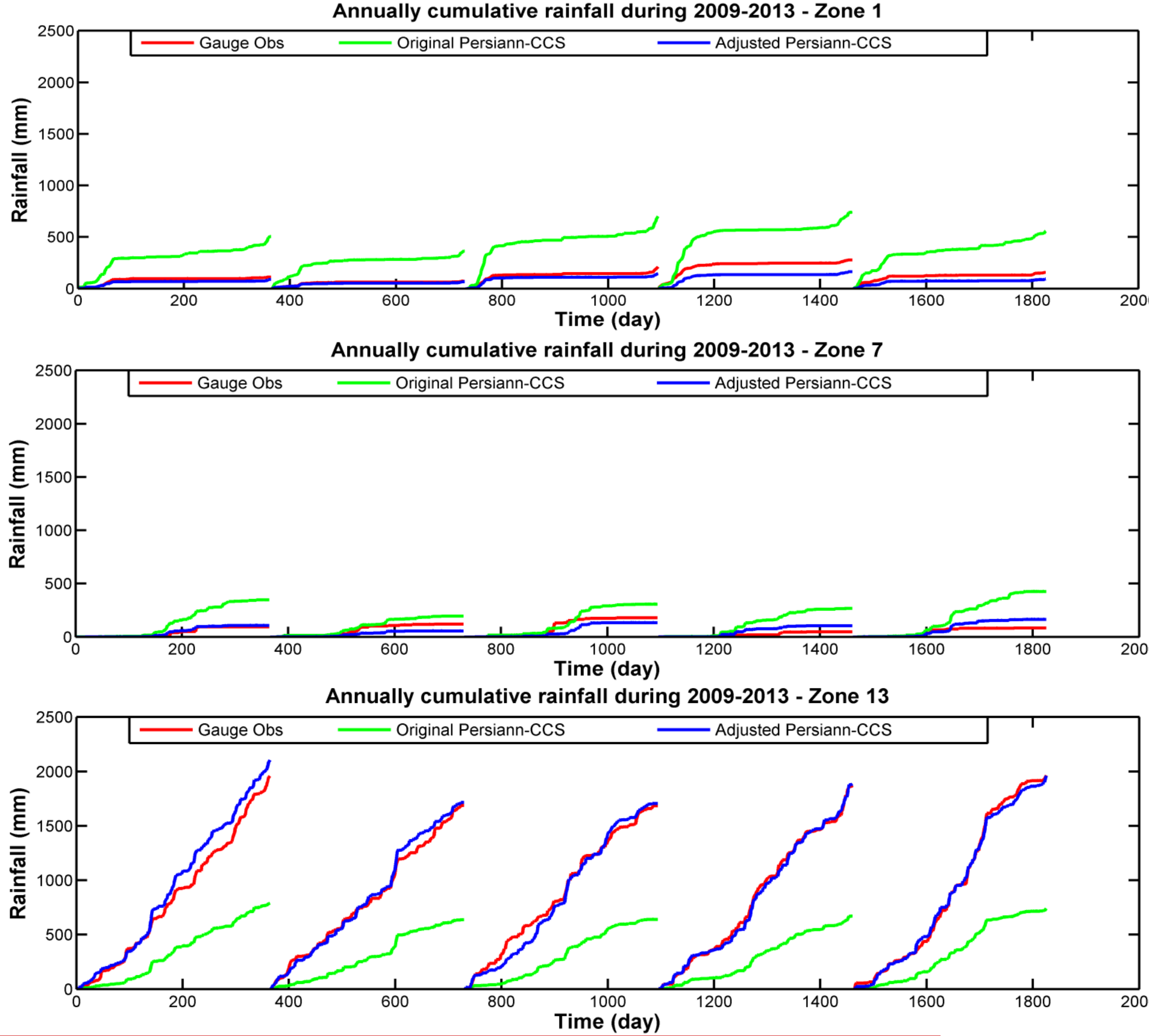
Results: Monthly Time Series (Zonal Average: #1, #7, #13)



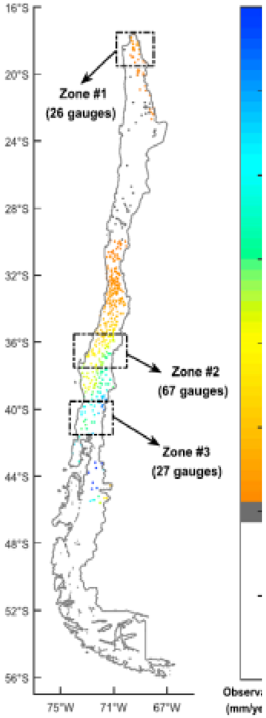


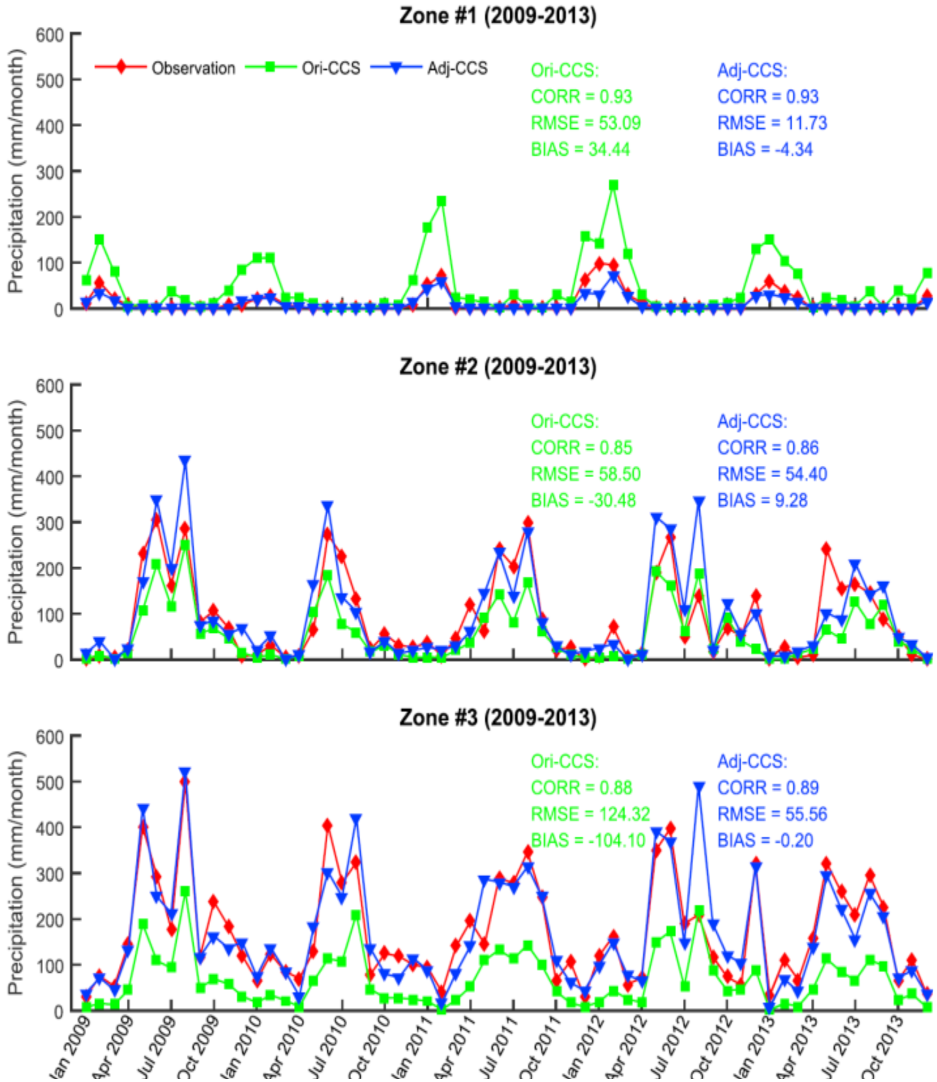
Results: Cumulative Time Series (Zonal Average: #1, #7, #13)

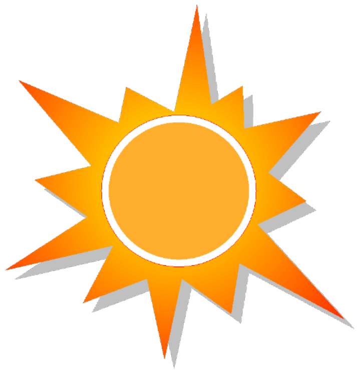




Validation (2014)







Thank you for your attention!