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Supplementary material for

# A multivariate bias correction algorithm for climate model predictions and projections

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**https://meetingorganizer.copernicus.org/EGU23/EGU23-10505.html**

## Contents of this file

Figures S1 to S21 and References.

## Introduction

This supporting information provides some figures that show i) schematic diagram of the different possibilities of model output statistics; ii) complete set of results for Brazil; iii) complete set of results for South Korea and iv) some references.

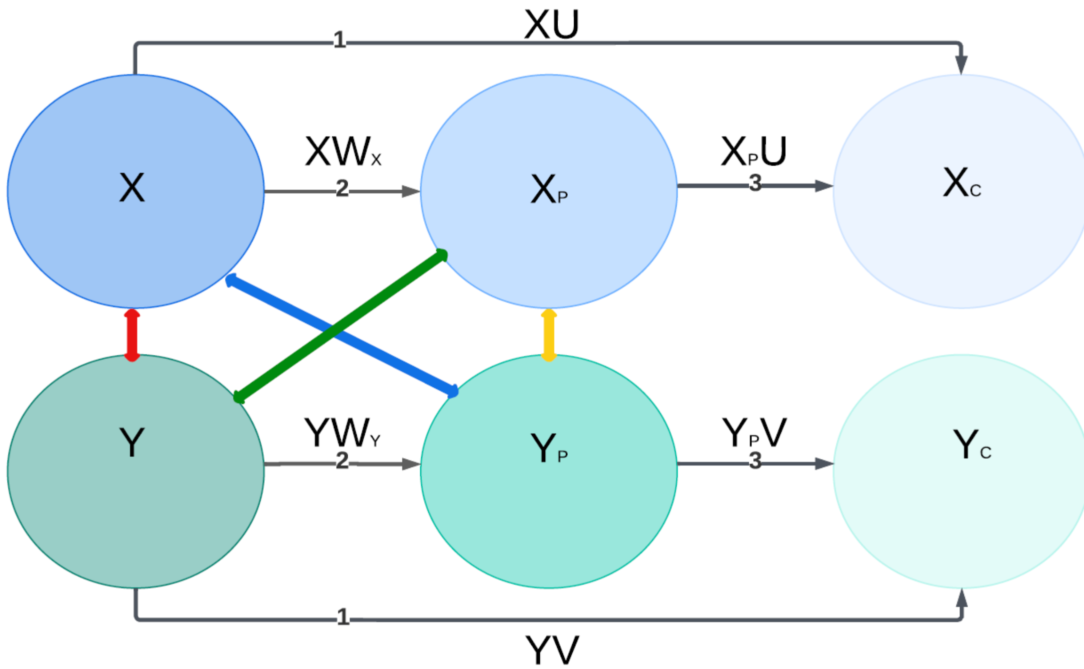


Figure S1 – Schematic diagram of the different possibilities of model output statistics. Here, X is the predictor variable matrix (in our case, the GCM forecasts) at some lead time t, with size n (number of observations) and dimension dx (number of grid points), Y is the response variable matrix (reference rainfall) with size n (number of observations) and dimension dy (number of grid points). Path 1 indicates a canonical correlation transformation with coefficients U and V from the original data space formed by X and Y to the canonical variate space XC and YC. Path 2 highlights the principal component (or sparse principal component) transformation with coefficients WX and WY from the original data space of X and Y to the principal component space of XP and YP. Finally, path 3 shows the canonical correlation transformation presently from the principal component space of XP and YP to the canonical variate space of XC and YC. The colored double sided arrows indicate the associations between the different data spaces in which canonical correlation analysis can be applied to obtain the canonical coefficients U and V. Adapted from Lima et al. (2022), available at [https://doi.org/10.1175/JHM-D-21-0233.1](https://doi.org/10.1175/JHM-D-21-0233.1).

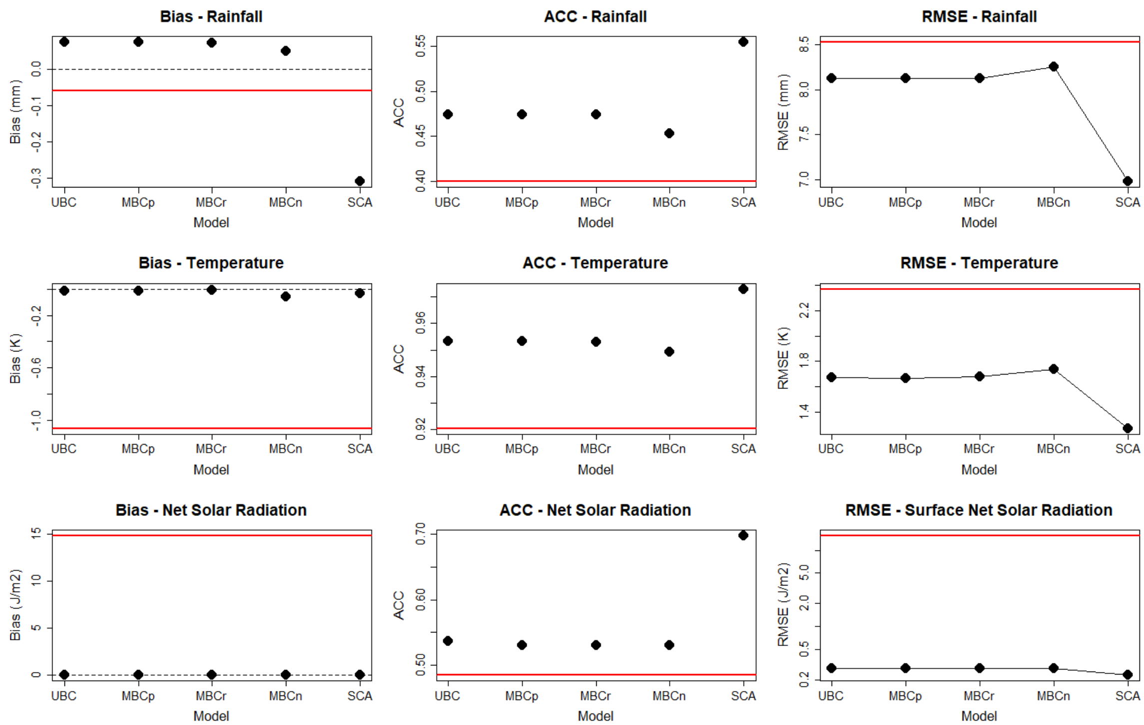


Figure S2 – Average (across days) bias, auto-correlation coefficient (ACC) and RMSE skill scores for Brazil during the training (1993-2016) period for the models: UBC (univariate bias correction based on the quantile delta mapping, see Cannon, 2016), MBCp (multivariate bias correction based on the Pearson correlation, see Bürger et al., 2011 and Cannon, 2016), MBCr (multivariate bias correction based on the rank correlation, see Bürger et al., 2011 and Cannon, 2016), MBCn (multivariate bias correction based on the N-dimensional probability density function transform, see Cannon, 2018) and proposed model (SCA) based on sparse PCA and CCA (see applications in Figure S1 and Lima et al., 2022 for details). The red lines show the metrics obtained for the raw forecast data without any bias correction.

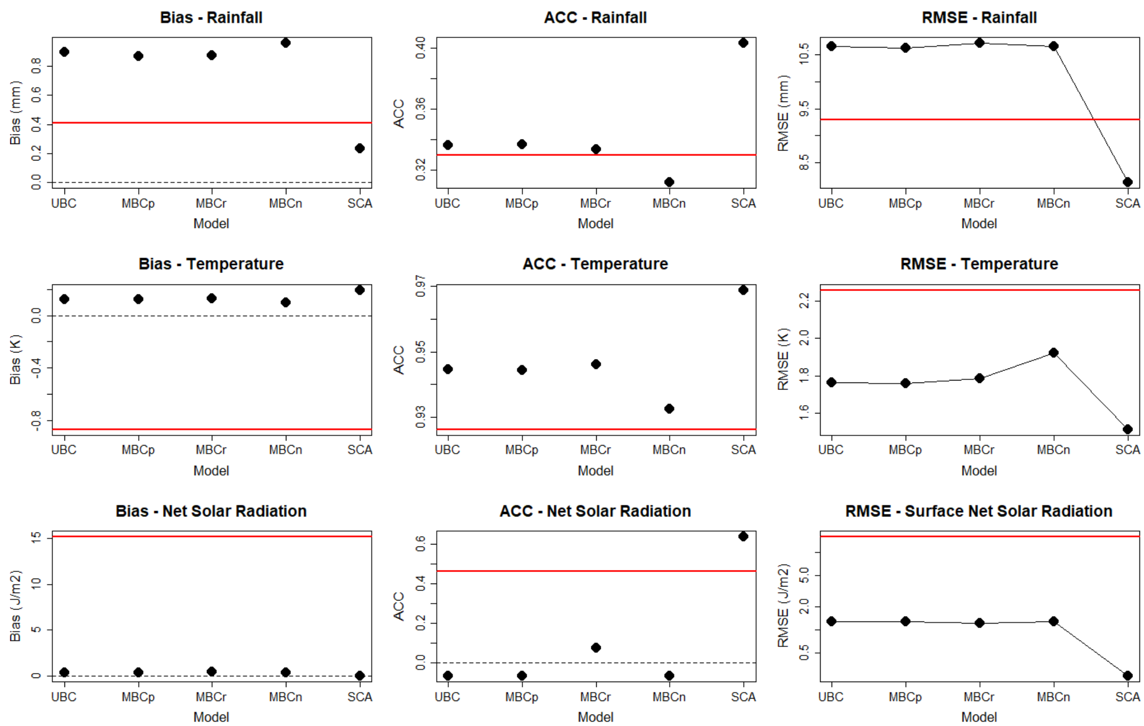


Figure S3: As in Figure S2, but for the testing period (2017-2021).

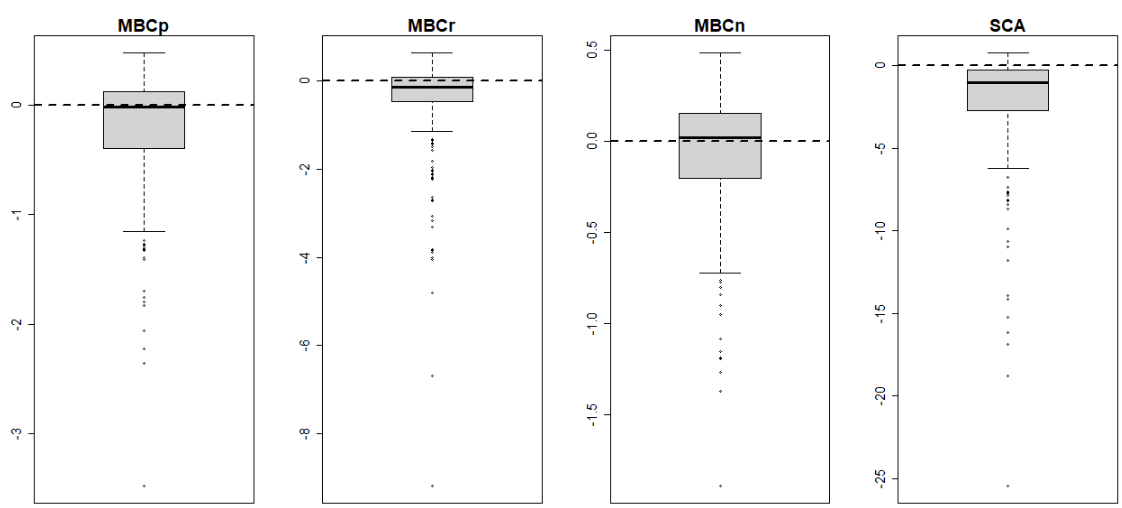


Figure S4: Distribution (across grid points) of the energy distance skill score (ESS, see Cannon, 2016 for details) for Brazil during the training (1993-2016) period. The ESS score is relative to the reference UBC model, so values greater than zero (dashed line) indicate a superior performance of the tested model over UBC.

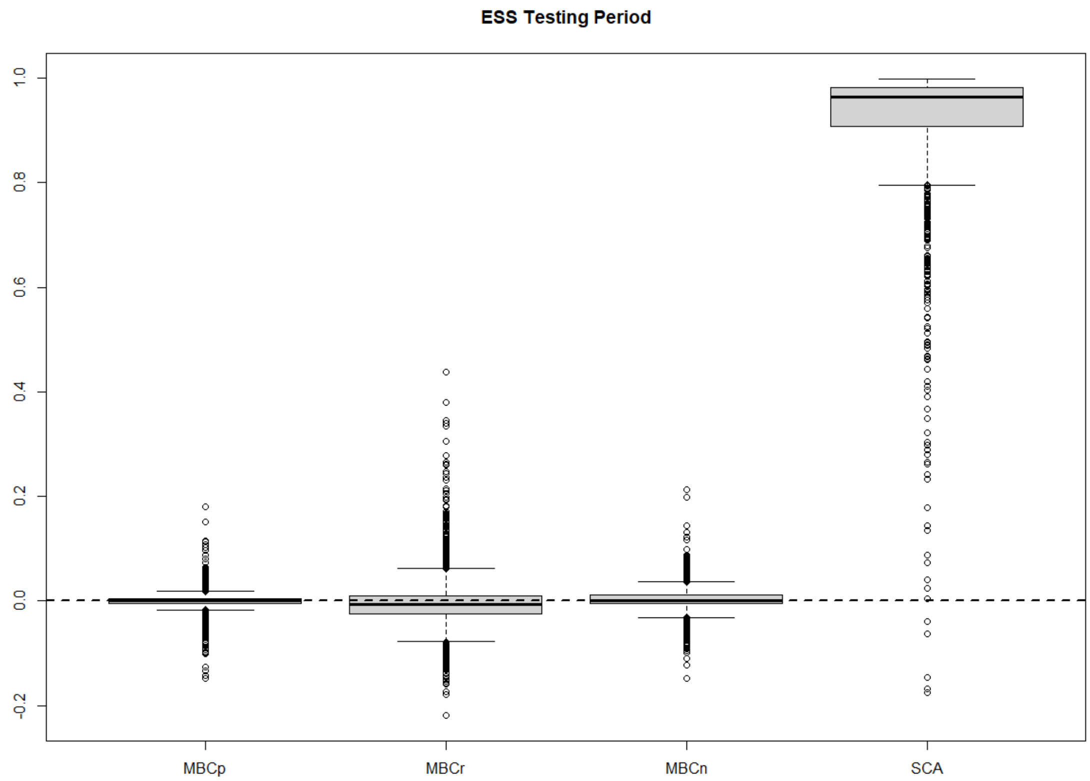


Figure S5: As in Figure S4, but for the testing period (2017-2021).

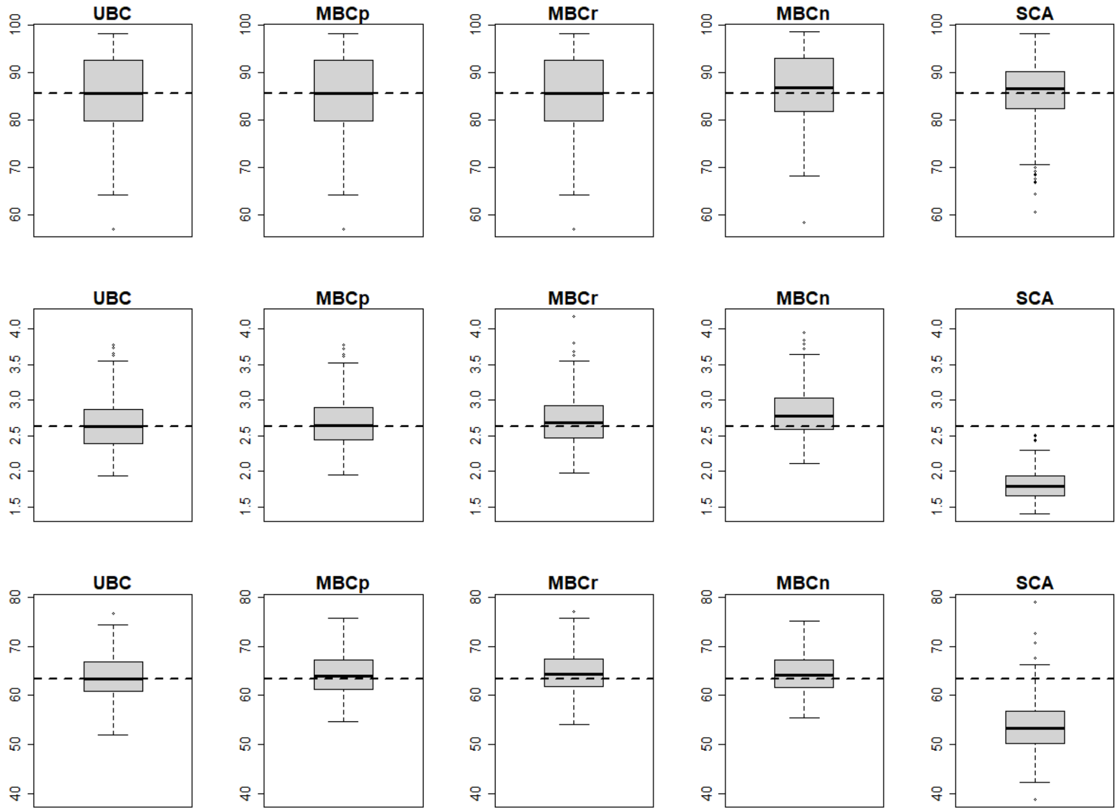


Figure S6: Distribution (across days) of S1 skill score (see Lima et al., 2022 for details) for Brazil during the training (1993-2016) period for rainfall (top row), temperature (middle row) and net solar radiation (bottom row). The lowest the values, the better the skill in reproducing the spatial variability of the gradient of the reference field. The dashed lines show the value of the UBC model (left hand panels).

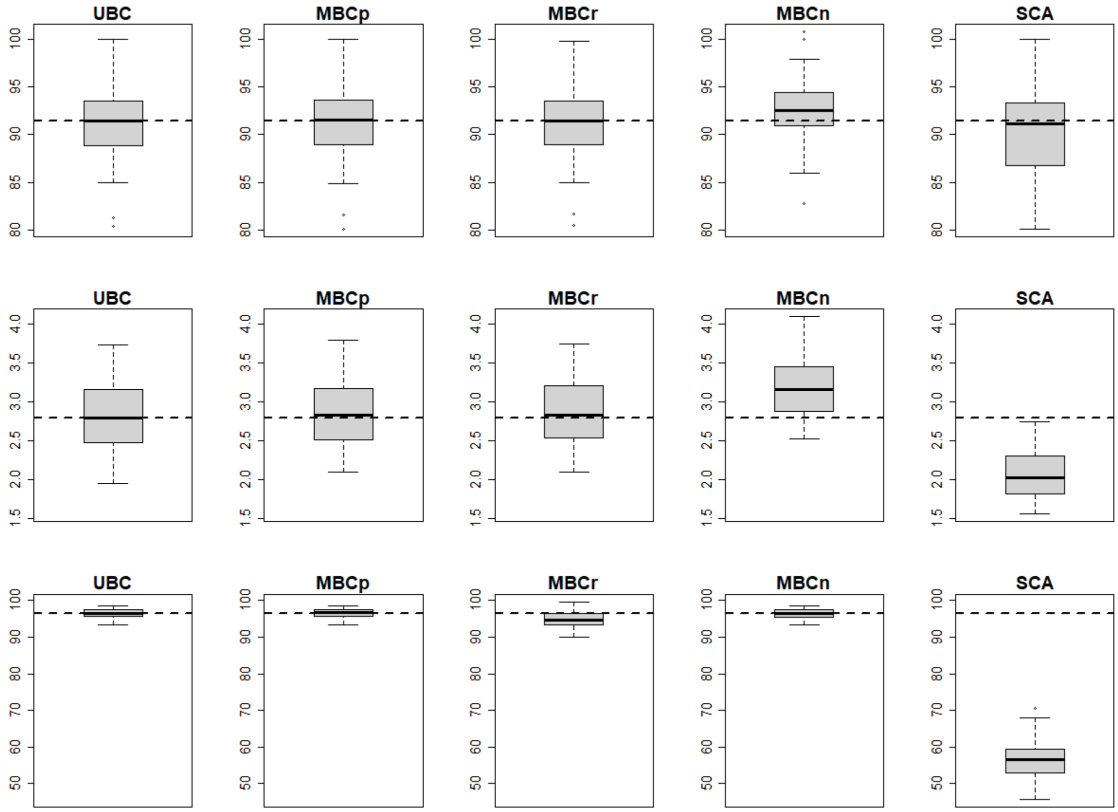


Figure S7: As in Figure S6, but for the testing period (2017-2021).

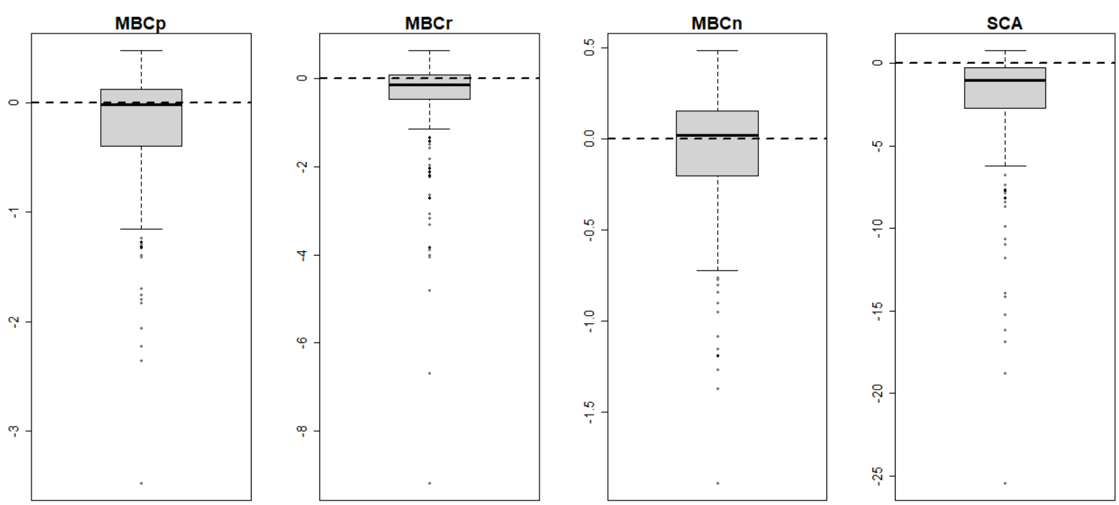


Figure S8: Distribution (across days) of the energy distance skill score (ESS, see Cannon, 2016 for details) applied for the multivariate distribution (of precipitation, temperature and solar radiation) of a single day for Brazil during the training (1993-2016) period. The ESS score is relative to the reference UBC model, so values greater than zero indicate a superior performance of the tested model over UBC.

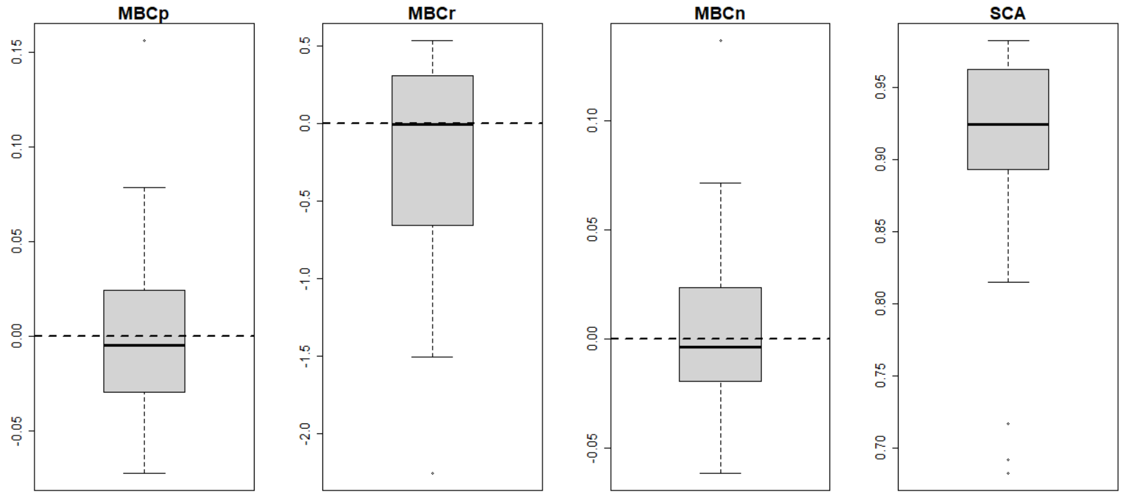


Figure S9: As in Figure S8, but for the testing period (2017-2021).

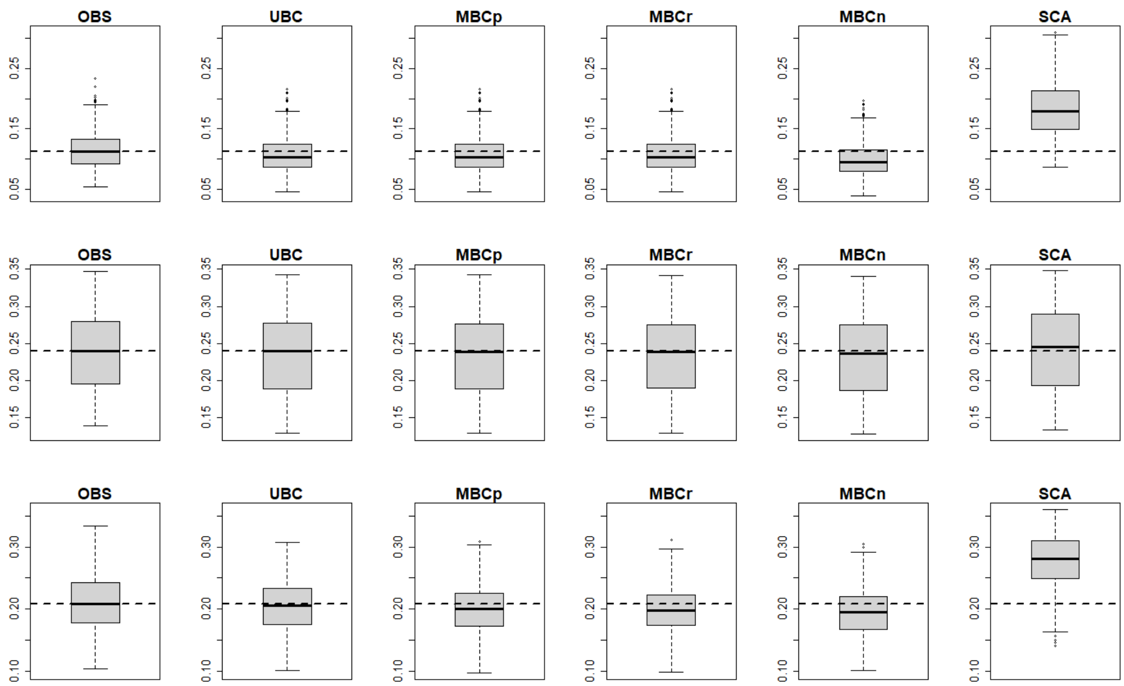


Figure S10: Distribution (across days) of the Moran´s I skill score (see Cannon, 2018 for details) for Brazil during the training (1993-2016) period. The dashed lines show the median values of the reference (OBS) data (left hand panels).

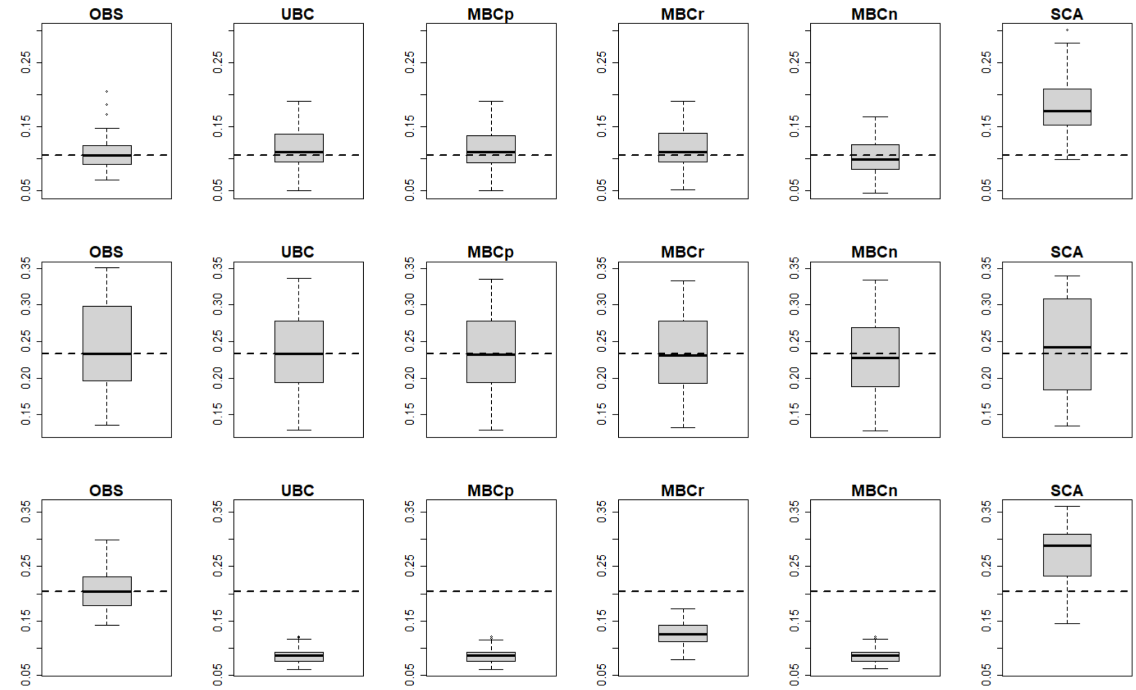


Figure S11 – As in Figure S10, but for the testing period (2017-2021).

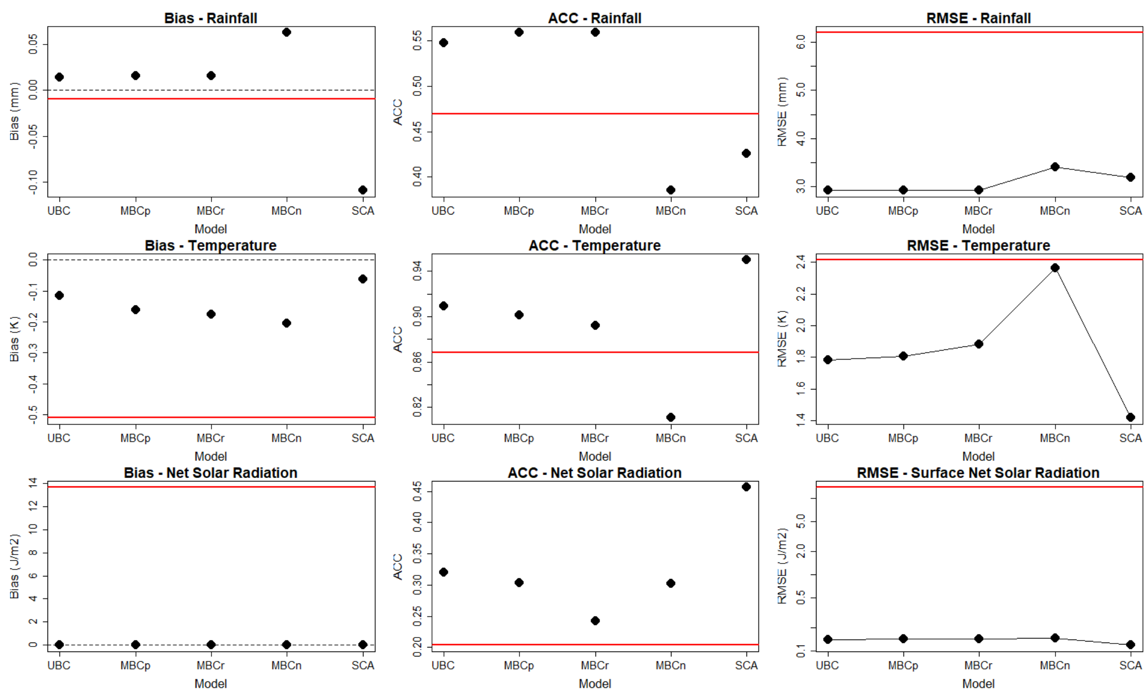


Figure S12 – As in Figure S2, but for South Korea.

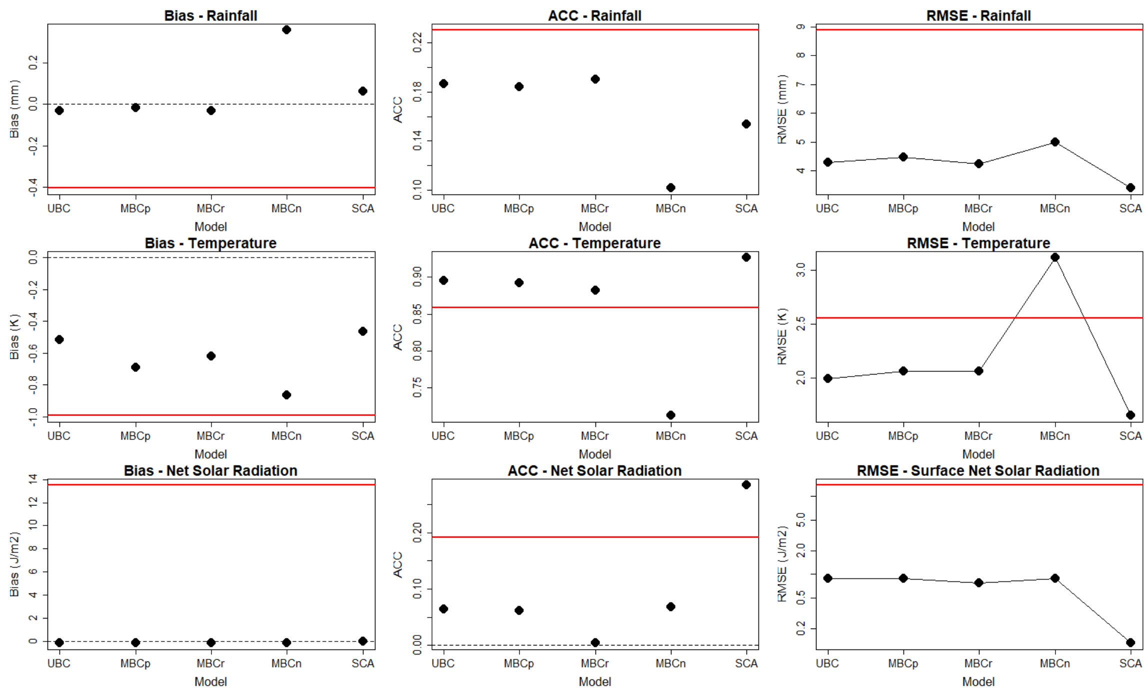


Figure S13 – As in Figure S3, but for South Korea.

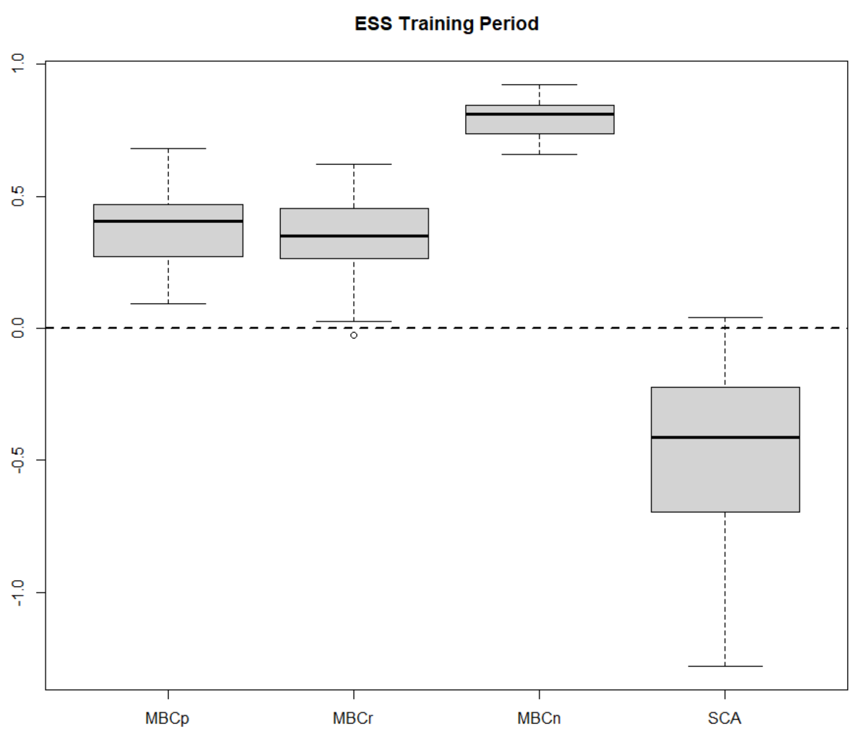


Figure S14 – As in Figure S4, but for South Korea.

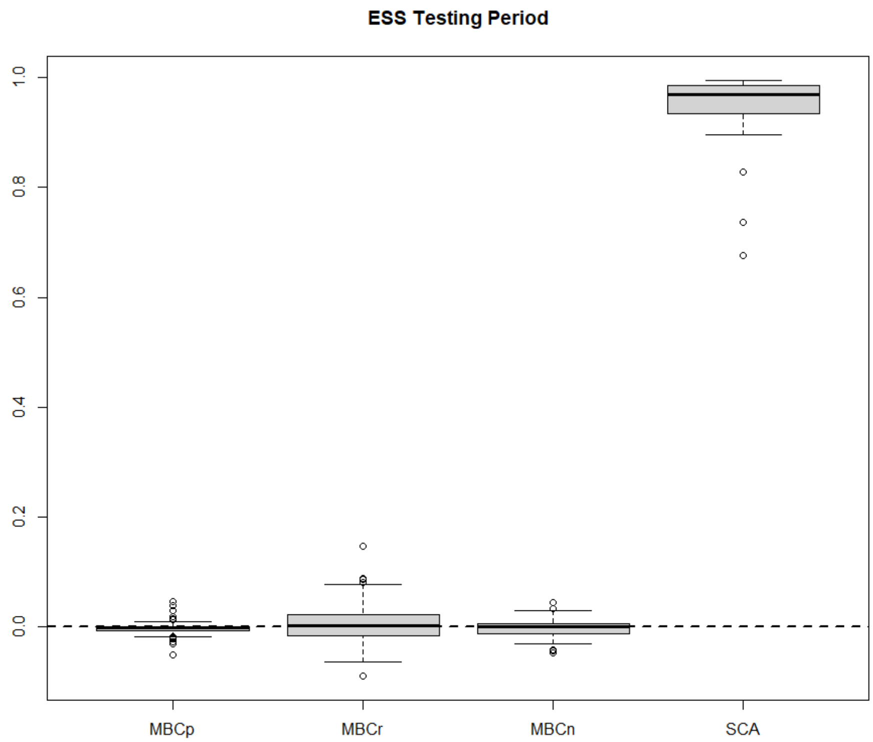


Figure S15 – As in Figure S5, but for South Korea.

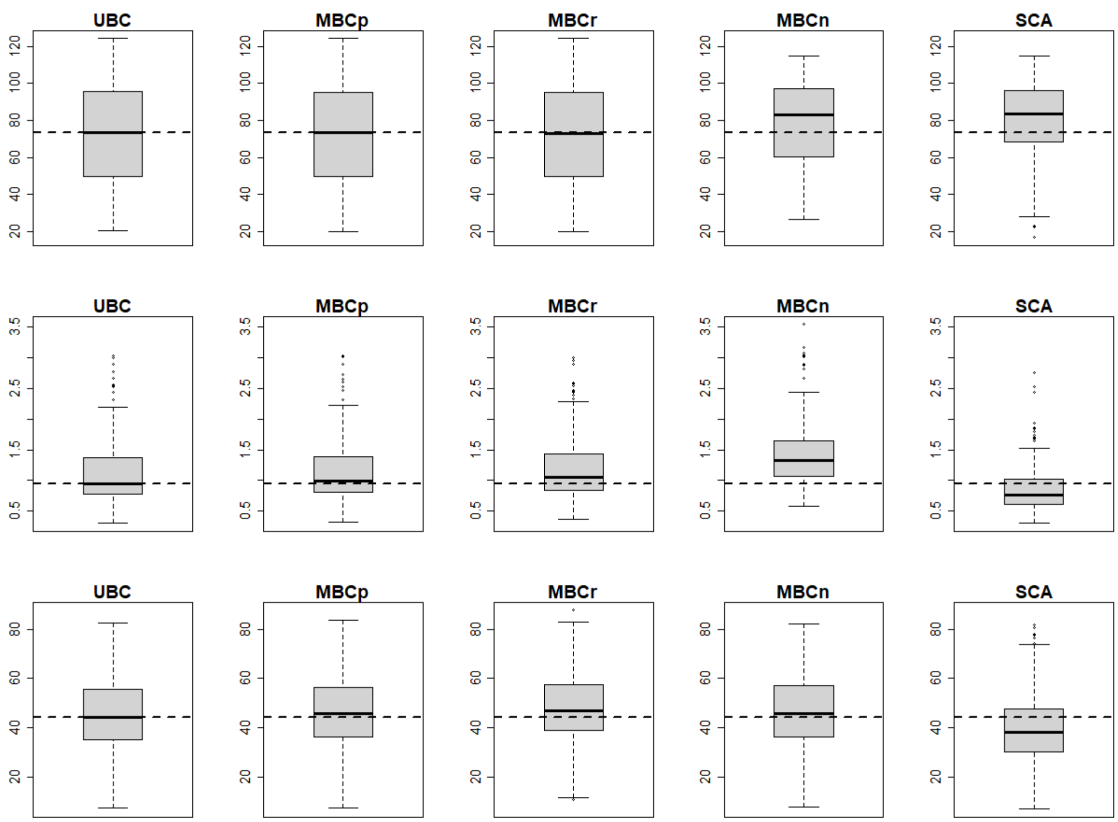


Figure S16 – As in Figure S6, but for South Korea.

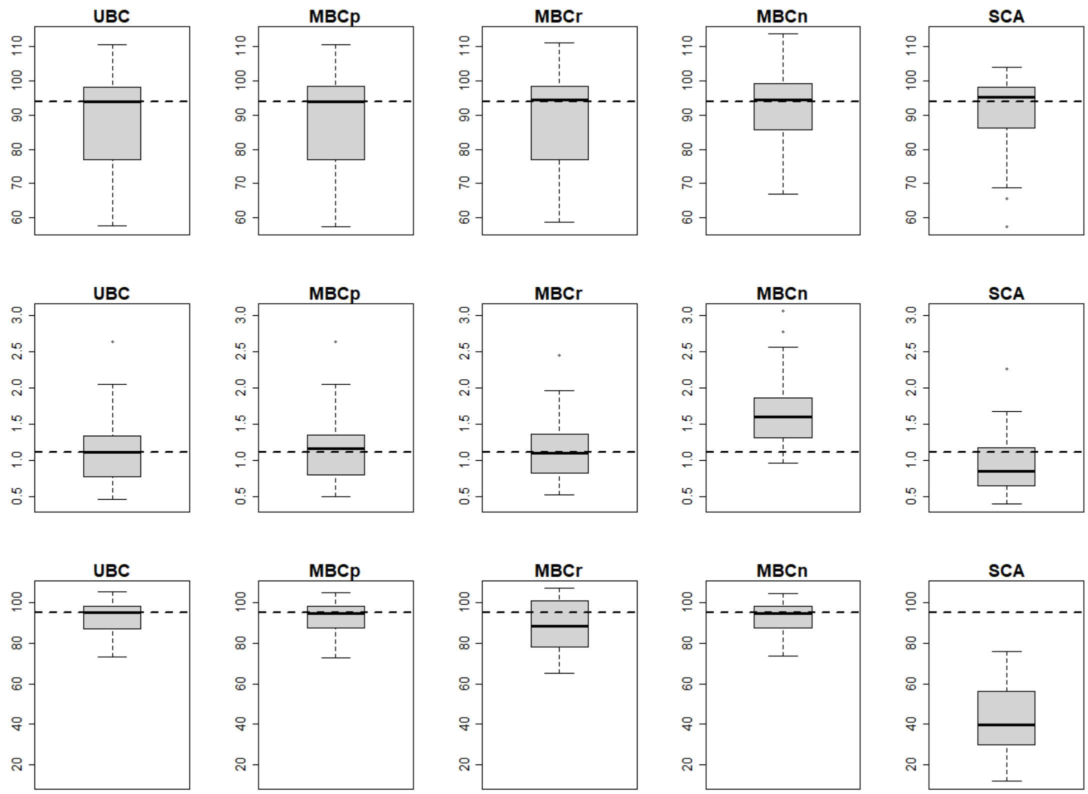


Figure S17 – As in Figure S7, but for South Korea.

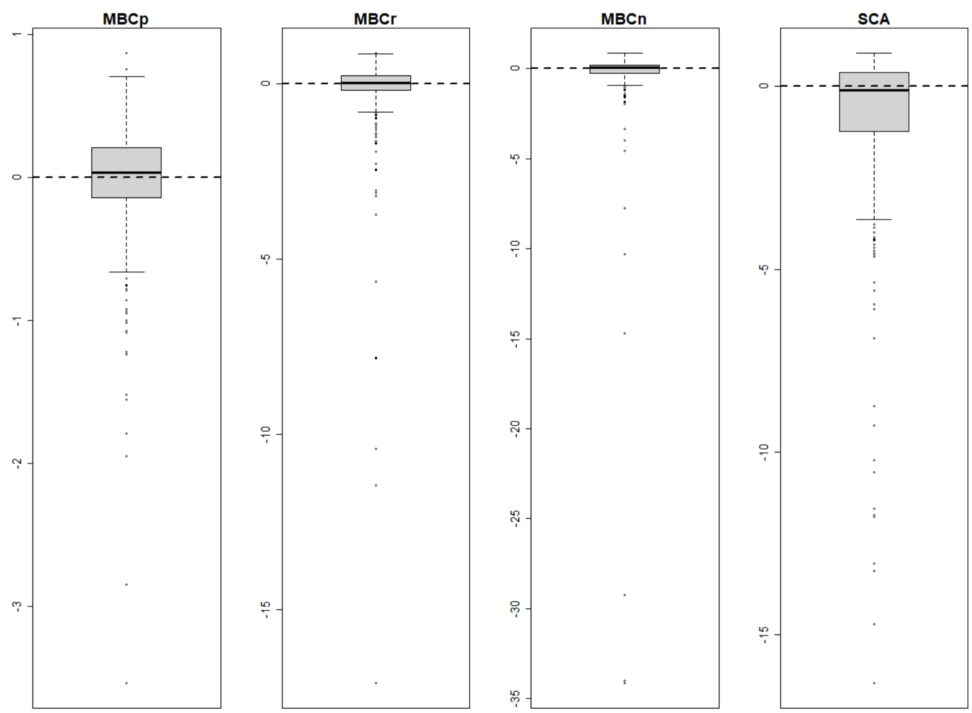


Figure S18 – As in Figure S8, but for South Korea.

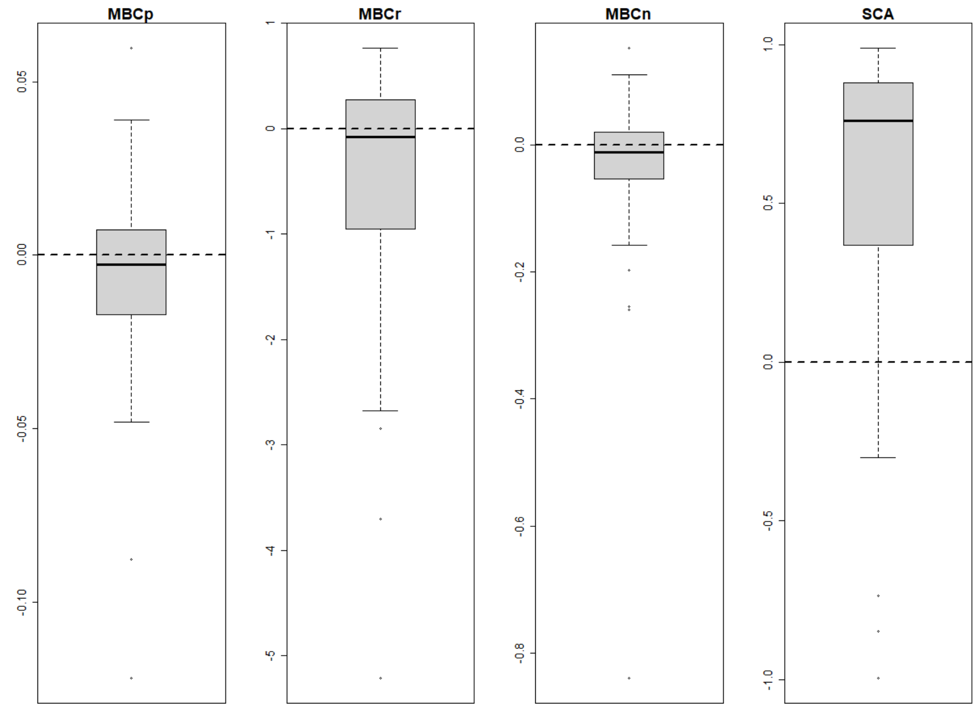


Figure S19 – As in Figure S9, but for South Korea.

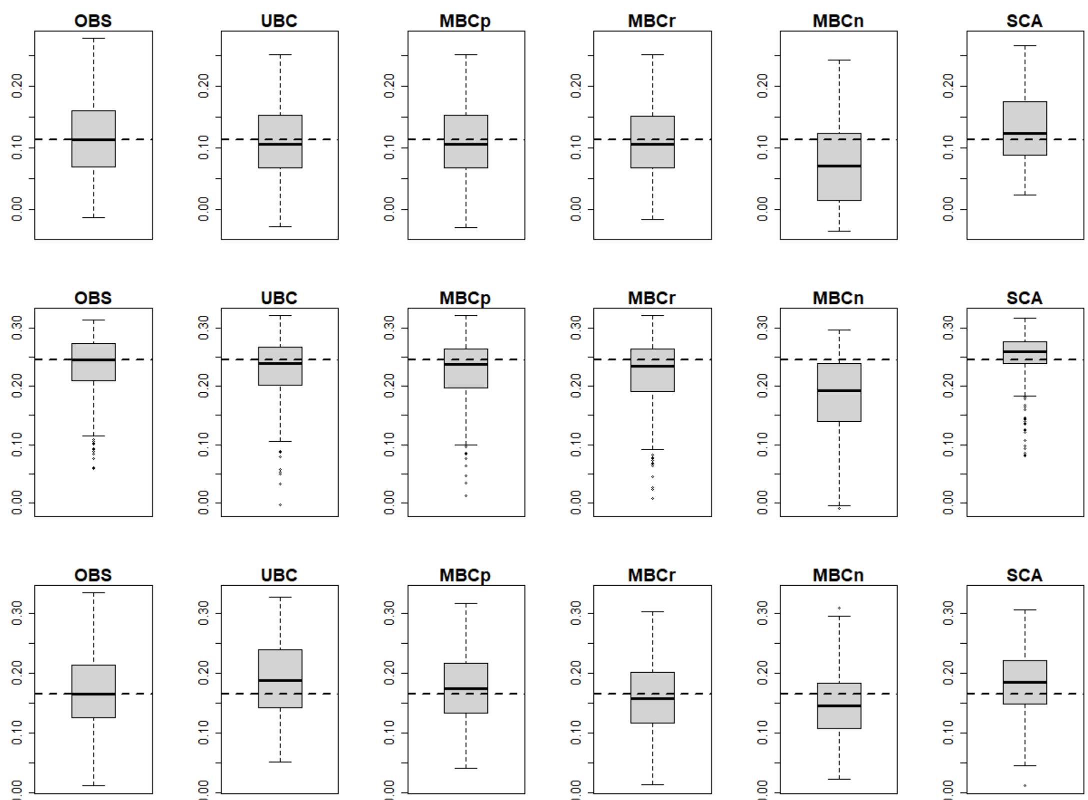


Figure S20 – As in Figure S10, but for South Korea.

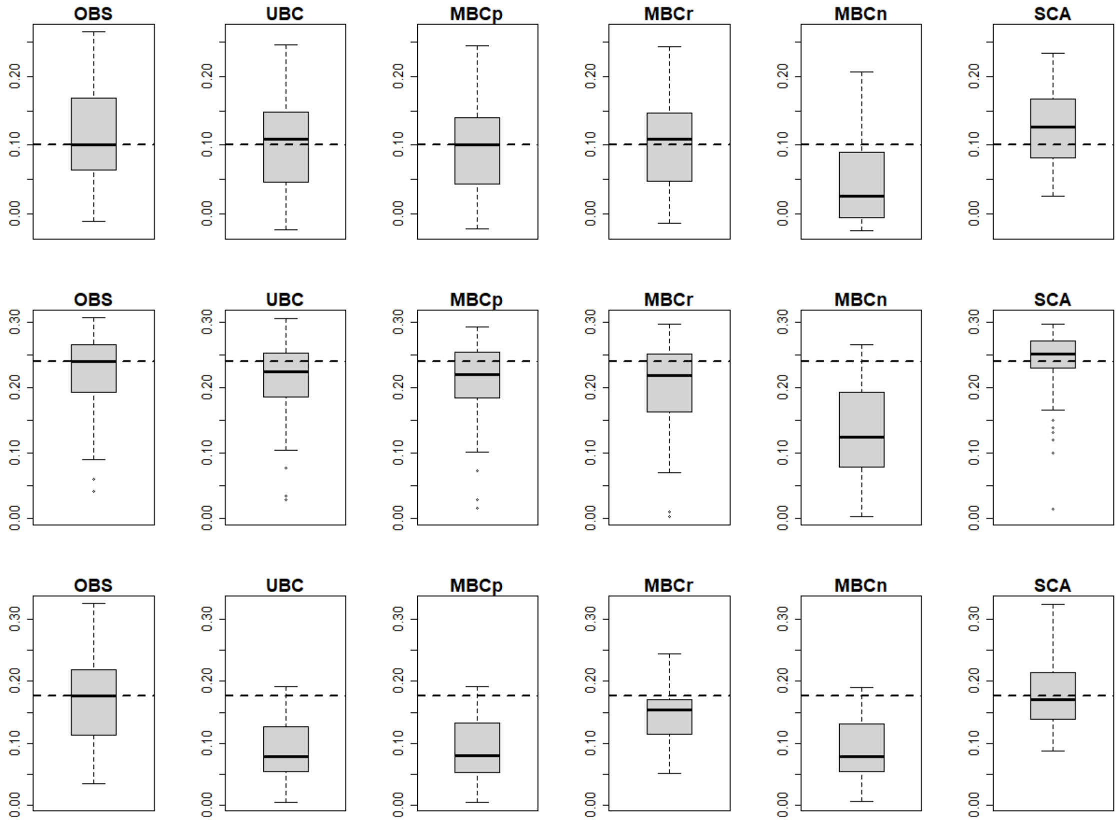


Figure S21 – As in Figure S11, but for South Korea.

## REFERENCES

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