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1 **Statistical adjustment, calibration and downscaling of**  
2 **seasonal forecasts: A case-study for Southeast Asia**

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8 **Abstract** The present paper is a follow-on of the work presented in Manzananas  
9 et al (2019) which provides a comprehensive intercomparison of alternatives for  
10 the post-processing (statistical adjustment, calibration and downscaling) of sea-  
11 sonal forecasts for a particularly interesting region, Southeast Asia. To answer the  
12 questions that were raised in the preceding work, apart from Bias Adjustment  
13 (BA) and ensemble Re-Calibration (RC) methods —which transform directly the  
14 variable of interest,— we include here more complex Perfect Prognosis (PP) and  
15 Model Outputs Statistics (MOS) downscaling techniques —which operate on a  
16 selection of large-scale model circulation variables linked to the local observed  
17 variable of interest.— Moreover, we test the suitability of BA and PP methods  
18 for the post-processing of daily —not only seasonal— time-series, which are often  
19 needed in a variety of sectoral applications (crop, hydrology, etc.) or to compute  
20 specific climate indices (heat waves, fire weather index, etc.). In addition, we also  
21 undertake an assessment of the effect that observational uncertainty may have for  
22 statistical post-processing.  
23 Our results indicate that PP methods (and to a lesser extent MOS) are highly case-  
24 dependent and their application must be carefully analyzed for the region/season/application  
25 of interest, since they can either improve or degrade the raw model outputs. There-  
26 fore, for those cases for which the use of these methods cannot be carefully tested

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27 by experts, our overall recommendation would be the use of BA methods, which  
28 seem to be a safe, easy to implement alternative that provide competitive results in  
29 most situations. Nevertheless, all methods (including BA ones) seem to be sensitive  
30 to observational uncertainty, especially regarding the reproduction of extremes and  
31 spells. For MOS and PP methods, this issue can even lead to important regional  
32 differences in interannual skill. The lessons learnt from this work can substantially  
33 benefit a wide range of end-users in different socio-economic sectors, and can also  
34 have important implications for the development of high-quality climate services.

## 35 1 Introduction

36 The state-of-the-art General Circulation Models (GCMs) used for seasonal fore-  
37 casting suffer from important systematic biases (mean errors) and drifts (leadtime-  
38 dependent biases) and have horizontal resolutions which are typically coarser  
39 than those needed for practical applications (see, e.g., Doblas-Reyes et al, 2013;  
40 Manzananas et al, 2014a). Therefore, some form of post-processing (i.e. adjust-  
41 ment, calibration and/or downscaling) is needed in order to make their raw out-  
42 puts usable. In a recent study, Manzananas et al (2019) intercompared the per-  
43 formance of Bias Adjustment (BA) —e.g. quantile mapping— and ensemble Re-  
44 Calibration (RC) —e.g. non-homogeneous Gaussian regression— methods for the  
45 adjustment/calibration of seasonal aggregated forecasts. At this particular time-  
46 scale, they found that the RC methods can result in modest improvement of  
47 some quality aspects (in particular reliability), although other aspects can be de-  
48 graded. Nevertheless, these improvements are restricted to regions/seasons with  
49 high model skill. In addition, these methods can be negatively affected by the lim-  
50 ited length of state-of-the-art seasonal hindcasts (which typically have less than 30  
51 years). They also found that, beyond removing their systematic biases, BA meth-  
52 ods can not improve the skill of the raw model forecasts (even more, some quality  
53 aspects can be degraded), since they do not modify their temporal structure.  
54 However, the application of these methods is straightforward and may constitute  
55 a pragmatic and simple alternative when the resolution of the model is similar to  
56 that of the observational reference (BA methods are not suitable for downscal-  
57 ing), or for regions with no expected potential for downscaling (e.g. flat inland  
58 regions). Moreover, beyond the adjustment of monthly/seasonal values, Manzananas  
59 et al (2019) pointed out the fact that BA techniques can be also applied to adjust  
60 daily data, which are often demanded in a variety of sectoral applications in order  
61 to run impact models (crop, hydrology, etc.) or to compute specific climate indices  
62 (heat waves, length of growing index, thermal comfort index, fire weather index,  
63 etc.).

64 Therefore, we put a special focus in this work on the post-processing of daily  
65 (rather than monthly/seasonal) values. For this aim, we consider not only BA  
66 methods acting directly on the variable of interest, but also more complex Perfect  
67 Prognosis (PP) downscaling techniques (see, e.g., Gutiérrez et al, 2013) which op-  
68 erate on a selection of large-scale model circulation variables (predictors) linked to  
69 the local observed variable of interest (predictand). Although there has been some  
70 indication that PP methods may add some value in terms of skill (e.g. interan-  
71 nual correlation) for cases where the dynamical model is better at reproducing the  
72 relevant large-scale features than the target variable being predicted (Manzananas

et al, 2018), they have the extra complexity of building the predictor-predictand relationship at a daily basis using reanalysis data (which provide day-to-day correspondence with observations). Typically, this requires a highly time-consuming screening process to detect robust predictors which are similarly represented in both the reanalysis and hindcast datasets. Moreover, PP methods may suffer from reanalysis uncertainty, which is particularly relevant in tropical regions (Brands et al, 2012; Manzanas et al, 2015). Therefore, in this type of methods, the existing windows of opportunity for improvement can be so narrow that the effort may be disproportionate to the benefit.

Moreover, we also include in this study Model Output Statistics (MOS) downscaling methods (see, e.g., Vannitsem and Nicolis, 2008), which are trained with predictors taken from the same GCM that is being postprocessed. A simple implementation of these methods considers as the only predictor variable the target predictand, e.g., coarse GCM precipitation for local precipitation. Following Manzanas et al (2019), these methods are included as part of the RC approach in this work. Standard downscaling MOS implementations consider large-scale variables from the GCM as predictors (see, e.g., Manzanas et al, 2017). These are referred to as MOS hereafter. Note that, as the relationship between the large-scale seasonal forecasts and observational reference records is established using directly the hindcast (without passing through reanalysis), the complexity and requirements for MOS methods are much lower than for PP ones. However, as for the case of RC methods, the main shortcoming of these techniques is that they can only be applied on monthly/seasonal data, since GCM predictors do not keep temporal correspondence with the local observations at the daily scale.

Given the complexity of this panorama, the relative merits and limitations of the approaches and techniques available for post-processing of seasonal forecasts need to be properly assessed. This is done here by intercomparing the performance of the alternatives described above based on different aspects of forecast quality: association, accuracy and discrimination for seasonally aggregated times-series and reproduction of extremes and spells for daily time-series. Besides, following from the fact that all the adjustment/calibration/downscaling methods rely on observations for the training process, observational uncertainty (see, e.g. Kotlarski et al, 2017; Herrera et al, 2018) may play a role in the statistical post-processing of model forecasts. To shed some light on this potential issue, we also undertake here a comprehensive assessment of the effect of this kind of uncertainty in the context of seasonal forecasting.

Jointly with the work done in Manzanas et al (2019), this study provides practical recommendations for the suitable post-processing of seasonal forecasts, which can substantially benefit a wide range of end-users in different socio-economic sectors, and can also have important implications for the development of high-quality climate services (see, e.g., Torralba et al, 2017).

The paper is organized as follows. In Section 2 we describe the data used and introduce the different methods applied and the verification metrics considered. The results obtained are presented through Section 3. The main conclusions obtained and a set of practical user recommendations are outlined in Section 4.

**Table 1** Potential predictor variables considered for the MOS and PP methods.

Code	Variable	Levels
SLP	Mean sea level pressure	Surface
Z	Geopotential height	850, 500, 300 (mb)
T	Temperature	850, 500, 300 (mb)
Q	Specific humidity	850, 500, 300 (mb)
U	Zonal component of wind	850, 500, 300 (mb)
V	Meridional component of wind	850, 500, 300 (mb)

## 118 2 Data and Methods

### 119 2.1 Data Used

120 We focus in this work on one illustrative region (Southeast Asia: 95-140° E, 10°  
 121 S-20° N) and season (boreal winter: DJF), for which overall good skill has been  
 122 documented (see, e.g., Manzananas et al, 2014b). As explained later, the choice of  
 123 this region is also supported by the fact that a high-quality observational grid is  
 124 available —SA-OBS (van den Besselaar et al, 2017),— which allows for an inter-  
 125 esting analysis of the effect of observational uncertainty on the results obtained  
 126 from the different post-processing techniques (see Section 3.2).

127 We consider one-month lead seasonal forecasts (i.e. predictions initialized in  
 128 November) of both temperature and precipitation from the ECMWF-System4  
 129 (Molteni et al, 2011), which provides the longest seasonal hindcast to-date —note  
 130 that one of the main conclusions of Manzananas et al (2019) is that as long as  
 131 possible hindcasts are needed for robust adjustment/calibration.— In particular,  
 132 we use here all the 51 members that are available for the November initialization  
 133 (only 15 members are available for other initializations) along the period 1982-  
 134 2014.

135 Besides the target variables of interest (temperature and precipitation) used  
 136 for BA and RC methods, the large-scale variables listed in Table 1 were considered  
 137 as potential predictors for MOS and PP methods in this work. For the training  
 138 phase of the PP methods, these predictor variables are taken from ERA-interim  
 139 reanalysis (Dee et al, 2011). In this case, ERA-Interim and ECMWF-System4 data  
 140 are harmonized by performing a simple local scaling to the latter. In particular,  
 141 for every large-scale model predictor, monthly mean values were adjusted towards  
 142 the corresponding reanalysis values, gridbox by gridbox, avoiding thus problems  
 143 that may arise due to the model mean biases.

144 We consider ERA-Interim as the common observational reference along the  
 145 study. However, for the assessment of the effect of observational uncertainty un-  
 146 dertaken in Section 3.2, we also consider two other datasets for precipitation:  
 147 SA-OBS and MSWEP. SA-OBS a high-quality observational dataset which pro-  
 148 vides daily gridded (0.25° spatial resolution) temperature and precipitation over  
 149 land for Southeast Asia. It has been built based on more than 8000 meteorological  
 150 stations and can be freely downloaded from <http://sacad.database.bmkg.go.id>.  
 151 MSWEP (version 1) (Beck et al, 2017) is a global terrestrial precipitation dataset  
 152 with a high 3-hourly temporal and 0.25° spatial resolution which combines gauge,  
 153 satellite and reanalysis information. For the sake of comparability with the results  
 154 shown in Manzananas et al (2019), all the different datasets used here (ECMWF-  
 155 System4, ERA-Interim, SA-OBS and MSWEP) have been bi-linearly interpo-

**Table 2** Validation metrics considered in this work.

Code	Description	Variable
Cor.	Correlation	Temp., precip.
CRPS	Continuous Ranked Probability Score	Temp., precip.
RPS	Ranked Probability Score	Temp., precip.
ROCA	ROC Skill Area	Temp., precip.
P2, P98	Percentile 2, percentile 98	Temp.
P98-wet	Percentile 98 of wet (precip. $\geq 1$ mm) days	Precip.
R01	Frequency (in %) of wet days	Precip.
ColdSpellP90	Percentile 90 of the length of cold spells	Temp.
WarmSpellP90	Percentile 90 of the length of warm spells	Temp.
WetSpellP90t	Percentile 90 of the length of wet spells	Precip.
DrySpellP90t	Percentile 90 of the length of dry spells	Precip.

156 lated from their native horizontal resolutions to the common  $1^\circ$  regular grid  
 157 in which the C3S models are provided through the Climate Data Store (see  
 158 <http://climate.copernicus.eu/seasonal-forecasts>). Moreover, daily data have  
 159 been used in all cases.

## 160 2.2 Validation Metrics

161 We have used for this study the Continuous Ranked Probability Score (CRPS),  
 162 the Ranked Probability Score (RPS), the ROC Skill Area (ROCA) and the Pear-  
 163 son correlation to validate the interannual series (the daily results from BA and  
 164 PP are seasonally aggregated in this case). RPS and ROCA are used for tercile-  
 165 based probabilistic predictions, being the terciles independently computed for the  
 166 observations and the predictions. Therefore, whereas CRPS is sensitive to changes  
 167 in the mean and variance (and hence to the effect of bias adjustment), the rest of  
 168 measures are not so they allow to explore the added value of the post-processing  
 169 techniques beyond the model bias removal. The reader is referred to Manzanas  
 170 et al (2019) for further details about the metrics considered. Moreover, for those  
 171 methods providing daily outputs, we also focus on further aspects of the forecasts  
 172 such as extremes and spells, which are of special interest for many practical appli-  
 173 cations. In particular, we have considered the 2nd and 98th percentiles for daily  
 174 temperature and the 98th percentile for daily precipitation (for the latter, only  
 175 wet days are considered). Additionally, for the case of precipitation, the frequency  
 176 of rainy days is also validated. Besides, the 90th percentile of the length of spells is  
 177 also analyzed. As in Maraun et al (2018), a cold/warm (dry/wet) spell is defined as  
 178 an episode of two or more consecutive days with values below/above the 10/90th  
 179 percentile (1 mm). These indicators are computed separately for each ensemble  
 180 member and the results are validated in a deterministic way based on the ensemble  
 181 mean. All the validation metrics considered in this work are shown in Table 2.

## 182 2.3 Methods

183 Among BA methods, we have considered two different implementations of quantile  
 184 mapping; one parametric and one empirical. The latter corresponds to the EQM  
 185 method presented in Manzanas et al (2019), which is applied here on daily (instead

of seasonal) data. The former (referred to as PQM henceforth) is based on the assumption that both observations and raw GCM outputs are well approximated by a given distribution (Gaussian for temperature and Gamma for precipitation), so only the parameters of the theoretical distributions are mapped (see, e.g., Themeßl et al, 2012). For the case of precipitation, the EQM method used here incorporates a frequency adaptation which is thought to alleviate the problem that arises when the frequency of dry days is larger in the model than in the observations (Themeßl et al, 2012). Note that quantile mapping is able to correct automatically the excess of light precipitation frequency or “drizzle effect”.

As representative of the RC family, we have considered the LR method introduced in Manzanas et al (2019), which performs a linear regression between the ensemble mean and the corresponding observations. To correct the forecast variance, the standardized anomalies are rescaled by the standard deviation of the predictive distribution from the linear fit. LR was shown in Manzanas et al (2019) to provide in general good results with a relatively low computational cost. Recall that this method calibrates directly the model temperature (precipitation), based on observed temperature (precipitation). Besides, we have also considered a MOS downscaling configuration in which this same LR method is applied considering T850 (Q300) —see Table 1— as unique predictor to forecast temperature (precipitation). As a compromise between capturing some skill in the model predictors (e.g. correlation with reanalysis data) and retaining a sufficiently large sample size for calibration, the LR method is applied in this work on the monthly means in both cases (referred hereafter to as LR and MOS-LR, respectively).

Among the wide range of alternatives proposed in the literature for PP downscaling, we have selected three of the most representative ones: Multiple Linear Regression (MLR), Generalized Linear Models (GLMs) and the analog technique. MLR (GLMs) are used in this work to downscale temperature (precipitation). The analog technique is common to both predictand variables. MLR is an extension of simple linear regression which attempts to model the relationship between two or more explanatory predictors and the predictand by fitting a linear equation by minimizing the sum of the residuals between the regression line and the observed data. A detailed description on the theory of this technique is provided by Helsel and Hirsch (2002). Regression-based methods have also been used in previous works to downscale seasonal forecasts of temperature (see, e.g., Pavan et al, 2005). GLMs were formulated by Nelder and Wedderburn (1972) in the 1970s and are an extension of the classical linear regression which allows to model the expected value for non-normally distributed variables. GLMs have been already applied to downscale seasonal forecasts (Manzanas et al, 2018). We follow here the two-stage implementation used in the latter reference, in which a GLM with Bernoulli error distribution and logit canonical link-function (also known as logistic regression) is applied to downscale daily precipitation occurrence (as characterized by a threshold of 1mm) and a GLM with gamma error distribution and log canonical link-function is used to downscale daily precipitation amount. In order to increase the predicted variance, which is usually underestimated in deterministic configurations (Enke, 1997), we introduce here a stochastic component in both GLMs (see Manzanas, 2016, for details). For this method, we considered as predictors the standardized anomalies of the predictors considered at the nearest model grid-box (for each predictand location). The popular analog technique (Lorenz, 1969) estimates the local downscaled values corresponding to a particular atmospheric

235 configuration (as represented by a number of model predictors defined over a cer-  
236 tain geographical domain) from the local observations corresponding to a set of  
237 similar (or analog) atmospheric configurations within a historical catalog formed  
238 by a reanalysis. Here, only the closest analog is considered (Zorita et al, 1995;  
239 Cubasch et al, 1996). Analogs are defined based on the standardized anomalies  
240 of the predictors considered at the 16 nearest model gridboxes (i.e., over a 4x4  
241 square centered around each predictand location which allows to encompass the  
242 main synoptic phenomena influencing the local climate) and the Euclidean norm  
243 is considered. Analog-based methods have been applied in several previous studies  
244 to downscale precipitation in the context of seasonal forecasting (see, e.g., Frías  
245 et al, 2010; Wu et al, 2012; Shao and Li, 2013; Manzanas et al, 2018). In spite of  
246 its simplicity, the analog technique performs as well as other more sophisticated  
247 ones (Zorita and von Storch, 1999) and it is one of the most widely used.

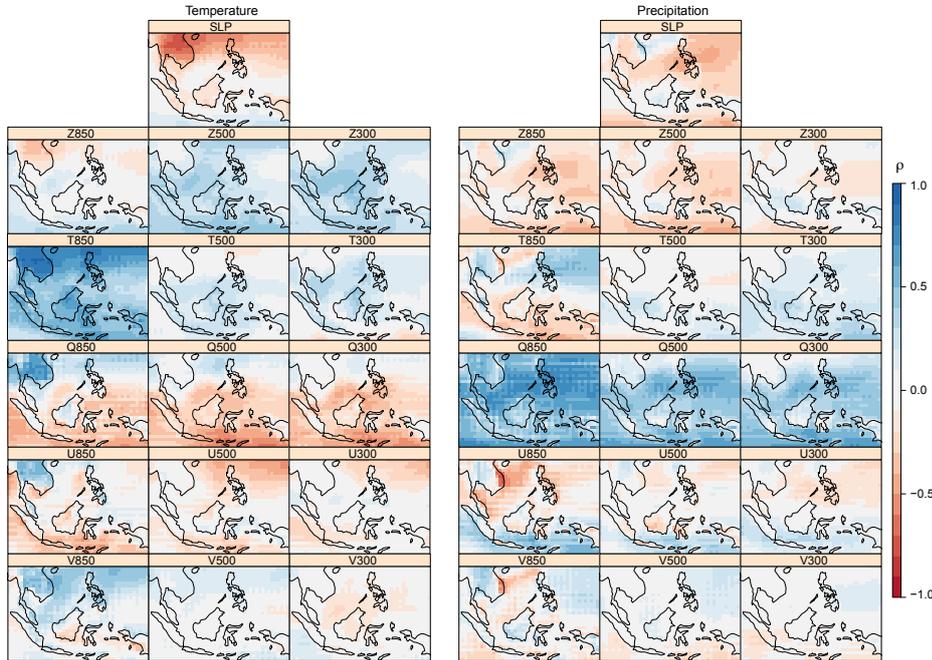
248 To avoid the artificial performance that may derive from model overfitting,  
249 all the methods considered in this work are applied under a Leave-One year-Out  
250 (LOO) cross-validation (Lachenbruch and Mickey, 1968) scheme, in which each  
251 year was separately considered for test, whilst the remaining ones were kept for  
252 training. Note that this is the most adequate framework to test the potential  
253 usefulness of any method for operational seasonal forecasting.

#### 254 2.4 Selection of predictors for MOS and PP methods

255 To cope with the issue of predictor selection in PP methods (see, e.g., Gutiérrez  
256 et al, 2013; San-Martín et al, 2016), Figure 1 shows the existing correlation between  
257 each of the large-scale variables listed in Table 1 and local temperature (left)  
258 and precipitation (right), computed on the daily time-series. The idea behind this  
259 analysis is that the higher the correlation (either positive or negative), the stronger  
260 the physical link between predictor and predictand is, which allows to make an  
261 initial selection of explicative predictors for PP downscaling. However, Manzanas  
262 et al (2018) have shown that the results coming out from PP methods in the  
263 context of seasonal forecasting also depend on the skill of the model predictors  
264 considered. Therefore, both the strength of the predictor-predictand relationship  
265 and the skill of the model in reproducing the large-scale should be taken into  
266 account when making the final selection of predictors for PP methods.

267 Figure 2 shows the interannual correlation between ERA-Interim and ECMWF-  
268 System4 for each of the variables listed in Table 1. Whereas high skill (understood  
269 as the agreement between model and reanalysis) is found for SLP, geopotential  
270 height and temperatures, significant discrepancies appear for some humidity fields  
271 (in particular Q850) and winds (both U and V). For this reason, we have ex-  
272 cluded Q850 and winds from the set of potential predictor variables, since they  
273 might negatively affect the results obtained from PP (and MOS) methods. With  
274 this limitation in mind, and with the idea of keeping the predictor sets as sim-  
275 ple as possible, the final combination considered for temperature (precipitation)  
276 was SLP+T850 (SLP+Q300). Note that, for the particular case of precipitation,  
277 although Q850 may be more explicative than Q300 (Figure 1), the former vari-  
278 able was discarded in favor of the latter since it is not well reproduced by the  
279 ECMWF-System4 (Figure 2).

280 For consistency with the LR method, T850 (Q300) is considered as unique pre-  
 281 predictor in the MOS configuration used here to predict temperature (precipitation).



**Fig. 1** Correlation between each of the large-scale predictors listed in Table 1 and local temperature (left) and precipitation (right), computed on the daily time-series.

## 282 3 Results

### 283 3.1 Intercomparison of approaches and methods

284 The top/bottom panel in Figure 3 shows the validation results obtained for the  
 285 raw and post-processed interannual predictions of temperature/precipitation, in  
 286 terms of different metrics (in rows). In all cases, column 1 refers to the raw model  
 287 outputs. The rest of columns correspond to the different methods considered from  
 288 the different approaches (BC: columns 2-3, RC: column 4, MOS: column 5 and  
 289 PP: columns 6-7). For all of them, results are expressed with respect to those  
 290 shown in column 1, either as skill scores (CRPSS, RPSS and ROCSS) or as direct  
 291 differences (for correlation). Thus, values above (below) 0, shown in blue (red),  
 292 indicate that the particular method improves (degrades) the raw model prediction.  
 293 Note that the RPSS and the ROCSS are computed for probabilistic forecasts of  
 294 tercile categories, which are separately computed for the observations and the  
 295 predictions (this entails an implicit bias adjustment in the forecasts).

296 This figure indicates that all the methods tested here provide a clear benefit in  
297 the CRPSS, which is a consequence of effectively removing the important model  
298 biases present over the region (see Figure 1 in Manzanas et al (2019)). Note that  
299 this result—which was already found for BA and RC methods in Manzanas et al  
300 (2019)—is key, since unbiased predictions are needed by many different commu-  
301 nities to run their seasonal impact models. However, beyond this improvement  
302 in the CRPSS, neither BA nor RC techniques (the latter represented by the LR  
303 method) are able to outperform the raw forecasts for any of the remaining met-  
304 rics, leading in general to slightly worse results over the entire domain for all of  
305 them. This deterioration is even more evident for the LR method, and especially  
306 for correlation—note that RC methods can lead to artificial anti-skill (i.e. anti-  
307 correlations) in regions of small (or negative) raw model correlations (Eade et al,  
308 2014).—It is worth to mention that the EQM tested here (and also the PQM) lead  
309 only to slightly better results than those shown for the same method in Manzanas  
310 et al (2019), where it was applied on the seasonal (instead of daily) time-series.  
311 Moreover, to assess the dependency of the results provided by BA methods on  
312 the temporal resolution considered, both EQM and PQM were also applied on the  
313 monthly time-series, finding only slightly worse (better) results than in the daily  
314 (seasonal) case. Therefore, we do not recommend the application of BA meth-  
315 ods on daily data in case only monthly/seasonal data is needed (note that the  
316 slight improvement found for higher temporal resolutions does not compensate  
317 the increasing computational costs).

318 Differently from BA and RC, MOS and PP methods provide much more local  
319 results, being possible to find areas where the downscaled predictions either out-  
320 perform or degrade (notably in some cases) the raw model forecasts. These results  
321 are in agreement with those found in Manzanas et al (2018), who suggested that  
322 the suitable application of PP methods was subjected to particular (and limited)  
323 windows of opportunity for which 1) there exists a strong link between the large-  
324 and the local-scale and 2) the model is better at reproducing the relevant large-  
325 scale predictors considered for downscaling than the local predictand of interest  
326 (this can typically happen for variables needing some kind of parametrization,  
327 such as precipitation). Again, the results from this work warn on the unexpert use  
328 of MOS and PP methods, as they must be carefully analyzed for the particular  
329 case-study of interest.

330 Figure 4 shows the results obtained for the extreme and spell indicators.  
331 Whereas column 1 corresponds to the observations, column 2 corresponds to the  
332 raw model outputs and columns 3-7 to the different the methods considered. In  
333 columns 2-7, the results are expressed as differences (e.g. bias) with respect to the  
334 observed values of column 1. Note that neither the RC nor the MOS version of  
335 the LR method are considered for this analysis since it cannot be applied at a  
336 daily scale. For temperature, the cold bias exhibited by the model in the analyzed  
337 percentiles is corrected by all methods except the MLR, which exhibits a warm  
338 (cold) bias for the 2nd (98th) percentile. This is due to an underestimation of the  
339 predicted variance which is typical of these methods, and could be alleviated by  
340 introducing some inflation procedure (see, e.g., Huth, 1999). For spells, the two BA  
341 methods maintain the same errors exhibited by the model (the more green/brown,  
342 the longer/shorter the predicted spell is, as compared to observations), since they  
343 are not able to modify its temporal structure. Differently, since PP methods can  
344 alter this temporal structure, they are found to modify the spatial patterns ex-

hibited for the model, being possible to find some areas where the model error is reduced. However, they can also introduce errors in new regions which can be even higher than those present in the raw model.

For precipitation, the two BA methods lead to different results. In particular, similarly as for temperature, the PQM method inherits a great part of the errors exhibited by the raw model, which are only partially corrected (see the results obtained for the frequency of rainy days and the percentile 98th of rainy days). However, as a consequence of the frequency adaptation implemented, these errors are corrected to a higher extent in the EQM method. Despite they lead in general to higher errors than the EQM, the spatial patterns found for the PP methods are, in some cases, more uniform (see, e.g., the results obtained for the 98th percentile of rainy days in the GLM method). Note that, in such situations, simple a-posteriori corrections (e.g. scaling) could be easily applied to further improve the results obtained for PP methods.

In summary, despite correcting marginal aspects such as extreme percentiles, our results indicate that BA methods are not in principle a good candidate to correct spells, since they mostly inherit the errors present in the model. However, for the particular case of precipitation, and provided that some form of frequency adaptation is applied, these methods can be a good alternative (see the results for the EQM). However, as main shortcoming, these methods do not improve (or even slightly degrade) the interannual model skill (see the results obtained for correlation, RPSS and ROCSS in Figure 3). Differently, PP methods are highly case-dependent and their application must be carefully analyzed for the case-study of interest, since they can either improve or degrade the raw model outputs. The strongest advantage of PP methods is that, whilst being competitive (as compared to BA ones) over some regions for predicting extremes and spells, it is possible to find windows of opportunity for which interannual model skill can be also improved (regions/seasons for which the model skill is higher for the large-scale than for the target predictand). Nevertheless, when the predictors selected for downscaling are not well reproduced by the model, PP methods can also lead to unsuitable results. For instance, if Q300 is substituted by Q850 in the predictor set used to downscale precipitation, the results shown in Figures 3 and 4 strongly worsen (not shown). As suggested in Manzanas et al (2018), an explanation for this behaviour comes from the fact that the model skill for reproducing Q850 is more limited (see Figure 2). As a result, the statistical link that is learnt using reanalysis data in PP methods becomes meaningless when applied to model predictors (the use of Q850 instead of Q300 leads to much better cross-validated results when using reanalysis predictors; not shown).

### 3.2 The effect of observational uncertainty

Observational uncertainty has been identified as one of the factors that may play a role in the statistical post-processing of model forecasts (see, e.g. Kotlarski et al, 2017; Herrera et al, 2018), since all the adjustment/calibration/downscaling methods rely on observations for the training process. To assess the potential impact of this factor, we repeat in this section some of the analysis above presented but replacing ERA-Interim by both SA-OBS and MSWEP.

390 In particular, we focus on precipitation —for which observational uncertainty  
391 is known to be larger— and consider SA-OBS (the only dataset purely based  
392 on gauge data) as the ground truth, since it has been found to closely resemble  
393 punctual gauge-based measures in terms of dry/wet frequency, timing of rainy  
394 days and extremes (van den Besselaar et al, 2017). Figure 5 provides a compari-  
395 son between ERA-Interim/MSWEP and SA-OBS (left/middle column), in terms  
396 of their interannual time-series. In addition, ERA-Interim and MSWEP are also  
397 compared (right column). Whereas ERA-Interim and MSWEP show in general  
398 good agreement (with correlation values above 0.8 in most of the gridboxes), im-  
399 portant differences are found between ERA-Interim and SA-OBS (with rather low,  
400 or even negative values over certain parts such as Sumatra). Comparison between  
401 ERA-Interim and MSWEP yields intermediate results. These findings point out  
402 the limitations of reanalysis data to reproduce the actual climate of the region,  
403 which presents thousands of islands, strong land-sea contrasts and a complex to-  
404 pography. In this regard, note that the inclusion of satellite information in MSWEP  
405 helps to correct the deviations from reality found in ERA-Interim.

406 For each of the metrics shown in Figure 6 (7), the middle/bottom row would be  
407 the equivalent to those shown in Figure 3 (4) but using SA-OBS/MSWEP instead  
408 of ERA-Interim for both training and verification of the different methods. For  
409 direct comparison, the top row shows the same results presented in Section 3.1,  
410 but only over land. Whereas the results for the interannual time-series (Figure 6)  
411 are almost identical for ERA-Interim and MSWEP —note from the comparison  
412 against raw model outputs (left column) that both datasets are very similar,—  
413 some regional differences (see, e.g., over Borneo and Papua) appear with respect  
414 to the results found for SA-OBS, in particular for MOS and PP methods (this  
415 effect is less pronounced for BA ones). However, when it comes to the extreme and  
416 spell indicators (Figure 7), these differences become more relevant and not only for  
417 MOS and PP methods, but also for BA ones. For instance, important performance  
418 discrepancies are found for most of the indicators for the case of the PQM method  
419 depending on the reference considered (even between ERA-Interim and MSWEP).  
420 Although analyzing in detail all the differences found region by region and method  
421 by method is not the purpose here, Figures 6 and 7 reveal that the choice of  
422 observational dataset can have important effects for the post-processing of seasonal  
423 forecasts. This issue seems to be specially relevant for MOS and PP methods, for  
424 which notable differences are found even in terms of interannual skill. This poses an  
425 important challenge for seasonal forecasting; in particular over the tropics, where  
426 large observational uncertainty has been identified, not only for observations but  
427 also for reanalysis (see, e.g., Brands et al, 2012; Manzananas et al, 2015). Moreover,  
428 seasonal models tend to exhibit the highest interannual skill in tropical latitudes  
429 (see, e.g., Manzananas et al, 2014b), being thus difficult to improve their raw forecasts  
430 there. As a consequence of these limitations, BA methods may be, in general,  
431 a more secure alternative for downscaling in the tropics. Nevertheless, beyond  
432 interannual skill, it is very important to warn on the potential conflicts that may  
433 arise related to the choice of observational uncertainty, even for BA methods, in  
434 terms of other forecast aspects such as extremes and spells.

#### 435 4 Conclusions and User Recommendations

436 This section summarizes the main conclusions obtained in Manzanas et al (2019)  
437 and in this work and provides a set of recommendations for practitioners on the  
438 advantages and limitations of the different approaches available for the appro-  
439 priate post-processing of dynamical seasonal forecasts. These approaches, which  
440 aim to reduce the systematic model biases and increase their skill (as measured  
441 by different quality aspects), range from bias adjustment (BA) and ensemble re-  
442 calibration (RC) methods —both acting directly on the variable of interest; e.g.,  
443 model precipitation— to more complex statistical downscaling techniques such  
444 as Model Output Statistics (MOS) and Perfect Prognosis (PP) methods —which  
445 operate on a selection of large-scale circulation predictor variables (e.g. model  
446 geopotential and humidity at different vertical levels) linked to the predictand  
447 variable of interest (e.g. observed precipitation).—

448 Besides the nature of the predictor/s used, one of the key differences between  
449 these approaches is the suitable temporal scale/s of application: daily for BA and  
450 PP and monthly/seasonal for RC and MOS methods (BA can be also directly  
451 applied to monthly/seasonal data; being thus the most versatile alternative). Note  
452 that MOS and PP are the most complex ones since they involve the selection of  
453 suitable large-scale predictors, which is typically a hard, time-consuming task that  
454 may require the guidance of an expert.

455 In terms of performance, all these approaches effectively adjust the large bi-  
456 ases exhibited by the raw model predictions, which is of paramount importance  
457 for users, particularly when climate information is needed to run impact models  
458 for different sectors (e.g. hydrology, agriculture, health, etc.) or for the computa-  
459 tion of indices that depend on absolute values/thresholds. However, there is no  
460 single approach/technique that systematically provides further benefits in terms  
461 of bias-insensitive metrics. In case of BA methods, this is due to their incapability  
462 to modify the temporal structure of the raw model forecasts (see, e.g., Maraun  
463 et al, 2017). However, the application of these methods is straightforward and  
464 constitutes a pragmatic and versatile simple choice in cases where a quick post-  
465 processing is needed, no expert knowledge on the regional climate is available, the  
466 resolution of the model is similar to that of the observational reference considered  
467 (BA does not perform downscaling) and/or for regions with no expected potential  
468 for downscaling (e.g. flat inland areas). Moreover, although this approach suffers  
469 from some limitations (Maraun et al, 2017), its application to seasonal forecast-  
470 ing does not build on strong extrapolation assumptions as in the case of climate  
471 change applications.

472 As compared to BA methods, RC ones can result in modest improvement of  
473 some quality aspects (in particular reliability, although other aspects can be de-  
474 graded). Nevertheless, these improvements are restricted to regions/seasons with  
475 high model skill. In addition, since they operate on a monthly/seasonal basis, RC  
476 methods can be negatively affected by the limited length of state-of-the-art sea-  
477 sonal hindcasts (which typically have less than 30 years; e.g. the C3S dataset)  
478 and, therefore, appropriate cross-validation (typically leave one-year out) is re-  
479 quired in order to avoid overfitting and spurious skill. Note however that this is  
480 not a worrying factor neither in PP methods nor in BA ones working with daily  
481 data.

482 Differently from BA and RC methods, MOS and PP methods can improve all  
483 quality aspects for particular and limited spatial regions for which the skill of the  
484 model is weaker for the target variable (e.g. precipitation) than for the informative  
485 predictors used in the downscaling process (e.g. humidity and/or winds). Never-  
486 theless, the reverse situation is also possible (see Manzanas et al, 2018, for a case  
487 study for PP methods), which warns on the uniformed use of these methods, as  
488 they must be carefully analyzed for the particular case-study of interest. Note that,  
489 although both MOS and PP methods rely on large-scale predictors, the complexity  
490 and requirements for the former are much lower than for the latter. Whereas MOS  
491 methods establish the relationship between the large-scale seasonal forecasts and  
492 observational reference records using directly the hindcast (with correspondence  
493 with observations at a monthly/seasonal scale), PP methods have the extra com-  
494 plexity of building the relationships at a daily basis using reanalysis data (with  
495 day-to-day correspondence with observations). This typically requires a compre-  
496 hensive screening process in order to detect robust predictors similarly represented  
497 in both the reanalysis and the model hindcast. Moreover, PP methods may suf-  
498 fer from reanalysis uncertainty, which is particularly relevant in the tropics (see,  
499 e.g., Brands et al, 2012; Manzanas et al, 2015), where seasonal forecasts exhibit  
500 the highest skill (see, e.g., Manzanas et al, 2014b). This supposes an extra over-  
501 head which needs to be appropriately assessed and planned before applying these  
502 techniques since, sometimes, the windows of opportunity for improvement are so  
503 narrow that the effort may result useless.

504 Based on all these findings, our overall recommendation would be the use of  
505 versatile, easy to implement BA methods for those cases for which the use of  
506 MOS and PP methods cannot be carefully tested by experts. Note that BA are  
507 suitable for both daily and monthly timescales and provide competitive results  
508 in most situations (especially over the tropics). However, we want to remark the  
509 fact that the choice of observational dataset can have important effects for the  
510 post-processing of seasonal forecasts. Even though MOS and PP methods seem to  
511 be more affected by this issue (which can lead to important regional differences  
512 in term of interannual skill), also BA methods may be sensitive to observational  
513 uncertainty, especially regarding the reproduction of extreme and spell indicators,  
514 which are important for many practical applications.

515 Finally, from a more practical point of view, it is also important to note that  
516 there are significant differences in terms of computational cost among distinct  
517 approaches (and even among different methods within the same approach) for  
518 adjustment/calibration/downscaling, which may be especially relevant for their  
519 potential usability in real-time user-tailored applications (e.g. certain climate ser-  
520 vices).

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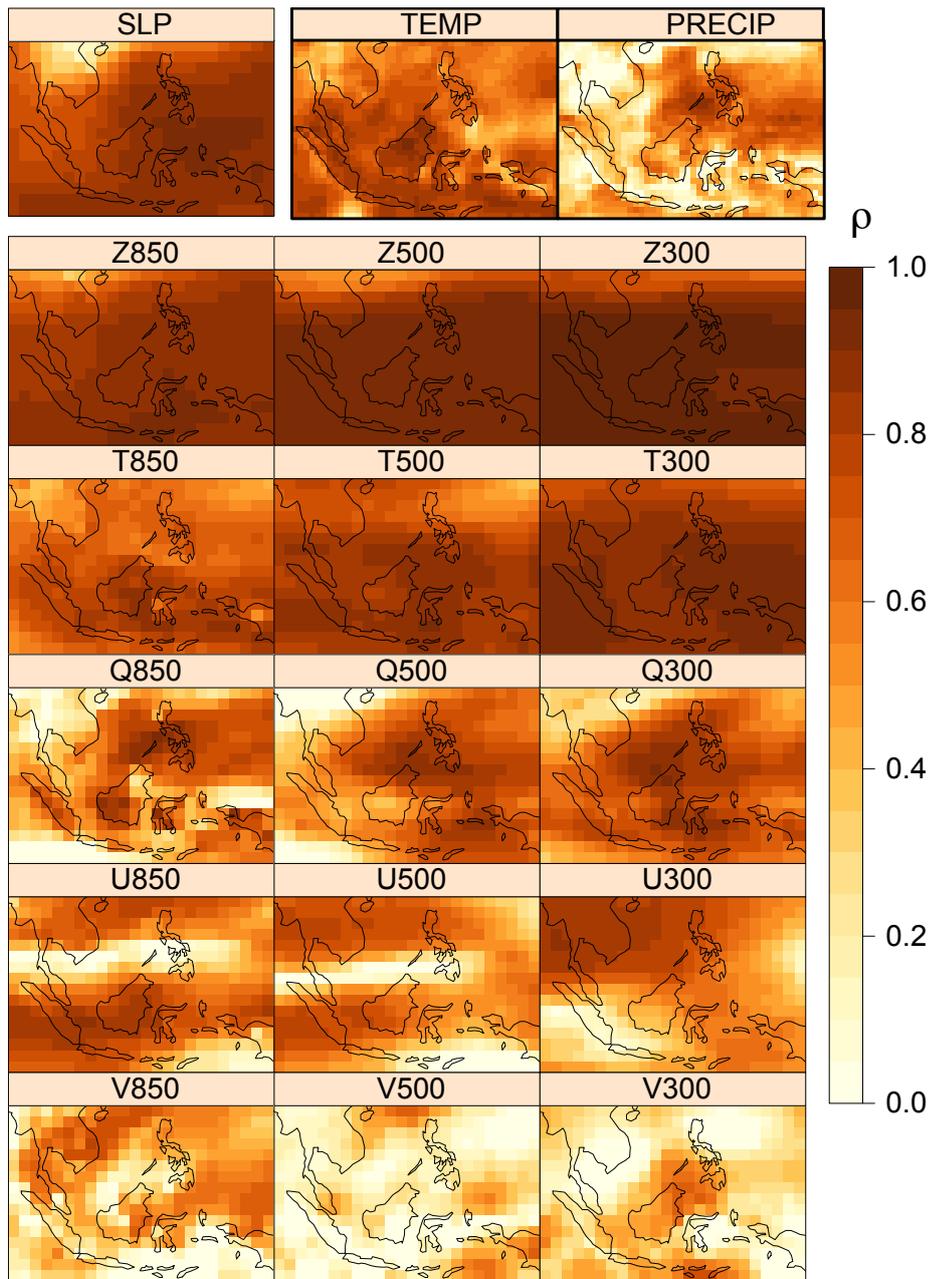
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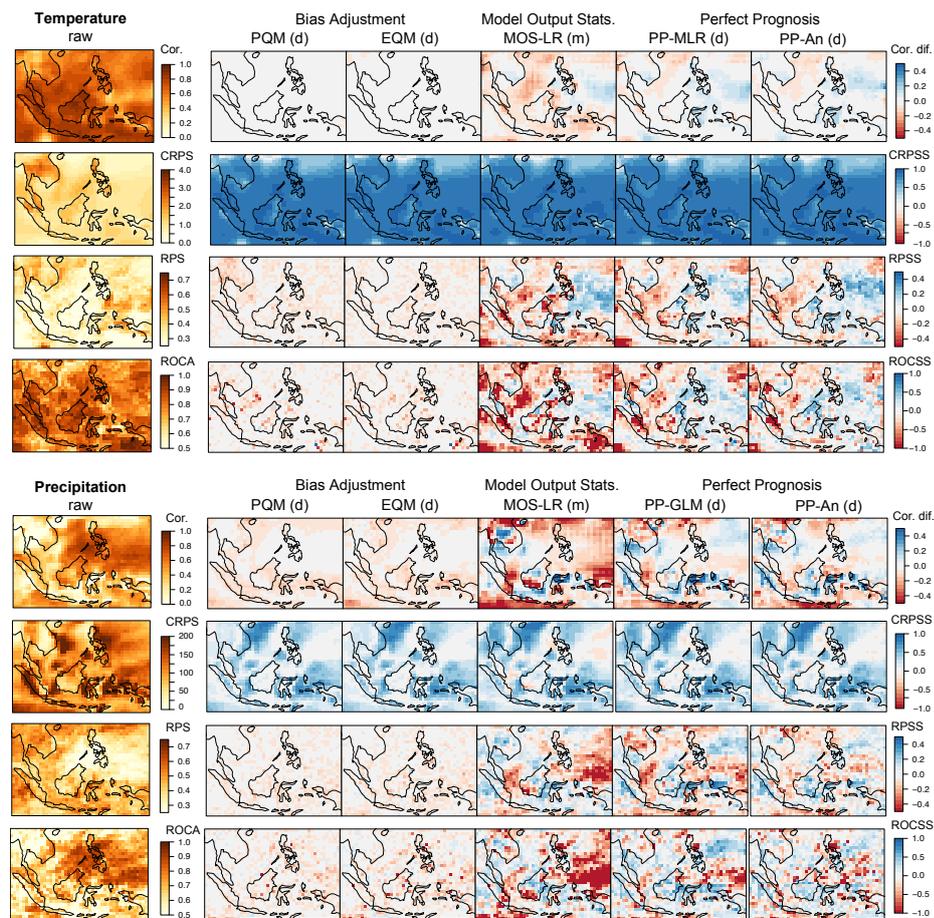
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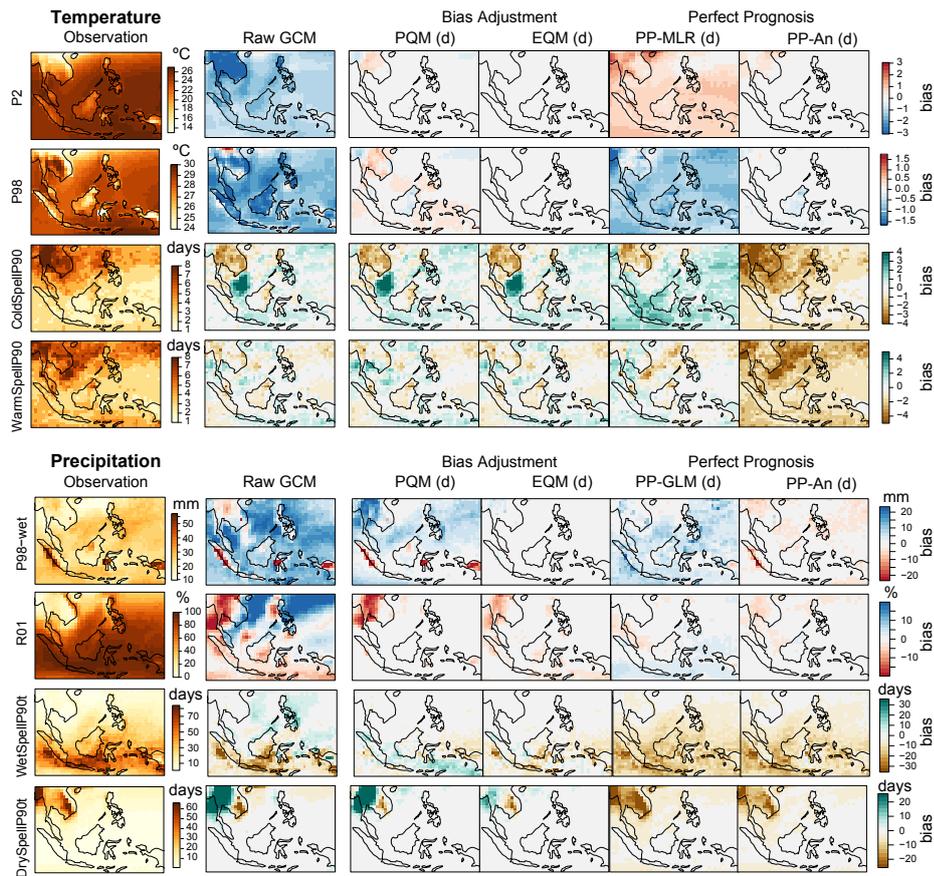
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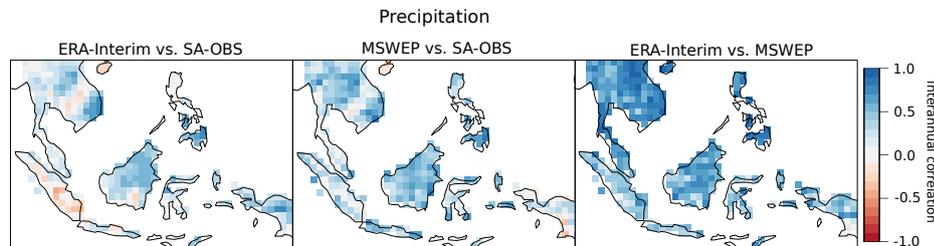
**Fig. 2** Interannual correlation between ECMWF-System4 and ERA-Interim for each of the variables (potential predictors) listed in Table 1. For completeness, results are also shown for temperature and precipitation (marked with a black border).



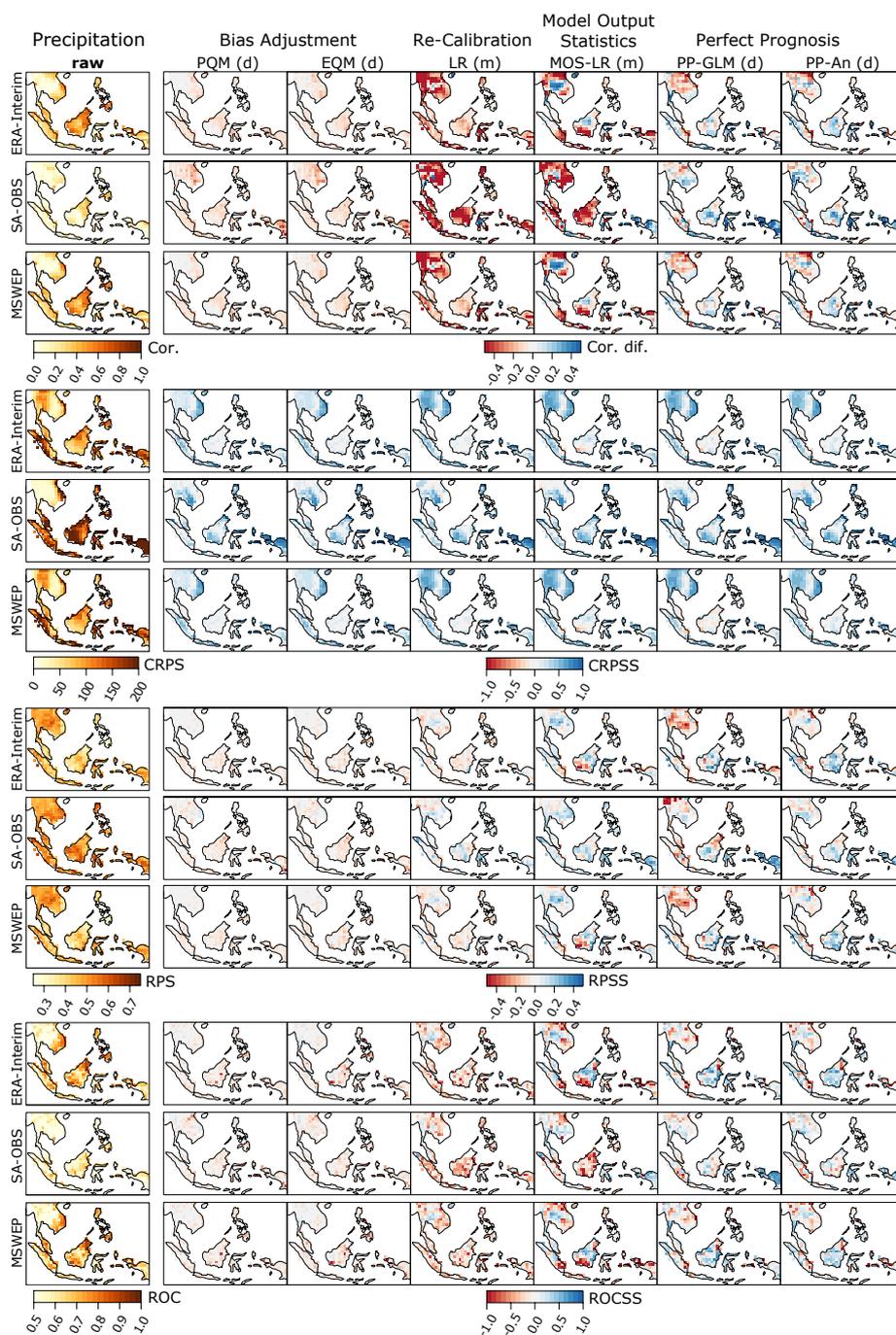
**Fig. 3** Validation results obtained for the interannual series of temperature (top) and precipitation (bottom). See the text for details.



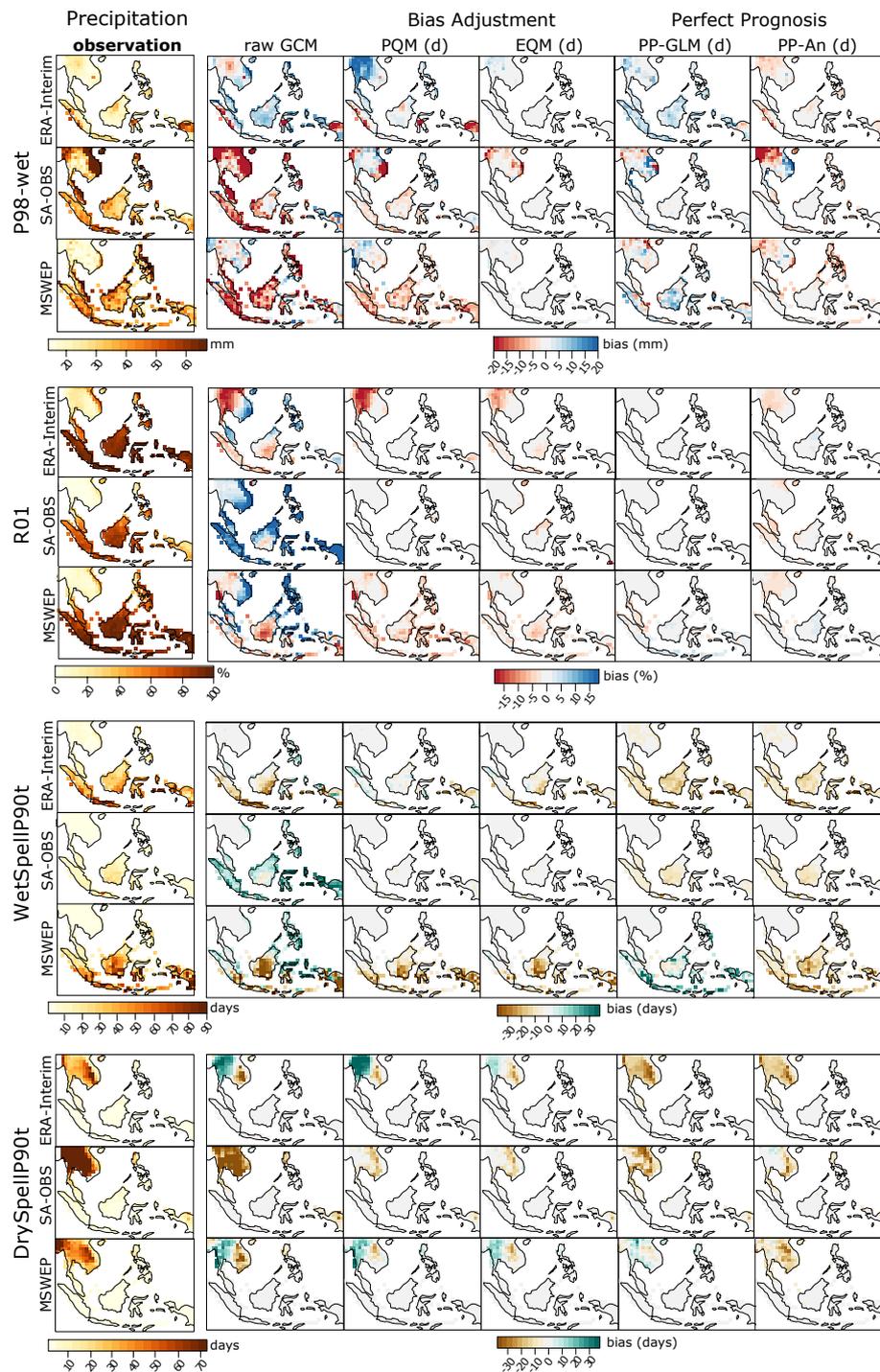
**Fig. 4** Validation results for a number of extreme indices obtained for the daily series of temperature (top) and precipitation (bottom). See the text for details.



**Fig. 5** Comparison of ERA-Interim, SA-OBS and MSWEP precipitation, in terms of correlation for the interannual time-series.



**Fig. 6** As bottom panel of Figure 3, but including the results obtained when using SA-OBS/MSWEP for both direct training and verification of the different methods (middle/bottom row of each metric). For direct comparison, the results shown in Figure 3 for ERA-Interim (top row of each metric) are only displayed over land.



**Fig. 7** As bottom panel of Figure 4, but including the results obtained when using SA-OBS/MSWEP for both training and verification of the different methods (middle/bottom row of each metric). For direct comparison, the results shown in Figure 4 for ERA-Interim (top row of each metric) are only displayed over land.