### Interactive comment on "Statistical downscaling with the downscaleR package: Contribution to the VALUE intercomparison experiment"

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Response to reviewer #2

We thank the referee for her/his time and the insightful feedback provided. In this document we include a point-by-point response to the comments received. The new revised version of the manuscript includes a number of modifications following the referee's advice, in which we have invested considerable effort and interest. We hope that the referee will deem the revised manuscript version of sufficient quality for publication. In this response, the referee's comments are indicated in black, and the author responses in blue fonts.

### Major Issues

The authors present the R package downscaleR. In principle this is a very useful contribution and worth publishing in GMD. But before publication I ask the authors to address the following major issues, plus a series of minor but still important ones.

In section 4 the authors consider a pan-European setting, and explore whether models using a European predictor domain with additional local predictors perform equally well as the corresponding models with predictors defined on regional domains as used in VALUE. If these models would indeed perform well, this would mean a substantial simplification, e.g., for large-scale ESD applications such as in EURO-CORDEX. I am afraid, however, that the reasoning is not quite stringent. The validation is based on ERA-Interim predictors, which should well represent local predictors

given that local observations have been assimilated. In a GCM context, these local predictors may not fulfill the perfect prog condition, i.e., they may not be bias free. If this were the case,the GCM-based projections could be substantially biased, and the use of local predictors were not permitted. In fact, biases may also affect the climate change signal. I therefore ask the authors to test the PP assumption: first, they should use the historical simulations of their GCM-predictor experiment and check the perfect prog assumption. And second, they should investigate whether the climate change signals simulated by the local implementations differs from those of the VALUE implementations. If the PP assumption was not fulfilled, and/or if the climate change signal was modified, the au-thors should change their conclusions correspondingly. Even in a positive result, the authors should mention that care is required for the reasons given above.

In the new revised manuscript we have addressed this question by evaluating the distributional similarity between GCM and reanalysis predictors. To this aim, we have created maps of the distributional similarity between ERA-Interim and the EC-EARTH historical simulation considering the Kolmogorov-Smirnov (KS) statistic.

The KS statistics are calculated separately for each season (winter and summer), considering the corresponding daily time series for each of the predictor variables and for each grid point. Moreover, in order to isolate distributional dissimilarities due to errors in the first- and second-order moments, we also consider anomalies and standardized anomalies. In the first case, the data are centered by removing the seasonal mean, and in the second case we additionally divide by the seasonal standard deviation. Due to the strong serial correlation present in the daily time series, the test is prone to inflation of type 1 error, that is, rejecting the null hypothesis of equal distributions when it is actually true. To this aim, an effective sample size correction has been applied to the data series to calculate the p-values (Wilks 2006). The methodology followed is similar to the steps followed in Brands *et al.* (2012; 2013).

In perfect-prog statistical downscaling the predictors are rarely used without transformation, and most often data are transformed in such a way that

distributional dissimilarities between reanalysis and GCM can be alleviated. To highlight this fact, we conduct the similarity analysis considering not only the raw time series, but also their corresponding anomalies (i.e., centered data to zero mean) and standardized anomalies (zero mean and unit variance), as introduced in the statistical models used in this paper. The following panels present the overall results. Please note one single summary figure displaying the overall results is presented in the revised manuscript version (Figure 7 of the revised manuscript). For brevity, in the paper the disaggregated results by seasons are omitted, and only two variables, the one that performs best (sea-level pressure) and the one that performs worst (specific humidity at 500 mb) are displayed. The figures displayed below and the code generating them is presented in the companion paper notebook of the revised manuscript. Also, a new measure (ts.ks.pval,

https://github.com/SantanderMetGroup/VALUE/blob/devel/R/measure.ks.pv al.R) has been introduced in the package VALUE in order to provide the p-values of the KS-test statistic.

In the figures below, the color darkening from pale to deep blue indicate increasing values of the KS-statistic. The significant grid cells (i.e., those for which the distributions of ERA-Interim and EC-EARTH significantly differ), are highlighted with red crosses.

In general terms, the distributions of GCM and reanalysis differ significantly when considering the raw time series, independently of the target season (Figs 1 and 2), thus violating the assumptions of the perfect prog hypothesis regarding the good representativity by the GCM of the reanalysis predictor fields. Centering the data (i.e, zero mean time series) greatly alleviates this problem for most variables, excepting specific humidity at 500 mb (hus@500), and near-surface temperature (tas), persisting some local problems over the British Isles for ta@850 and hus@850 (the latter only in summer, but not in JJA). This is depicted in Figs. 3 (DJF) and 4 (JJA).

Finally, data standardization improves the distributional similarity, attaining an optimal representativity of all the GCM predictors but hus@500 in the summer in southern in the Mediterranean. These results are consistent with

the findings in Brands et al. 2013, pointing to specific humidity in 500 mb as a less reliable predictor, although in the european domain used here problems in the representation of this variable by EC-EARTH are mostly fixed with data standardization.

2-sample KS test - Raw series - DJF

## hus@850 z@500 - 0.20 - 0.15 ta@700 ta@850 hus@500 - 0.15 psl tas ta@500 - 0.05

**Fig. 1**. Results of the KS test applied to the time series from the EC-EARTH ESM and ERA-Interim VALUE respectively, considering the original (not transformed) series, for the period 1979-2005 and the DJF season. The grid points showing low p.values (p<0.05) have been marked with a red cross, indicating significant differences in the distribution of both GCM and reanalysis time series.

### 2-sample KS test - Raw series - JJA

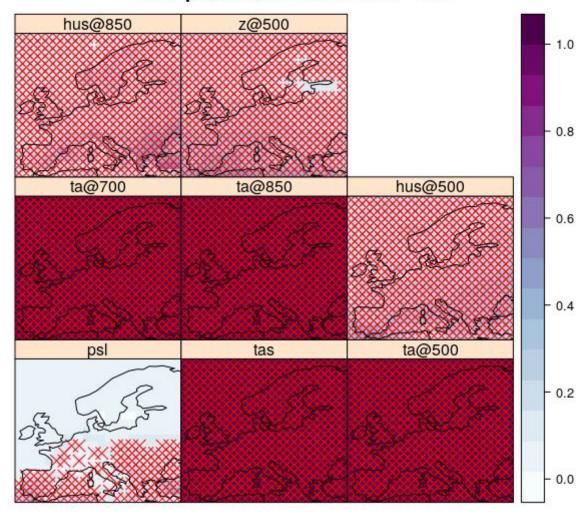


Fig. 2. Same as Fig 1, but for JJA

### 2-sample KS test - Centered anom - DJF

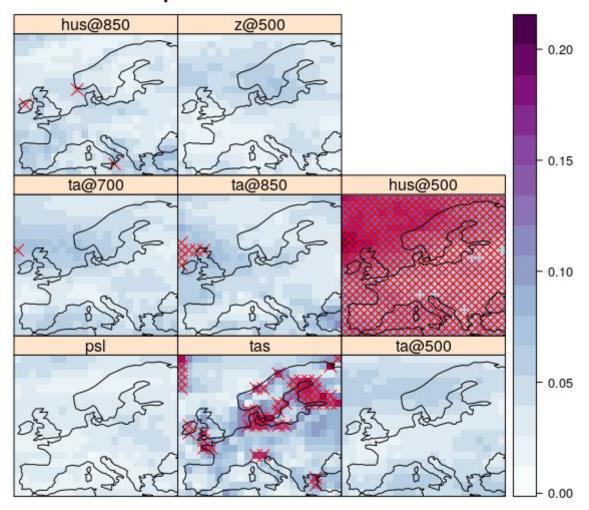


Fig. 3. Same as Fig 1 (DJF) but using the EC-EARTH and ERA-Interim transformed series, both centered to have zero mean

### 2-sample KS test - Centered anom - JJA

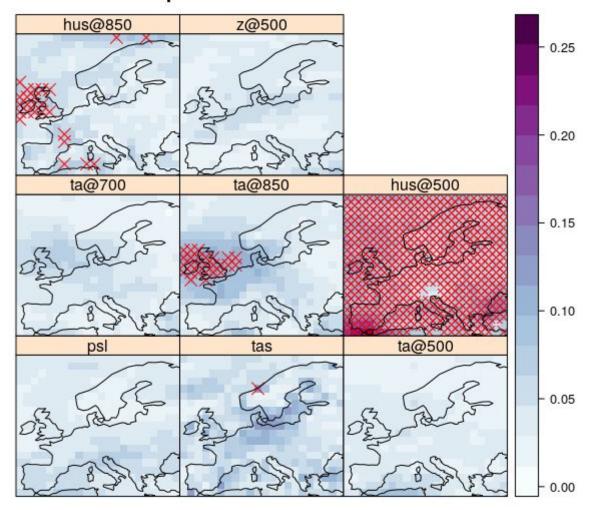


Fig. 4. Same as Fig. 3, but for boreal summer JJA.

### 2-sample KS test - Standardized anom - DJF

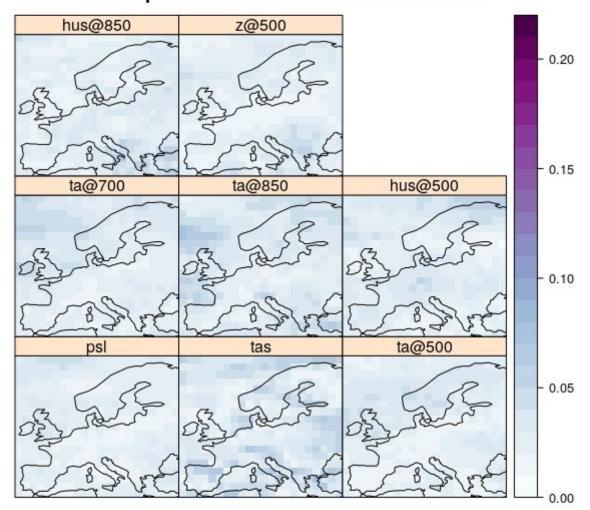


Fig. 5. Same as Fig. 3 (DJF), but using standardized anomalies instead of centered anomalies

# hus@850 z@500 - 0.20 - 0.15 ta@700 ta@850 hus@500 - 0.16 - 0.10

### 2-sample KS test - Standardized anom - JJA

Fig. 6. Same as Fig. 5 (standardized anomalies), but for JJA

1b. Second, they should investigate whether the climate change signals simulated by the local implementations differs from those of the VALUE implementations. If the PP assumption was not fulfilled, and/or if the climate change signal was modified, the authors should change their conclusions correspondingly. Even in a positive result, the authors should mention that care is required for the reasons given above.

After having verified the perfect-prog assumption regarding the adequate representation of the predictors by the GCM, we have investigated whether the projected climate change deltas are robust to the alternative use of the local predictor approach. Our results indicate that overall, the projected climate change signals for the target indices are not significantly altered.

Figure 7 depicts the relative climate change signals for the local-based (i.e., M1-L and M6-L) and VALUE (i.e., M1 and M6) configurations for the R01 (first row) and SDII (second row) indices. According to the R01 there is consistency among the methods to indicate that a decrease(increase) in the occurrence of precipitation will happen in Southern(Northern) Europe, whereas rainy days will be more intense on average overall in Europe. Slight differences occur when considering the downscaling technique (e.g., M1 and M6) however these differences do not vary as a function of the local predictor configurations taken into account within each downscaling technique. For example, whereas both analogs-based projections present negative relative delta values in the R01 for the Alps, GLM approaches do not predict changes for some of the stations located in the Alps.

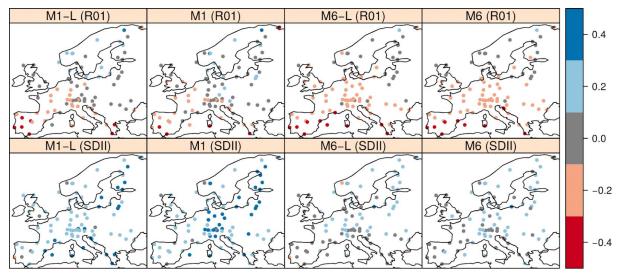


Fig. 7 Relative delta change signals of the R01 and SDII precipitation indices for the future period 2071--2100 (w.r.t. the baseline 1979--2005), obtained by the downscaled projections of the CMIP5 GCM EC-EARTH-r12i1p1, considering the RCP8.5 experiment. The SD methods used are M1-L, M1, M6 and M6-L.

In conclusion, local-based approaches obtain similar climate change signals for the R01 and SDII indices than the VALUE predictor configurations. There are some differences, but in any case these are smaller between local window/VALUE window than those between GLMs(M1)/Analogs(M6), and therefore the use of the local window does not add additional uncertainty to the climate change signal obtained. Therefore, these results further support the use of local windows centered

on the predictand locations, always subject to the cautionary assessments of the perfect prog hypothesis previously undertaken.

2. I am wondering how downscaleR is placed relative to ESMValTool. This is a widely used tool mainly (but not exclusively) in the GCM community, and it should be possible to combine analyses and results from the different tools. It would be disappointing if the two packages would not be compatible (beyond the exchange of NetCDF files), so a discussion is absolutely necessary, and compatibility very much desired.

ESMValTool is aimed at creating a unified framework for the assessment and evaluation of GCMs. Beyond this primary objective, it exists the possibility of adding further user-tailored layers of functionality by means of the so called "recipes" but, in general, the code is quite complex (using different languages for different modules) and extending the functionality is not straightforward (Moreover, the framework is not fully open source, since there is one private core version). The framework is conceived as a pipeline of data access (via CMOR compliant NetCDF files), post-processing, and evaluation (or recipes). Therefore, the most straightforward way to use ESMValTool is to produce NetCDF files (with downscaled results) and use the standard pipeline (with the standard GCM-oriented validation tools). downscaleR can export the results as NetCDF files, so in principle there is the potential to "integrate" both tools.

downscaleR is envisaged as a fully open specific tool for undertaking statistical downscaling experiments within a single computing environment (R), and seamlessly integrated with other components allowing for the development of end-to-end application, from data retrieval to transformation, visualization, analysis and validation, handling the typical data structures required in most climate applications (that is, regular/irregular gridded datasets and point observations, including additional dimensions such as members and/or initialization times). The whole framework has been branded as "climate4R", and it is since the beginning a completely independent development of the ESMValTool. Of course, this doesn't preclude from an eventual convergence to the ESMValTool workflow, although this idea has not been considered in the development of the different climate4R components.

ESMValTool applies validation measures to files or sets of files based on a convention for file/attribute naming that can be configured via recipes. ESMValTool has a default configuration for CMIP5 and CMIP6 with predefined DRS configurations. Some authors of the manuscript have previous experience in extending ESMValTool with some configurations for CORDEX in the framework of C3S, thus using the tool for the validation of other types of datasets different from GCMs. In principle, and based on this previous experience, it would be possible to apply the measures defined by ESMValTool to the downscaleR outputs, after export to netcdf using the climate4R tools to this aim (package loadeR.2nc, https://github.com/SantanderMetGroup/loadeR.2nc) using an appropriate recipe to this aim. However, the compatibility of ESMValTool to station data remains as something that requires more time and careful consideration. To our knowledge ESMValTool does not provide support to point data, thus precluding from a straightforward application of downscaling experiments to point stations, as in VALUE.

3. The conclusions are quite weak. I would really appreciate if the authors could discuss what the purpose of the package is, and where it sits in the wide landscape of downscaling and evaluation tools in climate sciences, and what the specific advantages are. This has been touched in the introduction, but here it should be referred back, and some substantial statements should be made.

Following the referee's advice, we have strengthened the conclusions of the manuscript, better highlighting the main features of downscaleR and its unique characteristics within the plethora of tools currently available.

### References

Brands, S., Gutiérrez, J.M., Herrera, S., Cofiño, A.S., 2012. On the Use of Reanalysis Data for Downscaling. J. Clim. 2517–2526. https://doi.org/10.1175/JCLI-D-11-00251.1 Brands, S., Herrera, S., Fernández, J., Gutiérrez, J.M., 2013. How well do CMIP5 Earth System Models simulate present climate conditions in Europe and Africa?: A performance comparison for the downscaling community. Climate Dynamics 41, 803–817. https://doi.org/10.1007/s00382-013-1742-8

Wilks, D. (2006) Statistical methods in the atmospheric sciences, 2nd ed. Elsevier, Amsterdam

### Minor issues

In general, some minor grammatical errors (e.g. I 192 "analogs performance") need to be corrected.

I 5: VALUE is a network, not a project. You might also call it an initiative. Fixed

I 25: "are not suitable" This is not always true. Please replace by "are often not suitable"

### Done

I 32: "SD" here you could refer to a recent review or introductory text, e.g., Maraun &Widmann, CUP, 2018.

### Done

I 40: "It must be noted" is a zero phrase. Start with "SD techniques are..."

Rephrased

I 45: Here it would be fair to cite Barsugli et al., EOS, 2013.

Thanks for the reference, this has been added

I 55: Here it would be useful to cite the synthesis article, Maraun et al., IJC, 2019, highlighting that this article aims at giving an overall assessment of relative merits and limitations.

### Done

I 66: "It is worth mentioning here": Again, a zero phrase. You could rather state "This toolbox complements/adds to other existing tools..."

### Done

I 106: somewhere in the introduction you should mention ECMValTool In this case, we don't see exactly where the ESMValTool fits here. For this reason, we did not include a specific mention to this tool.

I 113: here you should really also refer to Maraun & Widmann, CUP, 2018. It is the most comprehensive discussion of the two approaches in a climate change context.

### Done

I 119: no - the term "perfect" refers to the assumption that the predictors are bias free. In particular in weather forecasting, also for MOS the day-to-day correspondence is given. For the MOS discussion you should make clear that the limitation of having homogeneous predictor-predictand relationships applies only in a climate context. This is

also the reason why MOS in climate research is typically just bias correction. In weather forecasting, you are as free as in PP.

### Thanks for the clarification. The text has been modified accordingly

I 130: you may consider presenting the updated assumptions formulated by Maraun &Widmann, CUP, 2019. They are more precise and include the often neglected requirement that the model structure should be applicable. I 169: you may consider to add a comment that often predictors are proxies for physical processes, which is a main reason for non stationarities in the predictor/predictand relationship, as amply discussed in Maraun & Widmann, CUP, 2019. In this context, you should mention that predictor selection and the training of transfer functions are carried out on short term variability in present climate, whereas the aim is typically to simulate long term changes of short term variability (same reference, and Huth, J. Clim., 2004)

### These suggestions have been included

I 194: it should be pointed out that this is true only for analog methods, which use the same sequence of analogs for different locations. Otherwise spatial coherence is underestimated. This has been demonstrated by the cited Widmann et al., IJC, 2019.I 196: this statement could be formulated much stronger. I am not aware of any region in the world, where climate change will be so moderate, that the analog method still ap-plies in the far future, when temperature and directly related variables are considered.

### These clarifications have been included in the revised text

I 205: somewhere you should mention that the main advantage of GLMs is to simulate(non-normal) variance not explained by the predictors (e.g., von Storch, J. Climate,2000, although, strangely, not all models make use of that). Fig 5: the violin plot needs some explanation. It is not quite clear what the distribution shows. Densities across stations? Is there some kernel smoothing applied? Also: is this an annual analysis? The same holds for the following figures as well.

Violin plots have been explained in more detail in the revised version of the manuscript.