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Hydrology and Earth System Sciences Discussions

Interactive comment on "Development and comparative evaluation of a stochastic analog method to downscale daily GCM precipitation" *by* S. Hwang and W. D. Graham

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———General Comments: A point where the paper could be clearer is in describing how the proposed methodology combines the pro's of the three methods it is compared with, and why it improves them. This point is not clearly addressed in the paper.

Response: The three existing bias-correction and spatial downscaling approaches examined in this paper (i.e., BCSD, SDBC, BCCA) are available for CMIP3 over the entire U.S. from http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#Welcome). These

data have been used quite extensively for climate change impact assessments, particularly in the western US, by previous researchers cited in the manuscript. Furthermore the BCSD method was adopted for use in the recent U.S. Global Change Research Program's National Climate Assessment Report (http://ncadac.globalchange.gov/). However, while investigating the usefulness of these data for Florida, we found that the existing retrospective bias-corrected, downscaled CMIP3 datasets did not adequately reproduce the observed spatiotemporal variability of daily precipitation which is known to be regionally important for accurately simulating streamflow generation processes in small watersheds, especially in the summer when convective storms dominate. To overcome this problem we developed BCSA which uses the same bias-correction methodology but improves over the spatial interpolation (BCSD and SDBC) and constructed analog (BCCA) methods by synthetically generating a random rainfall field that matches both the mean areal bias-corrected rainfall estimated from the GCM and the small-scale variability exhibited by historical data. We term this synthetic random rainfall field a "stochastic analog". This terminology is analogous to the "natural analog" methodology in which an actual historical spatial distribution of daily rainfall that preserved the mean areal bias-corrected rainfall estimated from the GCM would be selected. In the conclusions of the paper we suggest, based on local knowledge and experience, that the BCSA should produce better climate impact assessments for small, low-relief rainfall-dominated watersheds where small-scale spatiotemporal precipitation characteristics are important (we are currently testing this hypothesis in on-going work). However we also emphasize that downscaling methods should be selected to reproduce whatever precipitation characteristics are important for the hydrologic system under study. For example, in the mountain-west, where streamflow is snowmelt dominated the existing bias-correction methods (BCSD, SDBC, BCCA) may be adequate for use. We will add the above information and further clarify the motivations of this study (why BCSA was developed and why the other methods were selected for comparison) in the introduction section of the revised manuscript. ———

SPECIFIC COMMENTS

——— Comment: Page 2143 Lines 21-25: introduce dynamical downscaling.

Response: The two main downscaling approaches currently used are statistical downscaling methods which use empirical relations between features simulated by GCMs at grid scales and surface observations at sub-grid scales, and dynamic downscaling techniques which use regional climate models (RCMs) based on physical mechanisms governing relationships between the climate at large and smaller scales. The major advantage of statistical downscaling is its computational effectiveness and ease of application, compared to dynamical downscaling modeling, which makes it feasible for use with large ensembles of GCM predictions. Because of its computational expense dynamic downscaling can only be conducted with a limited number of GCM outputs. Furthermore current RCMs predictions typically include systematic biases which require bias-correction after the dynamic downscaling, calling into question the usefulness of the additional computational burden. However, it is also well known that even skillful statistically downscaled results for the present climate do not necessarily guarantee reliable forecasts of future climate because statistical downscaling is ultimately limited by the assumption of stationarity in the empirical relations between global-scale predictions and historic observations. Dynamic downscaling techniques using RCMs are not limited by this assumption and therefore when fine-tuned should provide physically consistent local climate simulations for both current and future periods. We agree with the reviewer that ultimately it is most desirable to improve both the computational efficiency and the fidelity of RCMs so that dynamic downscaling becomes directly useful. This comparison of the pros and cons of statistical versus dynamical downscaling will be included in the introduction section of the revised manuscript.

———- Comment: Page 2144 Lines 4-5 Authors wrote "Additionally statistical downscaling has been shown to provide climate information at any specific resolution of interests so that is the outcome may be directly used for many climate change impact studies (Fowler et al., 2007; Murphy, 1999; Wilby et al., 2004)." This is partially true, the validity of the statistical relationships on which statistical downscaling methods are

based is limited by the spatial resolution of the dataset they are derived from, at any different spatial scale the results are affected by the interpolating scheme used.

Response: We agree with the reviewer that any statistical downscaling method will only reproduce the local precipitation statistics at the space and time scale observations are available, and we will clarify the manuscript to reflect this. Though the skill of downscaled precipitation fields will vary by downscaling method (and the temporal and/or spatial statistical features the method is designed to reproduce) in all cases the accuracy of outcomes is only guaranteed at the resolution of the observation data that were used in downscaling. As discussed in section 5.3 of the present manuscript, the BCSA method can be applied to downscale coarse resolution climate data into any temporal (e.g., monthly, sub-daily) and spatial (e.g., gridded or irregularly distributed points) scale for which observations are available to estimate the cumulative distribution functions and spatial correlation structure of precipitation. We will revise the manuscript to clarify these points.

———- Comment: Page 2145 Lines 10-14: The main disadvantage of using BCSD or SDBC method seems to be the spatialization method (inverse of the distance weighted), there is any attempt to improve these methodologies by using a different spatial disaggregation method, e.g. kriging?

Response: We agree with the reviewer that the main disadvantage of the BCSD and SDBC methods is the smooth inverse distance weighting spatial interpolation scheme that is used. That is, BCSD bias corrects at the large GCM scale then interpolates the large scale bias-corrected GCM predictions to the local scale using inverse distance weighting, whereas the SDBC method interpolates the large scale GCM predictions to the local scale using inverse distance weighting then bias corrects with the local scale data. Kriging is an alternate technique that could be used to interpolate the large scale GCM predictions to the small-scale, either before or after the bias-correction step. However, while kriging would perform the spatial interpolation in a way that honors the spatial correlation structure of the large scale GCM predictions it still would not reproduce the observed small-scale variability at the local scale, so it would not show a significant improvement over the other interpolation methods. In other words, unless bias-corrected observations are available at spatial scales much smaller than the local spatial correlation length kriging will still produce very smooth estimated fields. The method we propose BCSA , produces random fields at any spatial scale that, over their ensemble, honor the observed small-scale spatial correlation structure. Thus each individual random field however shows much higher spatial variability than a kriged field would.

———- From Section 3 General Comment

1) On the selection of downscaling methods

Response: See response to first general comment above.

2) On the selection of different GCMs for BCCA with other downscaling methods

Response: Originally 4 different CMIP3 GCMs (BCCR, CCSM3, CGCM, and GFDL) were selected to apply three different statistical downscaling methods (BCSD_daily, SDBC, and BCSA) based on availability and previous use in testing downscaling approaches. The GFDL, CGCM, and CCSM3 models have previously been used to drive a set of regional climate models (RCMs, dynamical downscaling models) over a domain covering the U.S. and most of Canada for the North American Regional Climate Change Assessment Program (NARCCAP). We selected those because we plan to use NACCAP in future work for comparative investigation of dynamical downscaling and statistical downscaling methods. BCCR was arbitrarily selected is an additional GCM to compare. Subsequently, in addition to the downscaling methods using interpolation (BCSD_daily, SDBC), we compared existing BCCA results, which use historical data to produce constructed analogs, to the new BCSA method because BCSA is also based on an analog approach. Unfortunately BCCA results, available at http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/, are not available for BCCR and CCSM3, so two models (CNRM-CM3 and MIROC3.2) were selected for BCCA in-

stead. Importantly, in this study we found that the differences among the GCMs downscaled with the same technique were not significant in terms of the spatiotemporal statistics reproduced by that method. This is because each method bias-corrected the GCM results using the same observational data so that properties of the downscaled fields fit those of observations (either at the observation or GCM scale), regardless of the GCM. In other words, differences among downscaling techniques were more significant than differences among GCM predictions. Thus use of different/consistent GCMs for each method does not affect the major findings and conclusion derived by the study. However, performance of the GCMs in reproducing daily precipitation patterns (e.g. continuity and intermittence of precipitation events) did show some variation among the GCMs as shown in the Figure 11. We will clarify these issues in the revised data section 2 instead re-applying each statistical downscaling for consistent GCMs.

———- Specific editorial recommendations for paragraphs on p 2148 and p 2149 will be made as suggested

———- Comment: Page 2151 point iv if for each day values are generated using independent Gaussian distribution how can this approach preserve the temporal distribution of precipitation? More specifically how it can reproduce the length of dry and wet spells, if each day is independently generated from the previous one?

Response: This is an interesting question raised by the reviewer. The temporal distribution of precipitation, including wet-dry transition probabilities and wet/dry spell length, for the BCSA method is dictated by the dynamics of the GCM model. If no precipitation is predicted at the large GCM scale, then no precipitation will be generated for any of the fine-scale grid cells. If precipitation is predicted at the GCM scale, a fine resolution stochastic analog is generated which reproduces the predicted areal precipitation over the large GCM grid cell. Within the fine-scale resolution wet cells and dry cells are generated that reproduce the ensemble spatial correlation structure and the mean areal precipitation. In general, for higher mean areal precipitation more fine-resolution cells are wet than for lower mean areal precipitation. Thus although the ensemble of daily precipitation fields originally generated over the fine grid scale are indeed produced independently, the realization selected from the ensemble depends on whether the GCM predicted a wet day over the large cell, and how much rainfall the GCM predicted. Furthermore they are generated to preserve the local (non-Gaussian) probability of being wet or dry on a daily basis. The fact that the downscaled BCSA precipitation fields reproduce the observed small-scale wet/dry spell lengths quite well indicates both that the large scale GCMs are reproducing wet/dry day sequences accurately and that the BCSA method, through the conditional selection of an appropriate realization from the ensemble, propagates this accurately to the local scale. This explanation will be added to the discussion of the revised manuscript. In addition we will emphasize that the local daily precipitation fields that are ultimately produced are not Gaussian. The non-Gaussian observed daily precipitation cdf is mapped onto a Gaussian distribution using a normal-score transform approach to produce the spatially correlated random fields over the fine grid (step i in the process). The resulting Gaussian random field values are ultimately inverse-transformed back to their original non-Gaussian distributions (step v). This will also be emphasized in the revised manuscript

———- Comment: Page 2151 equation (7) since in equation (2) G-1 has been defined as "the inverse transform function of the standard Gaussian CDF", here Fnorm should be defined as G.

Response: Fnorm in eq7 is the empirical CDF of generated normal score variables, not the closed-form solution of the Gaussian CDF. Though Fnorm should follow the Gaussian CDF very closely, we used the actual empirical CDF of generated normal score variables instead of the theoretical Gaussian distribution.

———- Concluding Comments: I think that Authors should indicate that this method is computationally more expensive than the other investigated, since an ensemble of 3000 replicates of spatially distributed precipitation fields for each month is generated and within these replicates the realization with the appropriate monthly ensemble with

spatial mean of the generated precipitation fields equal to the GCM prediction is selected. Thus, the BCSA method performs better than the others also because it allows to choose the best realization of the GCM.

Response: While the computational cost of generating the monthly ensembles for the BCSA method is larger than the interpolation procedure used for the BCSD or SDBC methods, it is an insignificant one time cost and those are all feasible to run using personal computer (e.g., about 3hours (using common PC; 64bit, Intel Core i5 CPU, 3.3GHz) are taken to downscale using BCSA over the state of Florida at 12x12km2 resloution), and approximately equal to the computation cost of the BCCA method. We will include specific information regarding the computational time and storage required for each of the downscaling methods in the revised manuscript.

——— Technical corrections suggested by the reviewer for p. 2146 will be made.

——— TABLES

1. To clarify Table 1 and 2, we will add the acronyms of GCMs, which are used through manuscript and the list of statistical downscaling method applied to each GCM in Table 1

——— FIGURES

1. Through all the figures, the name of GCMs and acronyms will be carefully rechecked and revised.

2. Figure 1 Legend: 1) 'only for BCCR' should be replaced 'only for BCCA'. 2) Other/colored symbols for the models will be used. 3) The grid resolution of observed data (12x12km2) will be drawn in Figure 1.

3. The caption of Figure 2 will be rephrased, the sentence "indicating ... over Florida" does not add any information to interpret the figure content it could probably be removed. It is not clear to me the meaning of the sentence "Mean and standard deviation of annual preciptiation predictions are represented in the panel". The only mean and

standard value I see is the one of Gobs but Gobs are not predictions. Please clarify it

4. Figure 6 will be revised to be consistent with figures 3 through 5.

5. Figures 9 and 10: wet to wet (dry to wet) transition probability will be symbolized by 'TP_{11}' consistently through the manuscript including figures.

6. Through Figures 12 to 14, the symbols for each downscaling methodology will be consistent in the revised manuscript.

7. Typos in Figure 11 will be revised.

8. In Figure 13, "I" (looks "/") and "C" will be replaced by the full name of index, 'Moran's I' and 'Geary's C', respectively.

We thank the reviewer for his/her constructive review and detailed comments. Comments were extremely helpful and we appreciate reviewer who has provided them because we know that such comments above could be given only from very careful review and fully understanding the methodology we presented.

——— References

Hwang, S., Graham, W., Adams, A., Geurink, J., Assessment of the utility of dyncamically-downscaled regional reanalysis data to predict streamflow in west central Florida using an integrated hydrologic model. Reg. Environ. Change, in press, DOI 10.1007/s10113-013-0406-x, 2013.

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