Regional climate downscaling with prior statistical correction of the global climate forcing

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[1] A novel climate downscaling methodology that attempts to correct climate simulation biases is proposed. By combining an advanced statistical bias correction method with a dynamical downscaling it constitutes a hybrid technique that yields nearly unbiased, high-resolution, physically consistent, three-dimensional fields that can be used for climate impact studies. The method is based on a prior statistical distribution correction of large-scale global climate model (GCM) 3-dimensional output fields to be taken as boundary forcing of a dynamical regional climate model (RCM). GCM fields are corrected using meteorological reanalyses. We evaluate this methodology over a decadal experiment. The improvement in terms of spatial and temporal variability is discussed against observations for a past period. The biases of the downscaled fields are much lower using this hybrid technique, up to a factor 4 for the mean temperature bias compared to the dynamical downscaling alone without prior bias correction. Precipitation biases are subsequently improved hence offering optimistic perspectives for climate impact studies. **Citation:** Colette, A., R. Vautard, and M. Vrac (2012), Regional climate downscaling with prior statistical correction of the global climate forcing, *Geophys. Res. Lett.*, *39*, L13707, doi:10.1029/2012GL052258.

1. Introduction

[2] Global Climate Models (GCM) improved notably in their representation of the climate system over the past couple of decades [*Intergovernmental Panel on Climate Change*, 2007a]. Their design is focused on the global scale, and their main scope consists in capturing the sensitivity of the global climate to changes in external natural and anthropogenic forcing. The fairly low resolution of such models does not allow for the detailed simulation of local atmospheric processes. In addition, the main focus being the global energy balance, coupled models may exhibit significant regional biases in important variables such as temperature or precipitation.

[3] However, climate risk assessment requires horizontal resolution of the order of half a degree or below and unbiased projections, especially when it comes to meteorological extremes. More generally such information is required in order to design adaptation measures for which impact models (e.g., with regards to food safety, energy, water, air pollution), tuned on current climate observations, need to be applied to future climate projections. Such a requirement cannot be met by current raw GCM outputs.

[4] The transformation of global model outputs into high spatial resolution products is referred to as climate downscaling. It can be divided into two broad types of approaches: statistical or dynamical downscaling. Statistical downscaling builds upon a prior knowledge of statistical relationships between the GCM and monitoring data. Statistical models representing those relationships are then applied over future time periods, without involving any additional physical modelling in addition to the GCM [*Wilks and Wilby*, 1999; *Vrac et al.*, 2007; *Semenov et al.*, 1998; *Maraun et al.*, 2010]. To downscale a global model in a dynamical way, one implements a Regional Climate Model (RCM) forced by the global fields at the boundaries [*Giorgi et al.*, 2009; *Laprise*, 2008]. Similarly to the GCM, the RCM provides a comprehensive physically-consistent representation of the climate system. However, GCM biases are conveyed to the RCM, and the latter can only compensate, or enhance, these flaws. In order to cope with these deficiencies, bias correction methods are often applied to RCM outputs prior to the implementation of an impact model [*Christensen et al.*, 2008; *Oettli et al.*, 2011]. However this methodology suffers from several caveats. On the one hand, the fields are generally corrected without considering spatial, temporal or intervariable correlation. On the other hand, the bias correction requires high-resolution observations, generally not available on a grid, but rather at scattered locations. These problems could be at least partly avoided if most of the GCM biases were removed before the dynamical downscaling, an approach that we investigate in this article. A few studies investigated the possibility to correct large scale forcing prior to applying a mesoscale model [*Rasmussen et al.*, 2011; *Schär et al.*, 1996] but none of them achieved that with a downscaling technique that matches the whole range of the distribution to meteorological reanalyses.

[5] We propose here an innovative downscaling methodology that combines both dynamical and statistical approaches, but in a different order compared to what is usually done. In a nutshell, our hybrid approach consists in applying a statistical correction of the GCM fields with respect to atmospheric reanalyses prior to performing a dynamical downscaling of these corrected fields. As such, this approach constitutes a hybrid climate downscaling technique building upon upstream statistical correction and downstream physical modelling.

[6] Like any probabilistic downscaling technique, the upstream statistical correction may alter the integrity of the forcing fields by matching it to reanalyses. The main strength

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of our hybrid approach lies in the implementation of a mesoscale model after the probabilistic downscaling that guarantees the physical consistency of the resulting fields and hence constitutes an essential advantage for climate impact studies [*Intergovernmental Panel on Climate Change*, 2007b]. Statistical downscaling that targets only a couple of surface variables has long been considered satisfactory for most climate impact studies (such as food safety or hydrological extremes). However other applications such as air quality modelling require physically-consistent 3D atmospheric fields. That is why regional air quality projection studies rely on raw RCM outputs, and our technique offers a unique perspective to derive unbiased, balanced, 3D forcing fields.

[7] In section 2, the statistical and physical downscaling methodologies are presented. The evaluation results are given in section 3 on a test case for present day simulation. The application to future projections is left for upcoming studies.

2. Methodology

2.1. Large Scale Climate Model

[8] The large scale climate model that we use to demonstrate the efficiency of our hybrid statistical and dynamical technique is the coupled climate model IPSLcm (Institut Pierre Simon Laplace Coupled Model) GCM [*Marti et al.*, 2010].

[9] The simulations used here are obtained with the "low resolution" versions prepared for the CMIP5 (Climate Model Intercomparison Project) stream of the Intergovernmental Panel on Climate Change (IPCC). The meteorological fields are computed on a global 96×96 points grid with a horizontal resolution of 3.75×1.875 degrees and 39 vertical levels.

2.2. Statistical Downscaling

[10] The probabilistic downscaling methodology used here is the CDF-t (Cumulative Distribution Function transform) of *Michelangeli et al.* [2009], based on a variant of the "quantile-matching" technique [*Déqué*, 2007]. Quantile-matching consists in associating to a modelled value, the value in a control distribution (e.g. observations) that has the same probability. In other words, from a quantile in the CDF of the simulations, the corresponding quantile in the CDF of the control data (e.g. observations) is determined. By scaling the quantile-quantile relationship, the correction changes the shape of the distribution so that the events whose frequency (or probability) is systematically biased in the model are better captured.

[11] While classical applications of quantile-matching consider that the CDF of the simulations is stationary in time [*Maraun et al.*, 2010; *Wilks and Wilby*, 1999], the scope of CDF-t consists in expanding this technique for the case where the CDF of the simulations for the future has changed. This is done, first, by estimating the CDF of the corrected variable for the future time period of interest [*Michelangeli et al.*, 2009]. Then, projections are obtained through a quantile-quantile technique between future uncorrected and corrected CDFs [*Vrac et al.*, 2012]. The methodology implemented here thus applies for future projections even though we decided to limit the scope of the present paper to historical periods in order to discuss its validation.

[12] This CDF-t technique has been used successfully in the past to downscale climate models [*Vrac et al.*, 2012; *Flaounas et al.*, 2012; *Michelangeli et al.*, 2009] but one should note the two major limitations of the approach. First, only the bulk CDF is matched, the temporal frequency and spatial patterns are not altered so that any flaw in the persistence or in the spatial distribution of the weather patterns is not improved. In addition, the major underlying hypothesis of the CDF-t downscaling is that, although the CDFs are not supposed to be stationary, the transformation T from model to observed variable CDFs is supposed to be valid under changed climate conditions, i.e. is supposed stationary in time. We emphasize that even though CDF-t is designed to be applied to future climate simulations, we decided to apply this technique in the present paper to a current period for validation purposes.

2.3. Dynamical Downscaling

[13] We use the Weather Research and Forecasting [*Skamarock et al.*, 2008] mesoscale model to downscale the IPSLcm fields in a dynamical way. The spatial resolution is 50 km and the domain covers the whole of Europe with 119×116 grid points. The setup is the same as that of *Menut et al.* [2012] who present a detailed evaluation of the performance of the IPSLcm/WRF regional climate modelling suite. However no nudging was applied in the present case in order to evaluate the full effect of prior correction on dynamical downscaling.

2.4. Experimental Design

[14] We perform a CDF-t based correction of the large-scale input fields produced with the IPSLcm model so that corrected fields will be used for the dynamical downscaling. Distributions are matched with those of reanalysed fields of the ERA-interim reanalysis. Unlike existing applications of CDF-t that perform a scaling of large-scale model outputs to point surface observations [*Michelangeli et al.*, 2009] or gridded surface analyses [*Flaounas et al.*, 2012] we scale several variables of the model to the whole 3D fields of the reanalysis.

[15] The correction is achieved at each GCM grid-point independently, where reanalysed fields were previously interpolated. There was no attempt to maintain the spatial consistency of the fields considering that (1) matched fields are coarse enough to avoid the introduction of high-frequency variability and (2) potential spurious features would vanish after having used the mesoscale model to downscale the corrected fields. For each variable and at each grid point, we extract the time series for the whole period to produce the two distributions (GCM and reanalysis) that will be matched. To account for seasonality, all training distributions are taken on a monthly basis. For 3D and surface temperature, the correction is performed independently for the 4 daily time steps to account for the diurnal cycle. Since we match the bulk distribution of the time series, there is no matching of sequences of event, on the contrary we maintain the temporal consistency of the input field.

[16] The correction is done for 3D zonal and meridional wind, 3D relative humidity, and 3D and surface (skin) temperature. Surface pressure and geopotential height are not matched in order to maintain flow consistency and quasi-geostrophy at the boundaries, but they are indirectly modified by the matching of the 3D temperature field. The hydrostatic balance of the corrected input field is recomputed before launching the mesoscale model in order to ensure physical

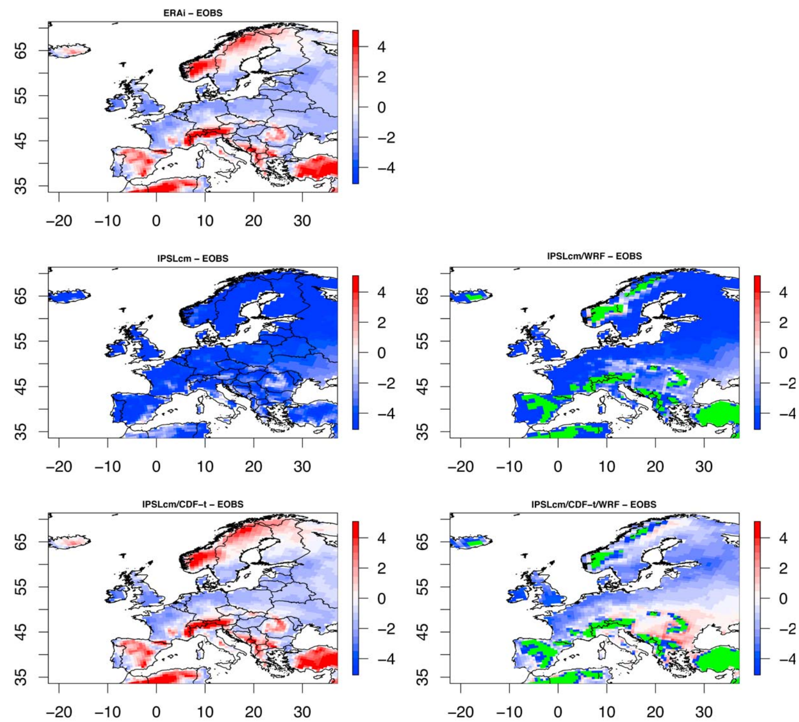

Figure 1. Difference between the mean modelled 950 hPa temperature and observed (E-OBS) 2-m temperature (K) over the 1990–1999 decade for ERA-interim, the GCM IPSLcm as well as its corrected version and the RCM WRF driven by raw IPSLcm fields and by downscaled IPSL fields corrected with the CDF-t technique. The green-shaded areas in the WRF field are unavailable because located below the 950 hPa level in the hybrid coordinates.

consistency along the columns; by proceeding to an upward integration of the hydrostatic balance, corrections applied to the temperature field are conveyed to the geopotential height.

[17] The evaluation experiment consists of simulations over a 11-year period for the downscaling. The first year is considered as a spin-up period and it is thus discarded from the following analysis. The last decade of the 20th century is chosen because of the full overlap between ERA-interim and IPCC historical simulations. This time period also allows comparing the efficiency of the methodology against observations. Two simulations are carried out, starting on 1 January 1989. The first one is done without applying the GCM correction prior to dynamical downscaling, while the second is done with application of the prior CDF-t approach. The two simulations are then compared to E-OBS data [*Haylock et al.*, 2008] over the same time period. Since the focus of this study is not to validate the performance of the CFD-t itself directly applied to the GCM fields (as it was demonstrated before [*Flaounas et al.*, 2012; *Michelangeli et al.*, 2009; *Vrac et al.*, 2012]), but the impact of CDF-t on the dynamical regional climate downscaling, it was unnecessary to implement a 'leave-one-out' testing approach. The duration of the simulations (10 years) is too short to address the benefits for meteorological extremes; this aspect is left for future work while we focus here on average biases.

3. Results

[18] The evaluation of the results is performed against the European Climate Gridded dataset (E-OBS) temperature and precipitation observations.

3.1. Surface Temperature

[19] The bias of temperature averaged over the 10-year time period is given in Figure 1 for the reanalysis (ERA-i), the large-scale climate model (IPSLcm) and its statistically corrected version, the dynamically downscaled climate model (IPSLcm/WRF) and the hybrid statistical/dynamical downscaling (IPSLcm/CDF-t/WRF). For all the models the temperature is interpolated at 950 hPa while the observations are provided at 2-m altitude. The discrepancies between E-OBS and ERA-i are confined to the outskirts of the domain where the gap filling procedure used in E-OBS has uncertainties as a result of the scarcity of the monitoring network. In addition, important differences are found over mountainous areas due to lack of resolution and methodological differences. On average, the difference between ERA-i and the observations is −1.41 K (standard deviation σ = 2.03) over the Western part of the domain (5W, 15E, 40N, 55N). Raw GCM temperatures exhibit a strong negative bias (−4.78 K, σ = 0.6), except over mountainous areas where the positive biases result from an artefact of the smooth orography. This strong negative bias of the low resolution version of the IPSLcm model was discussed before [*Hourdin et al.*, 2012] and was improved in a more recent version of the model including a higher resolution [*Cattiaux et al.*, 2012]. This feature constitutes a somewhat good test case for the hybrid downscaling methodology presented here. The statistical correction is efficient at reducing the temperature bias of IPSLcm, the average bias of the corrected GCM is −1.36 (σ = 2.07) and its pattern resembles that of ERA-i.

[20] The negative bias of IPSLcm is amplified in the raw regional climate model simulations (−5.06 K, σ = 1.49), as

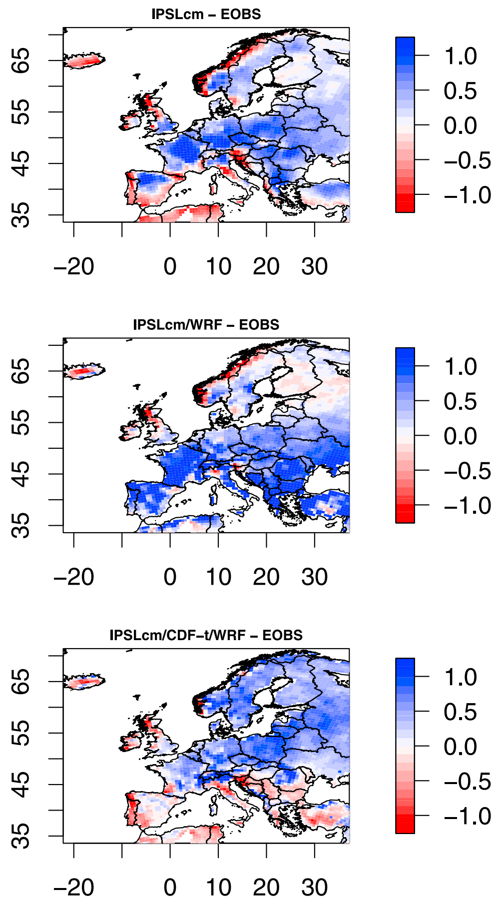

Figure 2. Same as Figure 1 for the precipitations (mm/day) except that only the results of the climate models are given and the colour scale is reversed.

was observed by *Menut et al.* [2012]. The dynamical downscaling does not constrain the distribution in any ways, and it appears that a negative feedback occurs here as the RCM increases the negative biases of forcing fields. On the contrary, the situation is better for the hybrid downscaling, the average bias is limited to -2.33 K ($\sigma = 1.35$). The mesoscale still tends to cool down the GCM, and the average bias is larger than for the corrected version of IPSLcm since the compensation that occurred over high elevation terrain vanishes. Despite the reduction of the mean bias, it still exhibits a regional pattern with negative values in Western and Northern areas and positive values in Mediterranean areas.

[21] The overall negative bias is primarily found for low temperatures during winter and to a lesser extent for warm temperatures, even though a bias remains over the lowermost part of the distribution.

[22] Seasonality has a strong impact, the mesoscale model tends to be warmer than the large scale forcing in winter (0.5 and 0.6 K average bias for IPSLcm and IPSLcm/CDF-t, respectively) and colder in summer (-0.3 and -1.67 K average bias for IPSLcm and IPSLcm/CDF-t, respectively). The upstream statistical correction influences indirectly the atmospheric flow. This feature is confirmed with average sea-level pressure maps (not shown) that exhibit larger differences in winter than in summer, explaining this uneven influence on temperature of the bias correction over the year.

3.2. Precipitation

[23] Beyond its relevance for climate impact studies, precipitation is an interesting variable to evaluate our methodology since, unlike temperature, this variable was not directly corrected by the prior statistical CDF-t method. The absolute differences between modelled and observed precipitations are provided on Figure 2.

[24] The GCM exhibits an overestimation of precipitations throughout the domain. Only West-facing coastal areas have a deficit, presumably because of the too coarse resolution that is not able to capture the precipitation local maxima over the coastlines. The overestimation is less pronounced over mountainous areas because of a compensation of errors.

[25] The dynamical downscaling of the raw GCM outputs yields an even stronger overestimation of the precipitation because of a negative feedback related to the low temperature bias. The deficit over coastlines and mountains is compensated by the higher resolution of the model.

[26] It is only with the hybrid downscaling that the results are significantly improved. The model still exhibits an overestimation of precipitation but, over low-lying area of Western Europe, the bias is decreased by a factor of two. An excess is found over the Alps. Precipitation deficits are found around the Mediterranean, the spatial patterns of these deficits do not appear highly correlated to coastlines. It may thus be attributable to other uncorrected deficiencies such as weather regime frequencies rather than resolution issues.

[27] The distribution of daily precipitation shows that the hybrid downscaling constitutes an improvement over the whole range of the distribution. Nevertheless, all the simulations still exhibit an overestimation of low precipitations and an underestimation of higher quantiles.

4. Conclusion

[28] We propose an innovative climate downscaling methodology that combines state-of-the-art statistical and dynamical approaches. We apply a statistical correction to large-scale fields of a Global Climate Model (GCM) prior to a regional simulation. The statistical correction makes use of the Cumulative Distribution Function transformation (CDF-t) designed by *Michelangeli et al.* [2009]. The GCM field distributions are matched to those of reanalysed fields in order to apply a correction over the whole 3D domain for several variables. The corrected fields are then provided to a dynamical Regional Climate Model (RCM), so that we can produce bias-corrected, yet physically consistent, 3D fields at higher spatial resolution.

[29] An application to present-day climate shows that the statistical upstream correction leads to a reduction of the surface temperature bias of a factor four in the regional climate simulation. This improvement yields, in turn, a lower overestimation of precipitations.

[30] The CDF-t upstream correction does not address yet spatial and temporal variability (climate modes, persistence and weather regimes), the technique remains sensitive to the choice of variables included in the correction and the location of the domain since the forcing is applied at the boundaries. The methodology carries some error compensation mechanisms whose effect is minimised thanks to the implementation of a dynamical downscaling in the lee of the statistical correction.

[31] Nevertheless, considering the magnitude of the improvement in terms of mean bias we conclude that this innovative hybrid statistical/dynamical climate downscaling offers promising perspectives for climate impact studies requiring unbiased, balanced, high-resolution 3D fields.

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