

Statistical downscaling of climate impact indices: testing the direct approach

A. Casanueva · M. D. Frías · S. Herrera ·
D. San-Martín · K. Zaninovic · J. M. Gutiérrez

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Abstract Climate Impact Indices (CIIs) are being increasingly used in different socio-economic sectors to transfer information about climate change impacts to stakeholders. Typically, CIIs comprise into a single index several weather variables—such as temperature, wind speed, precipitation and humidity—which are relevant for a particular problem of interest. Moreover, most of the CIIs require daily (or monthly) physical coherence among these variables for their proper calculation. This constraints the number of statistical downscaling techniques suitable for a component-wise approach to this problem. We test the suitability of the alternative “direct” downscaling approach in which the downscaling method is applied directly to the CII, thus circumventing the multi-variable problem and allowing the use of a wider range of downscaling methods. For illustrative purposes, we consider two popular CIIs—the Fire Weather Index (FWI) and the Physiological Equivalent Temperature (PET), used in the wildfire and tourism sectors, respectively—and compare the performance of the two approaches using the analog method, a simple and popular method providing inter-variable dependence. The results obtained with ‘perfect’ reanalysis predictors are comparable for both approaches, although smaller accuracy is obtained in general with the direct approach. Moreover, similar climate change ‘deltas’ are obtained with both approaches when applied to an illustrative future global projection using the

A. Casanueva (✉) · M. D. Frías · S. Herrera
Grupo de Meteorología, Dpto. Matemática Aplicada y Ciencias de la Computación,
Univ. de Cantabria, Avda. de los Castros, s/n, 39005 Santander, Spain
e-mail: ana.casanueva@unican.es

S. Herrera · D. San-Martín
Predictia Intelligent Data Solutions S.L., Avda. de los Castros, s/n, 39005 Santander, Spain

K. Zaninovic
Meteorological and Hydrological Service of Croatia, Grič 3, 10000 Zagreb, Croatia

J. M. Gutiérrez
Grupo de Meteorología, Instituto de Física de Cantabria, CSIC-Univ. de Cantabria,
Avda. de los Castros, s/n, 39005 Santander, Spain

ECHAM5 model. Overall, there is a trade-off between performance and simplicity which needs to be balanced for each particular application.

1 Introduction

The assessment of climate change impacts on the different ecosystems and human activities has become a major challenge in the last decades, especially for those regions that are particularly vulnerable to climate change. Several socioeconomic sectors of prime importance are directly affected by climate impacts, and therefore the provision of adequate climate information at regional/local scale is of paramount importance. Considerable efforts have been devoted to the development of Climate Impact Indices (CIIs) for different sectors —such as forest fires (Stocks et al. 1989; Willis et al. 2001) and tourism (Mieczkowski 1985; Morgan et al. 2000; Freitas et al. 2008) among others,— summarizing in a single daily (or monthly) index the information from the relevant meteorological variables (temperature, wind speed, humidity, etc.) for the problem under study. Moreover, physical coherence among these variables is required for the proper calculation of most of the CIIs. For instance, this is the case for the two popular indices used in this work, the Fire Weather Index (FWI) and the Physiological Equivalent Temperature (PET), from the forest fires and tourism sectors, respectively.

The calculation of CIIs require high resolution data in many impact studies, far beyond the large scale simulations of the state-of-the-art Global Climate Models (GCMs). Thus, some sort of downscaling process is required to bridge this gap in practical applications. Regional Climate Models (RCMs) provide a large number of physically consistent meteorological variables at a suitable spatial resolution (Giorgi 1990). However, the direct application of RCM outputs in impact studies is hampered by model biases (see e.g. Casanueva et al. 2013), thus making necessary the application of multi-variable bias correction techniques preserving this consistency (see Hempel et al. 2013; Wilcke et al. 2013, for some advances on this).

Alternatively, Statistical Downscaling Methods (SDMs) render local scale information using empirical relationships generally established between the large-scale synoptic variables from reanalyses (predictors) and the locally observed predictands, following the so-called perfect prognosis approach (Maraun et al. 2010); these relationships are then applied to the outputs of GCMs. SDMs are most often applied to derive local values of typical surface variables such as precipitation or temperature (Hewitson and Crane 1996; Timbal and McAvaney 2001; Frías et al. 2010), and less often to others like wind (Curry et al. 2012) or snow occurrence (Pons et al. 2010). More recently, the application of the SDMs has been extended to other non-standard (or “exotic” in the downscaling context) variables such as wind power (García-Bustamante et al. 2013) or river flows (Tisseuil et al. 2010) with promising results, suggesting the possibility of applying SDMs directly to the CIIs. However, many attempts to statistically downscale CIIs carried out to date are “component-wise” approaches, where the downscaled CIIs are derived a posteriori from the downscaled series of the corresponding weather component variables (see, e.g. Abatzoglou and Brown 2012; Bedia et al. 2013, for FWI).

In this paper we focus on CIIs built from several meteorological variables and assess the performance of the direct-wise downscaling, as compared to the component-wise one; to our knowledge there is not a previous comparison of both approaches —Table 1 summarizes previous studies, indicating the type of approach (direct- or component-wise) followed in each case.— Note that the main advantage of the direct approach is the

simplicity of dealing with a single predictand, thus circumventing the problem of physical consistency (see Maraun et al. 2010, for a discussion of this problem in the context of statistical downscaling techniques). Another advantage is that the distribution of the CII might be in some cases more suitable for statistical downscaling (e.g. more gaussian) than those corresponding to some of its meteorological drivers—for instance, this is the particular case of the two CIIs analyzed in this work.— These aspects widen the range of SDMs that can be used for a particular index, allowing the choice of those attaining a better performance, or which are more robust in climate change conditions (Gutiérrez et al. 2013). In this study we use two alternative techniques of wide application in statistical downscaling studies, the analog method and linear regression transfer functions, the latter being only suitable for the direct approach in this case—it does not provide physically consistent results and, more important, the underlying assumption of normality does not hold for some of the components, e.g precipitation and humidity.—

In Section 2 we describe the main characteristics of the FWI and PET, the data sets considered for their calculation and the downscaling approaches used in this study. The main results obtained are described in Section 3 and, finally, the main conclusions are summarized in Section 4.

2 Data and methods

2.1 Description of the indices and calculation

For illustrative purposes, in this paper we consider two CIIs, the Fire Weather Index (FWI) and the Physiological Equivalent Temperature (PET), which are popular in the wildfire and tourism sectors, respectively. Due to the different data requirements and the observational records available for the meteorological driving variables, FWI and PET are analyzed in different regions (Spain and Croatia, respectively; see Fig. 1a, shaded areas).

FWI is one of the most popular fire danger indices worldwide (van Wagner 1987; Wotton 2009). In particular, its suitability for different Mediterranean ecosystems has been already pointed-out by several authors (see, e.g. Viegas et al. 1999; Dimitrakopoulos et al. 2011). For this reason, it is the official fire danger indicator used by the European Commission to assess the current and future fire danger in Europe (see e.g. Camia et al. 2008). FWI has been previously applied to the estimation of future regional fire danger scenarios in Europe by several authors, considering both dynamical (Moriondo et al. 2006; Bedia et al. 2014) and statistical downscaling methods (Bedia et al. 2013). FWI is a dimensionless daily indicator of fire potential conditions based on four weather variables—instantaneous values of temperature, relative humidity and wind velocity at noon local standard time, and accumulated precipitation in the previous 24 hours—accounting for the effects of fuel moisture and wind speed on fire behavior (see van Wagner and Pickett 1985, for details on the calculation). In this work we analyze FWI considering 45 meteorological stations over Spain—provided by the Spanish Meteorological Agency (AEMET), see Fig. 1b—with historical records of the required data for the period 1979–2003. This data set has been previously used by Bedia et al. (2013), where a more detailed description of its characteristics is given.

PET is a thermal comfort index derived from the human energy balance which depends on temperature, humidity (relative humidity or water vapour pressure), wind speed and radiation or cloudiness. This index is well suited to the evaluation of the thermal component of different climates (Matzarakis et al. 1999). It is equivalent to the air temperature at which, in a typical indoor setting, the heat balance of the human body is maintained with core and

Table 1 Previous studies on statistical downscaling of exotic indices using direct- or component-wise approaches. The label “*” indicates that meteorological drivers are introduced in hydrological or phenological models after the downscaling is performed

Reference	Exotic Index (meteorological drivers)	SD approach
Li et al. (2012)	Reference evapotranspiration	Direct
Guo et al. (2014)	Evapotranspiration	Direct
Fealy and Sweeney (2008)	Radiation and potential evapotranspiration	Direct
Tian et al. (2014)	Reference evapotranspiration (maximum, minimum and mean temperature, solar radiation and wind speed)	Component
Rehana and Mujumdar (2013)	Reference evapotranspiration (rainfall, relative humidity, wind speed, radiation, maximum and minimum temperatures)	Component
Tukimat et al. (2012)	Evapotranspiration	Component
Zuo et al. (2011)	Potential evapotranspiration	Component
Bourqui et al. (2011)	Potential evapotranspiration, snow water equivalent and streamflows	Component*
Hamlet et al. (2013)	Potential evapotranspiration	Component*
Sultana and Coulibaly (2011)	Streamflows, snow storage, and evapotranspiration	Component*
Krause and Hanisch (2009)	Evapotranspiration, runoff generation, and groundwater recharge	Component*
Chu et al. (2010)	Evaporation	Direct
Charles et al. (2007)	Runoff	Component*
Ouyang et al. (2014)	Runoff	Component*
Samadi et al. (2013)	Runoff	Component*
Fu et al. (2013)	Runoff	Component*
Huang et al. (2010)	Water dynamics and river discharge	Component*
Cheung and Hart (2014)	Thermal comfort index (air temperature, wind speed, relative humidity and solar radiation)	Component
Anandhi et al. (2014)	Solar radiation (temperatures and cloud cover)	Component
Hoffmann et al. (2012)	Urban heat island	Direct
Wilby (2008)	Urban heat island and peak ozone concentrations	Component
Dehn et al. (2000)	Displacement rates of the mudslide (precipitation and temperatures)	Component*
Dehn (1999)	Landslide activity	Component*
Maak and Von Storch (1997)	First-flowering date	Direct
Hur and Ahn (2014)	First-flowering date (temperatures)	Component*
Hur et al. (2014)	First-flowering date (temperatures)	Component*

Table 1 (continued)

Reference	Exotic Index (meteorological drivers)	SD approach
García-Bustamante et al. (2013)	Wind power	Direct
Abatzoglou and Brown (2012)	Energy Release Component (temperature, precipitation and humidity) and the Fosberg Fire Danger Index (temperature, wind speed and relative humidity)	Component
Bedia et al. (2013)	Fire Weather Index	Component

skin temperatures equal to those under the conditions being assessed (Höppe 1999). In this work we analyze PET using the observed values of temperature, relative humidity, wind speed and cloudiness at 2pm for 21 meteorological stations in Croatia —provided by the Meteorological and Hydrological Service of Croatia, see Fig. 1c— covering from 1981 to 2010. We used the freely available RayMan software (<http://www.urbanclimate.net/rayman>) developed by Matzarakis et al. (2007, 2010) to estimate this index.

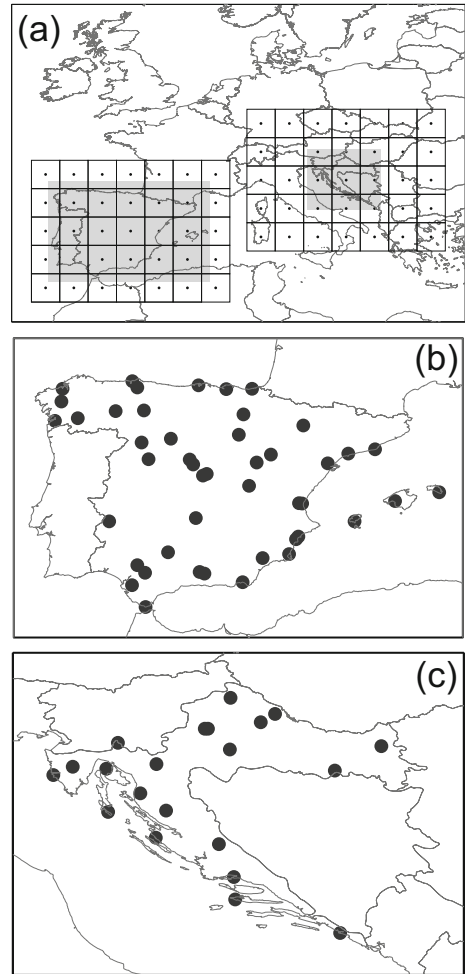
We focused our study in the warmest months, June to September (JJAS), since this is the season of critical fire danger over Spain and it is of particular interest for tourism in Croatia. FWI and PET were tested for normality and passed this requirement for the linear regression methods.

2.2 Reanalysis and global climate model projections

The predictor variables used in this study for the statistical downscaling methods are Sea Level Pressure (SLP), Temperature at 2 meters (T2m), relative and specific humidity, temperature and U and V wind components for 850 mb (R850, Q850, T850, U850 and V850, respectively) and geopotential height at 500mb (Z500). We consider daily predictor values at 12 UTC in order to better match the observation times (at noon for FWI and 2pm for PET). On the one hand, predictors are taken from ERA-Interim reanalysis (Dee et al. 2011), covering the observation periods. This reanalysis has proven to be suitable for FWI calculation over Spain (Bedia et al. 2012). On the other hand, the same predictor variables are also taken from the CMIP3 ECHAM5 model (run 3) for the control 20C3M scenario (1971–2000) and for the transient A1B scenario (2011–2100). Due to their different native horizontal resolutions, both data sets are re-gridded —using bilinear interpolation— to a regular 2.5° grid considering the gridded domains shown in Fig. 1a. Moreover, in order to correct systematic biases in the mean, the ECHAM5 data are preprocessed removing the mean bias for each predictor variable with respect to ERA-Interim at a monthly basis (the GCM monthly mean is replaced by the reanalysis counterpart for each predictor variable at a gridbox level). In particular we considered two windows with coordinates 45°N, 35°N, 10°W and 5°E (centered on the Iberian peninsula) and 39.5°N–49.5°N, 9°E–24°E (centered on Croatia) as geographical domains.

It is worth to remark that the predictors considered in this work include “signal-bearing” variables (e.g. temperature) in order to capture a potential climate change signal. Moreover, they are well reproduced in southwestern Europe —after bias removal— by the ECHAM5 model (Brands et al. 2011).

Fig. 1 **a** Case study regions (gray shaded) and the corresponding geographical domains/grids used in the downscaling process. Panels **b** and **c** show the stations/locations considered over the two regions, Spain and Croatia, respectively



2.3 Statistical downscaling methods

Statistical (perfect prog) downscaling is applied following two different approaches: 1) the required weather variables are downscaled and the CII series are computed afterwards (component-wise: the weather variables are the predictands), 2) the CIIs are downscaled directly (direct-wise: the CII is the predictand). In the former case the downscaling method must be generic—applicable to a number of different variables—and must preserve the physical consistency among the variables; this poses a serious limitation on the number of feasible downscaling methods (Maraun et al. 2010). The analogs method (Zorita and von Storch 1999; Frías et al. 2010) is a popular and simple generic downscaling technique which meets this requirement. Other statistical downscaling methods attempt to model the relationships between relevant variables by regressing other variables on the generated values of key variables (e.g. precipitation; see Kilsby and Wilby 2007), thus requiring different configurations for different CIIs.

In this work, the component-wise approach is applied considering the analog method to jointly downscale each of the input meteorological variables driving FWI and PET. Given an atmospheric state (as represented by a number of predictors defined on a particular geographical pattern) to be downscaled, this technique finds the most similar historical atmospheric state—the “analog” day, or nearest neighbor in terms of some metric, e.g. the Euclidean distance in this study—in a pool of historical states provided by a reanalysis data set. Then, the downscaled values for the predictands are computed as the corresponding historical outcomes for the analog date, thus preserving the physical consistency among the predictands. This analog methodology is also applied directly to the CII (considering the historical values of the CII) in order to compare the performance of both component- and direct-wise approaches.

In a previous study by Bedia et al. (2013), the performance of the analog method to downscale FWI over Spain was already validated following the component-wise approach. Several geographical domains over Spain and different sets of predictors were tested in that study (see e.g. Gutiérrez et al. 2013, and references therein). In the present work we build from that study and consider the same geographical window (see Fig. 1a) and predictors (T2m, R850, T850, U850, V850) for both component- and direct-wise FWI downscaling in Spain. For downscaling PET in Croatia we consider a similar geographical domain (see Fig. 1a). In this case we tested alternative predictor sets—SLP, T2m, T850, Q850, Z500—with similar results so, for the sake of consistency between the two case studies, we consider the same predictor set used for FWI. Note that by accepting a common set of predictors, some local skill will be sacrificed since the optimum combination of predictors is predictand, site and season specific.

For direct downscaling we consider an additional statistical downscaling method based on the popular linear regression model. In this case a Principal Component (PC) analysis is first applied to the atmospheric states retaining the first 10 principal components (PCs) of all the predictor variables altogether—that yield a fraction of explained variance around 90 % in the two regions considered in this work—as predictors for the linear model. Two alternative statistical downscaling methods based on linear regression were also tested—one method considering 30 PCs instead of 10 and a second one including the local predictor values for the nearest grid box—but similar results were obtained. For a detailed description of these methods we refer the reader to Gutiérrez et al. (2013).

2.4 Validation framework

In order to assess the performance of the different downscaling approaches with “perfect” predictors, we considered reanalysis data for both calibrating/training and testing the statistical downscaling methods; thus, for each CII we used the period that overlaps with the ERA-Interim reanalysis (1979–2003 for the FWI and 1981–2010 for the PET). A k -fold cross-validation approach is considered by splitting the data into k equal-size subsamples. Then, each subsample is retained as the validation data for testing the model, and the remaining ones are used as training data. We applied the same k -fold ($k = 5$) cross validation approach used in Bedia et al. (2013) for the FWI, considering a stratified sampling. For the case of PET, due to the longer period available, $k = 10$ different combinations of calibration and test periods were considered; in this case the first fold was formed by years 1981, 1991 and 2001, etc. In all cases, the statistical models have been trained and tested with JJAS data at a daily basis, and the resulting tests periods were concatenated into a single final downscaled multi-year JJAS series for validation. In the case of the component-wise

approach, the FWI and PET predicted series are computed from the downscaled series of the required weather variables.

Note that using stratified (or random) folds, the same distributions/climatologies are sampled for all folds, allowing to estimate the performance/deficiencies attributable to the downscaling methods themselves (Section 3.1), without mixing this with their extrapolation capabilities. This latter problem, key in the climate change context, is analyzed separately when applying the methods in climate change conditions (Section 3.2). Note that consecutive folds could be used instead in the cross-validation approach in order to include extrapolation capabilities. However, in this paper we analyze these two problems separately.

3 Results

3.1 Results in perfect model conditions

The Spearman correlation coefficient (Fig. 2a–d) and the standardized bias (Fig. 2e–h) (i.e. bias divided by the observations' standard deviation at each station) for the downscaled values from the direct analog (a-b, e-f) and linear regression (c-d, g-h) methods are obtained applying the validation framework described in Section 2.4. Spatially averaged values are indicated in each panel for the direct approach and also for the component-wise approach for the case of the analog method—the spatial patterns are very similar in both cases and, therefore, they are not shown for the sake of conciseness; some results for the FWI component-wise case are analyzed in Bedia et al. (2013).— Note that higher correlation values are obtained for the component-wise downscaling, particularly in the case of FWI. This indicates that some information carried by the weather variables is lost when downscaling directly the aggregated CII. However, the possibility of using alternative statistical downscaling methods under the direct approach is a clear advantage, since the results for linear regression exhibit higher correlation and smaller biases in all cases. Note that this can be largely explained by the different nature of the regression and analog methods (Gutiérrez et al. 2013), but anyhow illustrates the potential value of using a wider range of downscaling approaches.

Finally, note that the performance of the downscaling methods is higher for PET than for FWI in all cases. This is partly explained by the higher dependence of FWI on humidity-related variables (Bedia et al. 2012), more difficult to downscale than temperatures from the large-scale predictors.

3.2 Downscaling climate projections

Besides the assessment of the component- and direct-wise approaches in perfect model conditions, we compare their results when downscaling global climate change projections from a single global model (the ECHAM5 model; see Section 2.2). ECHAM5 is used here only for illustrative purposes and to explore the sensitivity of the downscaled CIIs to a given climate change signal, however a multi-model ensemble should be applied to account for the variability of different global projections. The downscaled results for the transient A1B scenario for three different future periods 2011–2040, 2041–2070 and 2071–2100 are compared with those corresponding to the reference period obtained from the control 20C3M scenario (for the period 1971–2000). To this aim, the delta method (Räisänen 2007) is applied to compute the relative future 'deltas' with respect to the reference values.

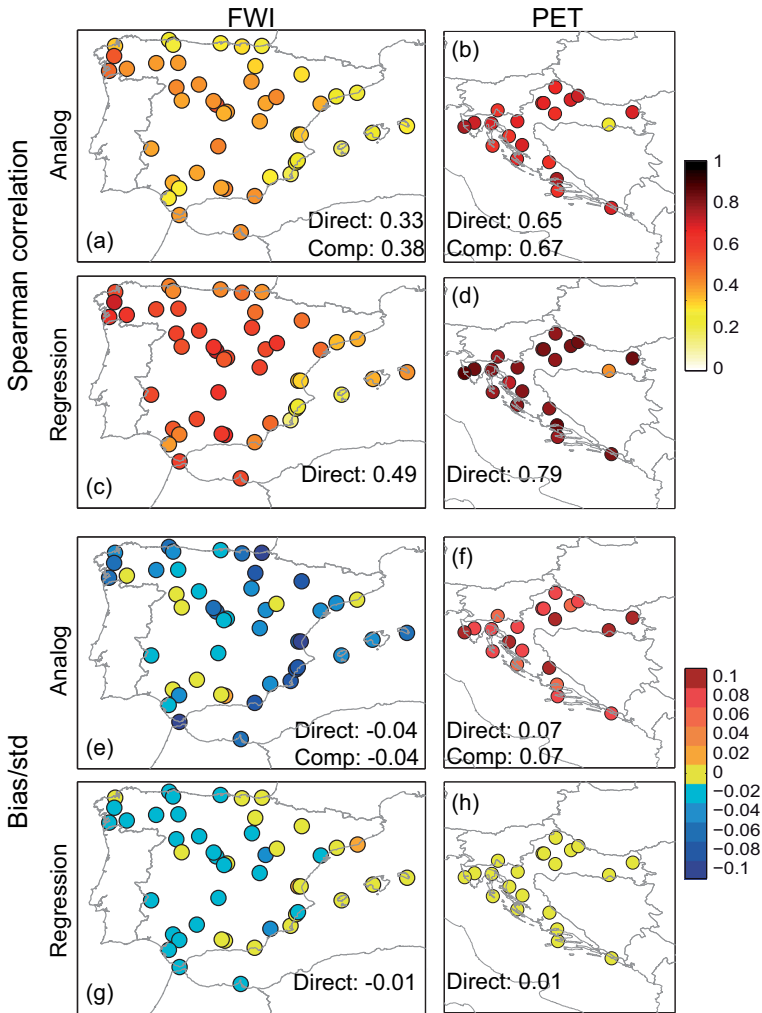


Fig. 2 Spearman daily correlation and standardized bias from the direct analog and linear regression downscaling approaches for the FWI (left panels) and PET (right panels). All results correspond to the season June-September. The numbers in the panels represent the spatially averaged scores (also shown for the component-wise approach for the analog method)

Figure 3a–b shows the relative ‘deltas’ (in %) for the FWI (left) and PET (right) from the component versus the direct analog downscaling method for every station. In general, these results show that the values from the component method are comparable to those from the direct downscaling method, with R^2 values ranging from 0.6 (for the 2011–2040 period, with small changes) to 0.83 for FWI and over 0.99 for PET. The almost perfect correspondence obtained by PET could probably be due to the main role that the temperature plays on the PET definition in warm conditions, contrary to the more pronounced influence of wind in winter, whereas FWI is more dependent on humidity-related variables, worst predicted by

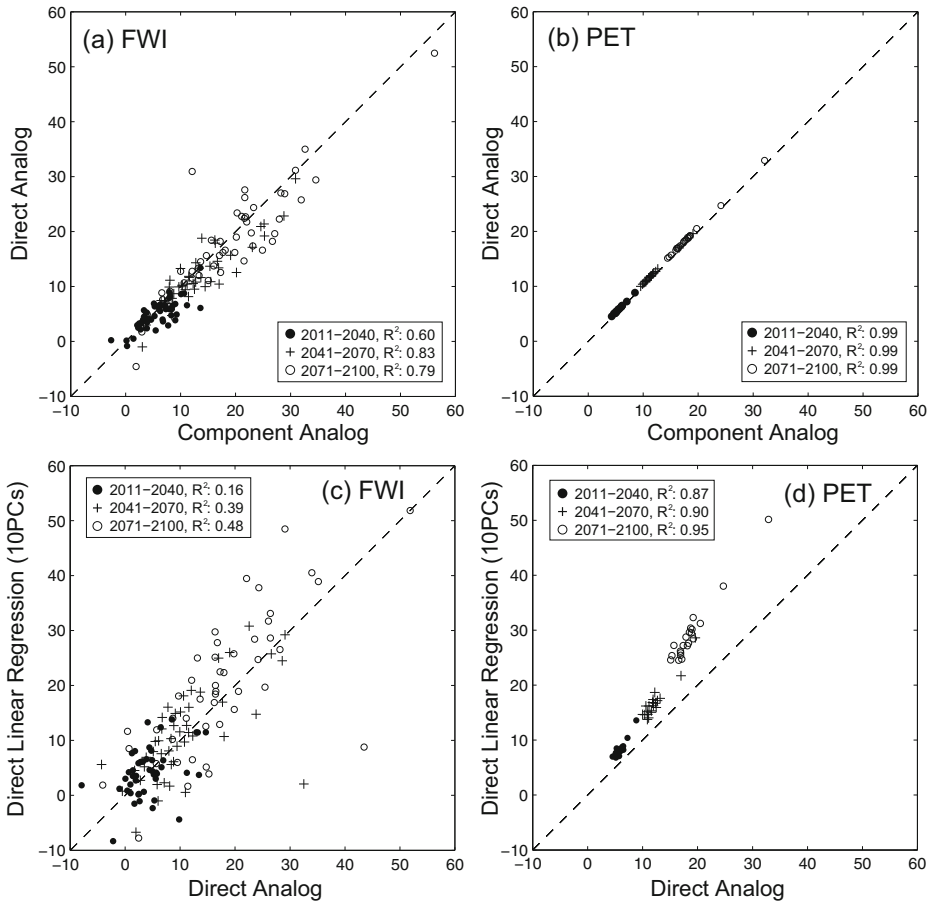


Fig. 3 Point-based percent delta changes for FWI (*left*) and PET (*right*): **a–b** Component versus direct analog statistical downscaling, and **c–d** direct analog versus the direct linear regression methods. Results for the three future periods are shown with different markers; goodness-of-fit estimates for the linear regression are provided in each case

statistical downscaling methods (Bedia et al. 2013)—and therefore, with larger uncertainty for different methods and/or approaches.—

A comparison of the FWI and PET deltas resulting from the direct downscaling approach based on analog versus those based on the linear regression is shown in Fig. 3c–d for the three future periods considered. It can be observed that the uncertainty associated to the selection of the downscaling method applied directly to the index (analog or linear regression in this case) is higher than the uncertainty due to the application of the direct or component downscaling approaches, with R^2 values ranging from 0.16 to 0.48 for FWI and from 0.87 to 0.95 for PET. Moreover, there is a clear trend in both cases, more noticeable for PET, with increasingly larger downscaled values obtained with the linear regression than with the analog technique, so, from a climate risk management perspective, scenarios produced by this technique might favour more precautionary adaptations. This increase can be

explained by the lack of robustness of the analog downscaling technique (see, e.g. Gutiérrez et al. 2013), which cannot extrapolate future atmospheric conditions, thus producing an underestimation of the results as compared to other techniques. Therefore, a key advantage of the direct downscaling approach in this context is the possibility of using a wider range of statistical downscaling methods.

4 Conclusions

Climate Impact Indices (CIIs) are becoming popular in order to summarize in a single index the multi-variable meteorological information relevant for a particular impact sector. Statistical downscaling methods have been recently applied to CIIs following an indirect component-wise approach—the weather variables forming the index are downscaled and the CII is computed from the resulting downscaled series.— The present study reveals the suitability of performing statistical downscaling directly on the CII, simplifying the application of this methodology and allowing to use a wider range of statistical downscaling methods. According to the experiments performed using “perfect” predictors, similar performance was obtained applying both approaches for both indices, with slightly better results for the component-wise approach. The comparison for future global projections from a single GCM (the ECHAM5 model) yields similar deltas with both approaches for different periods of the 21st century. Note that the goal of this paper is testing the performance of the direct- and component-wise approaches and, therefore, for illustrative purposes, we used a single global climate model. However, a general study of climate change projections should consider a multi-model ensemble approach, accounting for the variability of different global projections.

The suitability of the direct statistical downscaling approach widens the range of statistical downscaling methods that can be used (since only one index needs to be downscaled rather than multiple physically and spatially consistent variables). This is a clear advantage which is illustrated in this paper by considering an alternative statistical downscaling approach (based on linear regression). In this case, clear differences arise from the comparison of the deltas for the analog and the linear regression methods. This is in agreement with previous studies, reporting the problems of the analog method to extrapolate future climatic conditions, thus leading to underestimated values.

While this work focuses on particular indices (FWI and PET) and regions (the Mediterranean), the same study could be extended to other indices and areas of interest defined in other sectors which are particularly affected by climate change. Therefore, for those impact studies where the intermediate climate information is not relevant, it is advisable to use the direct downscaling approach in order to provide local scale information for a particular CII. However, there is a trade-off between performance and simplicity which needs to be balanced for each particular application.

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