Downscaling extremes with EDS, TreeGen, and BCSD

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§1 Introduction

Empirical downscaling is based in a statistical analysis of present climatic conditions for an area, usually recorded by a number of variables from weather stations. The result of this analysis is a set of recipes (algorithms) and parameters from which the present climate, or at least some of its crucial aspects, such as extreme temperature values, can be recovered. By assuming that climate itself is characterized by the parameters and the recipe remains valid under different climatic parameters, empirical downscaling proceeds by applying this recipe to other, e. g. future, climates. The main purpose is to obtain the correct parameters for the future climate.

Given the multitude of techniques and results, downscaling intercomparison projects provide guidance for choosing the best method for a purpose in question. Ideally, there should be just one big intercomparison including all possible methods, possibly stratified according to region. Here we study the performance of the three methods *Expanded Downscaling* [*Bürger*, 1996], *TreeGen* [*Stahl et al.*, 2008], and the *Bias Correction Spatial Disaggregation* [*Wood et al.*, 2002; *Salathe Jr et al.*, 2007], with respect to the simulation of the statistics of extreme events. These will be measured using the set of 29 core indices, *Climdex* , which is known to be relevant to a broad range of impact fields [*Peterson*, 2005].

Table 1. Climdex indices

ID	Indicator name	Definitions	UNITS
CDD	Consecutive dry days	Maximum number of consecutive days with RR<1mm	Days
CSDI	Cold spell duration	Days with at least 6 consecutive days when TN<Q_{10}	Days
CWD	Consecutive wet days	Maximum number of consecutive days with RR>=1mm	Days
DTR	Diurnal T range	Monthly mean difference between TX and TN	°C
FD0	Frost days	Annual count when TN(daily minimum)<0°C	Days
GSL	Growing season Length	Days between first and last span of at least 6 warm enough days	Days
ID0	Ice days	Annual count when TX(daily maximum)<0°C	Days
PRCPTOT	Annual total wet-day precipitation	Annual total PRCP in wet days (RR>=1mm)	mm
R10	Number of heavy precipitation days	Annual count of days when PRCP>=10mm	Days
R20	Number of very heavy precipitation days	Annual count of days when PRCP>=20mm	Days
R95p	Very wet days	Annual total PRCP when RR>95th percentile	mm
R99p	Extremely wet days	Annual total PRCP when RR>99th percentile	mm
Rnn	Number of days above nn mm	Days when PRCP>=nn mm, nn is user defined threshold	Days
RX1day	Max 1-day precipitation	Monthly maximum 1-day precipitation	mm
Rx5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	mm
SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days (PRCP>=1.0mm)	mm/day
SU25	Summer days	Annual count when TX(daily maximum)>25°C	Days
TN10p	Cool nights	Percentage of days when TN<10th percentile	Days
TN90p	Warm nights	Percentage of days when TN>90th percentile	Days
TNn	Min Tmin	Monthly minimum value of daily minimum temp	°C
TNx	Max Tmin	Monthly maximum value of daily minimum temp	°C
TR20	Tropical nights	Annual count when TN(daily minimum)>20°C	Days
TX10p	Cool days	Percentage of days when TX<10th percentile	Days
TX90p	Warm days	Percentage of days when TX>90th percentile	Days
TXn	Min Tmax	Monthly minimum value of daily maximum temp	°C
TXx	Max Tmax	Monthly maximum value of daily maximum temp	°C
WSDI	Warm spell duration	Days with at least 6 consecutive days when TX>Q_{90}	Days

As a target area we have chosen the two stations Shawnigan and Victoria in British Columbia, Canada, which have a sufficiently long data record and represent moderately different microclimates. The variables we are analyzing here are daily maximum and minimum temperature and precipitation. The methods we are comparing are the following:

a) Expanded downscaling (EDS)

EDS is an extension of classical multiple linear regression that preserves inter-variable and inter-station covariance. EDS is a linear model between selected large scale atmospheric fields and the local station variables. EDS has been used in numerous climate impact studies [*Menzel and Bürger*, 2002] and has recently also been applied to weather forecasts [*Bürger et al.*, 2009]. As predictors we have used upper air fields of specific humidity, precipitation, air temperature, and wind vectors, from the 700hPa and 850hPa levels, using the rectangular area between (133W, 44N) and (119W, 54N). All fields were normalized and EOF reduced, retaining 99% of the variance. Predictor selection from among the principal components (PCs) was done based on error statistics of the target variables, using 1961 to 1975 as calibration period and 1976 to 1990 for validation. This resulted in the selection of 80 PCs. There was no notable artificial skill, at least not with respect to the indices, as discussed below.

b) TreeGen (TG)

TG is a downscaling technique that determines empirical relationships, based on synoptic types, between coarse-scale daily observed (NCEP) fields and daily observations of climate at one or more stations. In the present study the predictor fields are sea-level pressure, surface temperature, and surface precipitation. The process consists of four steps. First, a principal component analysis (PCA) of NCEP and GCM predictor fields over the historical period is carried out in order to maximize the signal present in the historical record. Second, synoptic types were determined by grouping values of the PCA scores of predictor fields in such a way as to produce 25 distinct groups (synoptic weather types) of daily station observations that are as similar as possible. Third, the weather for each type is generated stochastically by re-sampling the corresponding observations (due to the stochastic element, we show three TG realizations below).

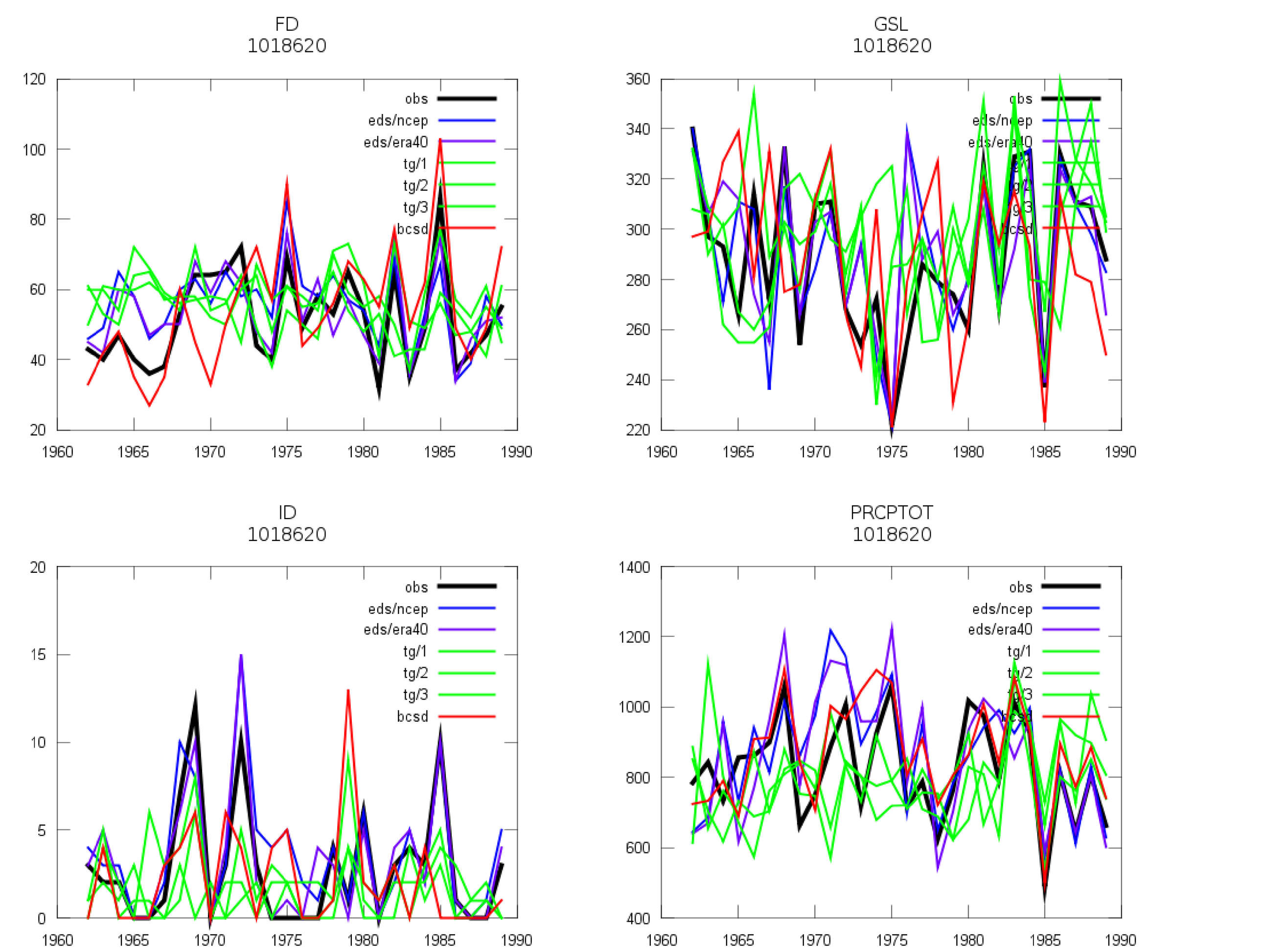

Figure 1. Downscaled Climdex indices (sample) for the station of Victoria (1018620), using EDS (blue), TG (green), and BCSD (red).

Finally, a linear trend is overlaid over each type to account for changes in underlying climate associated with each type. Note that the third step introduces a stochastic element into TG, which we have tried to capture by using three realizations of TG for this analysis.

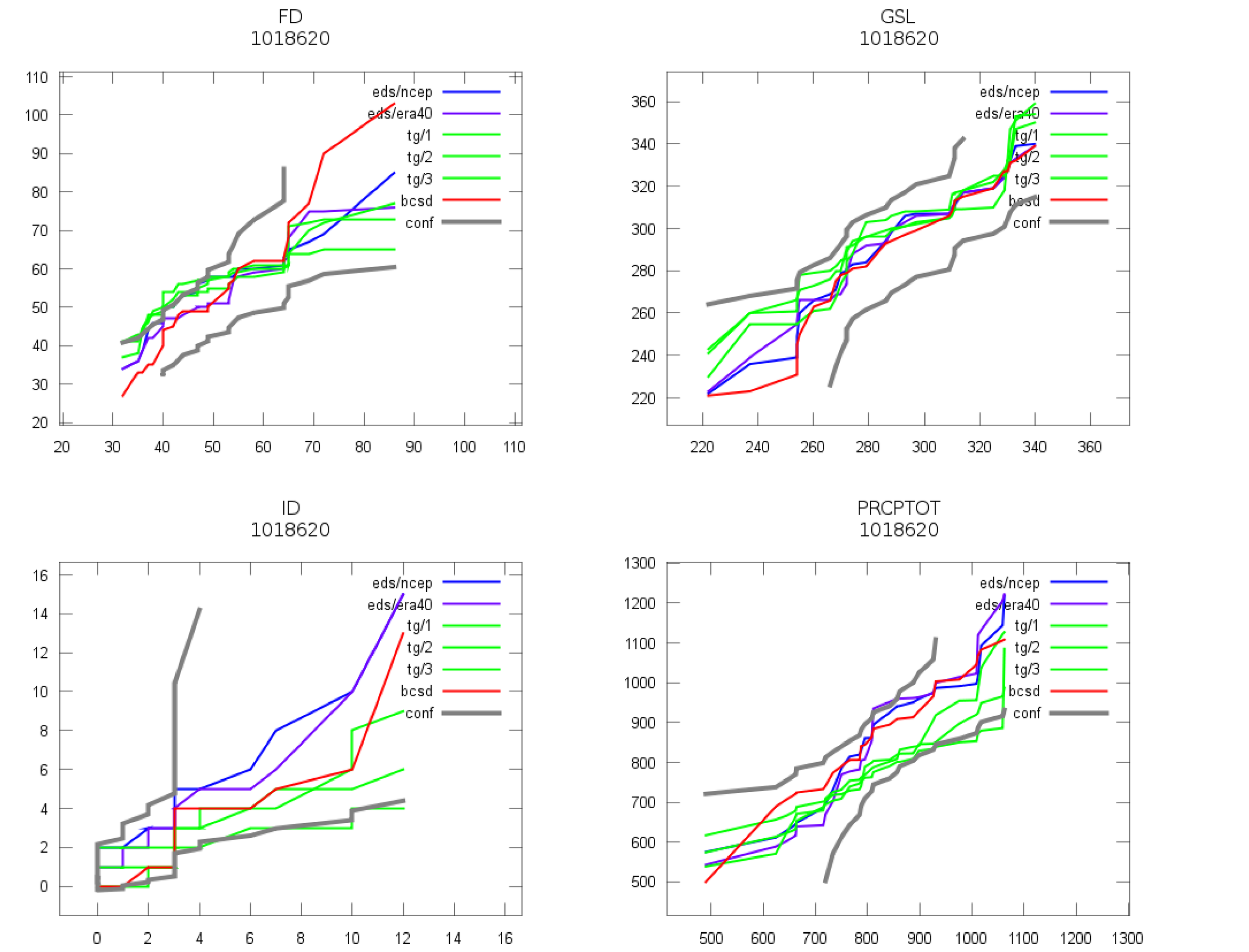

Figure 2. Quantile-quantile (qq) plot for the same indices as in Fig. 1. Confidence bands are based on the 99% level as obtained from the corresponding Kolmogorov-Smirnov test.

c) Bias corrected spatial disaggregation (BCSD)

BCSD originates from the requirement to downscale ensemble climate model forecasts as input to a macro-scale hydrologic model (VIC model) to produce runoff and streamflow forecasts at spatial and temporal scales appropriate for water management [*Salathe Jr et al.*, 2007; *Wood et al.*, 2002]. BCSD consists of three major steps to obtain spatial high resolution fields:

- bias correction of large scale monthly GCM fields against aggregated gridded observations, using quantile mapping (cf. the "empirical transformation of [*Panofsky and Brier*, 1958].
- spatial disaggregation of the monthly fields to the finer scale (of the VIC model) using a spatial delta approach.
- resampling of daily historical time series conditioned on the monthly fields (temporal delta approach).

Note that in the current setup BCSD is not geared towards point values (of stations) but average values of the nearest cell of the VIC grid (of size ~40 km²). This is certainly not a fair comparison, but the results do not change strongly when using the observed VIC grid instead as a reference.

§2 Reproducing present statistics

The Climdex software produces annual timeseries of the indices, a selection of which is shown in Fig. 1. We see EDS driven by NCEP and ERA40 fields, the three TG realizations, and BCSD. For the depicted indices the observed climate (mean and variability) appears to be reproduced quite well by all methods. Individual annual events are less well captured, depending on the method.

To analyze whether the observed climate, that is, the present statistical distribution of each index for the period 1961 to 1990, is reproduced by the downscaling of present large-scale climate we use the technique of quantile-quantile (qq) plots, an example of which is shown in Fig. 2 for the same selection of indices. The Figure demonstrates that for the four indices all methods reproduce the present climate quite well. Other indices are less well reproduced, even when driven by analyses. The present climate as downscaled from a GCM-simulated large-scale atmosphere (using the 20C3M simulation by EH5OM) is depicted in Fig. 3.

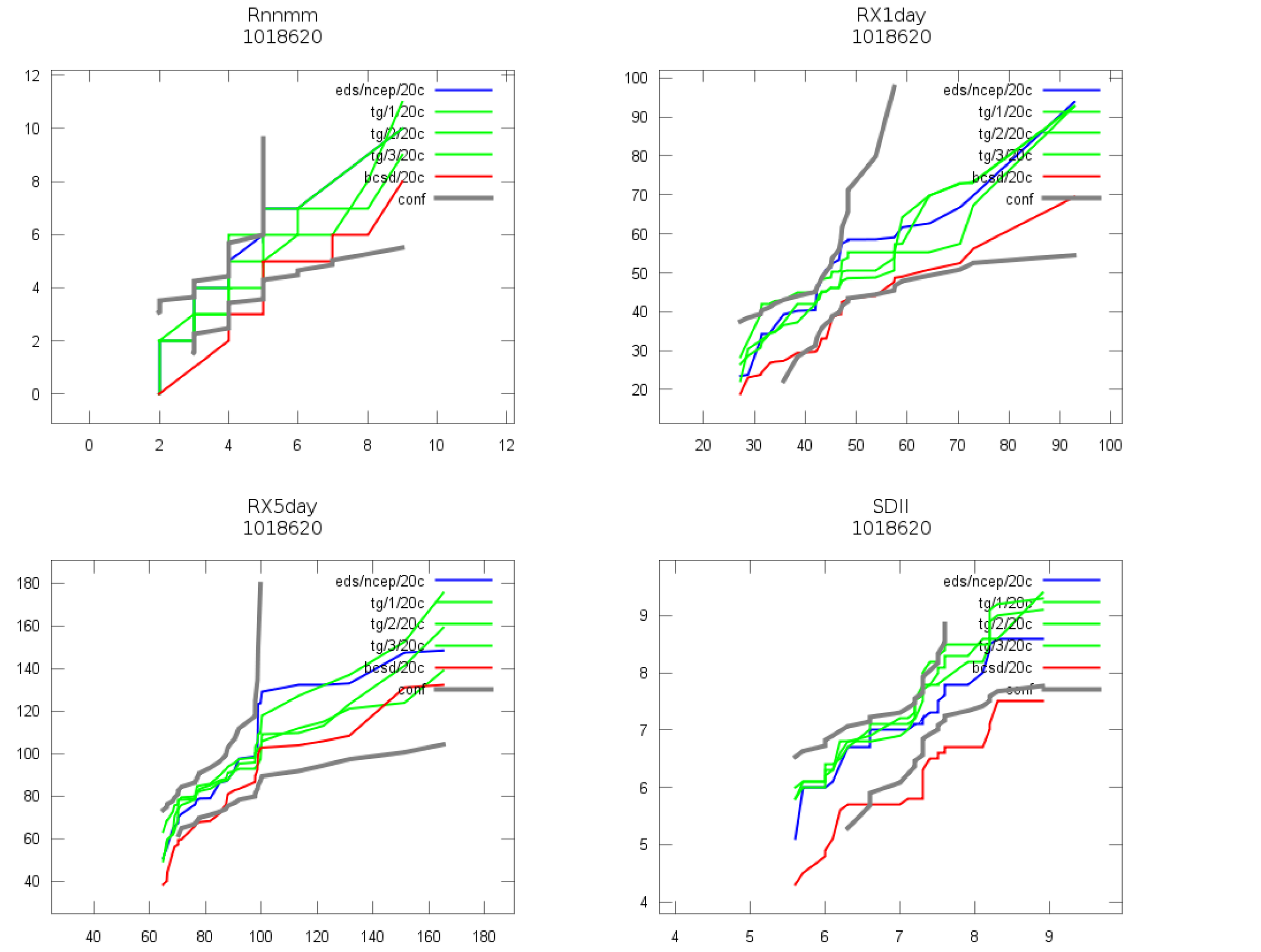

Figure 3. Same as Fig. 2, using the 20C3M simulation by EH5OM for a different set of indices.

The Figure shows, for another set of indices, that the downscaled values may be too low, as BCSD for SDII, or too high, as TG for Rnnmm and RX1day. In the two TG cases, although the downscaled values lie 'almost' completely within the confidence band, the details of the statistical test (Kolmogorov-Smirnov) require the dismissal of these simulations as being significantly biased.

§3 Reproducing single years

A reliable simulation of the present statistical distribution of the Climdex indices is a necessary condition for the downscaling to produce credible results. If shorter-term climatic fluctuations can be traced as well this will give additional reliability to a method. We have therefore also checked a method's capability to resolve the actual annual index fluctuations when driven by the analyses.

Table 2 shows the overall performance of the three downscaling methods. When no value is given for a particular combination of method and index, the method does not have enough skill to simulate the index's climate reliably. Otherwise, a number indicates the explained variance of the index by the method, based on the 1961 to 1990 period.

Table 2. Entries indicate that downscaled NCEP ***and*** *20C3M are within 99% confidence of observations, based on 1961 to 1990. Numbers are explained variance for NCEP in %. Left spade: Shawnigan, right spade: Victoria.*

index	EDS		TG (1)		TG (2)		TG (3)		BCSD	
CDD										
CSDI										
CWD				-67						
DTR	-8	39								
FD	70									-6
GSL	45	37	-6		-24		-78			-7
ID			-36							
PRCPTOT		10		-45			16	-37	53	36
R10mm		-9		-46				-27		32
R20mm				-86						
R95p	-29	-58	-64	-109	-119	-102	-75	-140	-50	-87
R99p										
Rnnmm			-33		-104		-10			
RX1day				-21		-108				
RX5day			-62	-99	-70		-72	-46	-53	
SDII	9	-20	-28	-63		-12	-1			
SU		46		-50				-59		
TN10p	38	40	-34						-55	-40
TN50p		47		-8					-159	-124
TN90p		28							-234	
TNn	41	31	-43	-25		-9				
TNx			-98					-51		
TR										
TX10p	-10	-11	-38	-2	20		9	0	-45	-131
TX50p	53	69								-178
TX90p	8	-15	-40	-89	-5	-59	-23	-62		
TXn	62	54		-40		-11	-45	-34		
TXx			-27	-25	-56	-43	-53	-61		
WSDI										

It should be noted that using 1991 to 2010 for verification has no systematic effect on the EV results. This is likely due to the fact that all three methods are not directly calibrated against any of these indices, so there is not much room for overfitting.

In summary, the statistical distribution of about half of the indices is reproducible for present climatic conditions. However, except for EDS there is little sensitivity of the methods to actual index anomalies in the annual record. Whether there is enough sensitivity to longer-term anomalies such as global warming remains unknown.

§4 References

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