Introduction

1 Perfect Prog

Perfect Prog (PP) is a statistical downscaling concept, where the statistical model is calibrated using observational data both for predictors and predictands. Traditionally, predictors are at a large-scale and often represent synoptic-scale information. Processes between this large scale and the aspired scale to be downscaled to are ignored (e.g. mesoscale features). As in the actual prediction (downscaling) step the observed predictors are replaced by those simulated with a numerical model. Thereby, the tacit assumption is made that the numerical model realistically and reliably reproduces the characteristics of the predictors. This assumption is justified by the fact that numerical models generally show higher skill in simulating large-scale features that are explicitly resolved compared to processes that had to be (statistically) parameterized. For PP methods, the relationship between predictors and predictands is established by sequentially relating the time series of predictors and predictands to each other. Depending on whether the downscaled time-series represents solely an expected value per given time-step or a distribution (distributional parameters), the PP methods can be classified into either deterministic (Section 1.1) or stochastic (Section 1.2) methods.

1.1 Deterministic

1.1.1 Linear Models

A common approach for PP downscaling is to rely on one or several predictors (e.g. geopotential height or humidity at a larger scale) using a linear regression model. The strength of co-variability between predictand and predictor is determined by the coefficients in an observational period and can be applied to output of a numerical model in a future period. In general, due to the high-dimensionality of a predictor field, the predictors need to be transformed first. Common methods are empirical orthogonal functions,
whose resulting principal components are subsequently used for a multiple linear regression analysis (e.g. described in Lutz et al. (2012) to downscale daily precipitation). Such an approach has also been used to downscale indices that describe the frequency and magnitude of extremes in daily temperature and precipitation (e.g. Hertig and Jacobieit, 2008; Hundecha and Bardossy, 2008; Cheng et al., 2007). A somewhat different approach in this respect are canonical correlation analyses (e.g. Barnett and Preisendorfer, 1987; Busuioc et al., 2008. This method uses predictor and predictand fields in parallel to search for modes of maximum co-variability (see e.g. Widmann, 2005).

If in a regression model context, the unexplained variance and hence the predictand is non-gaussian (e.g. daily precipitation), the downscaling model is usually formulated by means of a general linearized model (GLM). The conditional mean of a non-gaussian distributed predictand is modeled as a linear function of a set of predictors. GLMs have recently been applied in a deterministic context for downscaling precipitation characteristics, including both extremes and dry periods (Hertig et al., 2013).

Common to deterministic linear models is their disregard to model explicitly the residual (and hence unexplained) noise term in order to account for variability. It has been shown by von Storch (1999) that a simple inflation of the downscaled variance to match the one of observation (as suggested in Karl et al., 1990) is inappropriate in this context.

1.1.2 Non-linear models

In case of a non-linear relationship between predictand and predictors, non-linear downscaling techniques have been applied in a number of studies. These can be pooled to artificial neural networks and machine learning, respectively. In particular, these comprise radial basis functions (e.g. Haylock et al., 2006), support vector machines (e.g. Anandhi et al., 2007), relevance vector machines (e.g. Ghosh and Mujumdar, 2008), and multi-site multi-layer perceptrons (e.g. Haylock et al., 2006). Most of these studies concentrate on heavy precipitation as predictand, but can also be applied to other variables such as snow fall amounts (Sauter et al., 2010).

A special case of a non-linear model are weather-type based regression models. Weather typing is a straightforward method to categorize complex spatial and temporal airflow fields (e.g. of wind or geopotential height) based on physical arguments and to relate original predictors and predictands in a non-linear way (see e.g. Enke and Spekat, 1997).

Weather types have been shown to be useful predictors for extreme indices (Tolika et al., 2008), and have also been implemented for downscaling anomalous monthly climate, including episodes of heavy precipitation (e.g. Menndez et al., 2010). Additionally, weather typing has been alongside cumulative logit regression and non-linear regression procedures to estimate daily precipitation, including extremes (Cheng et al., 2010, 2011).

1.1.3 Analog Methods

Analog methods try to find historical weather (fields) that closely resemble the weather situation for a given day to be simulated. Usually these “analogues” are found with
an appropriate skill metric (e.g. Euclidian distance) that evaluates several predictor-parameters (e.g. large-scale circulation) (Cubasch et al., 1996; Wetterhall et al., 2005; Matulla et al., 2008). Resampling is a non-parametric approach implying that no assumptions about the statistical distributions of the variables, spatial and temporal structure of the field and mutual dependencies between variables need to be made. A major drawback of this method is that the artificially generated time series cannot produce daily amounts and spatial structures beyond the observed data. The method solely reshuffles the historical sequence of weather. Multi-day accumulated data however can substantially change (Goodess et al., 2012).

1.2 Stochastic (excluding weather generators)

1.2.1 Linear Models

While GLM-based downscaling models are often designed to model the mean of various different classes of distributions, they can be further used to describe other parameters of a distribution as predictand (e.g. extreme quantiles, variance or shape parameter). To describe different parameters of a distribution simultaneously, the concept of Vector GLMs has been developed (Yee and Stephenson, 2007). Maraun et al. (2010) and Maraun et al. (2011) have for instance relied on this concept to estimate parameters of generalized extreme value distributions of daily precipitation in the United Kingdom. Alternatively, predictor information may be included in the estimation of GEV parameters using the r-largest method (Coles, 2001). This method has been used, for instance, in downscaling winter extreme daily precipitation over North America (Wang and Zhang, 2008).

Mixture model to account for stochastic component each day

1.2.2 Non-linear models

Vrac and Naveau (2007) introduced a weather typing approach for stochastic downscaling of daily precipitation, linking large-scale upper-air circulation with local scale precipitation observations Vrac et al. (2007) extended this approach to downscale the entire precipitation distribution, including the extreme tail, using a probability mixture model of Gamma and Generalised Pareto distributions (discussed further in section 2.2.1).

1.2.3 Resampling Methods

Resampling techniques are essentially analog methods that includes a random process in addition. Instead of selecting the most similar historic day, the k most similar days are selected. From these k-nearest analogues the field for the current day is set by randomly drawing from the k fields (Beersma and Buishand, 2003). In Benestad (2010) an extension of the analog method was presented, where the downscaled heavy precipitation distributions were corrected a posteriori.
The Statistical DownScaling Model (SDSM) is a hybrid approach in that it first downscales area-averaged precipitation relying on regression-based methods and weather generators. As a second step, a resampling is applied for precipitation at individual sites that is conditioned on the downscaled area-average precipitation (Wilby et al., 2003). The approach has been implemented in numerous downscaling contexts, including precipitation extremes (e.g. Harpham and Wilby, 2005; Hashmi et al., 2010; Tryhorn and DeGaetano, 2011).

1.3 Weather Generators

Weather generators (WGs) are statistical downscaling tools that model random sequences of weather variables of unlimited length that are consistent with the key statistical properties of the observed meteorological records (i.e. where the WG was calibrated). Multivariate WGs usually model precipitation as a first variable. The remaining variables are then conditioned on the generated precipitation. WGs have the ability to generate synthetic series of unlimited length (Wilks and Wilby, 1999). Their main advantage lies in their computational efficiency allowing for multi-model probabilistic exploration of downscaled variables in a current and future climate.

Each day’s weather variable at any site is considered to be drawn from some probability distribution with mean and variance related to various predictors including previous days’ weather, time of year etc. as well as large-scale climate drivers. The probability distributions for each variable can be chosen from a flexible family (normal, gamma, Poisson, binomial, …) to suit the nature of the variable. In case of precipitation, its occurrence and intensity are in majority of models treated separately. Precipitation occurrence models are based on Markov chains (Richardson, 1981; Katz, 1996) or spell-length models (Semenov et al., 1998; Dubrovsky, 1997; Hirschi et al., 2012). Markov chains of first or higher orders are constrained on transition probabilities of occurrence of wet (dry) day after a given sequence of wet and dry days. Spell-length models represents wet and dry spell series taken from probability distribution. The precipitation amount is then modelled using probability distribution (exponential, mixed exponential, gamma, Weibull, kappa, log-normal or other) fitted to observed data (Wilks and Wilby, 1999).

The multivariate extension can be accomplished by dealing with each variable in turn, at each stage considering the previous variables as potential predictors in the “regression” relationships. Models are calibrated using maximum likelihood, fitting simultaneously to all available data (the models themselves contain flexible representations of seasonality so there is no need to fit them separately in different months/seasons). In multivariate generators other meteorological variables are often conditioned on occurrence or non-occurrence of precipitation. Usually first order vector autoregression is applied and multiple variables are modelled simultaneously. In Richardson model there are: maximum and minimum temperature and solar radiation (Richardson, 1981), in Wallis and Griffiths model there are also day- and night-time wind speed and daily dew point temperature. In Parlange and Katz model wind speed and dew point temperature, and in Bruhn model (Bruhn et al., 1980) minimum of daily relative humidity are
modelled together with variables predicted in Richardson model. K-nearest neighbour time series bootstrap approach can also be used in multivariate generators.

A somewhat different class of weather generators are point process models. They provide a simplified representation of the precipitation process in which storms appear according to Poisson process in a form of clusters of rainfall cells. The models are calibrated separately for different months/seasons, by matching theoretical properties of the model to observed properties of historical rainfall. The models can be divided into white noise or rectangular pulse models (Poisson white noise model, Neyman-Scott white noise model, Poisson rectangular pulse model, Neyman-Scott rectangular pulse model). Onof et al. (2000) review the basic ideas.

1.3.1 Linear Models

In order to downscale precipitation using weather generators, the parameters of the weather generator models (e.g. transition probabilities or the shape of a gamma distribution) is described with a linear model. To do this, the concept of generalized linear models (GLMs) is needed (see e.g. Yang et al., 2005; Frost et al., 2011). For multi-site downscaling, consistency between sites is built-in via the use of appropriate spatial dependence models. Among them are: multivariate normal distribution with transformations of daily precipitation distributions at a single site to the normal distribution, spatially-correlated but temporally independent random number derived by single site models at different locations (Wilks, 1998), k nearest-neighbour resampling techniques for simultaneous simulation of daily precipitation (Buishand and Brandsma, 2001), k nearest-neighbour resampling techniques conditioned on weather states, mainly circulation patterns (Bardossy and Plate, 1992), GLMs (Chandler and Wheater, 2002; Yang et al., 2005), nonhomogeneous hidden Markov model (Bellone et al., 2000) or spatial autocorrelation based approach (Khalili et al., 2007).

A general additive model (GAM) is an extension of a GLM in which the relationships between the predictors and the quantity of interest are specified non-parametrically rather than being assumed to follow a known functional form. In principle this provides added flexibility, and allows the data to ”speak for themselves” in determining the model structure (Hyndman and Grunwald, 1999).

1.3.2 Non-linear Models

On any day, the atmosphere is considered to be in one of a small number of distinct weather states, which influence both the large-scale circulation patterns and the spatial distribution of precipitation. The (unobserved) sequence of underlying state transitions can be assumed to follow a Markov chain (Non-homogenous hidden Markov Models) and the weather at each location is assumed to be conditionally independent given the weather state (Charles et al., 1999). In a downscaling context, the large-scale atmospheric drivers (obtained from GCM output) are used to infer the corresponding weather state on a particular day; and the precipitation for that day is then sampled from the corresponding distribution (Mehrotra and Sharma, 2006). Precipitation can
also be sampled from transformed and truncated Gaussian variables. This simplifies the process of incorporating inter-site dependence via an appropriate choice of correlation structure (Stehlík and Bárdossy, 2002).

1.3.3 Point Process Models

Relatively little work has been done on incorporating climate change signals into point process models. In this context, the main study by Kilsby et al. (2007) used this kind of generator for the UK Climate Impacts Projections (UKCP09). The biggest challenge with Poisson cluster models is their calibration. It can be hard to identify parameters without long enough records. Recent statistical advances at UCL have shown how the calibration can be improved considerably however; and this is being used to provide much more flexible representations of climate change signals in the models.

In Burton et al. (2008) a generalisation of the Neyman-Scott model was presented in which rain cells have a spatial extent as well as a temporal duration. Models are calibrated separately within different weather states; hence climate change signals are incorporated by inferring the weather states from GCM outputs.

2 Model output statistic

Model Output Statistics (MOS) is based on statistical models that are calibrated using simulated predictors and observed predictands. In typical applications where the predictands are given on a smaller spatial scale than the predictors it combines an error correction and a downscaling step. As the transfer function between simulated output and observations depends on the chosen model, it has to be calibrated individually for each model.

This concept originated in weather forecasting (Wilks, 1995), where it is used to remove systematic prediction errors. In that context, every predicted event could be directly related to the observed event. Such a setup, which we term eventwise, would in climate applications be given either by reanalysis-driven RCMs (so-called perfect boundary conditions), by the actual reanalyses, or by GCMs nudged towards reanalyses or run with some other form of data assimilation. As this setup is not always given, many applications in climate science do only consider transfer functions between simulated and observed long-term distributions, which we call distributionwise MOS. Although the fitting is based only on distributions, the relationships are usually applied to each individual event, for example in many applications of quantile matching.

As with PP, MOS may follow a deterministic, stochastic or weather generator approach. An additional possibility is to implement an ensemble MOS framework, which is particularly attractive for combining several models (e.g. Menndez et al., 2010; Schlzel and Hense, 2010. This approach decomposes the complicated relationship between the observations and the outputs of different models into simpler, hierarchical relationships that can be described in a reasonable and transparent way (Buser et al., 2009). Combination of an output from a multimodel ensemble of GCMs or RCMs and observations
allows a quantification of uncertainty in future climate changes that is especially applicable in impact studies.

2.1 Deterministic

2.1.1 Linear Models

Linear models in the MOS setup are based on the same statistical models already mentioned in the section on linear PP models (Section 1.1.1) and include (PC-filtered) MLR and pattern-based methods such as canonical correlation analysis and maximum covariance analysis (for method overview see Bretherton et al. (1992); Widmann (2005); Tippett et al. (2008). These methods are event-wise and thus can be applied either to reanalysis-driven RCMs (Themeßl et al., 2011), to the original reanalyses (Widmann et al., 2003) or to GCMs nudged to reanalyses (Eden and Widmann, 2013). In all these cases simulated precipitation has been downscaled.

2.1.2 Non-linear models

Quantile mapping (QM) counts for non-linear models and is a distribution-wise MOS on climate simulation. So far it has been used for downscaling and error-correction on GCMs (Schmidli et al., 2006; Déqué, 2007; Michelangeli et al., 2009; Piani et al., 2010; Haerter et al., 2010; Hagemann et al., 2011) and RCMs (Yang et al., 2010; Themeßl et al., 2011; Wilcke et al., 2013). QM essentially acts as a bias correction of GCM and RCM simulated variables but with a downscaling step. Correction and downscaling are only meaningful where temporal variability of observed precipitation is well-reproduced by the GCM precipitation given realistic large-scale climatic state (i.e. in the nudged simulation or the reanalysis). Circulation-dependent scaling factors and correction of wet-day frequencies are possible extensions of the method (Themeßl et al., 2011; Wilcke et al., 2013).

2.1.3 Analog/Resampling Methods

The Analog Method (AM) is described in the Perfect Prog chapter in Section 1.1.3. In a MOS setup one would compare with simulations rather than observed states which has been done by Cubasch et al. (1996); Themeßl et al. (2011).

2.2 Stochastic (excluding weather generators)

2.2.1 Linear Models

Maraun (2013) discussed the deficiencies of using deterministic MOS methods, such as quantile mapping, in order to correct simulated variability to sub-grid scales. This is particularly true when downscaling extremes as there is often insufficient observed data to calibrate a statistical correction for extremely rare events. Deterministic methods are thus limited and often rejected in favour of stochastic techniques.
Kallache et al. (2011) presented a stochastic downscaling approach that links the cumulative distribution functions (CDFs) of simulated and observed extreme precipitation using a transfer function. The method used, termed XCDF-t, is an extension of the nonparametric CDF-t transform method developed by Michelangeli et al. (2009) for specific application to extremes. Additionally, it was shown that the inclusion of large-scale covariate information in the transform model may improve performance, but that added value is heavily dependent on the choice of covariates. In the stationary case, the XCDF-t method may be considered a MOS approach but the addition of covariates places the method’s calibration in a PP context.

As discussed in section 1, when a simulation is forced to match the temporal evolution of the observed record (either using a reanalysis-driven RCM or a nudged GCM simulation) it is possible for to conduct an event-wise calibration between sequences of observed and simulated events. Wong et al. (2013) proposed an event-wise stochastic MOS approach for downscaling RCM-simulated precipitation to the point scale. In this case, wet day probabilities were modelled using logistic regression and precipitation intensities by a mixture model (Frigessi et al., 2002; Vrac and Naveau, 2007) that combines both gamma and generalised Pareto distributions. This was used in combination with a vector generalised linear model (VGLM), which has been previously applied in a PP context (e.g. Maraun et al. 2010). Precipitation simulated by a reanalysis-driven RCM was used to estimate the mixture model parameters.

2.2.2 Non-linear models

2.2.3 Analog/Resampling Methods

2.3 Stochastic (Weather Generator)

Stochastic weather generators described in Section 1.3 can be used as one of the possible strategies of treatment model output.

2.3.1 Non-linear Models

[no references yet]

2.3.2 Point Process Models

[no references yet]

References


