Report on downscaling/validation inventory WG 3–5

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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 Jacobeit, 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 upperr-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 multisite 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

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2.3 Stochastic (Weather Generator)

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

2.3.1 Non-linear Models

[no references yet]

2.3.2 Point Process Models

[no references yet]

References

Anandhi, A., Srinivas, V., and Nanjundiahb, R. S. (2007). Downscaling precipitation to river basin in india for ipcc sres scenarios using support vector machine. *Int. J. Climatol.*, 28:401–420.

Barnett, T. and Preisendorfer, R. (1987) Origins and levels of monthly and seasonal forecast skill for the United States surface air temperatures determined by canonical correlation analysis. *Mon Weather Rev*, 115:1825–1850.

Bardossy, A. and Plate, E. J. (1992). Space-time model for daily rainfall using atmospheric circulation patterns. *Water Resour. Res*, 28(5):1247–1259.

Beersma, J. J. and Buishand, T. A. (2003). Multisite simulation of daily precipitation and temperature conditional on the atmospheric circulation. *Clim. Res.*, 25:121–133.

Bellone, E., Hughes, J. P., and Guttorp, P. (2000). A hidden markov model for downscaling synoptic atmospheric patterns to precipitation amounts. *Clim. Res.*, 15:1–12.

Benestad, R. E. (2010). Downscaling precipitation extremes. *Theor. Appl. Climatol.*, 100:1–21.

Bretherton, C., Smith, C., and Wallace, J. (1992). An intercomparison of methods for finding coupled patterns in climate data. *J. Climate*, 5(6).

Bruhn, J. A., Fry, W. E., and Fick, G. W. (1980). Simulation of daily weather data using theoretical probability distributions. *J. Appl. Meteor.*, 19:1029–1036.

Buishand, T. A. and Brandsma, T. (2001). Multisite simulation of daily precipitation and temperature in the rhine basin by nearestneighbor resampling. *Water Resour. Res.*, 37(11):2761–2776.

Burton, A., Kilsby, C. G., Fowler, P. S. P., Cowpertwait, H. J., and O'Connell, P. E. (2008). Rainsim: A spatial-temporal stochastic rainfall modelling system. *Environ. Mod. Soft.*, 23:1356–1369.

Buser, C. M., Kunsch, H. R., Luthi, D., Wild, M., and Schar, C. Bayesian multi-model projection of climate: bias assumptions and interannual variability, *Clim. Dynam.*, 33:849-868.

Busuioc, A., Tomozeiu, R., and Cacciamani, C. (2008) Statistical downscaling model based on canonical correlation analysis for winter extreme precipitation events in the Emilia-Romagna region. *International Journal of Climatology*, 28(4):449–464.

Cheng, C.-S., Li, G., Li, Q., Auld, H. (2007) Statistical downscaling of hourly and daily climate scenarios for various meteorological variables in south-central Canada. *Theoretical and Applied Climatology*, 91(1-4):129–147.

Cheng C.-S., Li, G., Li, Q., Auld, H. (2010) A synoptic weather typing approach to simulate daily rainfall and extremes in Ontario, Canada: potential for climate change projections. *Journal of Applied Meteorology*, 49:845–866.

Cheng. C. S., Li, G., Li, Q., Auld, H. (2011) A synoptic weather typing approach to project future daily rainfall and extremes at local scale in Ontario, Canada. *Journal of Climate*, 24(14):3667–3685.

Chandler, R. E. and Wheater, H. S. (2002). Analysis of rainfall variability using generalized linear models: A case study from the west of ireland. *Water Resour. Res.*, 38(10):10–1–10–11.

Charles, S. P., Bates, B. C., Whetton, P. H., and P., H. J. (1999). Validation of downscaling models for changed climate conditions: case study of southwestern australia. *Clim. Res.*, 12:1–14.

Coles, D. (2001) An introduction to Statistical Modeling of Extreme Values, First Edition, Springer.

Cubasch, U., von Storch, H., Waszkewitz, J., and Zorita, E. (1996). Estimates of climate change in southern europe derived from dynamical climate model output. *Clim. Res.*, 7(2):129–149.

Déqué, M. (2007). Frequency of precipitation and temperature extremes over france in an anthropogenic scenario: Model results and statistical correction according to observed values. *Glob. Planet. Change*, 57(1–2):16–26.

Dubrovsky, M. (1997). Creating daily weather series with use of the weather generator. *Environmetrics*, 8:409–424.

Eden, J. and Widmann, M. (2013). Downscaling of gcm-simulated precipitation using model output statistics. *J. Clim*, submitted.

Enke, W. and Spekat, A. (1997). Downscaling climate model outputs into local and regional weather elements by classification and regression. *Clim. Res.*, 8:195–207.

Frigessi, A., Haug, O., and Rue, H. (2002). A dynamic mixture model for unsupervised tail estimation without threshold selection. *Extremes*, 5(3):219–235.

Frost, A., Charles, S., Timbal, B., Chiew, F. H. S., Mehrotra, R., Nguyen, K., Chandler, R. E., McGregor, J. L., Fu, G., Kirono, D. G. C., Fernandez, E., and Kent, D. (2011). A comparison of multi-site daily rainfall downscaling techniques under australian conditions. *J. Hydrol*, 408:1–18.

Ghosh, S. and Mujumdar, P. P. (2008). Statistical downscaling of gcm simulations to streamflow using relevance vector machine. *Adv. Water Resour.*, 31(1):132–146.

Goodess, C. M., Anagnostopoulou, C., Bárdossy, A., Frei, C., Harpham, C., Haylock, M. R., Hundecha, Y., Maheras, P., Ribalaygua, J., Schmidli, J., Schmith, T., Tolika, K., Tomozeiu, R., and Wilby, R. L. (2012). An intercomparison of statistical downscaling methods for europe and european regions–assessing their performance with respect to extreme temperature and precipitation events. Cru research publications, Climate Research Unit, University of East Anglia.

Haerter, J. O., Hagemann, S., Moseley, C., and Piani, C. (2010). Climate model bias correction and the role of timescales. *Hydrology and Earth System Sciences Discussions*, 7(5):7863–7898.

Hagemann, S., Chen, C., Haerter, J. O., Heinke, J., Gerten, D., and Piani, C. (2011). Impact of a statistical bias correction on the projected hydrological changes obtained from three gcms and two hydrology models. *J. Hydrometeor.*, 12(4):556–578.

Harpham, C., Wilby, R. L. (2005) Multi-site downscaling of heavy daily precipitation occurrence and amounts. *Journal of Hydrology*, 312(1-4):235–255.

Hashmi, M. Z., Shamseldin, A. Y., Melville, B. W. (2010) Comparison of SDSM and LARS-WG for simulation and downscaling of extreme precipitation events in a watershed. *Stochastic Environmental Research and Risk Assessment*, 25(4)475–484.

Haylock, M. R., Cawley, G. C., Harpham, C., Wilby, R. L., and Goodess, C. M. (2006). Downscaling heavy precipitation over the united kingdom: a comparison of dynamical and statistical methods and their future scenarios. *Int. J. Climatol.*, 26(10):1397–1415.

Hertig, E. and Jacobeit, J. (2008) Assessments of Mediterranean precipitation changes for the 21st century using statistical downscaling techniques. *Int. J. Climatol.*, 28:1025–1045.

Hertig, E., Seubert, S. Jacobeit, J. (2010) Temperature extremes in the Mediterranean area: Trends in the past and assessments for the future. *Natural Hazards and Earth System Sciences*, 10:2039–2050.

Hertig, E., Seubert, S., Paxian, A., Vogt, G., Paeth, H., Jacobeit, J. (2011) Changes of total versus extreme precipitation and dry periods until the end of the 21st century: statistical assessments for the Mediterranean area. *Theor. Appl. Climatol.*, 111:1–20.

Hirschi, M., Stoeckli, S., Dubrovsky, M., Spirig, C., Calanca, P., Rotach, M. W., Fischer, A. M., Duffy, B., and Samietz, J. (2012). Downscaling climate change scenarios for apple pest and disease modeling in switzerland. *Earth Sys. Dyn.*, 3(1):33–47.

Hundecha, Y., Bardossy, A. (2008) Statistical downscaling of extremes of daily precipitation and temperature and construction of their future scenarios. *International Journal of Climatology*, 28(5):589–610.

Hyndman, R. J. and Grunwald, G. (1999). Generalized additive modelling of mixed distribution markov models with application to melbourne's rainfall. Monash Econometrics and Business Statistics Working Papers 2/99, Monash University, Department of Econometrics and Business Statistics.

Kallache, M., Vrac, M., Naveau, P., Michelangeli, P. A. (2011) Nonstationary probabilistic downscaling of extreme precipitation. *Journal of Geophysical Research (Atmospheres)*, 116(D05113):1–15.

Karl, T. R., Wang, W.-C., Schleisinger, M. E., Knight, R. W., and Portman, D. (1990). A method of relating general circulation model simulated climate to observed local climate. part i: seasonal statistics. *J. Clim.*, 3:1053–1079.

Katz, R. (1996). Use of conditional stochastic models to generate climate change scenarios. *Climate Change*, 32:237–255.

Khalili, M., Leconte, R., and Brissette, F. (2007). Stochastic multisite generation of daily precipitation data using spatial autocorrelation. *J. Hydrometeor.*, 8:396–412.

Kilsby, C., Jones, P., Burton, A., Ford, A., Fowler, H., Harpham, C., James, P., Smith, A., and Wilby, R. (2007). A daily weather generator for use in climate change studies. *Envir. Model. Soft.*, 22(12):1705–1719.

Lutz, K., Jacobeit, J., Philipp, A., Seubert, S., Kunstmann, H., and Laux, P. (2012). Comparison and evaluation of statistical downscaling techniques for station-based precipitation in the middle east. *Int. J. Climatol.*, 32(10):1579–1595.

Mannshardt-Shamseldin, E. C., Smith, R. L., Sain, S. R., Mearns, L. O., Cooley, D. (2010) Downscaling extremes: A comparison of extreme value distributions in point-source and gridded precipitation data. *The Annals of Applied Statistics*, 4(1):484–502.

Maraun, D. (2013). Bias correction, quantile mapping and downscaling. revisting the inflation issue. *J. Climate*, 26:2137–2143.

Maraun, D., Osborn, T., and Rust, H. (2011). The influence of synoptic airflow on uk daily precipitation extremes. part i: Observed spatio-temporal relationships. *Climate Dynamics*, 36:261–275.

Maraun, D., Rust, H., and Osborn, T. (2010). Synoptic airflow and UK daily precipitation extremes. Development and validation of a vector generalised linear model. *Extremes*, 13:133–153.

Matulla, C., Zhang, X., Wang, X., Wang, J., Zorita, E., Wagner, S., and von Storch, H. (2008). Influence of similarity measures on the performance of the analog method for downscaling daily precipitation. *Climate Dynamics*, 30:133–144.

Mehrotra, R. and Sharma, A. (2006). A nonparametric stochastic downscaling framework for daily rainfall at multiple locations. *Journal of Geophysical Research: Atmospheres*, 111(D15).

Menndez, C., de Castro, M., Boulanger, J.-P., DOnofrio, A., Sanchez, E., Srensson, A.A., Blazquez, J., Elizalde, A., Jacob, D., Le Treut, H., Li, Z.X., Nez, M.N., Pessacg, N., Pfeiffer, S., Rojas, M., Rolla, A., Samuelsson, P., Solman, S.A., Teichmann, C. (2010) Downscaling extreme month-long anomalies in southern South America. *Climate Change 2010*, 98:379–403.

Michelangeli, P.-A., Vrac, M., and Loukos, H. (2009). Probabilistic downscaling approaches: Application to wind cumulative distribution functions. *Geophys. Res. Lett.*, 36(11).

Onof, C., Chandler, R. E., Kakou, A., Northrop, P., Wheater, H. S., and Isham, V. (2000). Rainfall modelling using poisson-cluster processes: a review of developments. *Stoch. Environ. Res. Risk Assess.*, 14:384–411.

Piani, C., Weedon, G., Best, M., Gomes, S., Viterbo, P., Hagemann, S., and Haerter, J. (2010). Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. *J. Hydrol.*, 395(3–4):199 – 215.

Richardson, C. W. (1981). Stochastic simulation of daily precipitation, temperature, and solar radiation. *Water Resour. Res.*, 17:182–190.

Sauter, T., Weitzenkamp, B., and Schneider, C. (2010). Spatio-temporal prediction of snow cover in the black forest mountain range using remote sensing and a recurrent neural network. *Int. J. Climatol.*, 30(15):2330–2341.

Schlzel, C. and Hense, A. (2010) Probabilistic assessment of regional climate change in Southwest Germany by ensemble dressing. *Climate Dynamics*, 36:2003–2014.

Schmidli, J., Frei, C., and Vidale, P. (2006). Downscaling from gcm precipitation: a benchmark for dynamical and statistical downscaling methods. *Int. J. Climatol.*, 26(5):679–689.

Semenov, M. A., Brooks, R., Barrow, E., and Richardson, C. (1998). Comparison of the wgen and the lars-wg stochastic weather generators in diverse climates. *Clim. Res.*, 10:95–107.

Stehlík, J. and Bárdossy, A. (2002). Multivariate stochastic downscaling model for generating daily precipitation series based on atmospheric circulation. *J. Hydrol.*, 256(1–2):120–141.

Sunyer, M. A., Madsen, H., Ang, P. H. (2011) A comparison of different regional climate models and statistical downscaling methods for extreme rainfall estimation under climate change. *Atmospheric Research*, 103:119–128.

Themeßl, M. J., Gobiet, A., and Leuprecht, A. (2011). Empirical-statistical downscaling and error correction of daily precipitation from regional climate models. *Int. J. Climatol.*, 31(10):1530–1544.

Tippett, M. K., DelSole, T., Mason, S. J., and Barnston, A. G. (2008). Regression-based methods for finding coupled patterns. *J. Clim.*, 21:4384–4398.

Tolika, K., Anagnostopoulo, C., Maheras, P., Vafiadis, M. (2008) Simulation of future changes in extreme rainfall and temperature conditions over the Greek area: a comparison of two statistical downscaling approaches. *Global Planetary Change*, 63:132–151.

Tryhorn, L. and DeGaetano, A. (2011) A comparison of techniques for downscaling extreme precipitation over the Northeastern United States. *International Journal of Climatology*, 31:1975–1989.

von Storch, H. (1999). On the use of "inflation" in statistical downscaling. *J. Climate*, 12(12):3505–3507.

Vrac, M. and Naveau, P. (2007). Stochastic downscaling of precipitation: From dry events to heavy rainfalls. *Water Resour. Res.*, 43(7).

Vrac, M., Stein, M., Hayhoe, K. (2007) Statistical downscaling of precipitation through a nonhomogeneous stochastic weather typing approach. *Climate Research*, 34:169–184.

Wang, J. F. and Zhang, X. B. (2008) Downscaling and projection of winter extreme daily precipitation over North America. *Journal of Climate*, 21(5):923–937.

Wetterhall, F., Halldin, S., and yu Xu, C. (2005). Statistical precipitation downscaling in central sweden with the analogue method. *J. Hydrol.*, 306(1–4):174–190.

Widmann, M. (2005). One-dimensional cca and svd, and their relationship to regression maps. *J. Clim.*, 18(14):2785–2792.

Widmann, M., Bretherton, C., and Salathé Jr., E. (2003). Statistical precipitation downscaling over the northwestern united states using numerically simulated precipitation as a predictor. *J. Clim.*, 16(5):799–816.

Wilby, R. L., Tomlinson, O. J., and Dawson, C. W. (2003). Multi-site simulation of precipitation by conditional resampling. *Clim. Res.*, 23:183–194.

Wilcke, R. A. I., Mendlik, T., and Gobiet, A. (2013). Multi-variable downscaling and error-correction of regional climate models. *Clim. Change*, submitted.

Wilks, D. (1998). Multisite generalization of a daily stochastic precipitation generation model. *Journal of Hydrology*, 210(1–4):178–191.

Wilks, D. S. (1995). *Statistical Methods in the Atmospheric Sciences*, volume 91. Academic Press.

Wilks, D. S. and Wilby, R. L. (1999). The weather generation game: a review of stochastic weather models. *Progress in Physical Geography*, 23(3):329–357.

Wong, G., Maraun, D.and Widmann, M., Vrac, M., and Eden, J. M. (2013). A stochastic model output statistics approach for precipitation downscaling including extremes. submitted.

Yang, C., Chandler, R. E., Isham, V. S., and Wheater, H. S. (2005). Spatial-temporal rainfall simulation using generalized linear models. *Water Resour. Res.*, 41(11).

Yang, W., Andréasson, J., Graham, L., Olsson, J., Rosberg, J., and Wetterhall, F. (2010). Distribution-based scaling to improve usability of regional climate model projections for hydrological climate change impacts studies. *Hydrol. Res.*, 41(3-4):211–229.

Yee, T. W. and Stephenson, A. G. (2007). Vector generalized linear and additive extreme value models. *Extremes*, 10(1-2):1–19.