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Simulating future precipitation extremes in a complex Alpine catchment

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Abstract. The objectives of the present investigation are (i) to study the effects of climate change on precipitation extremes and (ii) to assess the uncertainty in the climate projections. The investigation is performed on the Lech catchment, located in the Northern Limestone Alps. In order to estimate the uncertainty in the climate projections, two statistical downscaling models as well as a number of global and regional climate models were considered. The downscaling models applied are the Expanded Downscaling (XDS) technique and the Long Ashton Research Station Weather Generator (LARS-WG). The XDS model, which is driven by analyzed or simulated large-scale synoptic fields, has been calibrated using ECMWF-interim reanalysis data and local station data. LARS-WG is controlled through stochastic parameters representing local precipitation variability, which are calibrated from station data only. Changes in precipitation mean and variability as simulated by climate models were then used to perturb the parameters of LARS-WG in order to generate climate change scenarios. In our study we use climate simulations based on the A1B emission scenario. The results show that both downscaling models perform well in reproducing observed precipitation extremes. In general, the results demonstrate that the projections are highly variable. The choice of both the GCM and the downscaling method are found to be essential sources of uncertainty. For spring and autumn, a slight tendency toward an increase in the intensity of future precipitation extremes is obtained, as a number of simulations show statistically significant increases in the intensity of 90th and 99th percentiles of precipitation on wet days as well as the 5- and 20-yr return values.

1 Introduction

Global warming may cause an increase of the atmospheric water vapor content and an intensification of the global hydrological cycle (Solomon et al., 2007; O'Gorman and Schneider, 2009). Precipitation extremes may increase in frequency and intensity over many areas of the globe (Sun et al., 2007; Allan and Soden, 2008), with substantial consequences for a variety of socio-economic systems (e.g. Easterling et al., 2000; Diffenbaugh et al., 2005).

In the Alps, precipitation is among the major controlling meteorological variables for human–environment systems. Through its triggering effect, precipitation may be seen as the key variable for specific natural hazard processes, i.e. for flash floods (e.g. Frei and Schär, 1998; Beniston, 2007), debris flow (e.g. Chiarle et al., 2007; Szymczak et al., 2010), landslides (e.g. Raetzo et al., 2002; Crosta et al., 2004), hail (e.g. Vinet, 2001) and avalanches (e.g. Martin et al., 2001). In the period from 1982 to 2005, natural hazard processes caused economic losses in the range of €57 billion in the Alps (Agrawala, 2007). Potential future changes in the frequency and magnitude of precipitation extremes may have serious impacts on ecological, economic and sociological systems. Consequently, studying the effects of climate change on precipitation extremes is of high societal and economic relevance.

Despite the high significance of this topic for the Alps, investigations on climate change impacts on precipitation extremes have been very limited so far. Beniston (2006) reported a considerable increase in the frequency of heavy

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precipitation events in parts of Switzerland during autumn and winter, while Smiatek et al. (2009) found an increase in the frequency of high precipitation amounts for all over the Alps in winter only. According to Frei et al. (2006) and Schmidli et al. (2007), precipitation extremes are projected to increase north of about 45° N in winter, whereas there is an insignificant change or a decrease south of it. However, most of these studies have only used one General Circulation Model (GCM) and thus, the results only cover a small range of possible changes. Furthermore, most of these investigations were performed on a scale compatible with the grid spacing of Regional Climate Models (RCMs), and thus, the obtained results can only give an incomplete picture of possible changes at local scales. But, as changes in precipitation are expected to vary significantly on small horizontal scales within complex regions like the Alps (Solomon et al., 2007), investigations on more detailed scales are very relevant.

GCMs are the only physically based tools to assess changes in climate resulting from increasing atmospheric greenhouse gases in the atmosphere. The models perform well in reproducing the climate on a global to continental scale. However, the horizontal resolution of GCMs is too coarse for investigating processes on regional or even local scales. In recent years, a variety of different techniques have been developed to bridge this scaling gap. The methods can be divided into (i) dynamical downscaling and (ii) statistical downscaling (Fowler et al., 2007). A comprehensive review is given by Maraun et al. (2010).

Dynamical downscaling is based on highly resolved numerical computer models (Regional Climate Models – RCMs), nested into a GCM over a limited region of interest. The higher horizontal resolution of RCMs, typically 25 km or 50 km, captures regional climate processes much better. Statistical downscaling, instead, establishes an empirical relationship between large-scale fields (predictors) and local-scale variables (predictands) (Maraun et al., 2010). The process is based on the following assumptions for suitable predictors: (i) the predictors are well simulated by the GCMs, (ii) the statistical relationship remains valid in a changed climate, and (iii) the predictors incorporate the future climate change signal (Wilby et al., 2004; Benestad et al., 2008). According to Rummukainen (1997), the variety of statistical downscaling methods can be divided into two fundamental approaches, namely Perfect-Prognosis (Perfect-Prog) and Model Output Statistics (MOS). Perfect-Prog is based on a calibration between observed large-scale atmospheric data and observed local-scale data, whereas MOS is calibrated on model output and observed local-scale data (Maraun et al., 2010). Weather generators, which use change factors obtained from climate models to generate climate change scenarios, can be seen as simple MOS (Maraun et al., 2010).

In the recent past, the availability of RCM data led to a tendency to use dynamical rather than statistical downscaling. However, in regions with a complex topography the spatial resolution of RCMs is still too coarse to investigate local climate processes (Engen-Skaugen, 2007). Statistical downscaling is then the only way to generate higher-resolution climate change scenarios and is thus, particularly important for the Alps.

Despite the fact that a number of different statistical downscaling approaches exist, only a few techniques are reported to downscale extreme events reliably (e.g. Fowler et al., 2007; Tryhorn and DeGaetano, 2011). Modeling extreme events is known to be a difficult challenge, as these phenomena lie at the margins of the distribution functions and are often beyond the range of calibration data sets (Harpham and Wilby, 2005; Tolika et al., 2008; Benestad, 2010). So far only a few attempts have been carried out to compare different statistical downscaling techniques with a focus on extreme events.

Bürger and Chen (2005) compared three regression-based statistical downscaling techniques: randomization, inflation and Expanded Downscaling (XDS). The obtained results were quite diverse, highlighting that the choice of the downscaling approach is a considerable source of uncertainty. Bürger et al. (2012) compared five statistical downscaling methods in simulating climate extremes. The methods considered are: automated regression-based statistical downscaling, bias correction spatial disaggregation, quantile regression neural networks, a weather generator (TreeGen) and XDS. The XDS method was found to perform best, followed by the bias correction and spatial disaggregation and quantile regression neural networks methods. Liu et al. (2011) compared the nonhomogeneous hidden Markov model and the statistical downscaling model SDSM in terms of downscaling precipitation. Both models performed similar in simulating dry- and wet-spell length, while the nonhomogeneous hidden Markov model showed better skill in modeling the wet-day precipitation amount. Hundecha and Bárdossy (2008) tested two statistical downscaling techniques in their ability to reproduce indices of extremes of daily precipitation and temperature. They found that both methods (multivariate autoregressive model and multiple linear regression) are more reliable during seasons when the local climate is influenced by large-scale circulation than local convective processes.

However, the results of these studies show that the performance of statistical downscaling models varies with (i) the season, (ii) the variables, and (iii) the region under investigation (e.g. Maurer and Hidalgo, 2008). Still more research is necessary to compare different statistical downscaling techniques in their ability to reproduce extremes. Moreover, so far only little attention has been paid to test the assumption of the stationarity of the transfer functions, which is a major uncertainty when applying statistical downscaling techniques in climate change studies. Hundecha and Bárdossy (2008), for example, showed that the applied statistical downscaling models are sensitive to the period chosen for model calibration, which resulted in more uncertain projections.

Recent studies have shown that projections of single climate model simulations are subjected to large uncertainty (Maurer and Duffy, 2005), which can result from three main sources: (i) emission scenario, (ii) the GCM and (iii) the downscaling technique (e.g. Maurer, 2007). According to Déqué et al. (2011), the uncertainty from GCM structure is by far the largest source of uncertainty in climate change projections. Other studies associate large uncertainty with the choice of the downscaling method (e.g. Frei et al., 2006; Schmidli et al., 2007; Beldring et al., 2008; Chen et al., 2011). In addition, the uncertainties may be amplified by natural climate variability (e.g. Booij, 2005; Maraun et al., 2010), especially when focusing on extreme events. Hawkins and Sutton (2011) showed that for decadal means of seasonal mean precipitation, internal variability is found to be the most important uncertainty source for lead times up to 30 yr. Model uncertainty is the dominant source for longer lead times, while scenario uncertainty is found to be negligible for all lead times. However, as stated by Willems and Vrac (2011), good practice in climate impact assessments would involve an assessment of the uncertainty in the climate projections. A rough estimation of the overall uncertainty can be achieved by using multi-model ensembles consisting of different climate models as well as different downscaling techniques (Hanel and Buishand, 2012).

In this investigation, uncertainty due to the use of GCM and the downscaling technique is assessed. Downscaling is accomplished using two different statistical downscaling models: (i) Expanded Downscaling (XDS, Bürger, 1996) and (ii) the Long Ashton Research Station Weather Generator (LARS-WG, Semenov and Barrow, 1997). Recently, both techniques have been applied in several studies focusing on extreme events (e.g. Mavromatis and Hansen, 2001; Menzel and Bürger, 2002; Qian et al., 2004; Dibike and Coulibaly, 2005; Scibek and Allen, 2006; Semenov, 2007, 2008; Bürger et al., 2009). Comparative studies with other downscaling techniques have shown that both methods have significant skill in reproducing observed precipitation extremes (e.g. Bürger and Chen, 2005; Qian et al., 2008; Hashmi et al., 2011; Bürger et al., 2012). XDS is a Perfect-Prog approach that is based on regression while LARS-WG, instead, is a change factor-conditioned weather generator and is known as simple MOS (Maraun et al., 2010). The XDS technique is applied to downscale GCM output, whereas LARS-WG is used to downscale RCM output. Thus, both techniques are fundamentally different approaches. However, these differences are explicitly desired, because it seems to be very relevant to analyse climate change signals simulated by two different approaches, as aimed at in the present study. Besides the application of these two different statistical downscaling techniques, a number of GCMs and RCMs are used to assess the range of uncertainty in the climate projections.

The objectives of the present investigation are (i) to refine the understanding of climate change impacts on precipitation extremes in a complex Alpine topography and (ii) to assess the uncertainty in the climate projections. The study is performed on the Lech basin, located in the Northern Limestone Alps. The catchment has already been investigated in a previous application with a focus on climate change impacts on the runoff regime (Dobler et al., 2010). This study reports significant changes in the runoff regime, with an increase of winter runoff and a decrease of summer runoff.

The following section introduces the study area and the available data, followed by a description of the methodology. The results and discussions are presented in Sect. 3. Finally, conclusions are given.

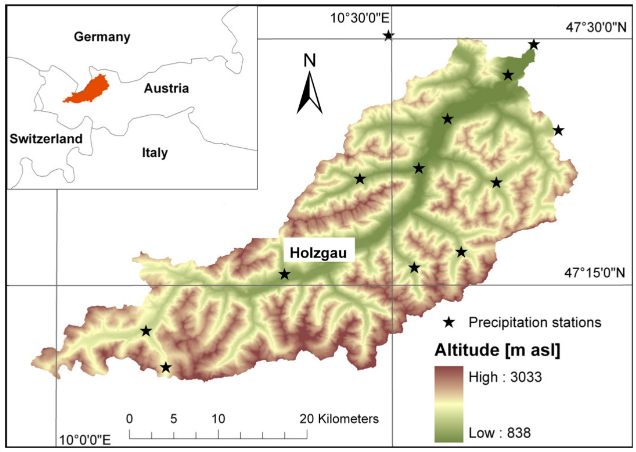

Fig. 1. Study area with rain gauges.

2 Material and methods

2.1 Investigation area

In the present investigation, the Lech watershed located in the Northern Limestone Alps, was selected as the study area. The catchment covers $\sim$1000 km^2 and can be characterized as a typical Alpine valley with high relief and steep slopes. Figure 1 gives an overview of the study area. The topography is rather complex, with elevation ranging from around 800 m to around 3000 m.

The Lech catchment is located at the northern rim of the Alps, a zone characterized by a significant wet anomaly in the European Alps (Frei et al., 1998). Orographic precipitation enhancement is understood as the main reason for this precipitation gradient towards the mountain rims (Frei et al., 1998). Annual precipitation shows strong variations within the catchment, ranging from around 1300 mm to 1800 mm, based on the period from 1971 to 2005 (see Table 1). At the weather station at Holzgau (see Fig. 1 and Table 1), maximum monthly precipitation occurs during July with an average of 172 mm, whereas minimum monthly precipitation is observed in April with 75 mm. Monthly minimum temperature occurs during January with $-3.5\,^{\circ}$C, whereas monthly

Table 1. Rain gauges.

Station	Station ID	Lat. (° N)	Lon. (° E)	Altitude (m a.s.l.)	Mean annual precip. (1971–2005) (mm)
Berwang	101 246	10.75	47.41	1295	1423
Boden	101 170	10.61	47.28	1355	1393
Forchach	101 212	10.58	47.42	910	1329
Gramais	101 162	10.54	47.27	1320	1326
Hinterhornbach	101 188	10.45	47.36	1100	1653
Höfen_Oberh.	101 220	10.68	47.46	870	1494
Holzgau	11 400	10.34	47.26	1080	1336
Lech	101 121	10.14	47.20	1480	1630
Namlos	101 204	10.66	47.36	1260	1585
Reutte	11 500	10.72	47.50	850	1385
Tannheim_Unt.	101 261	10.50	47.50	1090	1778
Vorderhornbach	101 196	10.54	47.37	960	1362
Zürs	101 113	10.17	47.17	1720	1664

maximum temperature is observed in July with +15.2 °C. Between November and March, most precipitation falls as snow in the Lech catchment (see Dobler et al., 2010). Note, however, that our study is entirely based on precipitation observations (apart from temperature); changes in the proportion of rain and snow, despite their importance, can therefore not be tackled here.

The Lech watershed is known as a flood-prone region as three extreme floods have occurred there in the recent past (in 1999, 2002 and 2005). For more details about these events see Dobler (2010) or Thieken et al. (2011). Thus, assessing the impacts of climate change on precipitation extremes is of high socio-economic relevance for this region.

2.2 Data

For the present study, thirteen rain gauges have been selected within or close to the catchment. The stations are shown in Fig. 1 and the main characteristics of the stations are given in Table 1. Observed data consisted of daily precipitation data covering the time period from 1971 to 2005. The data was obtained from the *Hydrographischer Dienst Österreich* and the *Zentralanstalt für Meteorologie und Geodynamik* (ZAMG). The data were quality controlled, but not homogenized. Precipitation events with 24-h duration were considered in this study.

Large-scale climate data comprise reanalysis, GCM and RCM data. For the period from 1989 to 2005, daily large-scale reanalysis data was derived from the ERA-interim dataset of the European Centre for Medium-Range Weather Forecasts (ECMWF) (Simmons et al., 2007). The data cover the domain from 40°–50° N to 0°–25° E. In addition, a number of GCMs and RCMs were selected to simulate current and future climate conditions. Table 2 provides an overview of the different climate simulations used in this work.

For the two GCMs, i.e. ECHAM5 and HadGEM2, an ensemble of three integrations was available with different initial conditions. Ensemble integrations are very helpful when focusing on extreme events, as interannual climate variability can be better assessed. Following the studies of Frei et al. (2006) and Tolika et al. (2008), the ensemble members were treated as one 90-yr experiment for the present and future scenario. The RCMs with a horizontal resolution of ∼25 km were obtained from the ENSEMBLES project of the European Union (EU; http://ensemblesrt3.dmi.dk/). In this study, the output of nine individual RCM experiments was utilized using seven different RCMs and four GCMs. The output of the two GCMs (ECHAM5, HadGEM2) was downscaled using the XDS model, while the output of the nine different GCM–RCM combinations was downscaled using LARS-WG.

All climate simulations are forced with the Special Report on Emission Scenario (SRES) A1B (Nakicenovic et al., 2000). The A1B scenario is a mid-range scenario in terms of global greenhouse gas emissions. From all simulations the time slices from 1971 to 2000, considered as reference period, and from 2071 to 2100, as future scenario, were extracted.

2.3 Statistical analysis

2.3.1 Indices

In order to investigate possible changes in the intensity of 24-h precipitation extremes, various indices summarized in Table 3 were selected. Due to the focus on precipitation extremes, the present investigation concentrates (i) on the upper tail of the cumulative distribution function of precipitation and (ii) on analysing precipitation events with higher return periods, i.e. 5 and 20 yr. Wet days are defined as days with precipitation of more than 1 mm day^{-1} (Diffenbaugh et al., 2005).

Table 2. Selected GCMs and RCMs.

GCM	RCM	Resolution	Ensemble members	Statistical Downscaling	Abbreviation
ECHAM5	–	250 km	3	XDS	EH5_XDS
HadGEM2	–	250 km	3	XDS	HG2_XDS
HadCM3Q0	CLM	25 km	–	LARS-WG	HC3_CLM_LWG
HadCM3Q0	HadRM3Q0	25 km	–	LARS-WG	HC3_HR3_LWG
ARPEGE	HIRHAM	25 km	–	LARS-WG	ARP_HIR_LWG
ECHAM5	RACMO	25 km	–	LARS-WG	EH5_RAC_LWG
ECHAM5	REMO	25 km	–	LARS-WG	EH5_REM_LWG
ECHAM5	RCA	25 km	–	LARS-WG	EH5_RCA_LWG
ECHAM5	HIRHAM	25 km	–	LARS-WG	EH5_HIR_LWG
ECHAM5	REGCM	25 km	–	LARS-WG	EH5_REG_LWG
BCM	RCA	25 km	–	LARS-WG	BCM_RCA_LWG

Model origins:
ECHAM5, REMO – Max-Planck-Institute for Meteorology (MPI), HadGEM2, HadCM3Q0, HadRM3Q0 – Met Office Hadley Centre (HC), CLM – Swiss Institute of Technology (ETHZ), HIRHAM – Danish Meteorological Institute (DMI), RACMO – Royal Netherlands Meteorological Institute (KNMI), RCA – Swedish Meteorological and Hydrological Institute (SMHI), ARPEGE – Meteo-France, BCM – University of Bergen

In order to assess precipitation events with return periods of 5 and 20 yr, a generalized extreme value (GEV) distribution was applied. The GEV distribution has been used extensively for a variety of applications in hydrology, climatology or meteorology (e.g. Frei et al., 2006; Beniston et al., 2007; Buonomo et al., 2007). It is defined as (Eq. 1):

$$F(x) = \exp\left\{-\left[1+\kappa\left(\frac{x-\varsigma}{\alpha}\right)\right]^{-\frac{1}{\kappa}}\right\}, \quad (1)$$

where ς, α, and κ are the location, scale and shape parameter, respectively. $F(x)$ is defined for $\left\{x : 1+\kappa\left(\frac{x-\varsigma}{\alpha}\right) > 0\right\}$, where $-\infty < \varsigma < \infty$, $\alpha > 0$ and $-\infty < \kappa < \infty$. In the case of $\kappa < 0$, $\kappa = 0$ and $\kappa > 0$, the well-known Weibull, Gumbel and Fréquet distributions are obtained (e.g. Russo and Sterl, 2012). In this study, we analysed the data using a block maxima approach (Coles, 2001). The block maxima approach is a well-established statistical framework in which the single highest daily precipitation amount over the entire year or season is selected.

The GEV parameters were estimated using the Maximum-Likelihood method. Finally, the assumption if the GEV distribution could be used was tested with the Kolmogorov–Smirnov test, based on a significance level of 5 %. The test indicates if the GEV distribution is a reasonable approximation of the distribution of annual and seasonal precipitation maxima. Note that the application of the GEV distribution is based on the key assumption that the data is independently and identically distributed (Wehner et al., 2010).

2.3.2 Confidence intervals

A non-parametric bootstrap simulation method was applied to estimate confidence intervals for the 90th and 99th percentiles as well as for the 5- and 20-yr return values. The technique is well recognized in climate impact assessments (e.g. Ekström et al., 2005). Bootstrap samples were generated for each meteorological station by resampling years. Thereby, the original dataset comprising n years was resampled with replacements 1000 times in order to generate independent samples of size n. Convergence experiments confirmed that 1000 samples are sufficient (not shown). The indices described in Sect. 2.3.1 were then calculated for each dataset, and the 5th and 95th percentiles were constructed.

In order to generate confidence intervals for the climate change signals, pairs of bootstrap samples from the reference and scenario simulations were resampled and the quotient between scenario and reference simulation was calculated (Frei et al., 2006). When the ratio of 1.0, which corresponds to no change, lies outside the 90 % confidence interval, the differences are statistically significant.

2.4 Statistical downscaling methods

2.4.1 Long Ashton Research Station Weather Generator (LARS-WG)

The Long Ashton Research Station Weather Generator (LARS-WG, version 5.11; http://www.rothamsted.bbsrc.ac.uk/mas-models/larswg.php) was applied to generate daily site-specific climate change scenarios for the meteorological stations illustrated in Fig. 1.

Stochastic weather generators are numerical models that produce temporally and spatially high resolution synthetic weather series, which have statistical properties similar to observations. Most of these tools are able to process multiple climate variables, such as precipitation, minimum and maximum temperature, and solar radiation (Semenov et al., 1998). Although weather generators are commonly used to generate long time series of synthetic weather for current

Table 3. Precipitation indices.

Abbreviation	Definition	Unit
$Q90$, $Q99$	90th and 99th percentiles of distribution function on wet days	mm d^{-1}
$x1d5$, $x1d20$	Intensity of a precipitation event with a return period of 5 and 20 yr	mm d^{-1}

climate conditions, they have been increasingly applied in climate impact assessments in recent years (e.g. Semenov, 2007; Butterworth et al., 2010).

LARS-WG models precipitation occurrence by alternating series of wet and dry days, based on semi-empirical probability distributions. The amount of precipitation is simulated by a semi-empirical distribution for each month. Semi-empirical distributions are defined as a histogram with several intervals (Semenov and Stratonovitch, 2010; Sunyer et al., 2012). For more details see Semenov et al. (1998) or Semenov and Stratonovitch (2010).

In a first step, the parameters of LARS-WG were calculated by analysing observed precipitation data from the period 1971 to 2000. The calibrated parameters were then used by LARS-WG to generate synthetic weather series of 100-yr for each site. A long time series allows a better assessment of climate extremes as differences between observed and simulated series do not result from the short sampling period (Qian et al., 2004). The performance of the weather generator was evaluated by comparing the synthetically produced 100-yr simulations with observations. In a second step, changes in mean and variability of precipitation as simulated by the RCMs were used to adjust the calibrated parameters of LARS-WG. Therefore, relative changes in monthly precipitation as well as monthly shifts in wet and dry series were calculated from the reference simulation (1971 to 2000) and the future scenario (2071 to 2100) of each RCM. The semi-empirical distributions for the future were obtained from the present distribution by multiplying the intervals of the histogram using the change factors (e.g. Semenov, 2007; Sunyer et al., 2012). A detailed description how the new parameters are generated is given by Semenov (2007).

It has to be noted, that LARS-WG is calibrated on observed station data only. Thus, in contrast to XDS, the calibration and reference simulation is identical for LARS-WG. As the future scenarios refer to the reference simulation, we decided to present the performance of the reference simulation of LARS-WG (denoted by OBS_LWG) in Sect. 3 together with the downscaled reference simulations using XDS.

2.4.2 Expanded Downscaling (XDS)

XDS is a statistical downscaling technique which belongs to the group of regression methods. It was developed by Bürger (1996) and has been applied in a variety of applications in recent years, e.g. flood risk assessment (Menzel and Bürger, 2002) or flood forecast (Bürger, 2009). In this study, XDS was applied to downscale GCMs output to finer spatial resolution.

XDS is based on establishing an empirical relationship between large-scale variables x, the "predictors", and the local-scale variables y, the so-called "predictands". In general, XDS follows the concept of multiple linear regression (MLR) by minimizing the least square error. The main weakness of MLR is that it reduces the local climate variability significantly, which is important for a realistic simulation of extreme events. In contrast to classical regression, XDS explicitly preserves local climate variability by adding a side condition so that local covariance is retained. Thus, XDS is found as the matrix Q that minimizes the least square error under the constraining side condition that the local covariance is preserved (Eq. 2). Although this leads to a larger mean error compared to MLR, extreme events are simulated much better by XDS. It is important to note that the estimation of XDS is entirely done in the normalized domain, which can be achieved for any random variable by means of the probability integral transform (probit). Therefore both, the annual cycle and the statistics of extremes, are mainly defined through the estimated probit parameters. A full description of the XDS technique is given by Bürger (1996) or Bürger et al. (2009).

$$\mathrm{XDS} = \underset{Q}{\mathrm{argmin}}\, \| x\,\boldsymbol{Q} - y \| \quad \text{subj. to } \boldsymbol{Q}'x'x\,\boldsymbol{Q} = y'y \tag{2}$$

As potential predictors, daily temperature, vorticity, divergence and specific humidity on the 700 and 850 hPa levels as well as precipitation on the surface were selected; these provide a balance of the available large-scale information and the need for parsimony to guard against model overfitting. The number of actually selected predictors, as the number of retained empirical orthogonal functions (EOFs), was determined during the calibration process (see Bürger et al., 2012). On the local scale, daily data of precipitation for the meteorological sites specified in Table 1 were used. The first 11 yr (1989–2000) of the available time series of 1989 to 2005 were considered for calibration, while the last 5 yr (2001 to 2005) were used for validating the model. Finally, the XDS model was applied to downscale GCMs output for both the reference (1971 to 2000) and the scenario (2071 to 2100) periods. In order to better present observed climate conditions, the GCM fields were bias corrected for mean and variance to match those of the ECMWF analyses; details can be found in Bürger et al. (2011).

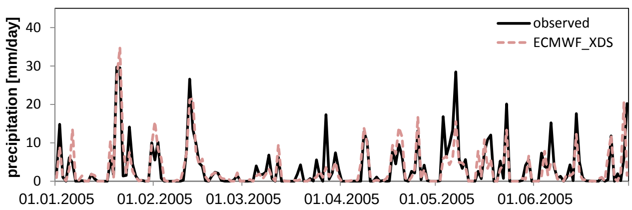

Fig. 2. Observed and statistically downscaled precipitation averaged over the entire catchment area from 1 January 2005 to 30 June 2005. The XDS model is forced using ECMWF reanalysis data (denoted by ECMWF_XDS).

It has to be noted that LARS-WG and XDS were calibrated on different time periods. Using the same period was not possible, as on the one hand, the period 1989–2000 seems to be too short for a reliable calibration of LARS-WG as at least 30-yr of data are typically used for the simulation of extremes (e.g. Semenov, 2008; Qian et al., 2008). This data shortage affects XDS in the same way but to a lesser extent, since that model is more process-based and requires "only" the sufficient sampling and learning of the most relevant synoptic conditions. On the other hand, the fact that ECMWF data are not available before 1989 restricts the potential calibration period for XDS; note that after the completion of this paper the ECMWF data set was extended to the year 1979 (Dee et al., 2011). Although other reanalysis sets with longer time series were available (e.g. those of NCEP), we selected the ERA-interim data because of their higher quality.

2.4.3 Calibration and validation of XDS

Figure 2 gives an example of the performance of the XDS model driven with ECMWF data during the validation period. In general, observed precipitation is reproduced fairly well by the XDS model. However, the figure indicates that some over- and underestimations are evident, especially in the case of the most extreme events. For daily areal precipitation, which is defined as the daily mean of all precipitation stations, the correlation coefficient between observed and simulated time series constitutes 0.78 for the calibration period (1989 to 2000) and 0.76 for the validation period (2001 to 2005). Note that five years are quite short for a validation period of extreme events, but at least a decade of daily data is necessary to calibrate the XDS model.

Figure 3 shows a comparison of the percentiles of observed and simulated precipitation series, based on the period from 1989 to 2005. In general, XDS performs very well in simulating precipitation extremes. Even for the highest percentiles, i.e. 99th percentile, a good agreement between observation and simulation is obtained.

XDS shows a slight seasonal bias with underestimating precipitation events of more than around 30 mm day^{-1} in spring. In contrast, slight overestimations are evident in winter. In autumn, the XDS model was found to perform best. However, also other studies using Perfect-Prog techniques like XDS report that these models perform generally better during autumn and winter than during spring and summer (e.g. Harpham and Wilby, 2005; Hundecha and Bárdossy, 2008; Tolika et al., 2008). This can be explained by the fact that during autumn and winter, the local climate depends more on the large-scale circulation, while during spring and summer local convective processes are important (Hundecha and Bárdossy, 2008).

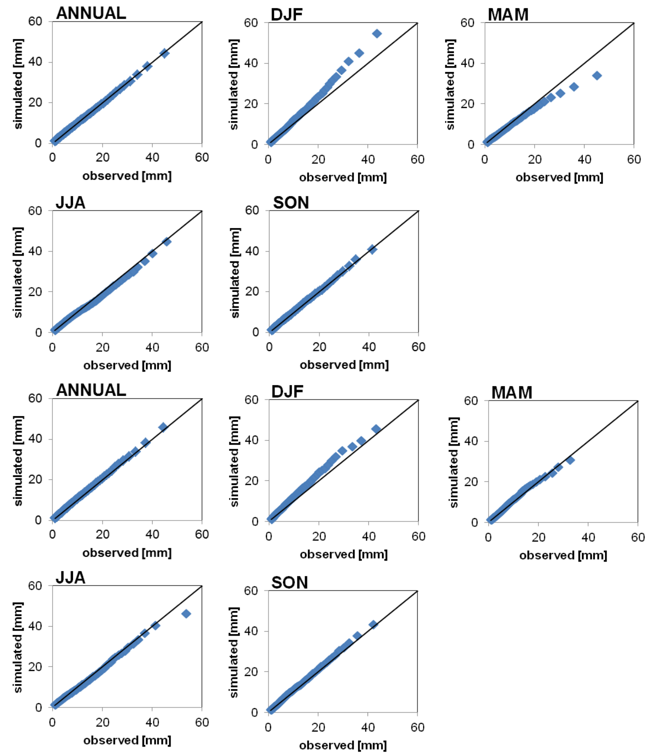

Fig. 3. Percentile-percentile plots showing observed versus downscaled precipitation on wet days (>1 mm day^{-1}) using XDS for **(a)** the calibration (1989–2000) and **(b)** the validation period (2001–2005). The XDS model is forced using ECMWF reanalysis data.

3 Results and discussion

Before applying the two downscaling models to generate future climate scenarios, it is important to evaluate the performance of both models for current climate conditions. It has to be noted that a comparison of both techniques is neither aimed at nor practicable due to (i) different time periods used for calibrating and validating the models and (ii) different data sets used to force both downscaling models. In order to better illustrate the results, station-wise results are calculated and then averaged (arithmetic mean) over the entire catchment area.

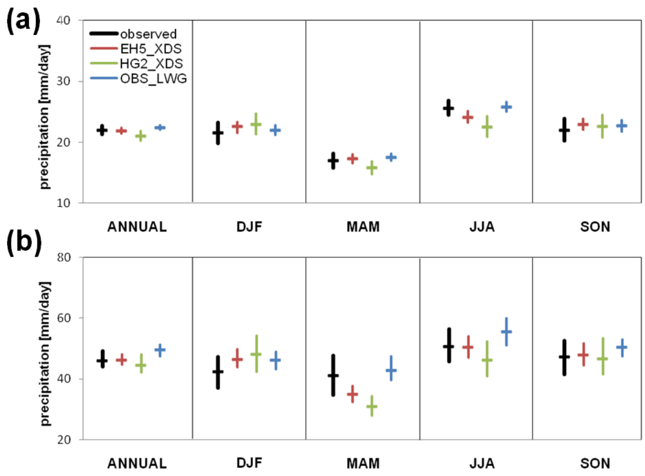

Fig. 4. (a) 90th and **(b)** 99th percentiles of observation (1971–2000) and reference simulations (EH5_XDS, HG2_XDS, OBS_LWG; 1971–2000). Vertical lines indicate 90% bootstrap confidence intervals. 24-h precipitation events averaged over the Lech catchment are shown.

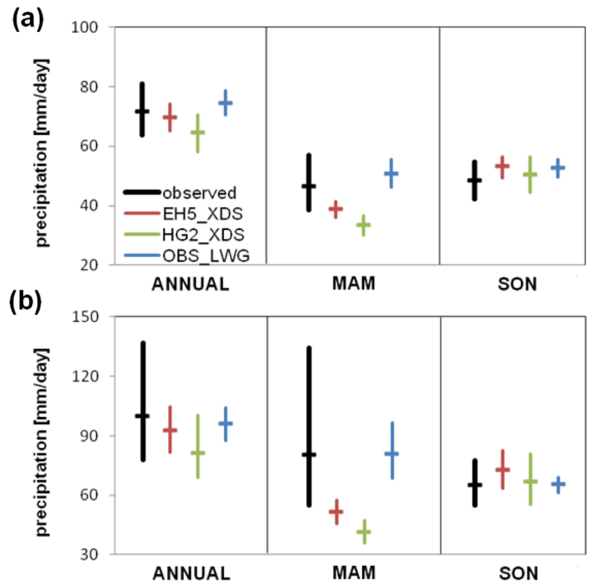

Fig. 5. (a) 5-yr and **(b)** 20-yr return values for observation (1971–2000) and reference simulations (EH5_XDS, HG2_XDS, OBS_LWG; 1971–2000). Vertical lines indicate 90% bootstrap confidence intervals. 24-h precipitation events averaged over the Lech catchment are shown.

3.1 Evaluation of reference simulations

Figure 4 illustrates the 90th and 99th percentiles of precipitation events, based on the observed time series and the reference simulations using the two downscaling techniques. Note that in the case of XDS, the precipitation variability is derived from the GCM control simulations, while for LARS-WG, the variability is obtained from observations.

In general, the reference simulations agree fairly well with observations. Even for the 99th percentile, which corresponds to the amount of daily precipitation exceeded with a probability of 0.01, a good agreement between observation and reference simulations is obtained. The figure reveals that all reference simulations reproduce the seasonal cycle of the two percentiles very well, with maximum values during summer and lower values during spring.

The performance of the EH5_XDS and HG2_XDS reference simulations varies with seasons, whereas the performance of OBS_LWG is similar for all seasons. Both EH5_XDS and HG2_XDS underestimate the 90th percentile in summer and the 99th percentile in spring, respectively, whereas they slightly overestimate the 99th percentile in winter. However, when comparing the results of Figs. 3 and 4, it can be seen that the agreement between observation and the XDS simulations driven with GCM data is similar to the agreement between observation and XDS simulation driven with ECMWF data. Thus, the quality of both GCMs in simulating the selected predictors seems to be relatively good.

OBS_LWG slightly overestimates the 90th and 99th percentiles in all seasons. The largest bias for OBS_LWG is found for the 99th percentile in summer.

Figure 5 shows the performance of the reference simulations in reproducing the 5- and 20-yr return values. Although the analysis was made for the whole year and all seasons, here only the results for the year as well as for spring and autumn are presented, as these are the periods with the most pronounced deviations.

Again, the seasonal variations of the 5- and 20-yr return values are captured fairly well by the reference simulations. Except the HG2_XDS simulation in spring, all reference simulations fall within the 90% confidence intervals of observation, showing that the downscaling techniques perform well in reproducing observed precipitation extremes. The EH5_XDS and HG2_XDS simulations underestimate the 5- and 20-yr return values in spring, whereas they perform well in autumn. For OBS_LWG, a good performance in simulating the 5- and 20-yr return values is found in both seasons.

It is worth noting that the confidence intervals increase with the rarity of the precipitation event. This is due to the increasing relevance of single extreme events, which have a large impact on the estimation of the selected indices. Thus, the results demonstrate that the uncertainty due to sampling is very relevant when focusing on precipitation extremes and has to be taken into consideration in future impact studies. Comparatively large sampling uncertainty is obtained in spring for the 20-yr return value. This is mainly due to a very extreme precipitation event which occurred in May 1999. At some stations, this event was the highest since the beginning of regular measurements around 130 yr ago (Amt der Tiroler

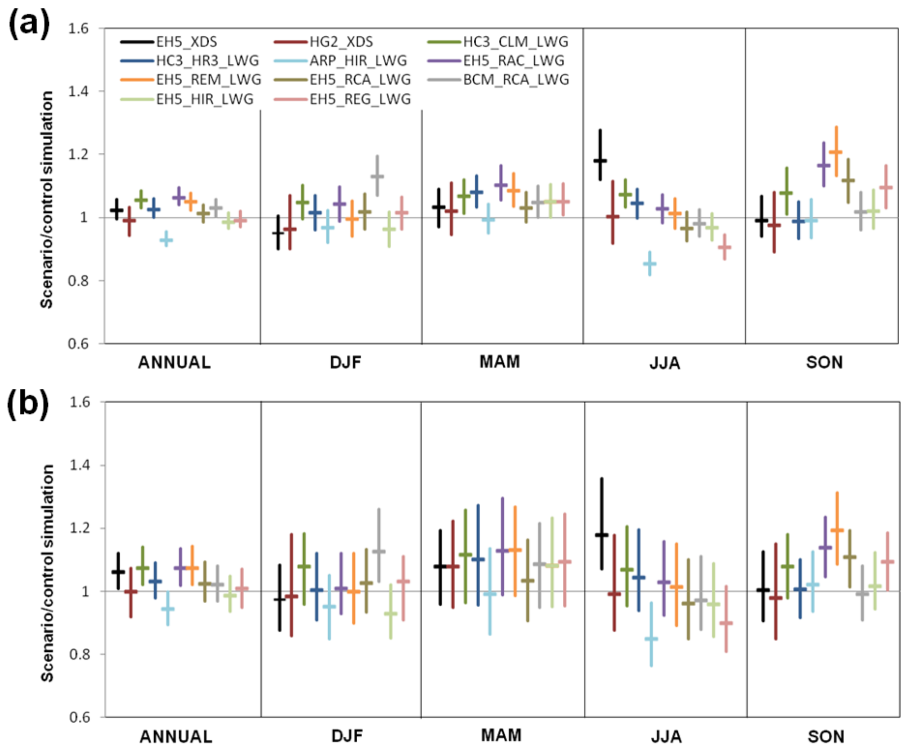

Fig. 6. Ratio between scenario (2071–2100) and reference (1971–2000) simulations for **(a)** 90th and **(b)** 99th percentiles. Vertical lines indicate 90 % bootstrap confidence interval. The results are statistically significant when the ratio of 1.0 lies outside the 90 % confidence interval. 24-h precipitation events averaged over the Lech catchment are shown.

Landesregierung, 1999; Meier, 2002). The inclusion of such extreme events in the sample considerably modifies the extreme value distribution and thus has a significant impact on the calculation of the 20-yr return value.

In summary, the reference simulations agree fairly well with observations, even for extreme events such as the 20-yr return value. Compared with the results presented in numerous other studies using different statistical downscaling techniques (e.g. Harpham and Wilby, 2005; Wetterhall et al., 2009; Quintana-Seguí et al., 2011), observed precipitation extremes could be reproduced very well in this study. In the case of XDS, this can be explained by the fact that this technique has been particularly designed to simulate climate extremes. XDS preserves the local climate variability by adding the side condition that local covariance is retained (see Sect. 2.4.2). Thus, extreme events are simulated much better by XDS than for example by multiple linear regression (Bürger, 1996). LARS-WG approximates daily precipitation with a semi-empirical distribution consisting of a histogram with 23 intervals (Semenov and Stratonovitch, 2010). A semi-empirical distribution is very flexible, does not assume a particular theoretical distribution function and can approximate a wide range of different distributions (e.g. Semenov et al., 1998; Semenov, 2008). The application of a semi-empirical distribution can thus improve the simulation of extreme events (e.g. Qian et al., 2004).

3.2 Climate change scenarios

We now study the impacts of climate change on extreme precipitation events by comparing the reference simulation (1971–2000) with the scenario simulation (2071–2100) of each climate run. The future scenario is based on the A1B emission scenario.

Figure 6 illustrates changes in the intensity of the 90th and 99th percentiles for the whole year and each season. In general, the figure indicates a wide range of results with both projected increases and decreases in precipitation extremes. However, the number of models which simulate a statistically significant increase is by far larger than those showing a decrease. Moreover, the magnitudes of the increases are more pronounced than the magnitudes of the decreases. The changes show strong seasonal variations. A slight tendency toward an increase in the intensity of future precipitation extremes is obtained for spring and autumn, as a number of models indicate a statistically significant increase in these seasons. Nevertheless, the figure reveals that the use of different climate models as well as different downscaling techniques is a necessary prerequisite to sufficiently assess the range of possible changes.

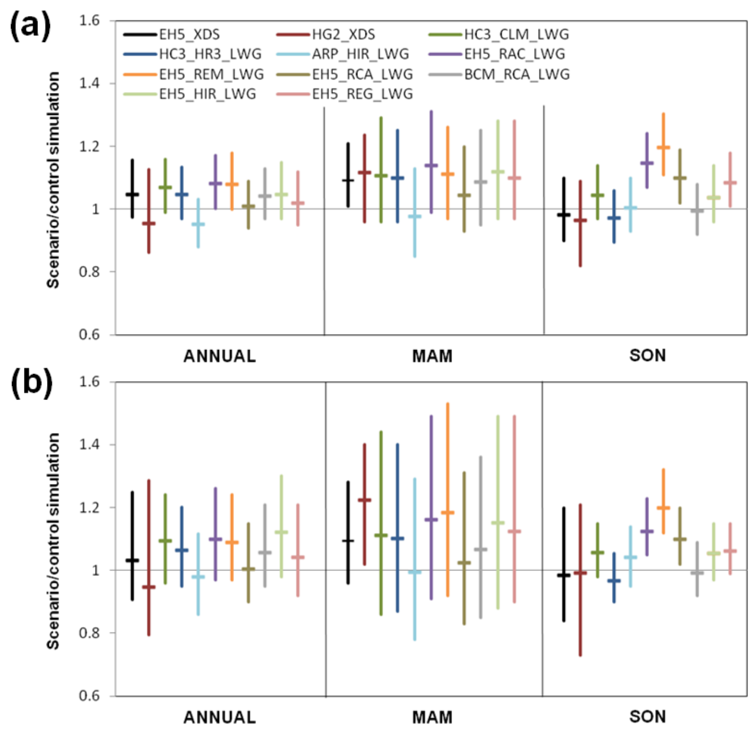

Fig. 7. Ratio between scenario (2071–2100) and reference (1971–2000) simulations for **(a)** 5-yr return value and **(b)** 20-yr return value. Vertical lines indicate 90 % bootstrap confidence interval. The results are statistically significant when the ratio of 1.0 lies outside the 90 % confidence interval. 24-h precipitation events averaged over the Lech catchment are shown.

The uncertainty in the projection is assessed by calculating the difference between the maximum and minimum of the future precipitation projections. In general, the uncertainty for both percentiles is comparatively small during winter and spring and relatively large during summer and autumn. This is in consensus with the findings of Schmidli et al. (2007), who obtained larger uncertainty in summer than in winter, too, when applying different statistical and dynamical downscaling methods over the European Alps.

The largest uncertainty is found for the 90th percentile in summer, in which the EH5_XDS simulation shows a statistically significant increase (+18 %), whereas the ARP_HIR_LWG simulation indicates a statistically significant decrease (−15 %). Except the ARP_HIR_LWG simulation, which indicates statistically significant decreases for the 90th and 99th percentiles in summer and the 90th percentile for the whole year, and the EH5_REG_LWG simulation for the 90th percentile in summer, all remaining simulations indicate either insignificant changes or statistically significant increases in all seasons.

Figure 7 illustrates changes in the intensity of 5- and 20-yr return values. Table 4 summarizes the changes for the selected indices. As can be seen, the confidence intervals generated by the bootstrapping approach are relatively wide and increase with the rarity of the event. This makes it very difficult to detect statistically significant changes in the case of extreme events. Although a number of climate scenarios shows an increase in the intensity of 5- and 20-yr return values, most of these changes are statistically not significant (see Table 4).

None of the climate models indicate a statistically significant decrease in the intensity of 5- and 20-yr return values, whereas several climate simulations indicate statistically significant increases. In spring, the HG2_XDS model simulates an increase in the intensity of the 20-yr return value of 23 %. In autumn, the EH5_REM_LWG simulation shows largest increases with 20 % for both the 5- and 20-yr return values. By means of extreme value analysis, the changes in return values can be expressed in terms of changes in the recurrence of precipitation extremes. Based on these two simulations, in spring a present 20-yr return value is expected to occur every 8 yr in the future, while in autumn a present 20-yr return value corresponds to a 6-yr return value in the future. Hence, the frequency of a 20-yr event could increase up to a factor of 2.5 in spring and 3.3 in autumn. However, most of the climate simulations which indicate statistically significant increases in the intensity of the 5- and 20-yr return values are forced by the ECHAM5 model. Hence, the results should be treated with caution as they only rely on one GCM.

Table 4. Ratio between scenario and reference simulations for the 90th and 99th percentiles as well as for the 5- and 20-yr return values. 24-h precipitation events averaged over the Lech catchment are shown.

	YEAR				MAM				SON			
	$Q90$	$Q99$	$x1.d5$	$x1.d20$	$Q90$	$Q99$	$x1.d5$	$x1.d20$	$Q90$	$Q99$	$x1.d5$	$x1.d20$
EH5_XDS	1.03	**1.06**	1.05	1.03	1.03	1.08	**1.09**	1.10	0.99	1.00	0.98	0.99
HG2_XDS	0.99	1.00	0.96	0.95	1.02	1.08	1.12	**1.23**	0.98	0.98	0.96	0.99
HC3_CLM_LWG	**1.06**	**1.07**	1.07	1.10	**1.07**	1.12	1.11	1.11	**1.08**	1.08	1.05	1.06
HC3_HR3_LWG	**1.03**	1.03	1.05	1.07	**1.08**	1.10	1.10	1.10	0.99	1.01	0.97	0.97
ARP_HIR_LWG	**0.93**	0.94	0.95	0.98	0.99	0.99	0.98	1.00	0.99	1.02	1.01	1.04
EH5_RAC_LWG	**1.06**	**1.07**	**1.08**	1.10	**1.10**	1.13	1.14	1.16	**1.16**	**1.14**	**1.15**	**1.13**
EH5_REM_LWG	**1.05**	**1.07**	1.08	1.09	**1.09**	1.13	1.11	1.18	**1.21**	**1.19**	**1.20**	**1.20**
EH5_RCA_LWG	1.01	1.02	1.01	1.01	1.03	1.03	1.05	1.02	**1.12**	**1.11**	**1.10**	**1.10**
BCM_RCA_LWG	**1.03**	1.02	1.04	1.06	**1.05**	1.09	1.09	1.07	1.02	0.99	1.00	0.99
EH5_HIR_LWG	0.99	0.99	1.05	1.12	**1.05**	1.08	1.12	1.15	1.02	1.02	1.04	1.06
EH5_REG_LWG	0.99	1.01	1.02	1.04	**1.05**	1.09	1.10	1.13	**1.10**	**1.09**	**1.09**	1.06

Bold numbers indicate statistically significant changes (see Sect. 2.3.2).

The projected increase in precipitation extremes agrees with theoretical considerations (Clausius-Clapeyron relation) that the maximum moisture content of the atmosphere increases with approximately 7 % for a 1 °C rise in temperature (e.g. Solomon et al., 2007). Under a constant relative humidity, increases in temperature result in increases in water vapor at the same rate (e.g. Solomon et al., 2007). Hence, it is expected that precipitation extremes increase as the climate warms (Allan and Soden, 2008; O'Gorman and Schneider, 2009; Lenderink et al., 2011).

Finally, we analyse the range of uncertainty resulting from different sources. Analysis of different GCMs downscaled by the same statistical downscaling technique reveals that the GCM is an essential source of uncertainty. As can be seen in Fig. 6a, large differences between the EH5_XDS and HG2_XDS simulations are obtained in summer. While the EH5_XDS simulation indicates an increase in the intensity of the 90th percentile of 20 % in summer, the HG2_XDS simulation shows no change. Similar results were found in a variety of studies, e.g. Déqué et al. (2011). Beside uncertainty resulting from the GCM, dynamical and statistical downscaling contributes to considerable uncertainty in the projections. For example, changes between −1 % (EH5_XDS) and +21 % (EH5_REM_LWG) in the intensity of the 90th percentile of precipitation on wet days in autumn are obtained for the same GCM downscaled by different techniques (see Fig. 6a).

4 Conclusions

The main objectives of this investigation were (i) to study the impacts of climate change on precipitation extremes and (ii) to assess the range of uncertainty in the climate projections by applying two statistical downscaling techniques as well as multiple GCMs and RCMs. The Lech catchment, located in the Northern Limestone Alps, was selected as the study area.

In general, downscaling precipitation extremes is a challenging task and is subjected to large uncertainty. Recently, several investigations have reported large model biases when focusing on precipitation extremes (e.g. Smiatek et al., 2009). In this investigation, two well-recognized downscaling techniques were selected to simulate precipitation extremes in a complex Alpine topography. The models are completely different in their underlying concepts: XDS is a Perfect-Prog approach whereas LARS-WG belongs to MOS. In the case of LARS-WG, changes in monthly means derived from climate models are used to alter the calibrated parameters. Hence, in contrast to XDS, LARS-WG does not directly use large-scale atmospheric data. However, these different characters of the two techniques are fully intended in order to assess the spread of climate change signals. The results showed that both downscaling models performed very well in reproducing observed precipitation extremes. The biases of all simulations were within an acceptable range, even for very rare events, e.g that one with a 20-yr return period. Thus, XDS and LARS-WG are valuable tools to study the effects of climate change on precipitation extremes on local scales.

Generally, it is difficult to compare the performance of both models, because they have been calibrated and validated on different types of data (observed station data for LARS-WG, large-scale reanalysis data for XDS) as well as different lengths of data. Thus, the results require a careful evaluation. For example, the better agreement between observation and LARS-WG simulation in the validation period is misleading, because the weather generator has been designed to match observed data perfectly. However, each approach comes with its own advantages and disadvantages when using it in climate change studies. The main advantage of LARS-WG over

XDS is that site-specific scenarios can be produced very easy, which makes the technique attractive for a common user, while the main disadvantage is that it cannot produce spatially correlated climate information, which is necessary in a variety of applications.

A special focus of this study was on assessing the uncertainty in the climate projections. Uncertainty originating from GCMs and downscaling was considered. The results demonstrate that the climate projections show large variations in the magnitude of the projected climate change signals. In some cases, the simulated changes even pointed towards different directions. Thus, it is emphasized to include and assessment of uncertainty in climate impact assessments in future studies, according to the recommendation of Willems and Vrac (2011). Otherwise, the reliability of such studies will be decisively reduced.

Although the present study addressed the main sources of uncertainty, only a rough estimation of the overall uncertainty in the climate projections could be given. This is mainly due to a comparatively small number of different GCMs and downscaling techniques selected in this investigation. However, beside uncertainty related to the GCM, the results of this study also demonstrate that downscaling is an important source of uncertainty. This has to be taken into consideration in future studies.

Nevertheless, when studying the impacts of climate change on precipitation extremes in the Lech basin, a variety of interesting findings were obtained. The majority of simulations indicate statistically insignificant changes or statistically significant increases during all seasons. Comparatively pronounced climate change signals could be obtained for spring and autumn as several climate simulations indicate statistically significant increase in the intensity 90th and 99th percentiles of precipitation on wet days and the 5- and 20-yr return values. In autumn, for example, a present 20-yr return event could occur every 6 yr in the future scenario and thus, the frequency could increase by a factor of up to 3.3. However, it should be noticed, that due to a strong spatial variability of precipitation in the Alps, the results of this study may not be valid for other Alpine catchments.

Recently, Dobler et al. (2010) assessed climate change impacts on the runoff regime of the same catchment. This study reports that climate change is expected to strongly affect the hydrological conditions in the basin, with decreases in runoff during summer and increases in winter. However, compared to assessing climate change impacts on average conditions, studying changes in extremes is much more difficult and subjected to large variability, with little evidence for clear trends.

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