

Dynamic downscaling of global climate projections for Eastern Europe with a horizontal resolution of 7 km

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Abstract Climate change is one of the key factors influencing the quantity and quality of water resources in hydrologically sensitive regions. In order to downscale global climate simulations from horizontal resolutions of about 125–200 km to about 7 km, a double nesting strategy was chosen. The modelling approach was implemented with the Regional Climate Model CCLM (COSMO-Climate Local Model) with a first nesting covering a central part of Europe and with a second nesting covering parts of Poland, Belarus, and the Ukraine. A control run—driven by global reanalysis data—was evaluated by comparing the model results with corresponding reference data. Long-term yearly and monthly mean differences of temperature and precipitation were statistically assessed. As reference data for the first nesting, the gridded CRU data set with a horizontal resolution of about 55 km was used. Station data of the NOAA and ECA databases were interpolated to provide an appropriate reference data set for the second nesting. Both nestings overestimated long-term yearly precipitation means. Seasonal evaluation of the first nesting showed positive precipitation biases for spring and winter months and negative biases in summer. Furthermore, differences in the spatial precipitation patterns occurred, especially in the high mountain area of the Carpathians. The second nesting overestimated precipitation in spring and summer with smaller biases than in the first nesting. Long-term area means of temperature were properly

reproduced. The first nesting showed an overestimation for all months with maximal deviations in summer and spring. In contrast, the second nesting was slightly too warm for summer and autumn and too cold for winter and spring.

Keywords Eastern Europe · Climate change · Regional climate model · CCLM · Dynamic downscaling

Introduction

Climatic changes have a major impact on the quantity and quality of water resources, especially in hydrologically sensitive regions, due to the close linkage between climate and the water cycle.

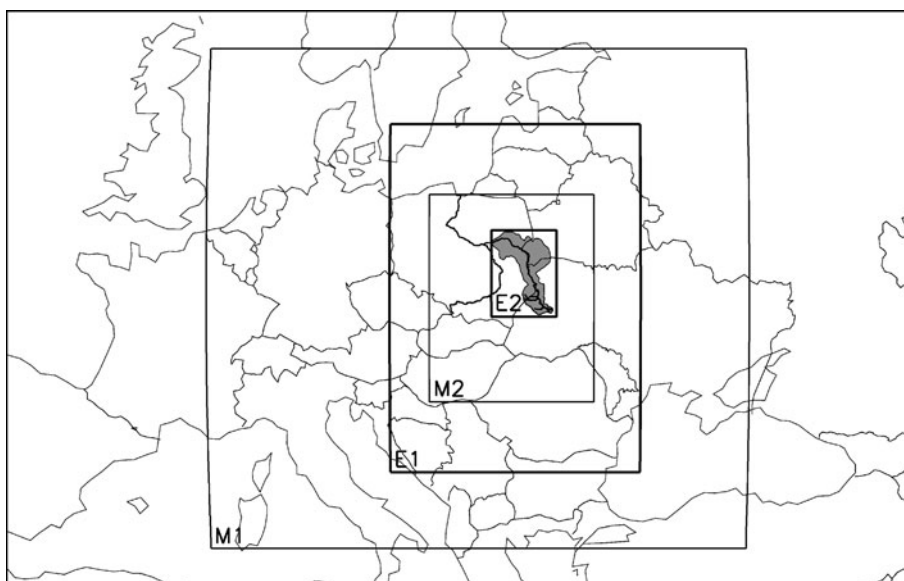
Based on the concept of integrated water resources management (IWRM), which is the current frame for water management worldwide (Leidel et al. 2011), the international water research alliance saxony (IWAS) operates on specific research topics in five model regions (Kalbus et al. 2011). Those regions are located in Eastern Europe (Ukraine/Poland), Latin America (Brazil), Central Asia (Mongolia), South East Asia (Vietnam) and Middle East (Oman). A successful IWRM in hydrologically sensitive regions needs reliable regional climate projections. Within the IWAS project, the results of the projections are intended for usage in further hydrological applications (cf. Delfs et al. 2011, Blumensaat et al. 2011), for the development of so called ‘parameterised regional futures’ (Schanze et al. 2011) as well as for the integration in the IWAS-Toolbox (Kalbacher et al. 2011).

General circulation models (GCM) provide the most reliable and stable method to assess the response of the climate system to changing greenhouse gas concentrations. But, the horizontal resolution of GCMs is too coarse for

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Fig. 1 The Western Bug catchment (shaded area) within the two model domains (M1) and (M2) and the according evaluation areas (E1) and (E2)



regional impact studies. Downscaling approaches are necessary to bridge the gap between the global and the regional scale (Hewitson and Crane 1996, Christensen et al. 2001). The two main approaches are dynamical and statistical downscaling (Benestad et al. 2008). Unfortunately, statistical downscaling was not practicable for a major part of the IWAS regions due to insufficient meteorological station data. Therefore, the dynamical approach was applied.

The objective of this study was to use a regional climate model (RCM) to implement the dynamical downscaling approach for the IWAS region Eastern Europe and to assess the model performance with respect to temperature and precipitation. In the following, the term temperature abbreviates 2 m air temperature and precipitation abbreviates total precipitation.

The study area is the Western Bug catchment, which is investigated by several working groups of the IWAS-Project (Scheifhacker et al. 2011, Ertel et al. 2011, Tavares Wahren et al. 2011, Blumensaat et al. 2011). It covers an area of about 40,000 km². Between Poland and the Ukraine the river forms a part of the eastern border of the European Union (Fig. 1). With an annual temperature average of about 7.4°C and a precipitation mean of about 700–800 mm/year, this region has a temperate and humid climate (Botyloch 2007). It tends to be more continental towards the east.

Methods and data

Modelling approach

Dynamical downscaling of global climate simulations is based on numerical modelling of the atmospheric processes

on a regional scale. The output of a global model serves as driver at the boundaries of a RCM grid (nesting).

According to CLM community recommendations for boundary conditions, downscaling factors higher than 17 are not recommended. Downscaling of global climate simulations from horizontal resolutions of about 125–200 km to about 7 km corresponds to downscaling factors of about 18–29, respectively. Therefore a double nesting approach was chosen with an intermediate downscaling step to about 50 km.

For reliable projections, the RCM must be able to reproduce the climate of the past from global climate data for the desired horizontal scale properly. To ensure this, a control run based on the ERA40¹ data set (Uppala et al. 2005) with a horizontal resolution of about 125 km was carried out for the period 1961–1990. The use of reanalysis data instead of arbitrary GCM data for this period allows an assessment of the RCM's skill for reproducing the current climate without influences of any possible GCM bias (Frei et al. 2003, Maraun et al. 2010).

The regional climate model CCLM

The described approach was implemented with the model CCLM 4.8 (Rockel et al. 2008), a RCM developed for applications on the meso- β (20–200 km) and meso- γ scale (2–20 km). The CCLM calculates atmospheric variables based on the primitive thermo-hydrodynamic equations describing compressible flow in a moist atmosphere on a regular latitude/longitude grid with a rotated pole and a

¹ ERA40—ECMWF Re-Analysis Project 40, European Centre for Medium-Range Weather Forecasts, Shinfield Park, Reading RG2 9AX, UK.

Table 1 Model configuration

Model parameter	First nesting	Second nesting
Grid resolution	0.44°	0.0625°
Number of grid points	51 × 47	135 × 107
Rotated northpole	lon −158.3°, lat 39.7°	lon −156.9°, lat 39.7°
Model time step	240 s	40 s
Output time step	3 h	3 h
Integration scheme	Runge–Kutta	Runge–Kutta
Convection scheme	Tiedtke	Tiedtke

terrain following height coordinate (Böhm et al. 2006, Rockel et al. 2008).

In recent years, model performance and uncertainties of model simulations have been explored in many research projects and climate studies (e.g. Roesch et al. 2008, Bachner et al. 2008, Dierer et al. 2009). Hence, there are recommended model configurations evaluated for applications in moderate climate regimes such as the Western Bug catchment.

Model configuration

According to the double nesting approach, the CCLM was applied for two different model domains covering a central part of Europe for the first nesting and parts of Poland, Belarus, and the Ukraine for the second nesting (Fig. 1).

Regarding to CLM community experiences, the boundaries of the model domains were chosen such that they do not cross high orographic barriers like the Alps or the Carpathians in order to avoid numerical problems. The use of already applied and evaluated model configurations should ensure a well working model setup.

Table 1 lists characteristic settings for this study.

Depending on the resolved scale, the RCM needs appropriate external data for orography, land use, and soil. These data were provided from the CLM community PEP tool (PEP Version 0.74, 18.02.2009) (Smiatek et al. 2008).

Reference data

As reference data for the first nesting, the gridded CRU² data set (New et al. 2000) with a horizontal resolution of about 55 km was used. Due to the higher spatial resolution of the second nesting, an appropriate resolved reference data set was necessary. This was derived from interpolated station data of the NOAA³ (NOAA 2010) and

ECA&D⁴ databases (Klein Tank et al. 2002). The data set was quality checked and bias corrected. For precipitation, the applied data quality check consists of four steps:

1. At least 80% of observed daily values in a month are required for calculation of monthly sums.
2. Monthly sums of time series with an availability of daily data between 80 and 100% are adjusted by the rule of three (according to Haylock et al. 2008).
3. Missing values are replaced using a linear regression model (fitted with a parallel data set⁵) if the coefficient of determination is equal or higher than 0.75.
4. A bias correction is applied to compensate wind-induced undercatch of precipitation at the rain gauges.

Due to deficient information about influencing factors, a simple approach based on monthly mean correction factors according to Groisman et al. (1991) for Tretyakov gauges and to Richter (1995) for Hellmann gauges was applied in step 4. The quality check of monthly temperature means consisted of step 1 and 3, whereby in step 1 the monthly means were calculated. Gridded monthly precipitation and temperature fields were generated by horizontal interpolation with the software packages InterMet (Hinterding 2003) and GSTAT (Pebesma and Wesseling 1998). Mainly, non-continuous time series with large gaps and insufficient data availability from Polish stations before 1973 lead to a reduction of the evaluation period of the second nesting to 1973–1990.

Evaluation

The model results were evaluated by comparison with the reference data. Long-term yearly and monthly means were compared by calculating the difference between model and gridded observed data as well as the statistical measures: bias (BIAS), spatial root mean square error (SRMSE), pattern correlation (PCOR), and ratio of spatial variances (RSV) (Eq. 1 to 4). The BIAS describes the mean error between model data and reference data and gives a simple overview of averaged underestimations or overestimations. The SRMSE is a measure of errors as well, but is more sensitive to outliers due to the squaring function (Eq. 2). It can be thought as typical magnitude of model errors (Wilks 2006). Spatial structures of the long-term means can be detected with the PCOR measure. PCOR is the correlation coefficient between the value pairs at the corresponding grid points of 2-D fields. The reproduction of spatial variances by the model can be assessed with the RSV.

² CRU—Climate Research Unit, School of Environmental Sciences Faculty of Science, University of East Anglia, Norwich NR4 7TJ, UK.

³ NOAA—National Oceanic and Atmospheric Administration, 1401 Constitution Avenue, NW Room 5123, Washington DC 20230, USA.

⁴ ECA&D—European Climate Assessment & Dataset project, Royal Netherlands Meteorological Institute (KNMI), P.O. Box 201, 3730 AE De Bilt, The Netherlands.

⁵ parallel data set means data from another database of the same station (NOAA or ECA&D database).

$$\text{BIAS} = \bar{m} - \bar{r} \quad (1)$$

$$\text{SRMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (m_i - r_i)^2} \quad (2)$$

$$\text{PCOR} = \frac{1}{(n-1)} \sum_{i=1}^n \frac{(m_i - \bar{m})(r_i - \bar{r})}{\delta_m \delta_r} \quad (3)$$

$$\text{RSV} = \frac{\delta_m^2}{\delta_r^2} \quad (4)$$

m is model value at a single point in a two dimensional data field, r is reference value at a single point in a two dimensional data field, \bar{m} is mean of model values, \bar{r} is mean of reference values, δ_r is standard deviation of reference values, δ_m is standard deviation of model values, n is number of values.

Results

Statistical measures for both nestings are summarized in Table 2 and spatial and temporal difference plots of the second nesting are shown in Fig. 2.

Evaluation of the first nesting with CRU data for the control run 1961–1990 led to the following: The long-term area mean of precipitation was overestimated with a BIAS of + 52 mm/year (8%) and a SRMSE of about 135 mm/year. More precisely, the low-land areas in the northern and central part of the study area have rather positive biases, whereas the high-mountain areas in the southern part show a higher variability in the differences of precipitation. Furthermore, the spatial variance of the modelled long-term means of precipitation is higher than in the CRU data with a RSV of 1.65. The spatial distribution of precipitation is reproduced by the model with a PCOR of 0.55. The BIAS of the long-term temperature means is about + 0.27 K and has spatial variations between –2.14 and 1.98 K. Maximum biases appear in the southern part of the study area, whereas the highest variability can be found in the high-mountain region. For the whole evaluation area (E1 in Fig. 1) the modelled long-term temperature means have a higher spatial variance than the reference data (RSV = 1.49), with a properly reproduced spatial temperature pattern (PCOR = 0.93).

Also, the second nesting overestimates the long-term area mean of precipitation by + 52 mm/year (7%). Compared to the first nesting, the spatial precipitation pattern was poorer reproduced (PCOR = 0.28). Precipitation was overestimated especially in the hilly source area of the Western Bug river (Fig. 2a).

Underestimations are found mainly in the south-western part of the study area. Contrary to the results of the first nesting, the modelled spatial variance of precipitation is

smaller than those of the reference data (RSV = 0.62). The SRMSE of 99 mm/year is lower than in the first nesting and the long-term monthly precipitation means are overestimated in spring, summer, and autumn with a maximum BIAS of about 20 mm/month (20%) in June (Fig. 2b). Winter shows only small underestimations up to –8 mm/month (–16%) in February.

The temperature of the second nesting is well reproduced by the model. There is a BIAS of about 0.0 K of the long-term area temperature mean for the catchment. Positive differences of more than 0.5 K are found in the western part of the study area outside the catchment, whereas negative differences less than –0.5 K occur in the north east and the south west (Fig. 2c). Despite the very small BIAS, the spatial temperature pattern is weakly reproduced, with a PCOR of 0.43. The spatial variance of the modelled temperature is repeatedly higher than those of the reference data (RSV = 1.63). Autumn and winter temperature is underestimated up to –0.2 K in December. Spring and summer temperatures show a slight overestimation, up to 0.3 K in May. Only the values for July and September do not fit into the seasonal pattern, with a slight underestimation for July and an overestimation for September. In spring, a positive temperature BIAS coincides with a positive precipitation BIAS and—to some degree—in summer.

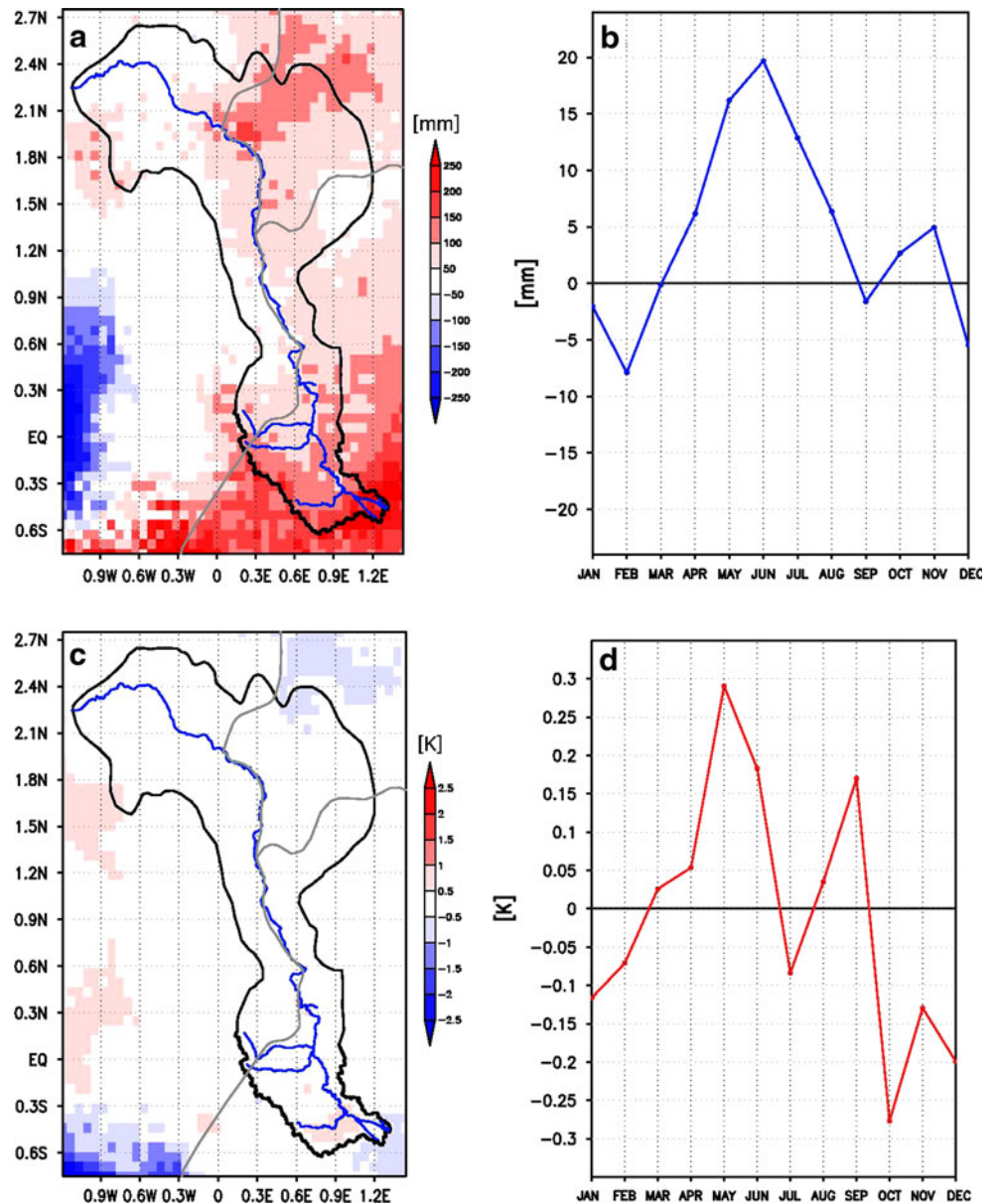
Discussion

>The possible reasons for the systematic deviations between model results and observations are widely discussed. Many processes that are represented in climate models occur on unresolved scales, e.g. radiation, convection, cloud microphysics, and land surface processes. Such processes are described with parameterization schemes, which represent a simplification of the real climate system and lead to inherent modeling uncertainty (Maraun et al. 2010). Simulating precipitation with climate models is very complex and uses physical based precipitation schemes. A key source of uncertainties is the parameterization of convective processes. This may be one cause why the highest deviations of precipitation in the second nesting occur in spring and summer months

Table 2 Statistical quality measures for the two nesting steps

	First nesting		Second nesting	
	Precipitation	Temperature	Precipitation	Temperature
BIAS	52 mm (8%)	0.27K	52 mm (7%)	0.00 K
SRMSE	135 mm	0.60 K	99 mm	0.40 K
RSV	1.65	1.49	0.62	1.63
PCOR	0.55	0.93	0.28	0.43

Fig. 2 BIAS of the second nesting: **a** and **b** precipitation; **c** and **d** temperature



(Fig. 2b), when rainfall is predominantly convective. Accordingly, Suklitsch et al. (2010) found a higher error range for precipitation in summer for regional climate simulations of the Alps. As the most likely reason they assumed the impact of the parameterized convection. Furthermore, the evaluation of CCLM simulations for the Alps showed that the model produces a higher frequency of days with precipitation, but with smaller rainfall intensities in comparison with observations in this region. Here, the spatial patterns of frequency bias were identical with the patterns of mean precipitation bias (Suklitsch et al. 2010). Feldmann et al. (2008) described some deficits in the parameterization of orographic precipitation effects for the Rhine valley. They especially mentioned an overestimation of precipitation at the upwind side of mountainous areas

which could also be a possible reason for the positive precipitation BIAS in the south-eastern part of the Western Bug river catchment, where height increases towards the Carpathians (Fig. 2a). A relationship between cloud cover overestimation and humidity bias with a subsequent positive precipitation bias in summer is discussed in Jaeger et al. (2008). Although cloud cover and humidity are not investigated in the present study, this relationship could be an additional reason for the precipitation overestimation in some areas of the Western Bug catchment.

The positive deviations of the mean temperatures in summer months (Fig. 2d) could probably result from overestimated daily maximum temperatures: Jacob et al. (2007) found in their intercomparison study for Eastern Europe that such a behavior is a general RCM problem.

Suklitsch et al. (2010) pointed out that the CCLM has problems with the reproduction of maximum winter and summer temperatures. They argued that this is related to an underestimation of snow cover in winter and spring and an overestimation of precipitation frequency and cloud cover in summer.

These arguments confirm that results of RCMs are subject to uncertainties arising from deficiencies in model formulations and parameterizations of unresolved processes. This requires a more detailed analysis including higher temporal resolution and additional variables like cloud cover, humidity, pressure fields, and wind. Simultaneously, deficiencies of the reference data (poor spatial and temporal resolution, missing corrections, e.g. for undercatch of precipitation) need to be considered. Specific reasons for the observed deviations of the model results from the observations and the sources of uncertainty in the presented simulations will be identified in further studies.

Summary and conclusion

A dynamical downscaling approach was implemented with the RCM CCLM for the Western Bug catchment in Eastern Europe. The model performance was evaluated based on long-term temperature and precipitation area means by comparison with reference data. Precipitation was overestimated for spring, summer, and autumn and underestimated for winter. The SRMSE of 99 mm/year is lower than in the first nesting, which suggests a better model performance for precipitation in the second nesting. The model reproduced the long-term temperature means very well with a slight underestimation in winter and overestimation in summer. The biases were in the range of current RCM performances (Jacob et al. 2007; Christensen et al. 2007; Jaeger et al. 2008).

Quantitative assessment of model results by different statistical measures gave the possibility to characterize deviations comprehensively and provided the opportunity to compare the quality of different model runs very fast. Considering only the BIAS as single measure for model performance may be insufficient for most cases, e.g. two results might have the same BIAS for precipitation but different spatial error ranges and different spatial pattern correlations as shown in Table 2. Furthermore, any validation method relies ultimately upon the quality and quantity of observational data (Maraun et al. 2010). A systematic reason for biases in precipitation is the underestimation of true quantities due to wind-induced undercatch of rain gauges. This might have been inherited from the uncorrected CRU data for the evaluation of the first nesting. But the evaluation of the second nesting included a bias correction of the reference data, as

described in the “[Methods and data](#)” section, which should have compensated for this systematic error. This suggests that the CCLM produced too little precipitation in winter months for the Western Bug catchment.

The downscaling was performed up to a horizontal resolution of approximately 7 km. However, this scale is partially too coarse for modelling hydrological processes like flood generation in fast reacting small catchments or discharge of urban drainage systems. Maraun et al. (2010) described this as “gap between dynamical models and the end user”. That means that the results of RCMs often cannot be used directly as input for hydrological models or other high resolving applications for impact studies. Thus, there is a need for robust transfer approaches to bridge this gap. The main problem of hydrological modelling for the Western Bug catchment is the overestimation of precipitation by the CCLM, especially in the source area of the river. In addition, the underestimation of winter temperatures could lead to more precipitation falling as snow and to larger storage of water in the snowpack, culminating in a delayed, and stronger snow melt in spring. Overestimation of precipitation in summer could also lead to abnormal high discharge rates and to a general unrealistic shift in the water balance.

In summary, the double nesting method for downscaling global climate projections with the CCLM was successful. However, for subsequent impact studies a consistent adjustment of the results will be necessary, particularly for rainfall.

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