On applications of regional climate change projections in the upper Danube and upper Brahmaputra river basin*

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Acknowledgements:
AD was funded by the EC project BRAHMATWINN (Contract No. 036592 (GOCE)).
Support of the CLM model by the COSMO consortium and the CLM community.

INTRODUCTION

For the application of regional climate change projections, large-scale ECHAM5 IPCC SRES scenario runs have been dynamically downscaled from 1.875° to 0.44° in the upper Danube and the upper Brahmaputra river basin (UDRB and UBRB resp., Fig.1). The downscaling has been carried out with the regional climate model CLM (www.clm-community.eu) for the scenarios A1B, A2, B1 and commitment.

APPLICATIONS

The downscaled fields have been used directly for projections of trends and as input to impact models. We discuss challenges and uncertainties for these applications and the influence of bias correction methods.

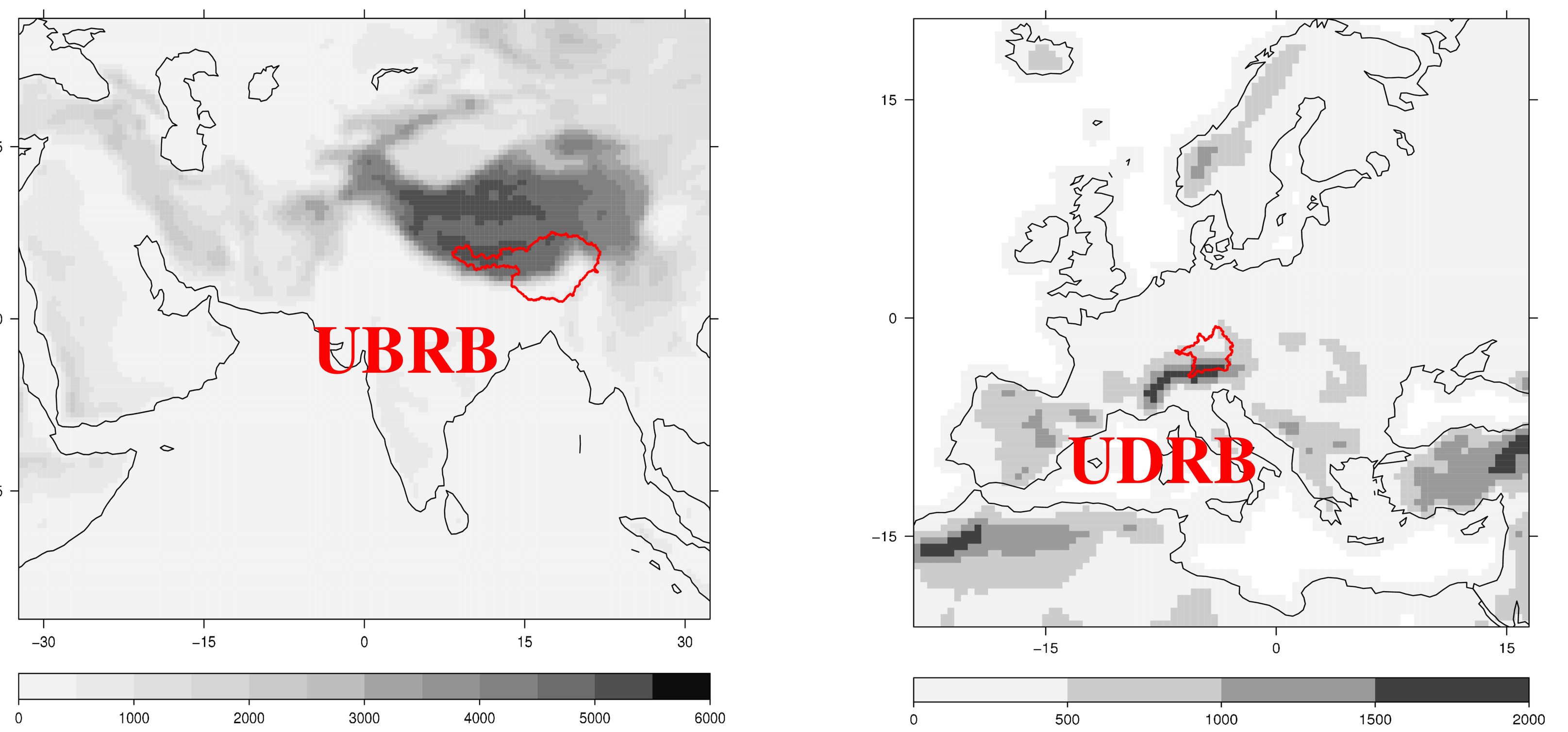

Fig. 1: CLM computational domains and model orography.

PROJECTIONS OF TRENDS

- Large differences among regions, seasons and scenarios
- Trends in precipitation less clear than in temperature
- Generally increasing variability in temperature & precipitation
- Normalization mostly sufficient to remove most of the model bias, for instance in max. 5-day precipitation (Fig.2) in the UBRB and the monsoon season (JJAS)

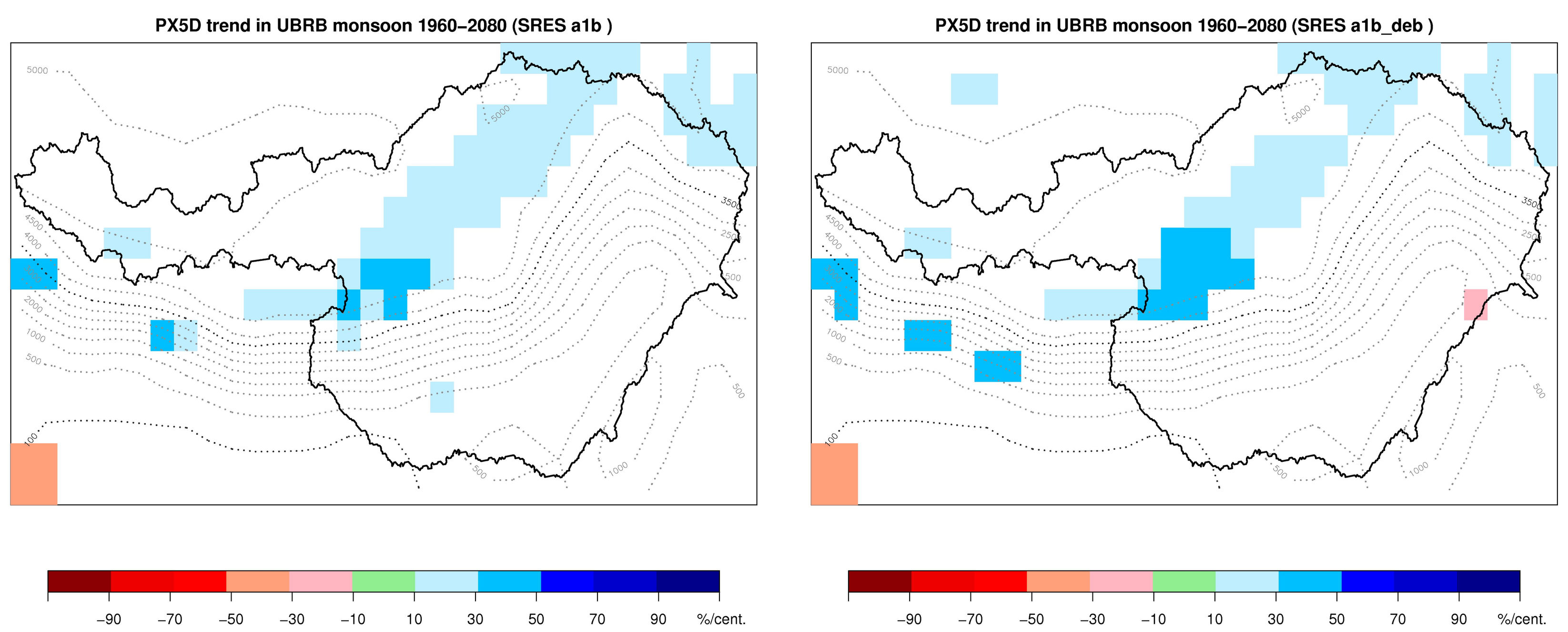

Fig. 2: Trends of max. 5-day precipitation after simple normalization (left) and bias correction via local intensity scaling (right).

INPUT TO IMPACT MODELS

- Bias corrections needed for application of hydrological or glacier modeling
- Non-linear error growth demands accurate input data
- Challenges and uncertainties:
  - observation uncertainties
  - a seasonal varying bias
  - too few events for a robust estimation of the model bias
- General drawbacks:
  - assumption of a constant model bias
  - physically inconsistency of independently corrected fields

Temperature bias correction (Fig. 3)

- Gaussian bias correction at grid points:

$$T_t^D = \frac{\left(T_t^S - \overline{T^S}\right)}{\sigma^S} \cdot \sigma^O + \overline{T^O}$$

- Mean and variance of the simulated 2m temperature fit to observations
- Small observation uncertainties
- Small seasonal bias variation, reduced by fit of variance
- Enough events for bias estimation

Precipitation bias correction (Fig. 3)

- Local intensity scaling at grid points:

$$\hat{s} = \frac{\overline{\mathrm{INT}^O} - threshold^O}{\overline{\mathrm{INT}^S} - threshold^S}$$

- Rain day frequency and intensity of simulated precipitation fit to observations

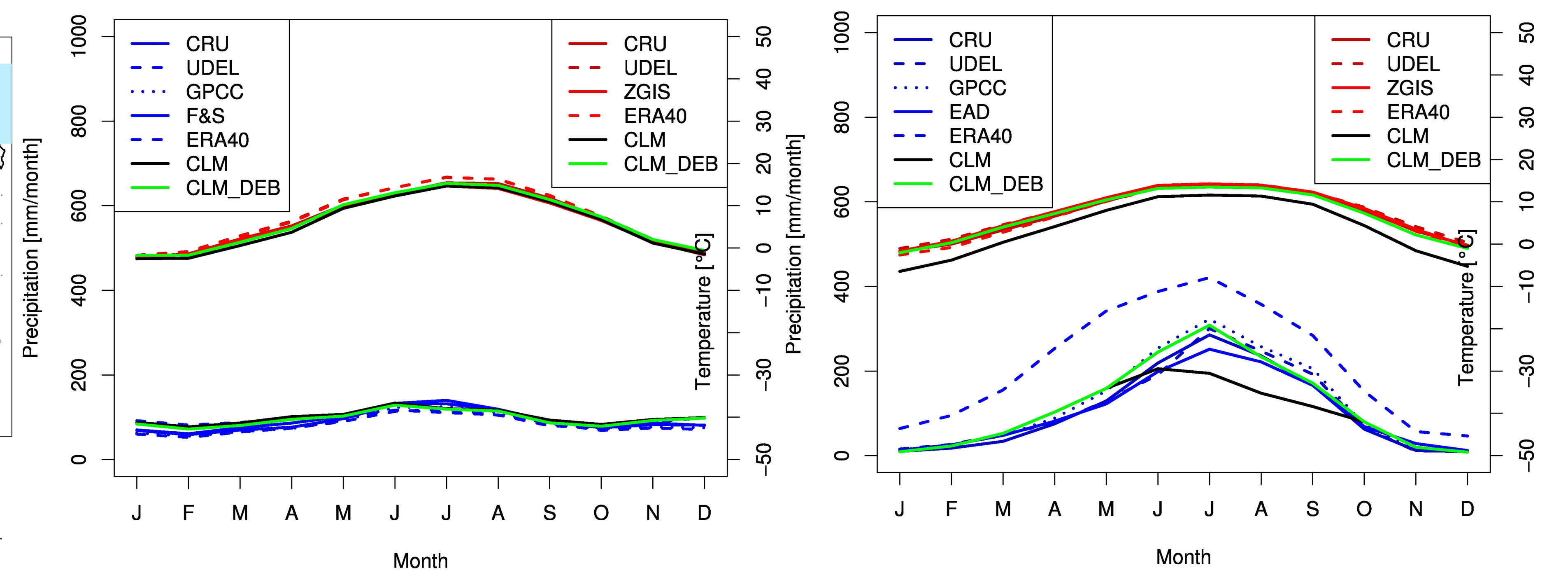

Fig. 3: Observation and simulation data of 2m temperature and precipitation in the UDRB (left) and the UBRB (right).

Precipitation bias correction (continued)

- UDRB: local intensity scaling applicable
- UBRB:
  - High seasonality of precipitation bias
  - Large observation uncertainties
  - Large uncertainty in bias estimation in winter (DJF) due to few events (Fig. 4)

-> Application of local intensity scaling on a monthly basis for June to September

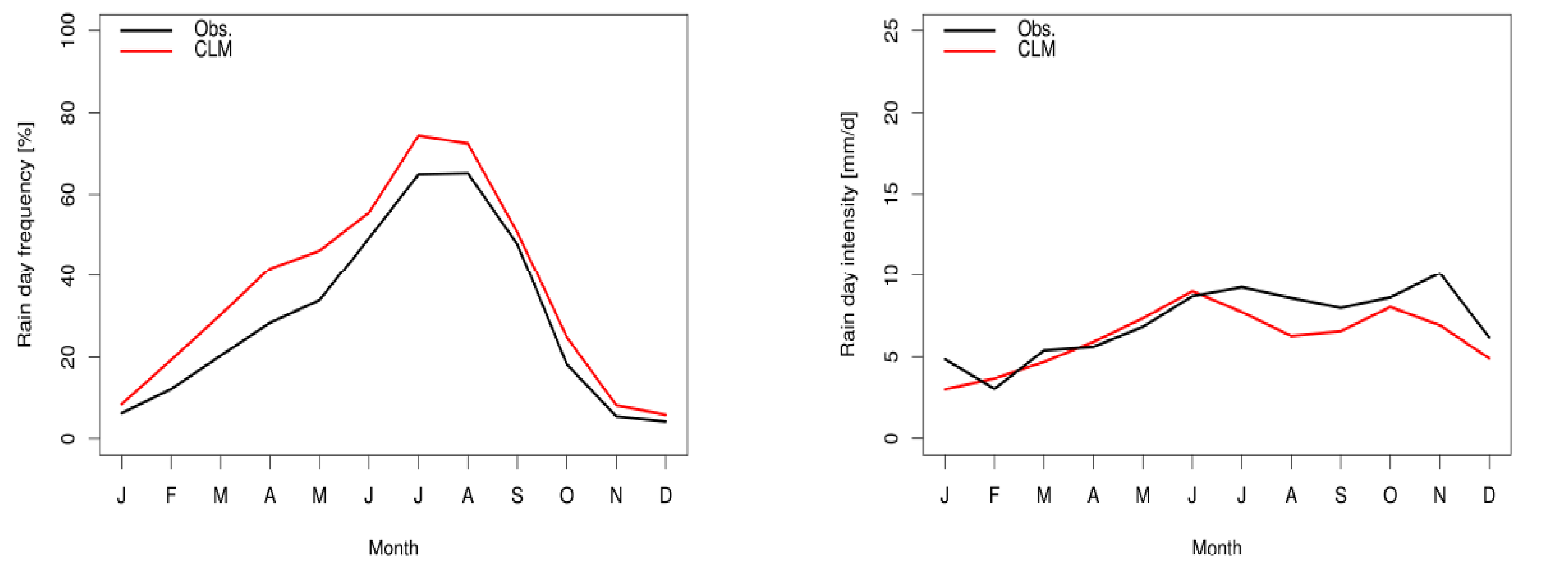

Fig. 4: Rain day frequency and intensity in the UBRB.

CONCLUSIONS

- Normalization sufficient for bias correction in index trends
- Good performance of temperature bias correction (Fig. 3)
- Application of bias correction methods for precipitation difficult in the UBRB (Fig. 3)
- Influences of uncertainties on impact model have to be evaluated

* presented at The EGU General Assembly, 2009