Instrument: **SP1 Cooperation**

Thematic Priority: **Priority Area 1.1.6.3 "Global Change and Ecosystems"**

FP7 Collaborative Project – Grant Agreement 212492

CLARIS LPB
A Europe-South America Network for Climate Change Assessment and Impact Studies in La Plata Basin

DELIVERABLES

D7.3: Recommendations on methods and datasets for regional climate projections

Due date of deliverable: Month 18

Start date of project: **01/10/2008** Duration: 4 **years**

Organisation name of lead contractor for this deliverable: UEA

Deliverable No	Deliverable title	WP	Lead beneficiary	Estimated person-months	Real person-months	Nature	Dissemination level	Delivery date
D7.3	Recommendations on methods and datasets for regional climate projections	WP7	P2-UEA	3	3.5	R	PU	v1 35 v2 45

Contents

D7.3: Recommendations on methods and datasets for regional climate projections

Partner involved: UEA

1. Introduction

The original title of this deliverable was 'Recommendations on methods and datasets for statistical and dynamical downscaling'. The responsible partner (UEA) has been involved in ongoing project discussions concerning the design, data archiving and analysis of the WP5 regional climate model (RCM) simulations, and also hosted a visit of Ariel D'Onofrio (a PhD student based at UBA) to UEA in early 2009 to discuss statistical downscaling and enhancement of the CHAC downscaling tool. Work on statistical downscaling in WP7 has also been undertaken by Maria Laura Bettolli of UBA – focusing on a two-step analogue method. Reflecting these activities, and discussions on desirable enhancements of the CLARIS-LPB Data Archive Center (CLDAC) during the 2010 annual meeting, the title and scope of this deliverable has been changed to better meet the overall WP7 objectives and the emerging project needs.

This deliverable now provides a general guide on working with regional climate projections and scenarios. It encompasses issues such as: handling and quantifying uncertainty in global and regional climate model simulations; evaluating model performance and the added value of downscaling: and, techniques for bias correction of RCM data for input to impacts models. It draws on expert guidance (e.g., from the IPCC on assessing and combining multi-model climate projections and the ETCCDI on the analysis of extremes) and the recent peer-reviewed literature – highlighting some of the areas of open debate on methods and approaches. It also draws on the experience of the earlier EU ENSEMBLES project (van der Linden and Mitchell, 2009).

Consistent with the objective of CLARIS-LPB WP7, this guide aims to bridge some of the gaps between the climate modeling and impacts communities (Fowler et al., 2007a; Maraun et al., 2010; Wilby et al., 2009). Quite a lot of the discussion relates to the uncertainties associated with regional climate projections. It is important that these uncertainties are addressed in impacts and adaptation assessments despite the challenges they represent to decision making (Dessai et al., 2009; Wilby and Dessai, 2010).

This general guide provides a broader framework and context for the more specific documentation and analyses of RCM uncertainty being produced by CLARIS-LPB WP5.

Section 2 discusses issues associated with the use of GCMs, while Section 3 focuses on RCM-related issues. Section 4 introduces the CLDAC developed by WP7, together with other software and guidance resources which may be relevant for CLARIS-LPB partners.

2. Issues associated with the use of GCMs

2.1 Model skill

The skill of any downscaling method (dynamical or statistical) is constrained by the ability of the driving GCM to simulate the large-scale circulation (i.e., to provide reliable boundary conditions/forcing). In this respect, the work of CLARIS-LPB WP4 on the analysis of low-frequency variability trends and shifts (focusing on modes of variability such as ENSO, Southern Annular Mode, Pacific Decadal Oscillation, and the North Atlantic Oscillation) and teleconnections with the La Plata Basin hydroclimate is particularly relevant.

Users of downscaled information are encouraged to familiarize themselves with the main findings of the WP4 evaluations. It may also be appropriate to undertake additional evaluations, e.g., validation of predictors selected for statistical downscaling.

It is because of the existence of global model biases that CLARIS-LPB WP5 has performed 'perfect boundary conditions' simulations using ERAinterim forcing, as well as GCM-forced simulations. The reanalysis-forced simulations allow evaluation of the RCM performance alone. They also contribute to the international CORDEX framework (Giorgi et al., 2009).

There are a number of recent papers discussing different approaches and metrics for GCM evaluation in the context of developing regional climate projections, including discussion of issues such as stationarity of biases and the relationship between model biases and climate change signals (e.g., Macadam et al., 2010; Matsueda and Palmer, 2011; Overland et al., 2011; Schaller et al., 2011; and references therein). These references focus on the CMIP3 ensemble and temperature and precipitation rather than the more dynamic variables and processes considered by WP4. Nonetheless they provide a useful context for the CLARIS-LPB work and highlight issues which are also relevant to RCM evaluation, such as spatial scale and smoothing (Masson and Knutti, 2011a). Better agreement between simulated and observed values tends to be found with spatial smoothing over several grid points, though this may be at the expense of the spatial detail desired by users (Masson and Knutti, 2011a). This recent literature reflects the fact that there are currently many open issues in the modeling/projections community with some contradictory views and evidence presented.

2.2 Model ensembles

There is, however, general agreement on the need to work with model ensembles. One ensemble strategy is to explore the uncertainties due to model parameterization using perturbed physics ensembles based on one model, but the approach taken in CLARIS-LPB (and in the IPCC assessment reports using the CMIP ensembles) is to explore uncertainties due to model differences and internal climate variability using multi-model ensembles. A recent IPCC good practice guidance paper focuses on assessing and combining multi-model climate projections (Knutti et al., 2010a). The recommendations for regional assessments include a reminder of the four factors that should be considered in assessing the likely future climate change in a region (Christensen et al., 2007): historical change; process changes (e.g., changes in the driving circulation); global climate change projected by GCMs and downscaled projected change. All these factors are addressed by CLARIS-LPB: WP3, for example considers recent past climate variability in La Plata Basin. The IPCC good practice guidance paper focuses on the use of global models, but many of the recommendations are also applicable to dynamical and statistical downscaling (Knutti et al., 2010a).

More detailed discussion of the issues involved in combining multiple global climate models, particularly from the CMIP3 ensemble, is provided in recent papers (e.g., Annan and Hargreaves, 2010; Knutti, 2010; Knutti et al., 2010b; Masson and Knutti, 2011b; Räisänen and Ylhäisi, 2011; Collins et al, 2012 and references therein). These issues include ongoing discussion of metrics for evaluating models, particularly with respect to the development of performance-based weighting schemes and probabilistic projections. Regional probabilistic projections have been constructed from global climate models as exemplified by Tebaldi and Sansó, 2009 and Tebaldi and Knutti, 2010. Care is needed in applying weighting schemes, however, in the light of shared/common model parameterization schemes and biases (Palmer et al., 2008; Knutti, 2010). In summary, a number of challenges exist with respect to: ensemble design and spread; model independence; structural uncertainty; how many models to use and how to combine them; model evaluation and metrics; and model calibration and evaluation (Knutti, 2010).

CLARIS-LPB D7.2 provides a review of methods for calibration and combination of multi-model ensemble simulations focusing on probabilistic approaches. Recommendations are made with respect to appropriate methods and datasets. Two methods [multiple linear regression (Greene et al., 2006) and fuzzy regression (Bisserier et al., 2010)] are investigated using temperature projections from five of the CMIP3 models (a total of 27 ensemble members for the A1B emissions scenario). Results are presented for three homogeneous regions (northern, central and southern) of La Plata Basin. In addition to this approach for calibrating temperature projections, the potential for spatial calibration of precipitation projections using forecast assimilation (Coelho et al., 2006) and focusing on El Niño-related relationships is explored using the HadCM3 model.

2.3 Representing uncertainty

Consideration of uncertainty in the wider CMIP3 ensemble is important in the context of the WP5 RCM simulations (see Table 1) which take boundary conditions from three GCMs (including three EC50M ensemble members). Though it should be noted that the CMIP3 ensemble is itself an 'ensemble of opportunity' (Annan and Hargreaves, 2010; Knutti et al., 2010b). While complex probabilistic approaches can be used to explore the spread of uncertainty, simpler presentations used in the IPCC AR4 include ensemble means and inter-model standard deviations, together with counts of the number of ensemble members showing projected changes in the same direction (e.g., IPCC AR4 Figure SPM7 showing seasonal changes in precipitation). The latter can be considered as an indication of the robustness of change – assuming that the greater the number of models in agreement (i.e., the greater the inter-model consistency), the greater the robustness (though results may be misleading when the projected changes are close to zero). No account is taken, however, of common biases which may affect the projected changes as well as present-day simulations. Model convergence will not provide an appropriate guide to the credibility of projections if all models, or the majority of models, are 'wrong'. Thus while used as a criterion in the original version of the Reliability Ensemble Averaging method (Giorgi and Mearns, 2003), model convergence was dropped in a later upgraded version of the method (Xu et al., 2010).

Ensemble means, standard deviations, consistency counts and box plots have been used in a number of papers exploring global changes in extreme events:

- Temperature and precipitation extremes in the CMIP3 multi-model ensemble: Tebaldi et al., 2006; Kharin et al., 2007; Orlowsky and Seneviratne, 2011
- Heatwaves in the Hadley Centre's QUMP perturbed physics ensemble: Clark et al., 2006; 2010
- Drought in the QUMP and CMIP3 ensembles: Burke and Brown, 2008; Sheffield and Wood, 2008

For La Plata Basin, these studies indicate fairly robust increases in warm extremes (more frequent warm days and nights and more frequent and longer heat waves and warm spells) and decreases in cold extremes (less frequent cold days and nights). Changes in precipitation extremes are less consistent between models, though there is some tendency towards more heavy precipitation in this part of South America. See Seneviratne et al (2012) for a detailed assessment of projected changes in extremes.

2.4 Partitioning GCM uncertainty

A number of studies attempt to partition or quantify the different contributions to uncertainty in the CMIP3 ensemble, in particular that due to internal variability of the climate system, model uncertainty and emissions scenario uncertainty (e.g, Hawkins and Sutton, 2009; 2011). Such studies are relevant in assessing the wider representativeness of the CLARIS-LPB regional simulations (see also Section 3.2) for the two selected future periods 2011-2040 and 2071-2100.

Hawkins and Sutton (2009; 2011) demonstrate that the sources of uncertainty are dependent on the future time period considered and also on the variable, region and spatial/temporal averaging used. In general, however, the balance of uncertainty is expected to be rather different for the earlier CLARIS-LPB scenario period (dominated by internal variability and model uncertainty) compared with the later period (where model and scenario uncertainty are important). This is particularly the case for temperature: emissions scenario uncertainty tends to be less important for precipitation on all timescales. This website http://climate.ncas.ac.uk/research/uncertainty/ provides maps and figures showing the signal-to-noise ratios and the relative importance of each source of uncertainty for each five-year period over the 21st century. In the case of temperature over La Plata Basin, in the first decade internal variability accounts for 40-50% of the total ensemble uncertainty, and model uncertainty 50-60%. By the ninth decade, model uncertainty is reduced to 30-40% and emission scenario uncertainty dominates at 70-80%. The maps also illustrate the very much weaker signal-to-noise ratio over La Plata Basin for precipitation compared with temperature.

With respect to the earlier CLARIS-LPB scenario period, 2011-2040, it should be noted that the GCM simulations used do not attempt to provide an estimate of the actual evolution of the climate in the future starting from well-defined initial conditions, i.e., they should be viewed as climate projections or scenarios and not as decadal predictions. The latter science is in its infancy and many methodological and scientific challenges remain to be addressed (Meehl et al., 2009; Solomon et al., 2011).

It should also be noted that modeling work to date has focused on the SRES and other non-mitigation emissions scenarios. The balance of uncertainties may be different for the mitigation scenarios included in the set of Representative Concentration Pathways (Moss et al., 2010) developed ahead of the IPCC Fifth Assessment Report.

Many of the uncertainty issues related to global climate models are also relevant in considering regional climate models (see Foley, 2010 for a rather general and non-technical review), though here the uncertainties associated with the downscaling itself must also be considered.

3. Issues associated with the use of RCMs

3.1 Ensemble design

A number of technical considerations and challenges specific to dynamical downscaling, relating to issues such as choice of boundary conditions and domain size (Wang et al., 2004; Laprise et al., 2008; Rummukainen, 2010; Arritt and Rummukainen, 2011; Rapaić et al., 2011), had to be considered in designing the WP5 RCM simulations.

In addition, decisions had to be made concerning the forcing GCMs – balancing scientific and pragmatic considerations. The final ensemble of 11 members (Table 1) consists of seven RCMs forced by three different GCMs. This offers a number of opportunities for analysis and intercomparison. Four RCMs are forced by HadCM3-Q0 and four by EC50M-R3 – allowing exploration of the effect of choice of RCM in both GCM cases. RegCM3 and LMDZ are both forced by two GCMs – providing some indication of the effect of GCM choice. RCA is forced by three ensemble members of EC50M-R3 – thus addressing intra-GCM variability. All simulations are for the A1B emissions scenario, so emissions scenario uncertainty is not addressed. However, as discussed in the previous section (Hawkins and Sutton, 2009; 2011), emissions scenario uncertainty is not so important for the earlier CLARIS-LPB scenario period (2011-2040) and is likely to be less important for precipitation than for temperature in the later scenario period (2071-2100).

GCM/RCM	*HadCM3-Q0*	*EC5OM-R3*	*IPSL*
MM5	x		
RCA		xxx	
RegCM3	x	x	
REMO		x	
PROMES	x		
LMDZ		x	x
Eta	x		

Table 1: GCM (columns) / RCM (rows) matrix of the 11 CLARIS-LPB RCM simulations.

3.2 Partitioning RCM uncertainty

The partitioning of uncertainty in RCM simulations was addressed in the EU ENSEMBLES and PRUDENCE projects. The general message emerging from the ENSEMBLES studies (Kendon et al., 2008; 2010; van der Linden and Mitchell, 2009; Déqué et al., 2011) and the earlier PRUDENCE work (Déqué et al., 2007), can be summarized as: the higher the climate change signal, the more important the GCM spread, the lower the signal, the more important the RCM. This implies that, for the end of the 21st century, it is important to fully sample the range of GCM uncertainty, whereas, for periods closer to the present day, more RCMs should be sampled. One study of flood hazards in Europe indicates that for the end of the century, the choice of GCM is more important than either RCM or emissions scenario uncertainty in determining the projected magnitude and even direction of change in extreme river discharge (Dankers and Feyen, 2009). All these conclusions are, however, based on the European case. Even within Europe, the balance of uncertainty shows regional variation (Déqué et al., 2007) and it may be different for La Plata Basin. As indicated above, the design of the CLARIS-LPB RCM ensemble provides opportunity for exploring a number of these issues.

3.3 Some general guidelines for users

The CLARIS-LPB RCM ensemble represents a major advance in the modeling information available for La Plata Basin. In using this information for the development of regional climate projections and in impacts applications, the following general guidance should be considered:

- The added value of downscaling should be demonstrated not assumed
- Even where RCMs provide added value, biases may exist which need to be corrected before the RCM data are used for impact applications
- Avoid using single grid points/boxes (if this has to be done, check their representativeness compared to neighbouring grid points both with respect to biases and projected changes)
- In coastal areas: check the model land-sea mask before extracting or averaging grid points/boxes
- Do not expect temporal (i.e., day-to-day or year-to-year) correlation between observations and GCM-forced simulations.
- RCM output are provided on the native model grids (which differ from model to model, and include rotated latitude/longitude grids and Lambert conformal projections). In order to ease inter-comparison and to facilitate use in impacts studies, it is useful to interpolate to a

common/standard grid, as is being done in CLARIS-LPB (though care may be needed with respect to the preservation of daily extremes and inter-variable relationships) – see the document on interpolation on the WP5 section of the CLDAC.

- RCMs provide area-averaged values rather than point values so grid-point values cannot be directly compared with station data (rain days are much more frequent and area-averaged extremes are less intense than point values – Frei et al., 2003; Barring et al., 2006; Chen and Knutson, 2008; Haylock et al., 2008). Thus the gridded observed datasets for temperature (available since June 2011 – and see Tencer et al, 2011) and precipitation (in preparation) developed by WP3 are of great value for model validation purposes.
- Working with 30-year baseline and future periods (1961-1990 and 2011-2040/2071-2100 respectively in CLARIS-LPB) helps to allow for inter-annual and inter-decadal variability in model simulations
- The baseline period used in CLARIS-LPB is 1961-1990 which means that a part of the projected change has already occurred
- Ideally, all available RCM simulations would be used for the CLARIS-LPB impacts work. Where this is not possible, it is important to assess where the selected simulations fall within the wider RCM range (as well as where the driving GCMs fall within the wider CMIP3 range)
- The quick-look plots provided on the CLDAC by WP5 provide a valuable overview of both ERA-interim and GCM-forced simulations.

3.4 Model evaluation

A set of metrics to be employed in evaluating regional model performance in CLARIS-LPB has been identified by WP5 (see deliverable D5.1). These encompass long-term annual and seasonal mean fields, the diurnal cycle, low-level winds, synoptic-scale variability, intraseasonal variability and interannual variability. Appropriate basic statistics, skill score indices, diagrams (such as Taylor diagrams) and tables are proposed. Additional evaluation focusing on extreme events is being undertaken by WP6.

The CLARIS-LPB approach to regional model evaluation recognizes that it is important to consider the full distribution of variables, their temporal and spatial variability and, at least implicitly, the underlying physical processes (Maraun et al., 2010). As part of the ENSEMBLES project, a set of metrics or weights was developed addressing various aspects of model performance including both their representation of large-scale features and their ability to add value on smaller scales (Christensen et al., 2010; Kjellström and Giorgi, 2010). The latter was assessed by decomposing the RCM signal of temperature and precipitation into a large-scale component coming from the GCM and the mesoscale signal (Coppola et al., 2010). Such approaches attempt to identify the 'true' added value of downscaling, rather than just the benefits of averaging over a smaller spatial area which will by itself tend to give more intense extreme events, for example, than averaging over a larger area (Kanamitsu and DeHaan, 2011). It is also interesting to determine the extent to which specific GCM biases propagate down through to the RCM and are reduced (Liang et al., 2008) or amplified (Kjellström and Lind, 2009) by downscaling.

3.5 Model selection

The ENSEMBLES performance-based weights were developed for use in the production of probabilistic climate change projections and are acknowledged as being exploratory in this respect (Christensen et al., 2010; Kjellström and Giorgi, 2010). It is not recommended that they be used for the selection of a subset of models since this might lead to an undersampling of uncertainty (Christensen et al., 2009). The minimum recommended requirement with respect to the ENSEMBLES RCMs (an ensemble of 25 members) is to use results based on two or more RCMs that are forced by at least two GCMs (i.e., an absolute minimum of four simulations). The full ensemble should then be used as supporting information on how the subset relates to the other cases. This is consistent with the advice based on the earlier PRUDENCE RCM ensemble (Christensen and Christensen, 2007).

Selecting a subset is not, however, easy. In general terms (and whether considering statistical and/or dynamical downscaling), no single model performs 'best' (in comparison with observations) for all variables, seasons and locations. Present-day performance may, however, be used to reject the 'worst' models' and/or to identify the 'least bad' or 'better models'. The alternative (and preferred) approach is to use all available simulations – either with equal weighting (all models treated equally, i.e., with an implied weight of 1) or performance-based weighting. This may, however, be precluded by the computational demands of impacts models.

Present-day performance is only one consideration in model selection. It is also necessary to consider the climate change signal and the relative sensitivity of the different ensemble members. An indication of this is provided by simple scatter plots of projected changes in temperature *vs* precipitation. It can also be helpful to plot the changes from any larger GCM ensemble at the same time in order to provide a broader picture of the uncertainty ranges (e.g., Figure 2.6 in van der Linden and Mitchell, 2009).

In the EU ClimateCost project (http://www.climatecost.cc/images/Policy_brief_1_Projections_05_lowres.pdf), a ranking system was used to identify which models lie closest or furthest away from the ensemble mean (this was done both for the ENSEMBLES RCMs and CMIP3 GCMs). The ranking was constructed by calculating the ensemble mean change and inter-model deviation. The 'deviation' of each model run from the ensemble mean was then scaled by the standard deviation. This was done for winter and summer, and for temperature and precipitation, and the results combined to give a single root-mean square value for the overall model deviation. Runs were then ranked on the basis of this deviation from the ensemble mean, with the least deviation being given a rank of 1 and a larger ranking indicating a larger deviation. Although such ranking systems can have some utility, they do not necessarily indicate the relative sensitivity of runs with respect to impacts applications. It may, however, be very hard to know in advance what aspects of climate change are most important for impacts and hence to devise appropriate selection criteria.

3.6 Bias correction

As noted above, even where RCMs provide added value over GCMs, they may still be subject to biases compared with the present day which require correction before time series can be used in impact models. This is particularly the case with respect to hydrological models which are sensitive to the absolute magnitude of simulated variables.

A number of bias correction methods have recently been developed (Maraun et al., 2010) and sensitivity studies indicate that hydrological and other impacts are more reliably simulated when using bias-corrected model outputs. Paeth et al (2011), for example, used multiple linear regression to adjust monthly precipitation, further postprocessed using a daily weather generator (Paeth and Diederich, 2011), for impacts applications in West Africa. Oettli et al. (2011) bias corrected the ENSEMBLES RCM simulations for West Africa (van der Linden and Mitchell, 2009) using quantile mapping and cumulative distribution function transforms (CDF-t). Crop yields are more reliability simulated using the CDF-t bias correction method, which was originally developed by Michelangeli et al. (2009), than when using raw model output. A recent extension of the method (XCDF-t), allows non-stationary downscaling of the extreme value distribution (Kallache et al., 2011). R software for implementing these methods is available (see Section 4.2).

An alternative, relatively simple approach uses a power law transform to correct biases in both the mean and variability (coefficient of variation) of daily precipitation (Leander and Buishand, 2007) and, together with a linear correction for temperature, has been tested in hydrological applications for the Rhine and Meuse river basins (van Pelt et al., 2009; Hurkmans et al., 2010; Terink et al., 2010).

Seven different methods for bias correction of RCM daily precipitation were evaluated by Themeβl et al. (2010) focusing on the alpine region of Austria. These include five indirect methods such as multiple linear regression and two direct methods employing the simulated precipitation fields (local intensity scaling and quantile mapping). Quantile mapping based on empirical distribution functions is shown to provide the best performance in this study, particularly for the higher quantiles. The quantile mapping method implemented by Themeβl et al. would need further modification for application to future time periods. Another mapping or distribution-based approach uses a fitted histogram equalization function in order to map the simulated probability distribution function onto the observed distribution (Piani et al., 2010a,b). This approach, referred to as 'statistical bias correction', has been applied to GCM simulations in the EU WATCH project (Piani et al., 2010b) as well as to RCMs (Piani et al., 2010a). It has also been used within the EU ClimateCost project to bias correct the ENSEMBLES RCM simulations before input to the Lisflood hydrological model (Dosio and Paruolo, 2011; Rojas et al, 2011). In a subsequent refinement of the method, a cascade of bias correction functions is produced, each function operating on a different timescale (hourly, daily, monthly) (Haerter et al., 2011).

Underlying all these bias correction methods is the assumption that the biases remain constant and can be applied to future projections. There is, however, some evidence that RCM biases may be non-linear (Christensen et al., 2008). As with the stationarity assumption underlying statistical downscaling (i.e., that the present-day predictand/predictor relationships will be unchanged in the future), the bias assumption cannot be fully tested. Though using cross-validation, one study demonstrates how over-adjustment of precipitation in the validation period may lead to overestimation of observed hydrological discharges (Terink et al., 2010). The effect of making different assumptions about the nature of the biases (i.e., assuming constant biases or constant relationships, equivalent to using additive or multiplicative approaches) is explored by Buser et al. (2009; 2010). It is shown that the different assumptions made can affect the spatial pattern of warming over Europe as well as the spread of the projections, with the effect depending in part on whether models under- or over-estimate inter-annual variability. In practice it is difficult to know which assumption is most appropriate (Buser et al., 2010). Most recently, Maraun (2012) has used RCM output as 'pseudo reality' to explore the stationarity of bias assumption.

All of the methods discussed above are univariate methods, i.e., each variable (temperature, precipitation) is corrected individually. Where temperature and precipitation relationships are weak this may not be an issue (Terink et al., 2010), but ideally multi-variate correction methods would be developed and used.

While bias correction should improve agreement between the time series input to impact models and observed data, the underlying assumptions and sensitivity to methodological choices mean that it should be considered as another source of uncertainty. The ability to undertake bias correction is also constrained by the availability of appropriate observed data – which are themselves subject to uncertainties (see Section 4.1). It should also be remembered that agreement between models and observations provides necessary, but not sufficient evidence for credible projections. Downscaling (whether based on statistical relationships or dynamical parameterizations) may not capture future changes due to mechanistic process changes if the models are used outside the range for which they were designed (Christensen et al., 2007).

Within CLARIS-LPB, two WP9 partners are applying bias correction to four selected RCM simulations: Promes driven by HadCM3, RCA driven by ECHAM5-r1, RegCM3 driven by HadAM3 and LMDZ driven by IPSL. UBA is bias correcting monthly temperature and precipitation using a method previously applied in La Plata Basin (Saurral, 2010) and SMHI is correcting daily temperature and precipitation using the distribution-based scaling method developed by Yang et al (2010) and observed/reference data from ERA-interim corrected using the GPCC (Global Precipitation Climatology Centre) monthly precipitation.

3.7 Presenting RCM ensemble information

Different ways of presenting ensemble information from GCMs were discussed in Section 2.3. These can also be applied to RCM ensembles. ENSEMBLES RCM results have been presented, for example, using the ensemble mean and inter-model standard deviations of temperature (Goodess et al., 2009, Figures 6.3 and 6.4) together with the ensemble mean and number of models showing an increase for precipitation (Goodess et al., 2009; Figures 6.5 and 6.6) in order to demonstrate the robustness of projected changes. Time series (Figures 6.1 and 6.2) and temperature *vs* precipitation scatterplots (Figure 2.6) were also used. It is important to consider the ensemble spread and not just the ensemble mean, particularly in the case of precipitation where changes projected by different models may be of opposite sign. Kjellström et al. (2011) provide examples of relatively simple but informative graphical techniques that can be used to display regional ensemble information.

Further examples of working with RCM ensembles, including the construction of probability distribution functions, are available:

- Based on the PRUDENCE European ensemble: Fowler et al., 2007b; Fowler and Ekström, 2009; Buser et al., 2009
- Based on the ENSEMBLES European ensemble: Goodess et al., 2009; Boberg et al., 2010; Buser et al., 2010; Déqué and Somot, 2010; Kendon et al., 2010; Kyselý et al., 2011
- Based on the NARCCAP North American ensemble: Gao et al., 2011

Working with probabilistic projections brings a number of challenges for impacts applications – which are discussed in ENSEMBLES deliverable D2B.26/D6.13 (Carter et al, 2009). This deliverable includes some practical examples of the use of the response surface approach (Jones, 2000) to impacts modeling – see also Morse et al (2009).

Finally, when evaluating model performance and considering future projections, it may be helpful to compare new results with those from earlier studies. Dynamical downscaling has been performed for South America using the Eta, RegCM3 and Hadley Centre (PRECIS and HadRM3) RCMs (Marengo et al., 2009; 2010), as well as MM5 (Solman et al., 2008; Nuñez et al., 2009) and RCA (Sorensson et al., 2010). The downscaling activities undertaken as part of the earlier CLARIS project are also relevant (Menendez et al., 2010a,b). Also as part of CLARIS, the skill of the CMIP3 GCMs in simulating the hydrologic cycle of La Plata Basin was explored (Saurral, 2010). A full list of publications arising from both the CLARIS and CLARIS-LPB projects is available from the internal pages of the CLARIS-LPB web site. The CLARIS-LPB papers produced by WP5 are particularly relevant to the issues discussed in this deliverable.

4. The CLDAC and other resources

4.1 The Claris-LPB Data Archive Center (CLDAC)

The CLDAC is accessible from the main CLARIS-LPB web site (www.claris-eu.org) and is described in CLARIS-LPB deliverable D7.1 and Goodess et al. (2011). Two principle types of data are provided – observed and simulated, together with associated metadata and links for downloading data. The simulated data include the CMIP3 ensemble, together with outputs from the WP5 RCM simulations and associated material: essential background documentation, useful Quick-Look ERA-interim and Climate Change plots, and links to observed data for model evaluation.

The present-day observed climate data include reanalysis and CRU TS3.0 monthly gridded data together with data assembled as part of CLARIS-LPB by WP3. Daily temperature, precipitation, radiation and riverflow data are available, all searchable by latitude/longtitude or station identification number and the data can also be filtered by time period before downloading. Interactive maps show the location of stations. The daily 0.5 degree gridded temperature data set developed by CLARIS-LPB (Tencer et al., 2011) is also accessible.

The observed datasets provided can be used for model evaluation, but are themselves subject to uncertainties. The CLARIS-LPB gridded temperature data set, for example, is constructed using a similar methodology to that used to construct the European E-OBS dataset (Haylock et al., 2008). Both datasets are subject to uncertainties relating, in particular, to variations in the density of the underlying station network over both space and time. E-OBS includes confidence estimates for each time/data point – but in practice these are quite difficult to incorporate in analyses.

CLDAC also provides access to two software tools developed within CLARIS-LPB. The first is APACH, an analysis and management platform for meteorological databases, including an error detection/correction tool (see Goodess et al., 2011 for more details). The second is the CHAC weather pattern classification system for regional climate downscaling of daily precipitation (D'Onofrio et al., 2010).

4.2 Resources for the analysis of extremes and other climate analyses

The Joint CCl/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI) provides useful guidance and resources for the analysis of climate and weather extremes, including guidelines on 'Analysis of extremes in a changing climate in support of informed decisions for adaptation' (Klein-Tank et al., 2009).

The ETCCDI/CRD Climate Change indices web pages http://cccma.seos.uvic.ca/ETCCDI/ provide:

- Approved definitions and guidance on the calculations of climate change indices, along with standard software packages
- Practical guidance on the homogenization of climate data
- Access to online resources of climate indices
- A place for the submission of new or updated indices data

Software packages are provided for data homogenization (RHtestsV3) and for the calculation of indices of extremes (RClimDex). Both of these are based on the freely available R statistical package http://www.r-project.org/.

R is also the basis of the Extremes Toolkit for Extreme Value Analysis developed at NCAR: http://www.isse.ucar.edu/extremevalues/evtk.html

The CRAN website http://cran.r-project.org/ provides a wide range of contributed R packages for statistical analysis, including a number for climate analysis such as clim.run (for statistical downscaling, developed by Rasmus Benestad – see http://rcg.gvc.gu.se/edu/esd.pdf) and Rclim (developed in the ENSEMBLES project for the analysis of extremes in gridded datasets http://www1.secam.ex.ac.uk/rclim-initiative.dhtml). The CDF.t package for bias correction (see Section 3.6) is also available from the CRAN website. The bias correction methods implemented by Themeβl et al. (2010) were also implemented in R. RNetCDF provides an interface between R and NetCDF datasets.

Another potentially useful tool is CDAT (Climate Data Analysis Tools) provided through the PCMDI software portal - http://www2-pcmdi.llnl.gov/cdat - and based on Python. It is particularly useful for the visualization of netCDF files provided by PCMDI.

Finally, the ClimateExplorer tool developed by Geert van Oldenborgh at KNMI provides a suite of analysis tools and a large climate data base for statistical studies: http://climexp.knmi.nl/

References

Annan, J.D. and Hargreaves, J.C. (2010) Reliability of the CMIP3 ensemble. *Geophysical Research Letters*, 37, L02703, doi:10.1029/2009GL041994, 2010.

Arrit, R.W. and Rummukainen, M. (2011) Challenges in regional-scale climate modelling. *Bulletin of the American Meteorological Society*, 92, 365-368.

Barring, L., Holt, T., Linderson, M.L., Radziejewski, M., Moriondo, M. and Palutikof, J.P. (2006) Defining dry/wet spells for point observations, observed area averages, and regional climate gridboxes in Europe. *Climate Research*, 31, 35-49.

Bisserier, A., Boukezzoula, R. and Galichet, S. (2010) Linear fuzzy regression using trapezoidal fuzzy intervals. *Journal of Uncertain Systems*, 4, 59-72.

Boberg, F., Berg, P., Thejll, P., Gutowski, W.J. and Christensen, J.H. (2010) Improved confidence in climate change projections of precipitation further evaluated using daily statistics from ENSEMBLES models. *Climate Dynamics*, 35, 1509-1520.

Burke, E.J. and Brown, S.J. (2008) Evaluating uncertainties in the projection of future drought. *Journal of Hydrometeorology*, 9, 292-299.

Buser, C.M., Künsch, H.R., Lüthi, D., Wild, M. and Schär, C. (2009) Bayesian multi-model projection of climate: bias assumptions and interannual variability. *Climate Dynamics*, 33, 849-868.

Buser, C.M., Künsch, H.R. and Schär, C. (2010) Bayesian multi-model projections of climate: generalization and application to ENSEMBLES results. *Climate Research*, 44, 227-241.

Carter, T.R., Goodess, C.M. and Fronzek, S. (2009) Recommendations and guidance on methods for the construction and use in impacts applications of probabilistic regional climate projections, ENSEMBLES Deliverable D2B.26/D6.13, http://ensembles-eu.metoffice.com/project_reporting/year5reporting/D2B.26_D6.13_recommendations_guidance_probabilistic_rc_projections.pdf.

Chen, C.-T. and Knutson, T. (2008) On the verification and comparison of extreme rainfall indices from climate models. *Journal of Climate*, 21, 1605-1621.

Christensen, J.H. and Christensen, O.B. (2007) A summary of the PRUDENCE model projections of changes in European climate by the end of this century. *Climatic Change*, 81, 7-30.

Christensen, J. et al. (2007) *Regional Climate Projections*. In: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [S. Solomon, et al. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Christensen, J.H., Boberg, F., Christensen, O.B. and Lucas-Picher, P. (2008) On the need for bias correction of regional climate change projections of temperature and precipitation. *Geophysical Research Letters*, 35, L20709, doi:10.1029/2008GL035694, 2008.

Christensen, J.H., Rummukainen, M. and Lenderink, G. (2009) Formulation of very-high-resolution regional climate model ensembles for Europe. In: van der Linden, P., and J.F.B. Mitchell (eds.) *ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project*. Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK.

Christensen, J.H., Kjellström, E., Giorgi, F., Lenderink, G. and Rummukainen, M. (2010) Weight assignment in regional climate models. *Climate Research*, 44, 179-194.

Clark, R.T., Brown, S.J. and Murphy, J.M. (2006) Modeling Northern Hemisphere summer heat extreme changes and their uncertainties using a physics ensemble of climate sensitivity experiments. *Journal of Climate*, 19, 4418-4435.

Clark, R.T., Murphy, J.M. and Brown, S.J. (2010) Do global warming targets limit heatwave risk? *Geophysical Research Letters*, 37, L17703, doi:10.1029/2010GL043898, 2010.

Coelho, C.A.S., Stephenson, D.B., Balmaseda, M., Doblas-Reyes, F.J. and van Oldenborgh, G.J. (2006) Towards an integrated seasonal forecasting system for South America. *Journal of Climate*, 19, 3704-3721.

Collins, M., Chandler, R.E., Cox, P.M., Huthnance, J.M., Rougier, J. and Stephenson, D.B. (2012) Quantifying future climate change. *Nature Climate Change*, DOI: 10.1038/NCLIMATE1414.

Coppola, E., Giorgi, F., Rauscher, S.A. and Piani, C. (2010) Model weighting based on mesoscale structures in precipitation and temperature in an ensemble of regional climate models. *Climate Research*, 44, 121-134.

Dankers, R. and Feyen, L. (2009) Flood hazard in Europe in an ensemble of regional climate scenarios. *Journal of Geophysical Research*, 114, D16108, doi:10.1029/2008JD011523, 2009.

Déqué, M. and Somot, S. (2010) Weighted frequency distributions express modelling uncertainties in the ENSEMBLES regional climate experiments. *Climate Research*, 44, 195-209.

Déqué, M., Rowell, D.P., Lüthi, D., Giorgi, F., Christensen, J.H., Rockel, B., Jacob, D., Kjellström, E., de Castro, M. and van den Hurk, B. (2007) An intercomparison of regional climate simulations for Europe: assessing uncertainties in model projections. *Climatic Change*, 81, 53-70.

Déqué, M., Somot, S., Sanchez-Gomez, E., Goodess, C., Jacob, D., Lenderink, G. and Christensen, O. (2011) The spread amongst ENSEMBLES regional scenarios: regional climate models, driving general circulation models and interannual variability. *Climate Dynamics*, doi:10.1007/s00382-00011-01053-x.

Dessai, S., Hulme, M., Lempert, R. and Pielke, R. (2009) Climate prediction: a limit to adaptation? In: *Adapting to Climate Change: Thresholds, Values, Governance*, eds. W.N. Adger, I. Lorenzoni and K.L. O'Brien. Cambridge University Press, pp 64-78.

D'Onofrio, A., Boulanger, J.P. and Segura, E.C. (2010) CHAC: A weather pattern classification systems for regional climate downscaling of daily precipitation. *Climatic Change*, 98, 405-427.

Dosio, A. and Paurolo, P. (2011) Bias correction of the ENSEMBLES high-resolution climate change projections for use by impact models: Evaluation on the present climate. *Journal of Geophysical Research*, 116, doi:1029/2011JD015934, 2011.

Foley, A.M. (2010) Uncertainty in regional climate modelling: a review. *Progress in Physical Geography*, 34, 647-670.

Fowler, H.J. and Ekström, M. (2009) Multi-model ensemble estimates of climate change impacts on UK seasonal precipitation extremes. *International Journal of Climatology*, 29, 385-416.

Fowler, H.J., Blenkinsop, S. and Tebaldi, C. (2007a) Linking climate change modeling to impacts studies: recent advances in downscaling techniques for hydrological modeling. *International Journal of Climatology*, 27, 1547-1578.

Fowler, H.J., Ekström, M., Blenkinsop, S. and Smith, A.P. (2007b) Estimating change in extreme European precipitation using a multimodel ensemble. *Journal of Geophysical Research*, 112, D18104, doi:10.1029/2007JD008619, 2007.

Frei, C., Christensen, J.H., Deque, M., Jacob, D., Jones, R.G. and Vidale, P.L. (2003) Daily precipitation statistics in regional climate models: Evaluation and intercomparison for the European Alps. *Journal of Geophysical Research – Atmospheres*, 108, 4124, DOI: 10.1029/2002JD002287.

Gao, Y., Vano, J.A., Zhu, C. and Lettenmaier, D.P. (2011) Evaluating climate change over the Colorado River basin using regional climate models. *Journal of Geophysical Research*, 116, D13104, doi:10.1029/2010JD015278.

Giorgi, F. and Mearns, L.O. (2003) Probability of regional climate change based on the reliability ensemble averaging (REA) method. *Geophysical Research Letters*, 30, 1629.

Giorgi, F., Jones, C. and Asrar, G.R. (2009) Addressing climate information needs at the regional level: the CORDEX framework. *WMO Bulletin*, 58, 175-183.

Goodess, C.M., Jacob, D., Déqué, M., Guttiérrez, J.M., Huth, R., Kendon, E., Leckebusch, G.C., Lorenz, P. and Pavan, V. (2009) Downscaling methods, data and tools for input to impacts assessments. In: van der Linden, P., and J.F.B. Mitchell (eds.) *ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project*. Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK.

Goodess, C.M., Boulanger, J-P., Coelho, C.A.S., D'Onofrio, A., Farral, A., Rolla, A., Tozzi, L.R.L. and de Zarate, M.I. (2011) The CLARIS-LPB interface for improving prediction capability of climate change societal impacts (WP7). *CLIVAR Exchanges*, 57 (Vol. 16 No. 3), 25-28.

Greene, A., Goddard, L. and Lall, U. (2006) Probabilistic multimodel regional temperature change projections. *Journal of Climate,* 19, 4326–4343.

Haerter, J.O., Hagemann, S., Moseley, C. and Piani, C. (2011) Climate model bias correction and the role of timescales. *Hydrology and Earth System Sciences*, 15, 1065-1079.

Hawkins, E. and Sutton, R. (2009) The potential to narrow uncertainty in regional climate predictions. *Bulletin of the American Meteorological Society*, 90, 1095-1107.

Hawkins, E. and Sutton, R. (2011) The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dynamics*, 37, 407-418.

Haylock, M.R., Hofstra, N., Klein-Tank, A., Klok, E.J., Jones, P.D. and New, M. (2008) A European daily high-resolution gridded data set of surface temperature and precipitation for 1950-2006. *Journal of Geophysical Research – Atmospheres,* 113(D20119).

Hurkmans, R., Terink, W., Uijlenhoet, R., Torfs, P., Jacob, D. and Troch, P.A. (2010) Changes in streamflow dynamics in the Rhine Basin under three high-resolution regional climate scenarios. *Journal of Climate*, 23, 679-699.

Jones, R.N. (2000) Managing uncertainty in climate change projections: issues for impact assessment. *Climatic Change*, 45, 403-419.

Kallache, M., Vrac, M., Naveau, P. and Michelangeli, P.-A. (2011) Nonstationary probabilistic downscaling of extreme precipitation. *Journal of Geophysical Research*, 116, D05113, doi:10.1029/2010JD014892, 2011.

Kanamitsu, M. and DeHaan, L. (2011) The Added Value Index: A new metric to quantify the added value of regional models. *Journal of Geophysical Research*, 116, D11106, doi:10.1029/2011JD015597, 2011.

Kendon, E.J., Rowell, D.P., Jones, R.G. and Buonomo, E. (2008) Robustness of future changes in local precipitation extremes. *Journal of Climate*, 21, 4280-4297.

Kendon, E.J., Jones, R.G., Kjellström, E. and Murphy, J.M. (2010) Using and designing GCM-RCM ensemble regional climate projections. *Journal of Climate*, 23, 6485-6503.

Kharin, V.V., Zwiers, F.W., Zhang, X. and Hegerl, G.C. (2007) Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations. *Journal of Climate,* 20, 1419-1444.

Kjellström, E. and Lind, P. (2009) Changes in the water budget in the Baltic Sea drainage basin in future warmer climates as simulated by the regional climate model RCA3. *Boreal Environment Research*, 14, 114-124.

Kjellström, E. and Giorgi, F. (2010) Regional Climate Model evaluation and weighting: Introduction. *Climate Research*, 44, 117-119.

Kjellström, E., Nikulin, G., Hansson, U., Strandberg, G. and Ullerstig, A. (2011) 21st century changes in the European climate: uncertainties derived from an ensemble of regional climate model simulations. *Tellus*, 63A, 24-40.

Klein-Tank, A.M.G., Zwiers, F.W. and Zhang, X. (2009) *Guidelines on 'Analysis of extremes in a changing climate in support of informed decisions for adaptation'*, ETCCDI, http://www.clivar.org/organization/etccdi/etccdi.php

Knutti, R. (2010) The end of model democracy? *Climatic Change*, 102, 395-404.

Knutti, R., Abramowitz, G., Collins, M., Eyring, V., Glecker, P.J., Hewitson, B. and Mearns, L. (2010a) *Good Practice Guidance Paper on Assessing and Combining Multi Model Climate Projections*. In: Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Assessing and Combing Multi Model Climate Projections [Stocker, TD, Qin, D, Plattner, GK, Tignor, M and Midgley, PM (eds)]. IPCC Working Group I Technical Support Unit, University of Bern, Bern, Switzerland.

Knutti, R., Furrer, R., Tebaldi, C., Cermak, J. and Meehl, G.A. (2010b) Challenges in combining projections from multiple climate models. *Journal of Climate*, 23, 2739-2758.

Kyselý, J., Gaál, L., Beranová, R. and Plavcová, E. (2011) Climate change scenarios of precipitation extremes in Central Europe from ENSEMBLES regional climate models. *Theoretical and Applied Climatology*, 104, 529-542.

Laprise, R., de Elía, R., Caya, D., Biner, S., Lucas-Picher, P., Diaconescu, E., Leduc, M., Alexandru, A., Separovic, K. and Canadian Network for Regional Climate Modelling and Diagnostics (2008) Challenging some tenets of Regional Climate Modelling. *Meteorology and Atmospheric Physics*, 100, 3-22.

Leander, R. and Buishand, T.A. (2007) Resampling of regional climate model output for the simulation of extreme river flows. *Journal of Hydrology*, 332, 487-496.

Liang, X-Z., Kunkel, K.E., Meehl, G.A., Jones, R.G. and Wang, J.X.L. (2008) Regional climate models downscaling analysis of general circulation models present climate biases propagation into future change projections. *Geophysical Research Letters*, 35, L08709, doi:10.1029/2007GL032849, 2008.

Macadam, I., Pitman, A.J., Whetton, P.H. and Abramowitz, G. (2010) Ranking climate models by performance using actual values and anomalies: Implications for climate change impact assessments. *Geophysical Research Letters*, 37, L16704, doi:10.1029/2010GL043877, 2010.

Maraun, D. (2012) Nonstationarities of regional climate model biases in European seasonal mean temperature and precipitation sums. *Geophysical Research Letters*, 39, L06706, doi:10.1029/2012GL051210, 2012.

Maraun, D., Wetterhall, F., Ireson, A.M., Chandler, R.E., Kendon, E.J., Widmann, M., Brienen, S., Rust, H.W., Sauter, T., Themeβl, M., Venema, V.K.C., Chun, K.P., Goodess, C.M., Jones, R.G., Onof, C., Vrac, M. and Thiele-Eich, I. (2010) Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user. *Reviews of Geophysics*,48, RG3003.

Marengo, J.A., Jones, R., Alves, L.M. and Valverde, M.C. (2009) Future change of temperature and precipitation extremes in South America as derived from the PRECIS regional climate modeling system. *International Journal of Climatology*, 29, 2241-2255.

Marengo, J.A., Ambrizzi, T., da Rocha, R.P., Alves, L.M., Cuadra, S.V., Valverde, M.C., Torres, R.R., Santos, D.C. and Ferraz, S.E.T. (2010) Future change of climate in South America in the late twenty-first century: intercomparison of scenarios from three regional climate models. *Climate Dynamics*, 35, 1073-1097.

Masson, D. and Knutti, R. (2011a) Spatial-scale dependence of climate model performance in the CMIP3 ensemble. *Journal of Climate*, 24, 2680-2692.

Masson, D. and Knutti, R. (2011b) Climate model genealogy. *Geophysical Research Letters*, 38, L08703, doi:10.1029/2011GL046864, 2011.

Matsueda, M. and Palmer, T.N. (2011) Accuracy of climate change predictions using high resolution simulations as surrogates of truth. *Geophysical Research Letters*, 38, L05803, doi:10.1029/2010GL046618, 2011.

Meehl, G.A., Goddard, L., Murphy, J., Stouffer, R.J., Boer, G., Dananasoglu, G., Dixon, K., Giorgetta, M.A., Greene, A.M., Hawkins, E., Hegerl, G., Karoly, D., Keenlyside, N., Kimoto, M., Kirtman, B., Navarra, A., Pulwarty, R., Smith, D., Stammer, D. and Stockdale, T. (2009) Decadal prediction: Can it be skillful? *Bulletin of the American Meteorological Society*, 90, 1467-1485.

Menendez, C.G., de Castro, M., Boulanger, J.P., D'Onofrio, A., Sanchez, E., Sorensson, A.A., Blazquez, J., Elizalde, A., Jacob, D., Le Treut, H., Li, Z.X., Nunez, M.N., Pessacg, N., Pfeiffer, S., Rojas, M., Rolla, A., Samuelsson, P., Solman, S.A. and Teichmann, C. (2010a) Downscaling extreme month-long anomalies in southern South America. *Climatic Change*, 98, 379-403.

Menendez, C.G., de Castro, M., Sorensson, A. and Boulanger, J.P. (2010b) CLARIS project: towards climate downscaling in South America. *Meteorologische Zeitschrift*, 19, 357-362.

Michelangeli, P.-A., Vrac, M. and Loukos, H. (2009) Probabilistic downscaling approaches: Application to wind cumulative distribution functions. *Geophysical Research Letters*, 36, L11708, doi:10.1029/2009GL038401, 2009.

Morse, A., Prentice, C. and Carter, T. (2009) Assessments of climate change impacts. In: van der Linden, P., and J.F.B. Mitchell (eds.) *ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project*. Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P. and Wilbanks, T.J. (2010) The next generation of scenarios for climate change research and assessment. *Nature*, 463, 747-756.

Nuñez, M.N., Solman, S.A. and Cabré, M.F. (2009) Regional climate change experiments over southern South America. II: Climate change scenarios in the late twenty-first century. *Climate Dynamics*, 32, 1081-1095.

Oettli, P., Sultan, B., Baron, C. and Vrac, M. (2011) Are regional climate models relevant for crop yield prediction in West Africa? *Environmental Research Letters*, 6, (2011), 014008.

Orlowsky, B. and Seneviratne, S.I. (2011) Global changes in extreme events: Regional and seasonal dimension. *Climatic Change*, in press.

Overland, J.E., Wang, M., Bond, N.A., Walsh, J.E., Kattsov, V.M. and Chapman W.L. (2011) Considerations in the selection of global climate models for regional climate projections: the Arctic as a case study. *Journal of Climate*, 24, 1583-1597.

Paeth, H. (2011) Postprocessing of simulated precipitation for impact research in West Africa. Part I: model output statistics for monthly data. *Climate Dynamics*, 36, 1321-1336.

Paeth, H. and Diederich, M. (2011) Postprocessing of simulated precipitation for impact research in West Africa. Part II: a weather generator for daily data. *Climate Dynamics*, 36, 1337-1348.

Palmer, T.N., Doblas-Reyes, F.J., Weisheimer, A. and Rodwell, M.J. (2008) Toward seamless prediction: calibration of climate change projections using seasonal forecasts. *Bulletin of the American Meteorological Society*, 89, 459-470.

Piani, C., Haerter, J.O. and Coppola, E. (2010a) Statistical bias correction for daily precipitation in regional climate models over Europe. *Theoretical and Applied Climatology*, 99, 187-192.

Piani, C., Weedon, G.P., Best, M., Gomes, S.M., Viterbo, P., Hagemann, S. and Haerter, J.O. (2010b) Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. *Journal of Hydrology*, 395, 199-215.

Rapaić, M., Leduc, M. and Laprise, R. (2011) Evaluation of the internal variability and estimation of the downscaling ability of the Canadian Regional Climate Model for different domain sizes over the north Atlantic region using the Big Brother experimental approach. *Climate Dynamics*, 36, 1979-2001.

Räisänen, J. and Ylhäisi, J.S. (2011) Can model weighting improve probabilistic projections of climate change? *Climate Dynamics*. DOI 10.1007/s00382-011-1217-8.

Rojas, R., Feyen, L., Dosio, A. and Bavera, D. (2011) Improving pan-European hydrological simulation of extreme events through statistical bias correction of RCM-driven climate simulations. *Hydrology and Earth System Sciences*, 15, 2599-2620.

Rummukainen, M. (2010) State-of-the-art with regional climate models. *WIREs Climate Change*, 1, 82-96.

Saurral, R.I. (2010) The hydrologic cycle of La Plata Basin in the WCRP-CMIP3 multimodel dataset. *Journal of Hydrometeorology*, 5, 1083-1102.

Schaller, N., Mahlstein, I., Cermak, J. and Knutti, R. (2011) Analyzing precipitation projections: A comparison of different approaches to climate model evaluation. *Journal of Geophysical Research*, 116, D10118, doi:10.1029/2010JD014963, 2011.

Seneviratne, S.I., Nicholls, N., Easterling, D., Goodess, C.M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C. and Zhang, X. (2012) *Changes in climate extremes and their impacts on the natural physical environment.* In: A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change [Fields, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor and P.M. Midgley (eds.)]. Cambridge University Press, Cambirdge, UK, and New York, NY, USA, pp 109-230

Sheffield, J. and Wood, E.F. (2008) Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. *Climate Dynamics*, 31, 79-105.

Solman, S., Nuñez, M. and Cabré, M.F. (2008) Regional climate change experiments over southern South America. I: present climate. *Climate Dynamics*, 30, 533-552.

Solomon, A., Goddard, L., Kumar, A., Carton, J., Deser, C., Fukumori, I., Greene, A.M., Hegerl, G., Kirtman, B., Kushnir, Y., Newman, M., Smith, D., Vimont, D., Delworth, T., Meehl, G.A. and Stockdale, T. (2011) Distinguishing the roles of natural and anthropogenically forced decadal climate variability: implications for prediction. *Bulletin of the American Meteorological Society*, 92, 141-156.

Sorensson, A.A., Menendez, C.G., Ruscica, R., Alexander, P., Samuelsson, P. and Willen, U. (2010) Projected precipitation changes in South America: a dynamical downscaling within CLARIS. *Meteorologische Zeitschrift*, 19, 347-355.

Tebaldi, C. and Knutti, R. (2010) The use of the multi-model ensemble in probabilistic climate projections. *Philosophical Transactions of the Royal Society A*, 365, 2053-2075.

Tebaldi, C. and Sansó, B. (2009) Joint projections of temperature and precipitation change from multiple climate models: a hierarchical Bayesian approach. *Journal of the Royal Statistical Society A*, 172, 83-106.

Tebaldi, C., Hayhoe, K., Arblaster, J.M. and Meehl, G.A. (2006) Going to the extremes. An intercomparison of model-simulated historical and future changes in extreme events. *Climatic Change*, 79, 185-211.

Tencer, B., Rusticucci, M., Jones, P.D. and Lister, D. (2011) A southeastern South American daily gridded data set of observed surface minimum and maximum temperature for 1961-2000. *Bulletin of the American Meteorological Society*, DOI: 10.1175/2011BAMS3148.1.

Terink, W., Hurkmans, R.T.W.L., Torfs, P.J.J.F. and Uijlenhoet, R. (2010) Evaluation of a bias correction method applied to downscaled precipitation and temperature reanalysis data for the Rhine basin. *Hydrology and Earth System Sciences*, 14, 687-703.

Themeβl, M.J., Gobiet, A. and Leuprecht, A. (2010) Empirical-statistical downscaling and error correction of daily precipitation from regional climate models. *International Journal of Climatology*, DOI: 10.1002/joc.2168.

van der Linden, P., and J.F.B. Mitchell (eds.) (2009): ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project. Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK. 160pp.

van Pelt, S.C., Kabat, P., ter Maat, H.W., van den Hurk, B.J.J.M. and Weerts, A.H. (2009) Discharge simulations performed with a hydrological model using bias corrected regional climate model input. *Hydrology and Earth System Sciences*, 13, 2387-2397.

Wang, Y., Leung, L.R., McGregor, J.L., Lee, D-K, Wang, W-C, Ding, Y. and Kimura, F. (2004) Regional climate modelling: progress, challenges, and prospects. *Journal of the Meteorological Society of Japan*, 82, 1599-1628.

Wilby, R.L. and Dessai, S. (2010) Robust adaptation to climate change. *Weather*, 65, 180-185.

Wilby, R.L., Troni, J., Biot, Y., Tedd, L., Hewitson, B.C., Smith, D.M. and Sutton, R.T. (2009) A review of climate risk information for adaptation and development planning. *International Journal of Climatology*, 29, 1193-1225.

Xu, Y., Gao, X.J. and Giorgi, F. (2010) Upgrades to the reliability ensemble averaging method for producing probabilistic climate-change projections. *Climate Research*, 41, 61-81.

Yang, W., Andreasson, J., Graham, L.P., 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. *Hydrology Research*, 41.3-4, doi: 10.2166/nh.2010-004.