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***FU**ture E**N**vironmental Scenarios*

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– METHODOLOGIES FOR DOWNSCALING SOCIO-ECONOMIC, TECHNOLOGICAL AND EMISSION SCENARIOS, AS WELL AS METEOROLOGICAL SCENARIO DATA, TO COUNTRY LEVEL AND SMALLER REGIONS –

PART II: CLIMATE

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Contents

Abstract

Climate change impacts are very dependent on regional geographical features, climate, and socio-economic conditions. Impact studies should therefore be performed at the local or at most a regional level. However, climate scenarios are produced for the entire Globe, at a spatial resolution of several hundred kilometres. Therefore, methods are needed to bridge the gap between the large scale of climate scenarios and the fine scale where local impacts happen as a consequence of changed weather conditions.

A set of methodologies is presented that enable this downscaling of climatic data for future scenarios to a specific site or small region. This document presents the context where downscaling is required. It also discusses the main downscaling approaches: using dynamical models or using statistical methods.

Statistical approaches produce data of similar quality to current-day dynamical models, but they are simpler, less demanding on resources, and faster to implement. For teams with limited computing power and the non-climate expert, statistical downscaling, with its main variations, is currently the most feasible approach at obtaining climate data for future impact studies.

Information for understanding the value of the various types of statistical downscaling methods is provided in this document, enabling the selection of the most adequate solution to adopt for a specific case.

Guidelines for the use of the various statistical downscaling models are provided, as well as practical information (in Annexes) on how to implement algorithms, how to obtain software tools already available for these purposes, and how to get access to sources of the indispensable observed and climate change scenario data. Procedures for model building, calibration, validation and generation of daily weather sequences are discussed in depth for some of the most useful freely available software tools.

1. Overview of the climate scenario downscaling context

The main goal of this document is to provide up-to-date information on climate downscaling tools and methods, and to help non-experts selecting and using one of the available methods to produce climate change scenarios for impact assessment at a local scale.

1.1. Scenarios of global Climate Change

In its 2007 report, the IPCC concluded that evidence from observational records that warming of the climate system is unequivocal. On a global level, the main global climate changes are increases in average temperature, changes in cloud cover and precipitation, melting of ice caps and glaciers and reduced snow cover, increase in intense tropical cyclone activity, and increases in ocean temperatures and acidity. Rising sea level is consistent with warming. Precipitation increased significantly in eastern parts of North and South America, northern Europe and northern and central Asia but declined in the Sahel, the Mediterranean, southern Africa and parts of southern Asia.

The IPCC report also concludes that global climate change is mostly due to man-made emissions of greenhouse gases like carbon dioxide (CO_2) and methane (CH_4). Over the past century, CO_2 atmospheric concentrations increased from a pre-industrial level of 278 ppm to 379 ppm in 2005. During this period the average global mean temperature rose by 0.74^{o}C and sea level rose by 0.17 meters since 1960. This is believed to be the fastest and largest warming trend in the history of Earth. Changes have also occurred in other important features of climate, such as the warm episodes of the El Nino Southern Oscillation.

Global climate model predictions for the 21st century indicate that global warming will continue and accelerate (even if humanity can successfully restrain its emissions). By 2100 the global average temperature predictions show increases ranging from 1.8^{o}C to 4^{o}C and sea level rise between 0.18 and 0.59 meters. Extreme events such as floods, droughts and heatwaves are expected to increase in frequency and intensity even with relatively small average global temperature increases.

Climate change is not homogenous. Some geographic areas are more sensitive to climate change than others. Small islands are particularly sensitive to climate changes as well as regions like the Mediterranean where precipitation and temperature changes will be significant stressors.

Definitions of Climate Terms

Climate is the average state of the atmosphere and the underlying land or water in a particular region over a specific time period.

Weather is the day-to-day manifestation of climate in a particular place at a particular time.

Climate change is a statistically significant variation in either the mean state of the climate or in its variability, persisting over an extended period (typically decades or longer).

Climate variability refers to variations around the mean state, including the occurrence of extreme weather events.

The Earth's climates result from interactions between many processes in the Atmosphere, Ocean, Land surface and Cryosphere. In the long term geological processes and changing orbital parameters of the Earth also come into play. In the earlier 20th century mathematicians and meteorologists started to try to explain the general circulation of the atmosphere, with the main practical purpose of producing weather forecasts using the basic physics of the atmosphere. However, it was only after 1988 the advances on computer power enabled the first coupled ocean-atmospheric models to appear. These models have since grown to be very sophisticated – including effects such as solar activity fluctuations, volcanoes, shallow and deep ocean interactions, biosphere responses, airborne sulphates and parts of the atmospheric chemistry – and can run climate simulations under different conditions. In particular they can analyse the result of changing the amount of greenhouse gases in the atmosphere, during one or more centuries (American Institute of Physics, 2007), with rising confidence in the results. The aim is to obtain an "Earth model" that can simulate all important physical, chemical and biological mechanisms, on a high resolution computational grid covering the whole globe.

Today's coupled Atmosphere-Ocean General Circulation Models (AOGCMs) – e.g. HadCM3, HadGEM1, GFDL-CM2.1, CCSM3, CGCM3.1, CSIRO-MK3.5, ECHAM5… see a complete list in PCMDI (2007) – are based in weather forecasting models but have evolved to be used for understanding climate and projecting climate change. In this context they are referred to as Global Climate Models (GCMs). As mentioned before (see Part I), projecting climate change with GCMs is based on scenarios of the future, in particular on the greenhouse gas emissions at each scenario, driving the greenhouse gas concentrations in the atmosphere.

It is important to understand that scenarios are consistent and coherent alternative stories of the future, but they are neither predictions nor forecasts (Nakicenovic et al, 2000). Since the late 1990s there has been a big international effort to construct realistic future emissions scenarios representing the complex and interrelated dynamics of demographic development, socio-economic development and technological change (IPCC, 2000).

The most useful of these exercises in the current context is the IPCC Special Report on Emissions Scenarios, better known by its acronym SRES. This is because the greenhouse gas emissions from this set of scenarios served as input for most GCM future climate studies.

The SRES present four storylines for possible future scenarios (A1, A2, B1 and B2). The A1 scenario describes a future world of very rapid economic growth, a global population that peaks the mid-century and declines thereafter and a rapid introduction of new and more efficient technologies. The A2 scenario describes a very heterogeneous world with continuously increasing global population and regionally oriented economic growth. The B1 scenario describes a convergent world with the same global population as in the A1 storyline but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. Finally the B2 scenario describes a world in which the emphasis is on local solutions to economic, social, and environmental sustainability, with continuously increasing population (lower than A2) and intermediate economic development.

Although many global socio-economic and technological scenarios were and are being built, so far only SRES have been used as inputs for the more sophisticated GCM runs. Therefore SRES scenarios are actually the only candidates when it comes to performing a coherent downscaling of (simultaneously) future panoramas of demography, society, economy, technology, emissions and climate.

1.2. Downscaling global warming studies

GCMs are widely used to assess climate change at a global scale, i.e. the global warming. However, the GCMs outputs alone can not assess the detailed changes at regional/local levels. Most impact studies are done for spatial resolutions of the order of a few square kilometres. This is much less than the horizontal areas of the grid-boxes used by GCMs – hundreds of kilometres a side – especially for regions of complex topography, coastal or island locations, and in regions of highly heterogeneous land-cover (Wilby, 2004).

In these cases it would be adequate to resort to Regional Climate Models (RCMs), with spatial resolution of the order of tens of kilometres or even less. But bridging the gap between the resolution of global climate models and local scale weather and microclimatic processes represents a considerable technical problem. Recently there has been a lot of effort from the climate community on the development of dynamical and statistical downscaling techniques to represent climate change at a local and regional scale, respectively.

RCMs are the paradigmatic example of dynamical downscaling. They take as input the larger scale parameter values supplied by the global AOGCMs at the boundaries of the region they survey (domain) – both those relating to the atmosphere and those related to the sea surface conditions – in a process called “nesting”, as the RCM grid-boxes nest inside one or more GCM grid-boxes. Like for GCMs, RCMs are based on numerical simulations of the physical processes operating in Nature.

Unfortunately RCM still have several drawbacks, for example, they have limited number of experiments/scenario runs and time periods. The main problem generally is that, depending on the domain size and resolution, they can be very demanding from a computational viewpoint. Additional problems relate to the need of sophisticated training for the modellers and to difficulties in calibration and validation.

As an alternative to dynamic models, statistical downscaling models have been developed. They are based on the view that regional climate is mostly a result of the large scale climatic state and regional/local physiographic features, e.g. topography, land-sea distribution and land use (Wilby, 2004). Statistical downscaling methods are generally classified in three groups: (i) regression models; (ii) weather pattern classification schemes and (iii) weather time series generators. A major advantage of these techniques in comparison with dynamical models is that they are computationally much cheaper, and can be more easily applied to the output of different GCM experiments, for various scenarios – this enabling an assessment of the uncertainty in future scenarios. The major theoretical weakness of statistical downscaling is that their basic assumption is not verifiable, i.e., that the statistical relationships developed for the present day climate will also hold for the different forcing conditions in the future climates (Fowler, 2007).

This guidance document (Part II) provides up-to-date information on the available techniques and datasets to assess local and regional climate change scenarios and explain how to apply in practice statistical downscaling.

A simple proportional scaling method and two statistical downscaling tools in particular will be analysed: (i) the so called delta change method; (ii) LARS-WG, mostly a sophisticated stochastic weather generator and (iii) SDSM, a hybrid of stochastic weather generator and of regression methods. The latter uses circulation patterns and moisture variables to condition local weather parameters, and stochastic methods to describe the variance of the downscaled climate series.

Many practical lessons are presented, which were obtained when trying to apply these techniques and tools at an actual downscaling exercise: performing a simulation of daily weather under current as well as future climate conditions, for one meteorological station in Lisbon (Portugal), using the A2 SRES scenario and the HadCM3 model as the GCM starting point.

2. Climate scenario downscaling approaches

A good text to read on statistical downscaling methods is the IPCC document “Guidelines for Use of Climate Scenarios Developed from Statistical Downscaling Methods” (Wilby et al., 2004). The general scheme for obtaining climate scenarios using downscaling approaches is summarized in the Figure A.1 presented bellow.

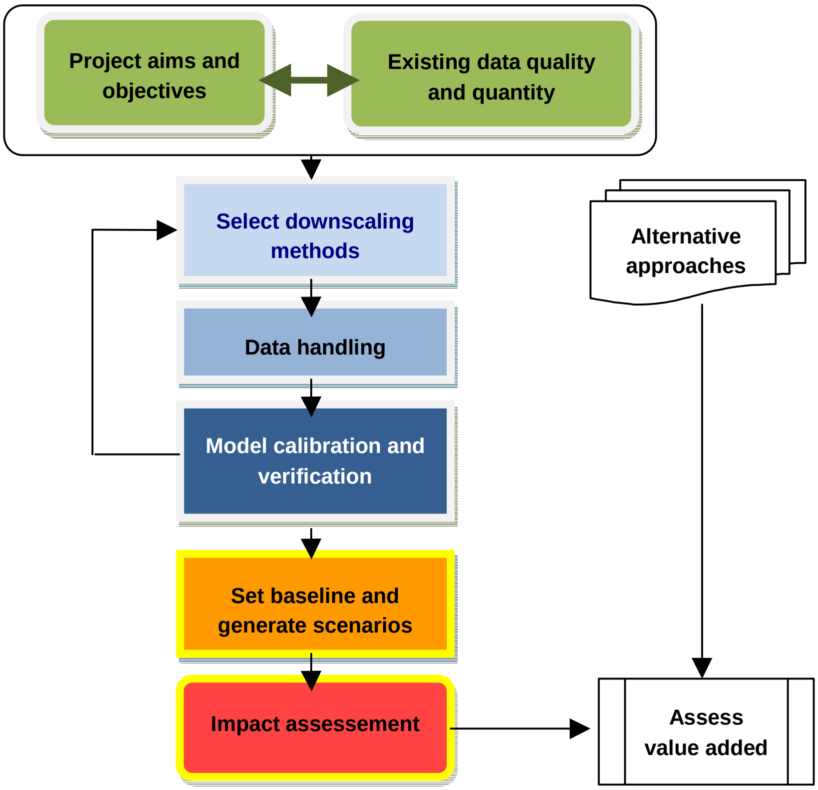


Figure 1: Main steps in obtaining and using downscaled climate scenarios by way of statistical approaches.

2.1. Dynamical Downscaling

RCMs use dynamical downscaling methods for obtaining climate information at a regional scale, which can be considered as the minimum adequate scale to evaluate climate change impacts. These models parameterize physical atmospheric processes at high spatial resolution in a limited area and use as input values and boundary conditions for that small area, supplied by a low spatial resolution GCM – a process which is usually called “nesting”.

2.1.1. Value of Regional Climate Model data

Most of today's regional climate models (e.g. ARPEG, CHRM, HadRM, HIRHAM, etc...) have spatial resolution between 20 and 60 km and are able to simulate regional climate features such as orographic precipitation, regional scale microclimates and some extreme events.

A growing number of studies are being published, comparing the ability of RCMs to simulate climate variables, particularly those relevant for hydrological studies. In general RCMs behave well in respect to temperature related statistics, but demonstrate problems when representing some features of precipitation. For instance, Pan et al. (2001) evaluated the uncertainties of two regional climate models, at the spatial resolution of 50 km, with realistic orographic precipitation, east-west transcontinental gradients and reasonable annual cycles over different geographic locations. In this case, both models behaved well in respect to temperature, but missed when representing extreme precipitation events. Another similar analysis conducted by Dankers et al. (2007), for the regional climate model HIRHAM at the spatial resolutions of 12 km and 50 km, showed that the higher resolution simulations presented good results for orographic precipitation patterns and extreme rainfall events. But again, the average precipitation rates were generally higher than observed, while extreme precipitation levels were mostly underestimated.

A comparison study of ten RCMs developed by the European Project PRUDENCE concluded that most of the uncertainties sources of RCMs do vary according the spatial domain, region and season. However, it was also concluded that the role of boundary forcing, i.e. the choice of the driving GCM, has generally a greater role on the sources of uncertainty than the RCM used, in particular for temperature (Deque et al., 2007).

Since the mid nineties local adaptation and mitigation measures of global warming started to be considered. The need to support this type of policy making with objective and more accurate data lead to the necessity of improving and developing new dynamical downscaling methods and prompted many model comparison and validation studies. In 1997 the Project MERCURE (Modelling European Regional Climate, Understanding and Reducing Errors) established five main goals to overcome and understand RCMs uncertainties (Busch, 2001).

These goals where:

i. to understand the sources of errors that hinder the representation of physical processes;
ii. to improve the representation of the hydrological cycle;
iii. to assess the ability of regional models to reproduce observed precipitation frequency;
iv. to characterize errors in regional climate simulations nested in general circulation models;
v. to provide statistical-dynamical tools linking RCM and GCM simulations;

Currently, they seem to have been reached to a good extent.

2.1.2. Perspectives for the dynamic downscaling approach

There has been a strong effort to perform and release to the scientific community more regional climate models simulations carrying less uncertainty. However, this approach continues to be computationally expensive, so this goal is still distant. In fact existing RCMs runs are usually restricted to one or two climate change scenarios for a limited area, and for limited time periods; usually 30 years for a control baseline climate, viz. 1961-1990.

The regional climate model PRECIS (Providing REgional Climates for Impacts Studies) was developed by the Hadley Centre to help generate high resolution climate change information, based on the Hadley Centre's regional climate modelling system, and its main innovation was that it can run in a regular PC under the Linux operating system. It is an excellent technological advance but still has some important limitations. A typical experiment, covering a 100-by-100 grid-box domain including a representation of the atmospheric sulphur cycle run on a 2.8 GHz machine, takes up to 4.5 months to complete a 30 year simulation (UNDP, 2003).

However it can be expected that this type of technology will became faster and simpler to use in the coming years, enabling smaller teams and even specialists from other fields to perform their own dynamic downscaling of global warming impacts for different periods, scenarios and geographical locations.

2.2. Statistical Downscaling

While the dynamic downscaling approach is only feasible for some large specialised teams and relatively few results are available for other researchers to use, in many cases statistical downscaling methods can produce quite useful results, using lower resources. The main variations of this type of approach will be discussed hereafter.

Regardless of the downscaling approach used, there will be a need to obtain meteorological data for baseline ("current climate") and future scenario conditions. Although these are not *per se* technical components of the downscaling methods, in practice they are crucial for selecting and using adequate downscaling procedures. Valuable information on these matters is provided in Annex I.

The application of the following methods to obtain future weather data is to be considered first for just one location, where one meteorological station exists that can provide long term daily records of the weather. Then other more complicated cases will be approached: working with several stations, allowing for microclimates, obtaining gridded data.

2.2.1. The delta change or anomaly approach

One simple method of assessing climate change at a local scale is to apply GCM projections in a form of "change factors" which is usually referred to as the "delta-change" approach (Fowler, 2007). In some contexts this is also known as the "anomaly" method. The basic process can be explained as follows:

i. "baseline" climatology is established for the specific location of interest, e.g. 1961-1990 long term monthly averages of temperature and monthly accumulated precipitation. For some types of studies other meteorological parameters that may be required, such as solar radiation, humidity and wind intensity and direction;

ii. similar statistics are compiled from the GCM or RCM results for the respective region / grid cell where the location of interest is included, both for the control run, i.e. the “current climate” simulation, and for the one (or several) future scenario runs;

iii. the changes (from present to future) in these long term monthly data of the GCM or RCM are computed – these are the “delta-changes” or “anomalies”;

iv. the delta changes are applied to the baseline *climatology* of the specific location to obtain the respective specific future climatology scenarios – for example, if in some region the temperature difference between a certain 2060-2090 GCM scenario and the GCM baseline is 4ºC, just add 4ºC to the current climate temperature dataset of the reference meteorological station in that region, to obtain the future climate for that station (see Fig. 2);

v. to obtain weather *time series*, not just the monthly mean values, three methods can be used

   a. the delta changes are applied also to the sequences of daily data;
   b. “fragments” of recorded data are used, with the desired monthly means;
   c. a stochastic weather generator that need as input only the monthly means is used.

The main advantages of this methodology are speed, simplicity and transparency.

However, it has some drawbacks and its practical implementation can be more difficult than it would seem at first sight, in particular for step (v), as will now be discussed.

First of all for option a) in step (v), note that the change factors can be computed and used in an additive or multiplicative way, see again Fig. 2. Either option is generally acceptable in practice with yearly or monthly data, but not so for daily data.

Additive change factors keep the variance and thermal amplitude; multiplicative change factors amplify (or reduce) them – for instance check the minima and maxima of both scenario series. The amount of the changes in variance introduced by multiplicative change factors is clearly proportional to the change factor and does not represent any physical effect (except for coincidence). Therefore the (more conservative) use of additive change factors would seem preferable.

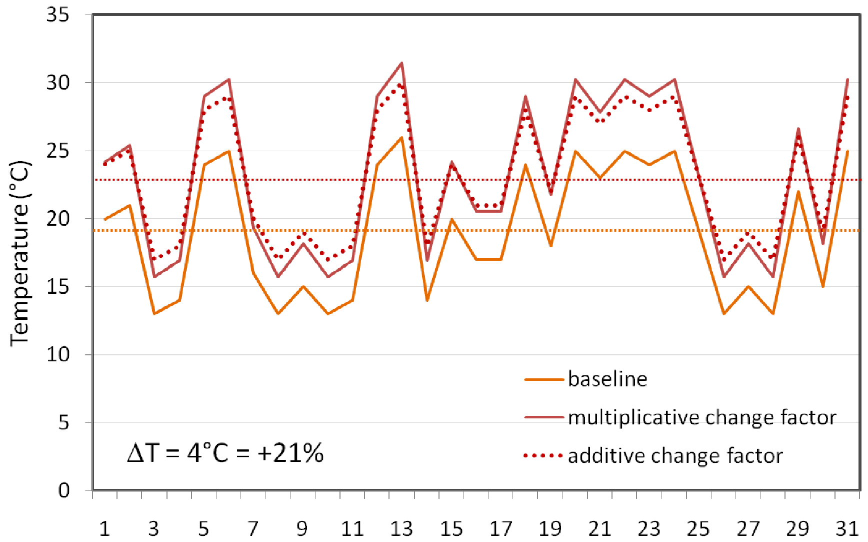
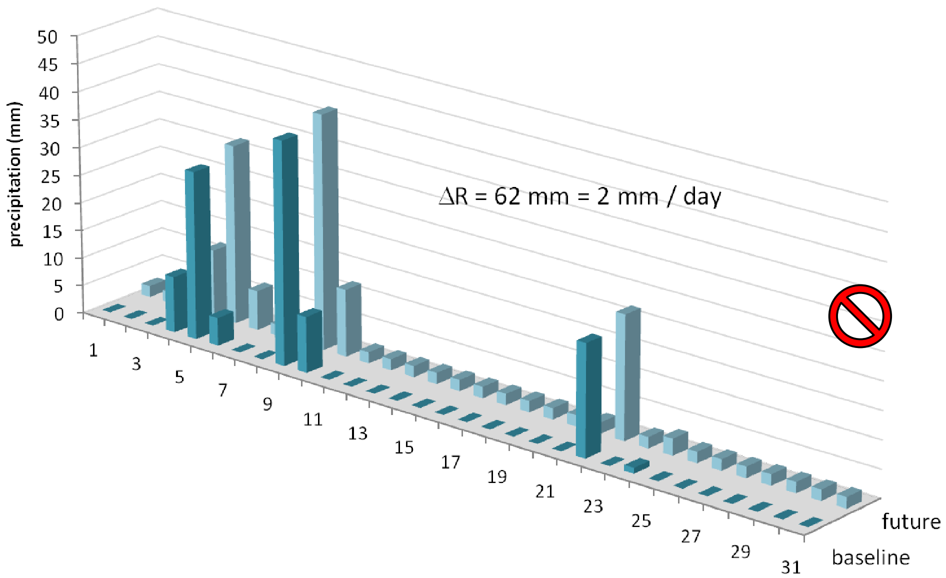


Figure 2: A same monthly delta change applied to a daily sequence of mean temperature using two methods.

However, additive change factors are not adequate for parameters such as wind speed or, most remarkably, precipitation, which often display zero values.

For instance – see Fig. 3 – if one adds a fixed positive amount to a (baseline) sequence of mixed wet and dry days, one obtains for the future a sequence where every day is wet, which is not realistic. The result is even worse if the delta change is negative, in case many days would present "negative" precipitation. In this case the best solution would be indeed to use multiplicative change factors, see Fig.4.



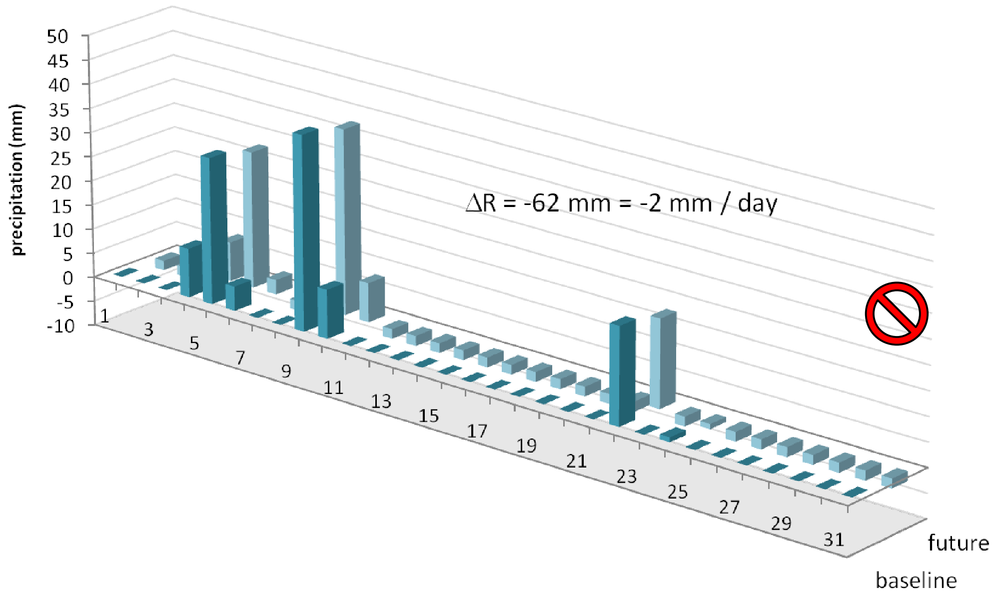
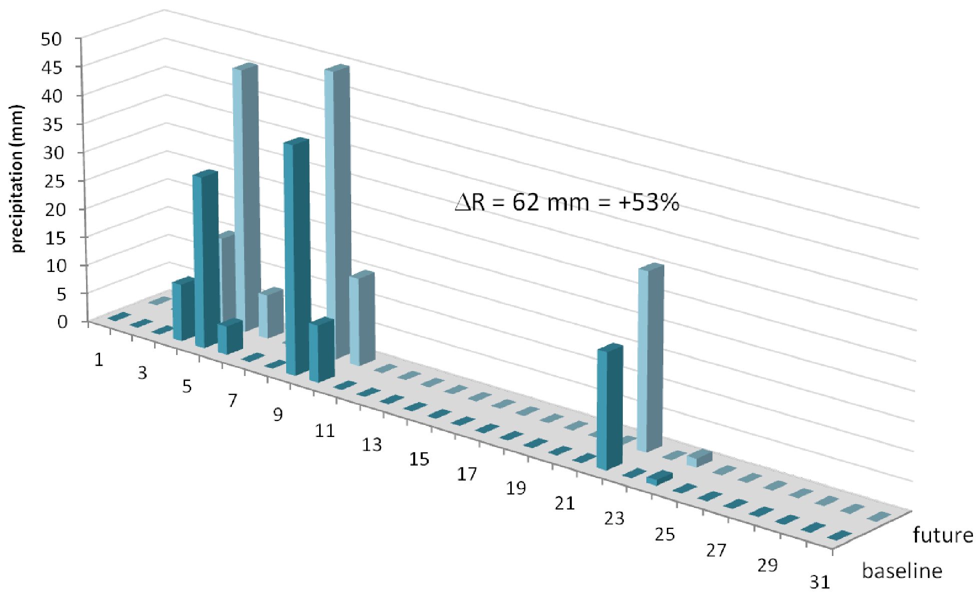


Figure 3: Demonstration of why it is not adequate to apply additive delta changes to a sequence of daily precipitation.



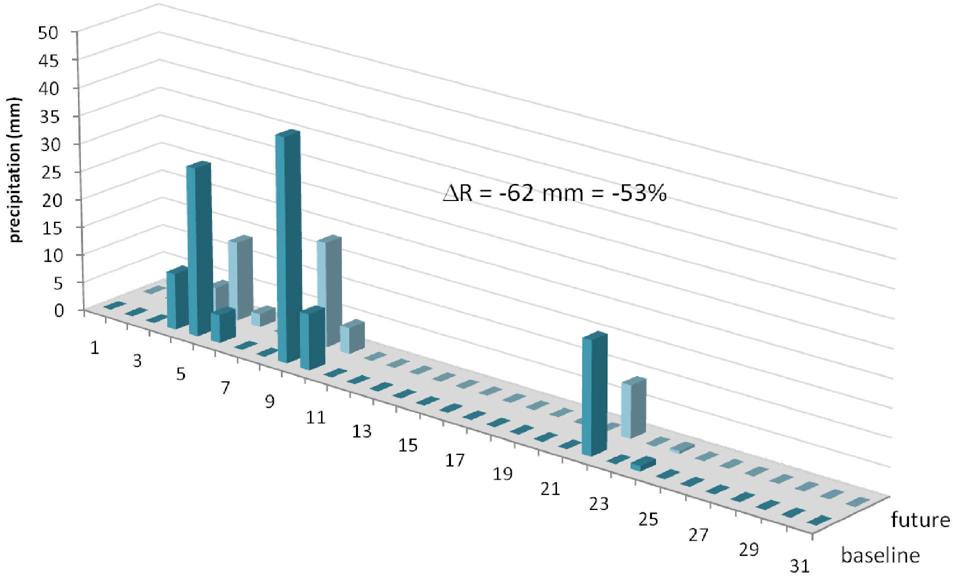


Figure 4: Multiplicative delta changes applied to a sequence of daily precipitation.

But even using multiplicative delta changes there is always the risk of computing values that break some physical limit. For instance, relative humidity values are at most 100%; solar radiation cannot raise above some clear sky value, say for instance 1100 W/m². Even ambient temperature has practical limits, say 50 °C for the hourly maxima. Furthermore one can ask about the meaning of multiplicative change factors. For instance in Fig. 2 the percent change in temperature is computed relative to the baseline mean temperature, which is in degree Celsius. What if the baseline is zero or negative? Also, shouldn't absolute temperatures (Kelvin scale) be used instead of the practical but arbitrary Celsius scale?

Indeed, to use this method the range of the parameter under analysis should always be transformed so that the lowest value is 0. For instance, temperature data should be converted from °F or °C to K.

It is also often useful to set an upper bound, such as a physical limit or the highest value recorded. For instance, if the maximum average daily temperature on record for a certain site is about 33°C, a highest bound T_{high} =306,15 K (= 33 + 273,15) or maybe a few degrees above, say T_{high} = 308 K, might be assumed. Then, the rescaled values outside the [0, T_{high}] limit would be reset to 0 or to T_{high}. The rescaling process would be applied again and again until the average of the series of daily values would fall into a small distance (say, 0,1 K) of the target mean value. Finally the rescaled series would be converted to the more usual scales of °F or °C.

Besides these practical difficulties, from a theoretical point of view this approach does not take into account any modifications brought by climate change in the sequential properties of time series, such as auto or cross-correlation between meteorological parameters. Modifications of variance, and other details of the probability functions and spatial patterns are also ill-represented.

Take for example the case of a raise in monthly mean temperature. This can be brought about not by having all days of the month a bit warmer than in the baseline, such as in Fig. 2, but by having more hot days, see Fig. 5.

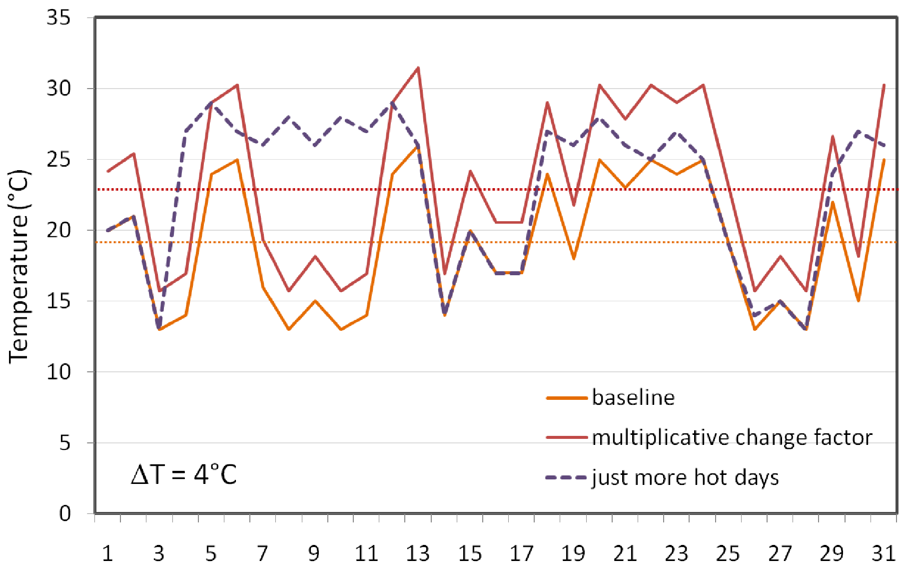


Figure 5: A same monthly delta change of a daily sequence of mean temperature caused by two different mechanisms.

These problems with this method are of concern for assessing extreme events such as heat waves, or in the case of precipitation when misrepresenting the length change of wet and dry spells that are so important in climate change studies (Diaz-Nieto and Wilby, 2005).

Option b) in step (v), the so called method of "fragments", avoids many of the problems discussed for option a) by using a different approach to obtain sequences of daily values compatible with certain monthly data. It works as follows:

i. the recorded data is separated in monthly series, or fragments, and these are classified in respect to their mean (or accumulated) values;

ii. for each monthly value obtained for a future climate, search the databank of fragments for one that displays a similar monthly mean (or accumulated) value; this is the sequence adopted for mounting the future climate scenario data;

iii. as the data pool is limited in size, step (ii) will generally yield sequences with monthly values similar but not quite identical to the target monthly data, therefore some small adjustment (multiplicative in principle, as seen before) must be applied to the daily sequence.

This procedure can and should be used also for sets of parameters, e.g. mean temperature and accumulated precipitation, in which case step (iii) is applied independently to the temperature and precipitation series.

An advantage of the method of fragments is that the auto- and cross-correlations between meteorological parameters is naturally conserved – although as it was mentioned before, different statistical relationships might apply for the real future climate.

The method of fragments requires a reasonably large pool of observed data, which for many regions unfortunately is not available. In this case option c) in step (v) can provide a solution: use a stochastic weather generator to obtain the series of daily (often also hourly) data, using as input the target monthly data. One advantage of this procedure is that these weather generators usually include parameterizations of variance, autocorrelation, etc. of the daily series with the respective monthly values and so the downscaling results are in principle more realistic.

In principle using such tools might even be the best approach, but unfortunately they are rarely available. Indeed although many software tools exist, but they are seldom calibrated / validated for the region of interest, and usually yield only one parameter - e.g. temperature or solar radiation, but not simultaneously these two and in plus precipitation, humidity, wind, etc., as needed.

Construction and calibration of multi-parameter stochastic models demands data pools even larger than for the method of fragments, and most of all, the work involved is incomparably larger. Therefore this approach is more effective when used *directly* for downscaling (see the following section), instead of as a downstream application to handle the monthly data supplied by the delta-change approach.

Two final remarks: first, note that directional wind data is an exception to these recommendations, as it features a circular scale (0° = 360°) and therefore additive change factors are more adequate to adjust the GCM data than multiplicative change factors. Also, note that using any of the approaches suggested for step (v) one ends with a set of monthly sequences of daily data, that then need to be concatenated together to form an yearly series. This may require some smoothing at the days nearest to the beginning / end of the months.

2.2.3. Statistical downscaling models

Statistical downscaling models (SDMs) are in principle a more powerful tool than delta changes, with the potential of yielding more realistic results because they should capture more of the physical relationships at work between local and global climate.

SDMs rely on the fundamental concept that regional or local climate strongly depends on larger scale atmospheric variables, such as mean sea level pressure, geopotential height, wind fields, humidity, and temperature. These relationships can be expressed as deterministic and/or stochastic functions of the large-scale atmospheric variables (predictors) and regional or local climate variables (predictands) like temperature.

Perhaps the main weakness of the SDM approach is that, although less demanding on computational resources and requiring less specialized training than RCMS, they still can be very time consuming when applying it to many sites – such as a set of meteorological stations or at the knots of a grid covering the area of study. Another problem with SDMs is that it is difficult to obtain the meaning and sometimes the actual values of the model parameters, i.e. its transparency is often low.

There are several SDM methods and approaches that can be used to generate climate change scenarios at a local scale. Without going too deep in this subject, it can be said that there are three categories of SDM methods:

(i) weather pattern classification schemes;

(ii) regression models and

(iii) weather generators.

In the first category weather patterns are grouped according to their similarity and the predictand is then assigned to the prevailing weather state, and replicated under climate changed conditions (Corte-Real et al., 1999). Regression models include linear and non-linear relationships between predictands and large scale atmospheric forcing, like multiple regression, canonical correlation analysis and artificial neural networks. Finally, weather generators are simple stochastic models that replicate the statistical attributes of local climate and are used for downscaling by conditioning their parameters on large-scale atmospheric predictors, weather states or some statistical properties of the data (Semenov and Barrow, 1997).

To get a better understanding of the value of the various methods, consider the following examples. Huth et al. (2008), compared linear and non-linear methods for winter daily temperature at eight European stations. The linear methods were represented by linear regressions and the non-linear methods by artificial neural networks. The results showed that linear regressions appear to be the best method, but neural networks showed better results when representing extreme or abnormal events. Another study conducted by Dibike and Coulibaly (2006), tested the use of temporal neural networks for downscaling daily precipitation and temperature, analyzing extremes in northern Quebec, Canada. In this case, the temporal neuronal network generally outperformed other statistical models, but again and especially when representing extreme precipitation and time series variability.

While comparison studies for specific places, such as those mentioned above, can show that some methods can be better than others when representing climate variability and extremes, such a ranking of methods is however not valid for all situations. An inter-comparison study between Multiple Linear Regression, Canonical Correlation Analysis and Artificial Neural Networks approaches developed by Kostopoulou et al. (2007), for minimum and maximum temperature in Greece, showed that all methods tends to reproduce better the maximum temperature during the cool season, while minimum temperature was overestimated. During the warm season the minimum temperature was better represented while the maximum temperature presented greater divergences. But the most important conclusion to draw from the study was that none of the methods was found clearly superior to the others.

Statistical downscaling methods are continually evolving towards better reproduction of climate variability and extremes. For example, Vrac et al. (2007) have recently presented a new statistical downscaling approach combining large-scale upper-air circulation with surface precipitation fields, based on a non-homogeneous stochastic weather pattern classification scheme. The method combines two different types of weather states; precipitation patterns and circulation patterns, improving important precipitation features like local rainfall intensities and wet/dry spell behaviour.

2.2.4. Implementing a statistical downscaling model approach

The application of SDM methods presupposes some *a priori* knowledge of the relationship between local-climate and large scale atmospheric processes, in particular for selecting the best predictors from

GCMs. Even when a modeller has at hand (say embedded in software) statistical tools that help in this task, experience and knowledge of meteorology and of local climatology should be obtained by the modeller to get sensible results.

Selecting the proper grid-box from a GCM, for establishing predictor-predictand relationships, can also present difficulties. For example, if the location is near the border of various grid-boxes of the GCM used, or also near e.g. an ocean, or a high mountain range, it is not at all obvious which GCM grid-box should be chosen to supply the scenario data. Take for instance the case of ocean / land complex interface for a station located at an estuary. The closest grid-box is not necessarily the best one, as the ocean areas display higher wind speeds and very small thermal amplitudes compared with adjacent land areas.

In conclusion, there seem to be no determined rules for selecting predictor-predictand relationships and the more adequate GCM grid-boxes: at the end of the day it will require an expert judgment taking into account knowledge of meteorology in general, of the GCM characteristics, of local terrain, regional weather patterns and microclimatic variability.

There are several free statistical downscaling tools available for download on the internet but few offer a Graphical User Interface. For those not familiar with computer programming languages a Graphical User Interface comes in handy and helps in getting the job done almost intuitively. Nevertheless, it is fundamental to have some knowledge on statistics in order to select the best methods and the best predictor-predictand relationships. We will explore three of these statistical downscaling tools.

Developed by Masoud Hessami, in collaboration with the INRS-ETE and the Environmental Canada, the Automated Statistical Downscaling (ASD) software is a hybrid of stochastic weather generator and regression-based downscaling methods that generates single-site scenarios of surface weather variables under current and future climate forcing (e.g. Hessami et al., 2008). This tool runs on all platforms that support MATLAB and is available for download, after registration, at the Data Access Integration web site (http://quebec.ccsn.ca). It is also possible to find daily normalized predictor variables for the 1961-2001 period derived from the National Centre of Environmental Prediction (NCEP) reanalysis and the third generation Coupled Global Climate Model (CGCM3), for the SRES A2(4) scenario experiment, developed by the Canadian Centre for Climate Modeling and Analysis (CCCMA).

This ASD software was inspired by SDSM (Statistical DownScaling Model) approach developed by Wilby et al. (2002). SDSM is a decision support tool for assessing local climate change impacts using a robust statistical downscaling technique. But it also performs ancillary tasks of data quality control and transformation, predictor variable pre–screening, automatic model calibration, basic diagnostic testing, statistical analyses and graphing of climate data (Wilby, 2007). This software is also freely available at the SDSM web site (https://co-public.lboro.ac.uk/cocwd/SDSM/), and the statistical downscaling input, such as the HadCM3 predictors for the A2 and B2 scenarios, can be downloaded from the Canadian Climate Change Scenario Network web site (http://www.cccsn.ca). Both format and extensions of the predictors files are compatible with the ASD and SDSM software.

Developed at the Long Ashton Research Station by Mikhail Semenov, LARS-WG is a stochastic weather generator used for simulating weather for a single-site, under both current and future climate conditions. This tool includes a new approach in simulating wet and dry spell lengths, overcoming some limitations of the Markov chain models for precipitation occurrence (Richardson, 1981). Instead of the predictor-predictand relationship, LARS-WG uses climate projections, such as precipitation, minimum temperature and maximum temperature, from GCMs and RCMs. The British Atmospheric Data Centre (BADC) holds the simulations from many models runs from several projects. Of special interest are the results from the Climate Impacts LINK Project (http://badc.nerc.ac.uk/data/link/) containing both RCMs and GCMs climate projections for different emission scenarios of the UK MetOffice Hadley Centre models, processed into text files at the Climate Research Unit of the University of East Anglia.

In Annex II indications for the practical use of SDMs are provided to the reader; in particular, the use of the SDSM and the LARS-WG software tools is explained in detail.

2.3. Downscaling climate scenarios for an entire area

While so far only the case of downscaling climate data for a single location has been discussed, for many studies there will be a need to have data for a certain area, for instance a large city, or a Nature reserve, or a coastal strip.

For some studies gridded data is needed, e.g. to be fed into a Geographical Information System (GIS) that will display the data and/or run some impact model for the entire area. Other times the study only needs to examine what happens in two or more locations as a result of climate change, e.g. impacts at downtown vs. suburban areas in a large metropolitan area, or at a valley site vs. a site upper on a mountain.

Criteria useful for when a decision is to be taken for selecting a downscaling approach are now presented.

A first and very pragmatic criterion is based on time (e.g. Project schedules and deadlines) and resources available (human and computational). When a fast response is required from the “climate team” of a Project – maybe because other teams are waiting for the meteorological data to proceed with other tasks – and/or human and computational resources seem low for the task of downscaling the climate scenario data, in practice the only solution is to resort to the delta change approach.

The second criterion relates to the availability of observed daily data. If the region to be surveyed is known to have marked microclimates, but only one good reference meteorological station exists, with trustable long term records for all the parameters desired, then a SDM approach is again not feasible. It could be said that in this case the delta change method would also fail, but it can handle this situation if climatic maps of monthly data exist. Indeed for many areas these spatial data exists, or it can be generated if necessary, using geostatistical software or simple regression models, often dependent on altitude, type of terrain, and calendar month of the year; also sometimes latitude, distance to coast, etc. for large areas. For example for the particular but important case of wind see the method recommended by EN ISO 15927-1:2003. Therefore when in presence of microclimates the delta change approach can be used, as explained in the previous section, over gridded monthly data, either existence, or developed for the study at hand.

A third criterion relates to the need (or not) for spatial correlation between the data at the various sites, or grid knots. If an impact model is to be run independently for each site or grid knot, spatial correlation is not an issue. If the impact model needs simultaneous inputs from various sites – such as when dealing with water resources, pollens or pollution dispersion by wind, between many examples – the meteorological data at the various sites, or grid knots, should display the type of cross-correlations so often detected in Nature over many kilometres.

If spatial correlation is not needed, then the downscaling approach selected depends just on the available time and resources, in a similar way to the first criterion. As a rule-of-thumb it will be hard and lengthy to handle more than five sites with a SDM approach (the chosen SDM must be calibrated, and validated for each site), and a delta change approach will be preferable – however the actual circumstances will dictate the best solution.

A fourth criterion relates to the importance of uncertainty in future climate for the study where the weather data is to be used. Various GCMs exist, with different sophistication on the mechanisms included, spatial resolution, schemes for numerical solving of the complicated equations involved, etc. This produces a range of predictions for the impacts of global warming on the weather. Furthermore, there are various greenhouse gas emission scenarios (four in the case of SRES, or six if counting the flavours of scenario A1), all equally probable by their very principles of construction. Consider also that many impacts depend on thresholds of weather parameters, thus several time windows should be checked.

The combinations of GCM, emission scenario and time window are thus very numerous. To obtain at least an estimate of the order of magnitude of the uncertainty in an impact study, it is recommended to analyse at least two scenarios, two GCMs and two time windows, thus a minimum of six combinations. Therefore, while if for a certain study the use of SDMs for climate downscaling could be attractive – having passed the first three criteria –, if the role of uncertainty for a study is important (generally it is) the SDMs approach can become too time consuming to be used.

So in conclusion, downscaling climatic scenarios for an area is likely to imply adopting a delta change method approach for technical and practical reasons – even if SDMs as a method would be preferable in theoretical terms. On the other hand, when downscaling climate scenarios for many points (i.e. large area) is needed and when no spatial correlation is needed, it may also be helpful to analyse RCMs since by default they already cover large areas.

2.4. Statistical-dynamical downscaling

Some teams have large resources and expertise on meteorology, so they hold the ability to supply others with high resolution climatic data. For these teams, deciding whether to use a statistical or a dynamical downscaling method to assess climate change scenarios can be challenging. For some areas they can be lead to the conclusion that a dynamic method simply can't be used by lack of adequate data for input, calibration and validation.

When both dynamic and statistic methods can be used because there is enough information to feed them, it is still difficult to select the best one. For instance, an inter-comparison study between statistical and dynamical downscaling for surface temperature in North America published by Spak et al. (2007) showed that the two methods projected similar mean warming over the period 2000-2087 but developed different spatial patterns of temperature across the region. Another inter-comparison study by Diez et al. (2005) of precipitation downscaling over Spain during four seasons did not reach any conclusion on which would be the best method, as results varied depending on the specific season and region.

Also, the IPCC Fourth Assessment Report (2007), quoting results from the European Projects PRUDENCE (dynamical downscaling) and STARDEX (statistical downscaling), remarks that none of the different techniques surveyed was clearly superior: to obtain better results and a quantification of uncertainties, the best way was to use and compare them all. Of course, this is not usually feasible when working on Projects where the main object of research is not climate itself.

In this context of the state-of-the-art, combining statistical and dynamical methods has become a priority for the next generation of climate downscaling methods. Projects like ENSEMBLES, UKCIP08 and NARCCAP are advancing along this path, combining the state-of-the-art, high resolution, global and regional Earth System models, to produce objective probabilistic estimates of future climates.

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Annex I. Obtaining baseline and future scenario climatic data

AI.1. Obtaining baseline meteorological data

The possibility of using statistical downscaling methods and the particular approach used in downscaling strongly depends on the available local meteorological data quantity and quality. Getting some decades of daily precipitation and temperature data for a certain reference meteorological station is often no easy task, but is indispensable for model calibration and validation. If available, other data such as humidity, wind, or solar radiation can be used to improve the climate scenarios.

Usually model calibration is done with thirty years of daily meteorological records, often from 1960 to 1990. Most of the observed predictors for model calibration also correspond to the 1960-1990 period allowing the establishment of the predictor-predictand relationships that provide the basis for producing climate change scenarios when using statistical downscaling models.

Also very important are the model validation steps that will check if, for the reference meteorological station, the predictor-predictand relationship is well represented or not. For this purpose it is necessary to use additional independent meteorological records: usually ten years' data from a period not used in the model calibration, e.g. 1951-1960 or 1991-2000.

Local climate data can often be obtained from national meteorological institutes, but other institutions hold valuable weather data, including airbases, universities, public laboratories, governmental bodies in charge of water resources, forests, agriculture, air quality, etc. Although it is becoming more frequent to have that information freely available online, in many cases one must expect that a payment will be asked for, at least for covering data processing costs.

Another way to assess useful climatic data is by way of international data centres. The European Climate Assessment & Dataset (ECA&D) holds daily climate data from meteorological stations for Europe and the data are freely available for download at the ECA&D web site (http://eca.knmi.nl/). The World Data Center for Climate (WDCC) and the British Atmospheric Data Centre (BADC) also hold available observed climate data, gathered from several European and international research Projects.

AI.2. Obtaining climatic data for future scenarios

Since the Third IPCC Assessment Report in 2001 a growing number of projects where conducted to determine the impact of climate change at a regional and local scale. One example is Project PRUDENCE (Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects). It is part of a co-operative cluster of projects exploring future changes in extreme events in response to global warming, together with Projects STARDEX (STAtistical and Regional Downscaling of EXtremes) and MICE (Modelling the Impact of Climate Extremes). The simulation results from different model runs of seasonal, monthly and daily datasets for the A2 and B2 scenario and for the period of 2070 to 2100 can be downloaded from the PRUDENCE web page (http://prudence.dmi.dk/). The files are in the NetCDF (network Common Data Form) format, wich is a set of interfaces for array-oriented data access and a freely-distributed collection of data access libraries for C, Fortran, C++, Java, and other languages.

The North American Regional Climate Change Assessment Program (NARCCAP) is also producing high resolution climate change scenarios for the United States, Canada, and northern Mexico, investigating uncertainties in regional scale projections of future climate. After registration, is possible to download the simulation results (A2 scenario from 2041 to 2070 with 50 km spatial resolution) from the Earth System Grid web page (www.earthsystemgrid.org). The access requirements are described at the NARCCAP web page (www.narccap.ucar.edu/data/access.html).

Annex II. Using statistical downscaling models

In this section the main steps on how to use statistical downscaling tools SDSM and LARS-WG will be described. As mentioned in the main text, both methods offer a Graphical User Interface and are freely available at their respective websites: SDSM at https://co-public.lboro.ac.uk/cocwd/SDSM/ and LARS-WG at http://www.rothamsted.bbsrc.ac.uk/mas-models/larswg.php.

The procedures detailed below were tested in practice using a data set consisting of observed daily precipitation, maximum temperature and minimum temperature for Lisbon, recorded by the meteorological station with the World Meteorological Organization (WMO) ID 08535. The data was downloaded from the ECA&D web site. The GCM chosen was the coupled atmosphere-ocean HadCM3 developed by the Hadley Centre, with a horizontal resolution of 2.5 degrees of latitude and 3.75 degrees of longitude, producing a global grid of 96 x 73 grid cells. This state-of-the-art GCM meets the following stringent IPCC criteria (IPCC, 2001):

- fully coupled 3D ocean-atmosphere model;
- extensively documented in the peer reviewed literature;
- has performed a multi-century control run (stability check);
- has participated in CMIP2 (Second Coupled Model Intercomparison Project);
- has performed a 2 x CO2 mixed layer run;
- has participated in AMIP (Atmospheric Model Intercomparison Project);
- has a resolution of at least T40, R30 or 3º latitude x 3º longitude, and
- explicitly considers greenhouse gases (CO_2, CH_4, etc.).

AII.1. LARS-WG: a stochastic weather generator

LARS-WG uses GCMs climate projections to create scenarios. For the HadCM3 GCM these files are available for download at British Atmospheric Data Centre, in the Climate Impacts LINK Project, processed into text files at the Climate Research Unit (CRU) at the University of East Anglia.

Daily, monthly and seasonal climate projections for precipitation, minimum temperature and maximum temperature are available. These files contain global information for the knot of a 2.5° latitude by 3.75° longitude grid, as described at the IPCC website (http://www.ipcc-data.org/sres/hadcm3_grid.html). They are written so that each complete record contains 10 values with 8 digits and two decimal places (FORTRAN format 10f8.2). For example, in the daily datasets each day is represented by 7008 values that correspond to a 96 x 73 grid. For instance, to retrieve a grid box for Portugal, column 95 and row 21 will correspond to 352.5º E longitude and 40.0º N latitude and to grid box number 2015. In the files processed by the CRU one would thus count all data from left to right until reaching the datum number 2015.

Before attempting to use the LARS-WG an obvious recommendation is to read the user manual also available at the LARS-WG web site.

LARS-WG can generate synthetic datasets of precipitation, minimum and maximum temperature and solar radiation based only on one year of observed weather. However, it is recommended to have 20 or 30 years of daily climate data in order to correctly capture climate variability and seasonality. This process can be divided in three distinct steps: (i) site analysis; (ii) model validation and (iii) generation of synthetic weather data.

AII.1.1. Site Analysis

After having obtained all the required input data, viz. observed and future climate datasets, site analysis is the first step to construct climate change scenarios. Note that to generate solar radiation and minimum / maximum temperatures, LARS-WG will need precipitation data. The geographical coordinates of the meteorological station and of the centre of the adequate GCM grid box enclosing the area where the station is located will be needed as input. It is also required to input the altitude; note that for the GCM it is represented with a missing value, coded -99.0.

LARS-WG will then check for errors, like minimum temperature higher than maximum temperature limits and negative precipitation values. It will then process the weather data and generate a file with its statistical characteristics. This step has to be performed for the observed period, for the GCM baseline period (usually 1960-1990) and for the GCM future scenario (e.g., 2040-269 to represent the 2050s).

AII.1.2. Model validation

Model validation, viz. assessing how well the model performs when simulating the climate at a given site, is indispensable to in order to determine whether improvements are still needed or if it is already suitable for use.

LARS-WG offers two ways to perform model validation: (i) generating synthetic daily weather data (using the GENERATOR option) and statistically compare them with daily records, or (ii) using the QTest option.

The QTest option will temporarily generate synthetic weather data and compare the probability distributions for the synthetic and observed data using the Chi-square goodness-of-fit test; and compare the synthetic and observed datasets means and standard deviations using the t-test and F-test, respectively.

Model validation therefore must be done carefully. On the one hand, it may happen that by mere chance the observed weather sequence used for validation includes unusual phenomena, meaning trends or fluctuations that are not typical of the climate at the site. On the other hand, the stochastic model can as well randomly produce atypical datasets.

Therefore both the recorded and synthetic data series must be checked and quality controlled. When problems are detected in the synthetic weather data, the stochastic model must be run again. When the problems are at the observed data side, subsets without spurious effects might be extracted from the recorded data pool and the process can be restarted from the site analysis stage.

AII.1.3. Creating climate change scenarios

To incorporate changes in climate variability and generate scenarios it is needed to calculate the relative change between the GCM baseline period and the GCM future scenario. All the parameters for this step are already available from the statistical file created in the site analysis stage for the GCM baseline and future time periods. Section 3.3.1 of the LARS-WG user manual describes how to calculate the required statistics: relative change in wet and dry series length; relative change in mean temperature standard deviation for each month; and mean changes in precipitation amount, mean temperature and solar radiation for each month.

This information is then applied much like in the delta change approach, only they are applied to the weather generator parameters rather than directly to the time series. The changes in mean temperature and solar radiation are additive changes, and changes in monthly precipitation, length of the wet and dry spells and standard deviation of temperature are multiplicative. For example, say, if the wet spell relative change in August is 1.71, the length of the wet spells produced by LARS-WG for August will be multiplied by 1.71 when creating the future climate synthetic datasets.

AII.1.4. Summary statistics for Lisbon using the A2a SRES scenario

As an example, the figures 6 to 11 summarizes some results for one meteorological station in Lisbon – Portugal using LARS-WG tool, based on the data from the GCM HadCM3 processed by the Climate Research Unit of the Hadley Centre.

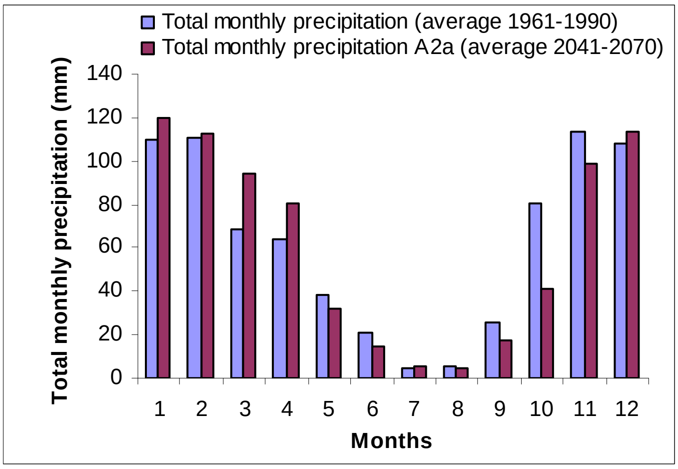

Fig. 6 - Total monthly precipitation over the period 1961-1990 and 2041-2070

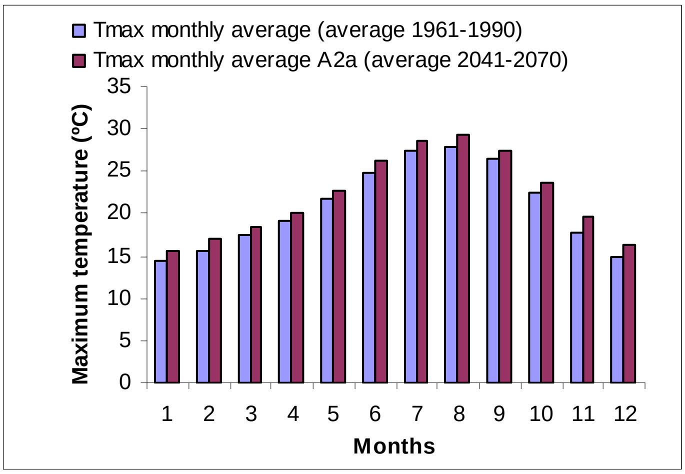

Fig. 7 – Maximum temperature over the period 1961-1990 and 2041-2070

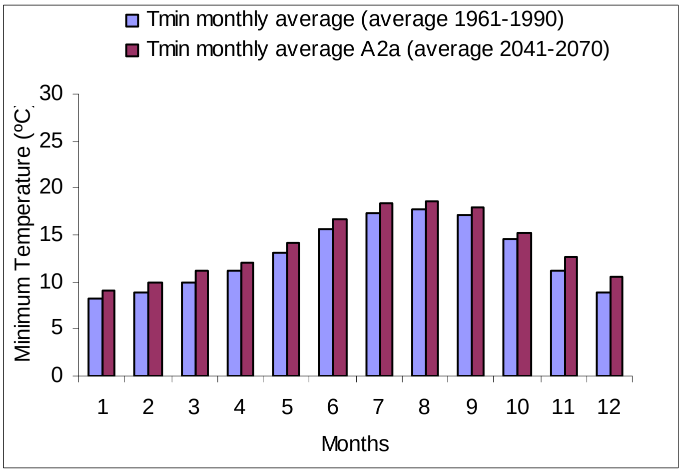

Fig. 8 – Minimum temperature over the period 1961-1990 and 2041-2070

Figure 6 to 8 compares the total monthly precipitation and the monthly average of minimum and maximum temperature between 1960-1990 and 2041-2060 to represent the climate of the 1970s and the 2050s, respectively. For precipitation the results show that the monthly distribution can change, increasing between January and March and decreasing between September and November. On the other hand, temperature shows a slightly, but not significant, increase in all months.

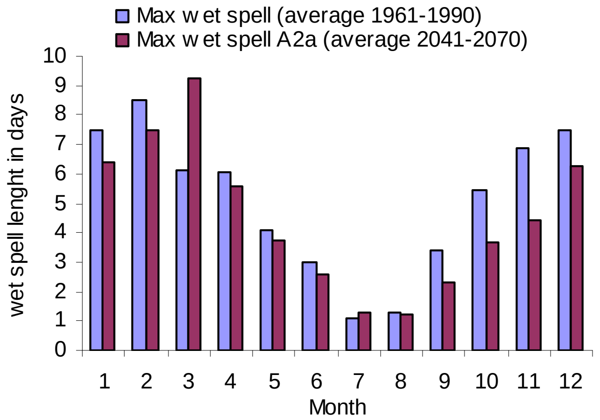

Fig. 9 – Maximum wet spell length in days over the period 1961-1990 and 2041-2070

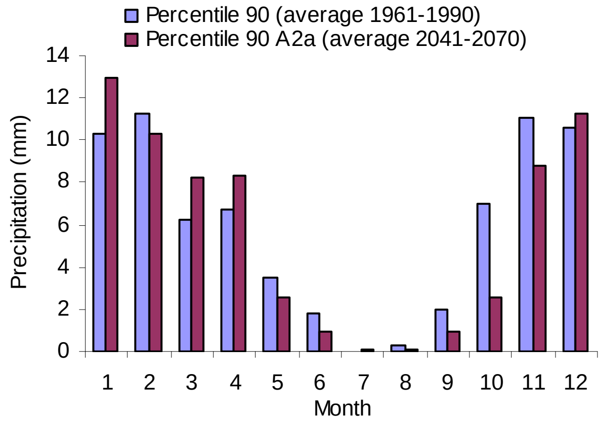

Fig. 10 – Precipitation 90th percentile over the period 1961-1990 and 2041-2070

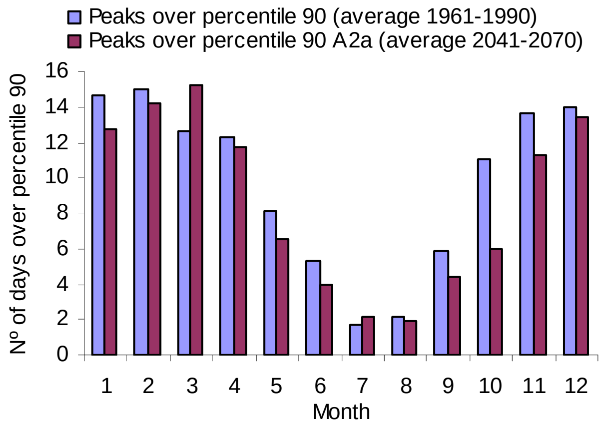

Fig. 11 – Number of days over the 90th percentile over the period 1961-1990 and 2041-2070 for precipitation

Figures 9 to 11 shows more detailed information about the monthly behaviour of precipitation. For example if the total monthly precipitation for January increases in the A2a scenario and the maximum wet spell decreases, this means that we will have more rain concentrated in fewer days. These results can also be analysed when looking at the monthly 90th percentile (figure 10) and the number of days over that value (figure 11).

This general information is very important when analysing extreme events in future scenarios and can be used to support policy making on mitigation and adaptation measures to climate change.

AII.2. SDSM: a multi-regression model

Hereafter the main processes involved when using SDSM 4.2 software will be described. Again it is of course recommended to read the respective user manual (Wilby and Dawson, 2007) available at the SDSM web site.

SDSM reduces the task of statistically downscaling weather series into seven discrete steps, but for the current document they are grouped in five steps: (i) quality control and data transformation; (ii) screening of predictor variables; (iii) model calibration; (iv) weather generation and analysis of the observed data; and (v) scenario generation from GCM predictors.

SDSM also uses predictors, such as mean sea level pressure and geopotential height. These data can be downloaded from the NCEP / NCAR reanalysis project from the respective website address (http://www.cdc.noaa.gov/cdc/data.ncep.reanalysis.html). Also, pre-prepared predictor datasets for many cases can be downloaded from the Canadian Climate Change Network (http://www.ccsn.ca/), although only for the A2 and B2 SRES scenarios. These datasets are also derived from the mentioned NCEP / NCAR reanalysis but they where firstly interpolated to the same grid used by HadCM3 and then computed over the entire 1961-1990 period.

AII.2.1. Quality control and data transformation

During this step SDSM checks for missing data and outliers. It is also possible to transform data files to make them more adequate for modelling. For instance if a data set includes many zero values as well as large values, a logarithmic transformation is often useful. Other available transformations include for instance power functions, inversing, introducing lags, etc.

AII.2.2. Screening of downscaling predictor variables

At this is very important – but also very time consuming – step, the relationships between predictors and a single site predictand are established, assisting the user in the choice of appropriate variables for model calibration.

In a first step the user selects a seasonal subset to establish the predictor-predictand seasonal relationship. This is based on knowledge of local weather and on the inter-month variability characteristics.

At a second step, the type of predictor-predictand process must be specified. If the predictand is not regulated by an intermediate process, as in the case of minimum and maximum temperatures, the “unconditional” process type should be selected. Otherwise the “conditional” process is selected – e.g. it is the case with precipitation, where precipitation amounts depend first on the occurrence of a wet day.

At a third step, the significance of the predictor-predictand correlations is tested, at the confidence level desired (default value 95%, i.e. significance level $p < 0.05$).

Finally, it is possible to include an autoregressive term. Positive autocorrelation of lag one or more days is frequent in weather data. Including this feature the predictor-predictand relationship can be much improved.

The SDSM software can produce correlation matrices and scatter plots that help the user to choose the best predictors.

AII.2.3. Model calibration

After selecting the most suitable predictor variables, SDSM is then able to assemble a downscaling model based on multiple regression equations. SDSM can also use two methods to optimize the model, either dual simplex or ordinary least squares. These options are available at the "Advanced settings" panel.

A typical sequence of steps for obtaining an adequate calibration proceeds as follows. The monthly temporal resolution is selected, meaning that the model will generate sequences for each month using different model parameters. Then the unconditional processes are selected for minimum and maximum temperature, and a conditional process for precipitation. For model validation, scatter plots are made of the residuals versus the explanatory variable, as well as a quantile-quantile (Q-Q) plot. SDSM outputs a statistical file with the calibration results, showing R-squared, standard errors and the Durbin-Watson statistic for each month. It is important to check the normality, homogeneity and independence assumptions. In the scatter plots the goal is to have the spread of the residuals versus fitted values uniformly distributed and with no patterns: this means that, respectively, the homogeneity and independency assumptions are supported by the data. To double-check the independence assumption is also possible to compute the autocorrelation function. The normality assumption can be validated using the Q-Q plot: if the graph shows a straight line, this assumption is validated.

If the results of the model calibration are not satisfactory, the screening of downscaling predictor variables is restarted and new predictor variables must be chosen.

AII.2.4. Weather generator and analysis of observed data

The "weather generator" feature produces synthetic time series, representative of the climate conditions. At this stage it is possible to validate the models by comparing the synthetic series with an independent dataset of observed data.

SDSM offers a complete package of statistics and model validation tools to help the user to improve and validate the predictor-predictand relationship: for instance, averages, maxima and minima, variance, peaks above/below thresholds, percentiles, percent wet days, and lengths of wet/dry day spells.

AII.2.5. Future scenario generation using GCM predictors

While until this phase the NCEP reanalysis predictors were used, to build and validate the model that establishes the predictor-predictand relationships. For generating weather sequences for future climate scenarios the NCEP predictors are just replaced with the GCM predictors and use the "scenario generator" feature is used. Using it is very similar to using the "weather generator" feature, but depending on the GCM chosen it may be necessary to make some adjustments. For example the year length – which for many GCMs is 360 days (12 months of 30 days each), not 365 days – can be adjusted at the "settings" menu.

AII.2.6. Summary statistics for Lisbon using the A2a SRES scenario

As an example, the figures 12 to 17 summarize some results for one meteorological station in Lisbon – Portugal using SDSM tool based on the data from the GCM HadCM3 from the Canadian Climate Change Scenarios Network.

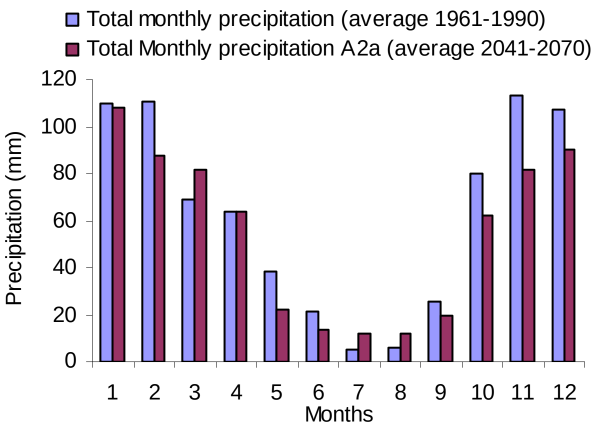

Fig. 12 – Total precipitation over the period 1961-1990 and 2041-2070

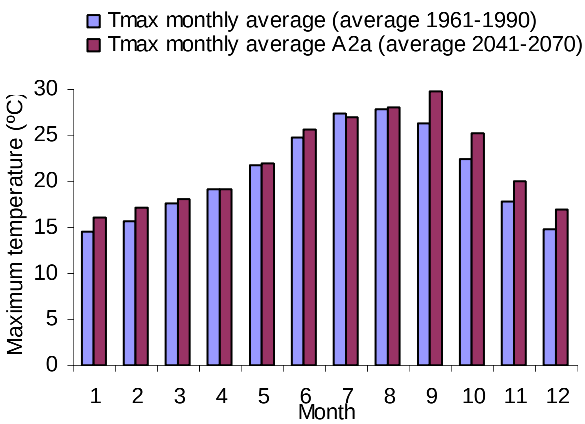

Fig. 13 – Minimum temperature over the period 1961-1990 and 2041-2070

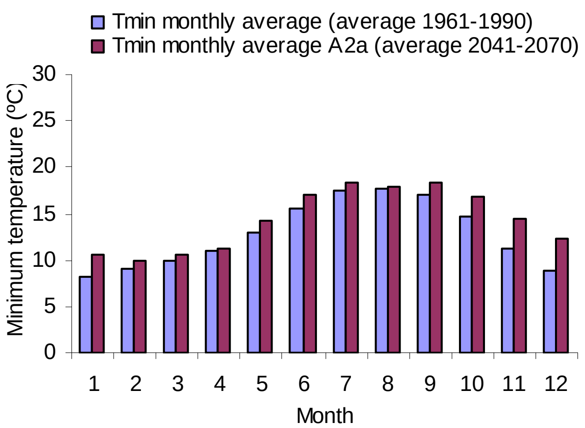

Fig. 14 – Maximum temperature over the period 1961-1990 and 2041-2070

Figure 12 to 14 compares the total monthly precipitation and the monthly average of minimum and maximum temperature between 1960-1990 and 2041-2060 to represent the climate of the 1970s and the 2050s, respectively. For precipitation the results show that the monthly distribution can change, decreasing between September and December. The analysis of the minimum and maximum temperature shows that in the A2a scenario is possible to have a slight increase in temperature between November and December.

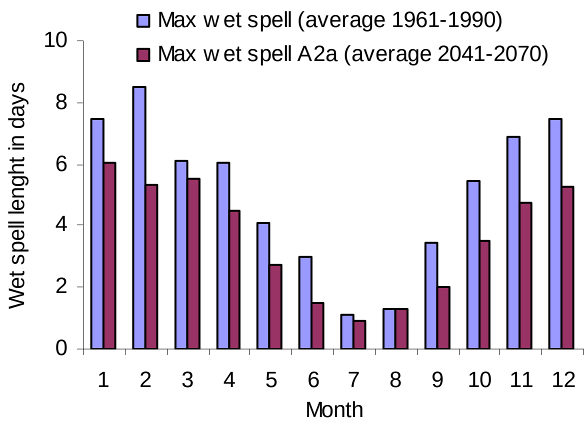

Fig. 15 – Maximum wet spell length in days over the period 1961-1990 and 2041-2070

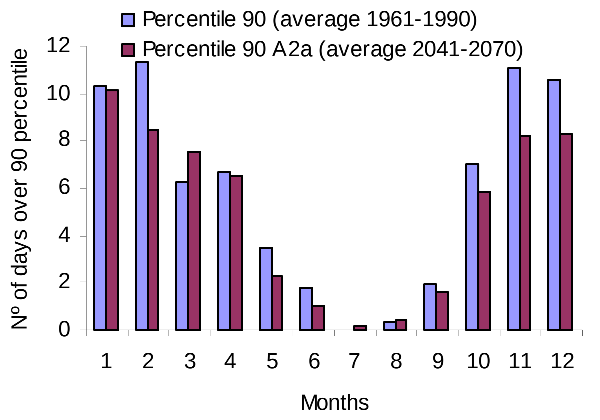

Fig. 16 – Precipitation 90th percentile over the period 1961-1990 and 2041-2070

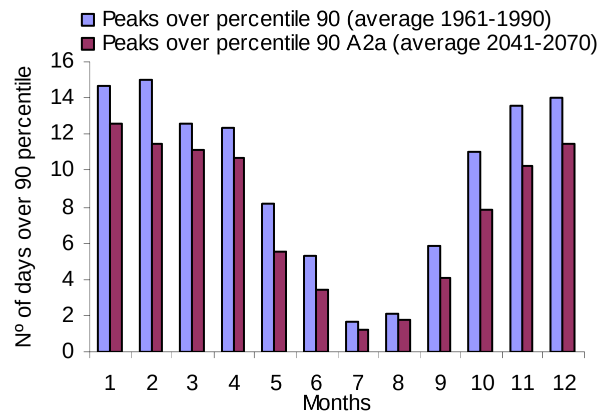

Fig. 17 – Number of days over the 90th percentile over the period 1961-1990 and 2041-2070

The analysis of the figures 15 to 17 clearly shows a decrease for all months of the wet spell length and the number of events over the 90th percentile for the A2a scenario indicating more rain in short periods.

Both the LARS-WG and the SDM tool generate several assembles of data and the results can slightly different depending on witch assemble we are analysing. The overall result doesn't change much, especially when using some of the statistical analysis indices to evaluate extremes from the STARDEX European project.

It is also important to be critical about the results and if possible compare multiple GCMs runs and multiple downscaling methods.