Bioclim

2003

Deliverable D8b :

Development of the physical/statistical downscaling methodology and application to climate model CLIMBER for BIOCLIM Workpackage 3.

Modelling Sequential Biosphere Systems under Climate Change for Radioactive Waste Disposal

EC-CONTRACT : FIKW-CT-2000-00024

Work package 3: Simulation of the future evolution of the biosphere system using the hierarchical strategy

Foreword

The BIOCLIM project on modelling sequential BIOsphere systems under CLIMate change for radioactive waste disposal is part of the EURATOM fifth European framework programme. The project was launched in October 2000 for a three-year period. The project aims at providing a scientific basis and practical methodology for assessing the possible long term impacts on the safety of radioactive waste repositories in deep formations due to climate and environmental change. Five work packages have been identified to fulfil the project objectives:

Work package 1 will consolidate the needs of the European agencies of the consortium and summarise how environmental change has been treated to date in performance assessments.

Work packages 2 and 3 will develop two innovative and complementary strategies for representing time series of long term climate change using different methods to analyse extreme climate conditions (the hierarchical strategy) and a continuous climate simulation over more than the next glacial-interglacial cycle (the integrated strategy).

Work package 4 will explore and evaluate the potential effects of climate change on the nature of the biosphere systems.

Work package 5 will disseminate information on the results obtained from the three year project among the international community for further use.

The project brings together a number of representatives from both European radioactive waste management organisations which have national responsibilities for the safe disposal of radioactive waste, either as disposers or regulators, and several highly experienced climate research teams, which are listed below.

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- United Kingdom Nirex Limited (NIREX), UK – **P. Degnan**
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For this report, deliverable D8b of the BIOCLIM project, the main contributor is the climate modelling group of the CEA/LSCE.

Public should be aware that BIOCLIM material is working material.

Content List

1. Introduction and objectives

The overall aim of BIOCLIM is to assess the possible long term impacts due to climate change on the safety of radioactive waste repositories in deep formations. This aim is addressed through the following specific objectives:

- Development of practical and innovative strategies for representing sequential climatic changes to the geosphere-biosphere system for existing sites over central Europe, addressing the timescale of one million years, which is relevant to the geological disposal of radioactive waste.
- Exploration and evaluation of the potential effects of climate change on the nature of the biosphere systems used to assess the environmental impact.
- Dissemination of information on the new methodologies and the results obtained from the project among the international waste management community for use in performance assessments of potential or planned radioactive waste repositories.

This deliverable has the following specific motivations and objectives:

Its main aim is to provide time series of climatic variables at the high resolution as needed by performance assessment (PA) of radioactive waste repositories, on the basis of coarse output from the CLIMBER-GREMLINS climate model.

The climatological variables studied here are long-term (monthly) mean temperature and precipitation, as these are the main variables of interest for performance assessment (see Ref.1, section 3.2). CLIMBER-GREMLINS is an earth-system model of intermediate complexity (EMIC), designed for long climate simulations (glacial cycles). Thus, this model has a coarse resolution (about 50 degrees in longitude) and other limitations which are sketched in this report (further details are provided in Ref.2). For the purpose of performance assessment, the climatological variables are required at scales pertinent for the knowledge of the conditions at the depository site. In this work, the final resolution is that of the best available global gridded present-day climatology, which is 1/6 degree in both longitude and latitude (this will be called “regional scale” here, although it is a reasonable approximation of local (site) temperature and precipitation when there is no complex local topography).

To obtain climate-change information at this high resolution on the basis of the climate model outputs, a 2-step downscaling method is designed. First, physical considerations are used to define variables which are expected to have links which climatological values (i.e. predictors, such as continentality); secondly a statistical model is used to find the links between these variables and the high-resolution climatology of temperature and precipitation. Thus the method is termed as “physical/statistical” : it involves physically based assumptions to compute predictors from model variables and then relies on statistics to find empirical links between these predictors and the climatology.

The simple connection of coarse model results to regional values can not be done on a purely empirical way because the model does not provide enough information – it is both too coarse and simplified. This is why we first need to find these “physically based” relations between large scale model outputs and regional scale predictors. This is a solution to the specific problem of downscaling from an intermediate complexity model such as CLIMBER. There are several other types of downscaling methodologies, such has the dynamical (model) and rule-based method presented in other BIOCLIM deliverables. A specificity of the present method is to attempt to use physical considerations in the downscaling while a detailed “dynamical” approach is out of reach because

CLIMBER only (or mainly) provides the average climate. By contrast, an input of time-variability at various scales (preferably up to meteorological events) is necessary for a more dynamical approach (see e.g. Ref.3 ; Ref.4).

This report is organised as follows:

Section 2 relates to the design and validation of the method, while section 3 reports the application to BIOCLIM simulations. We first present the employed data sources, which are the model results and the observed climatology (subsection 2.1). We then present the principles of the downscaling method (2.2), the formulation of the predictors (2.3) and the calibration of the statistical model, including results for the last glacial maximum (2.4). In section 3, the results are first presented as time series for each site (3.1), then as maps at specific times, or snapshots (3.2).

2. CLIMBER outputs and the downscaling issue

2.1. - Basic data

2.1.1. - Climatology

Climatological data is a key element in this work, because it will be used to statistically estimate the parameters of the empirical part of our method. These high resolution observation-based data will also serve as a guide to find which kind of «physical information» we may want to add to coarse climate model outputs in order to provide regional details, as it will appear later. As the CLIMBER model itself does not represent day to day variability nor year to year changes, we seek a monthly climatology. We need at least precipitation and temperature on land areas, at a high spatial resolution. This is conveniently provided by the recent, 10' resolution (1/6 degree) global gridded climatology from the Climate Research Unit [Ref.5], which proved more trustworthy than formerly available data (during our preliminary tests). The corresponding temperatures for January and July are plotted on figure 1. The resolution of that dataset will be the target resolution of our downscaling, i.e. all our data will be computed or interpolated on that grid.

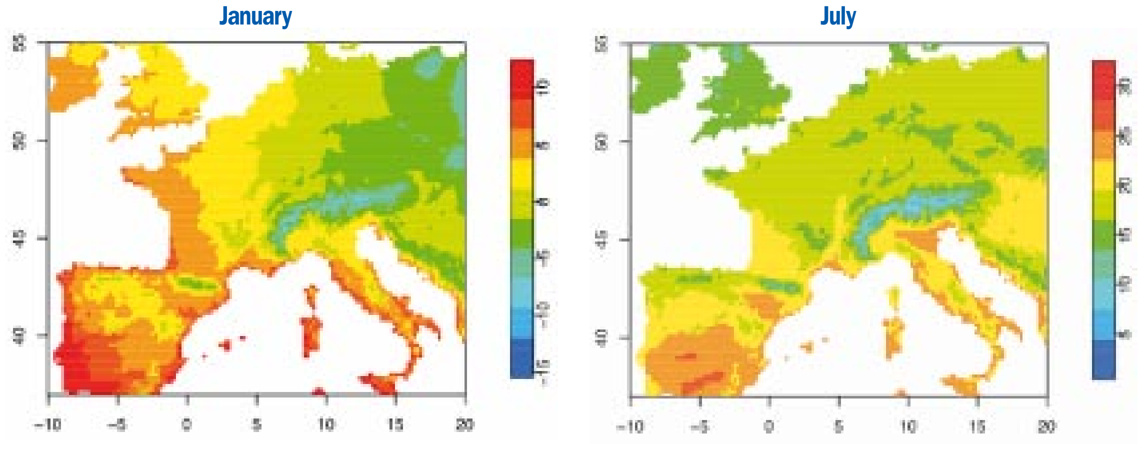


Figure 1 : Monthly mean temperature climatology (CRU 10' data, see text)

2.1.2. - CLIMBER model

The climate model, CLIMBER2.3 [Ref.6] is described in deliverable D7 (Ref.2, section 2.1.2). It has a coarse longitudinal-latitudinal grid: each atmospheric grid box is 51° in longitude and 10° in latitude. Also important for our application, it is an "intermediate complexity model": with comparison to 3D general circulation models, it includes less explicit representations of atmospheric features, thus relying on more parametrisations. In particular, it doesn't represent mid-latitude low pressure systems, but accounts for their effects on the meridional heat transport. Thus it ignores the variability at the time scale of meteorological events (e.g. winds associated with low pressure systems) and also at the time scale of a few years, in particular the North Atlantic Oscillation (NAO).

Our domain of interest is entirely covered by the longitudinal sector 2 in CLIMBER's atmosphere. Surface-air temperature for this sector are shown on figure (upper panels). Here, the model data for the sector which covers the domain are simply linearly interpolated in the meridional direction. It might be desirable to try interpolating CLIMBER outputs in the zonal direction too, i.e. using data from the sectors 1 and 3. The result of this 2-dimensional (2D) interpolation between the centres of CLIMBER meshes is shown in figure , bottom panels. However, sector 1 is above the Atlantic Ocean, while sector 3 has a high surface altitude because it include the Himalayas. The 2D interpolation seems to provide a somewhat more realistic field, in particular because it is likely including a continental effect, i.e. with warmer air above ocean than above inner land areas in winter and the opposite in summer. But it must be remembered that this interpolation is done between sectors which differ largely from the one we are interested about – i.e. we focus on land, not sea, and not at the mean altitude of the Himalayas. It thus remains unclear whether this 2D interpolation would provide a better input temperature for our downscaling work. A solution might be to use temperatures from the free atmosphere rather than surface, but if we don't take model surface temperature, it would seem logical to represent the effect of various surface and vegetation types inside the downscaling method : this might be an attractive perspective, but it goes beyond the scope of the present study. More importantly, the fact that the 2D interpolated field includes a "continentality" effect may conflict with the representation of that effect in the downscaling approach, as explained below.

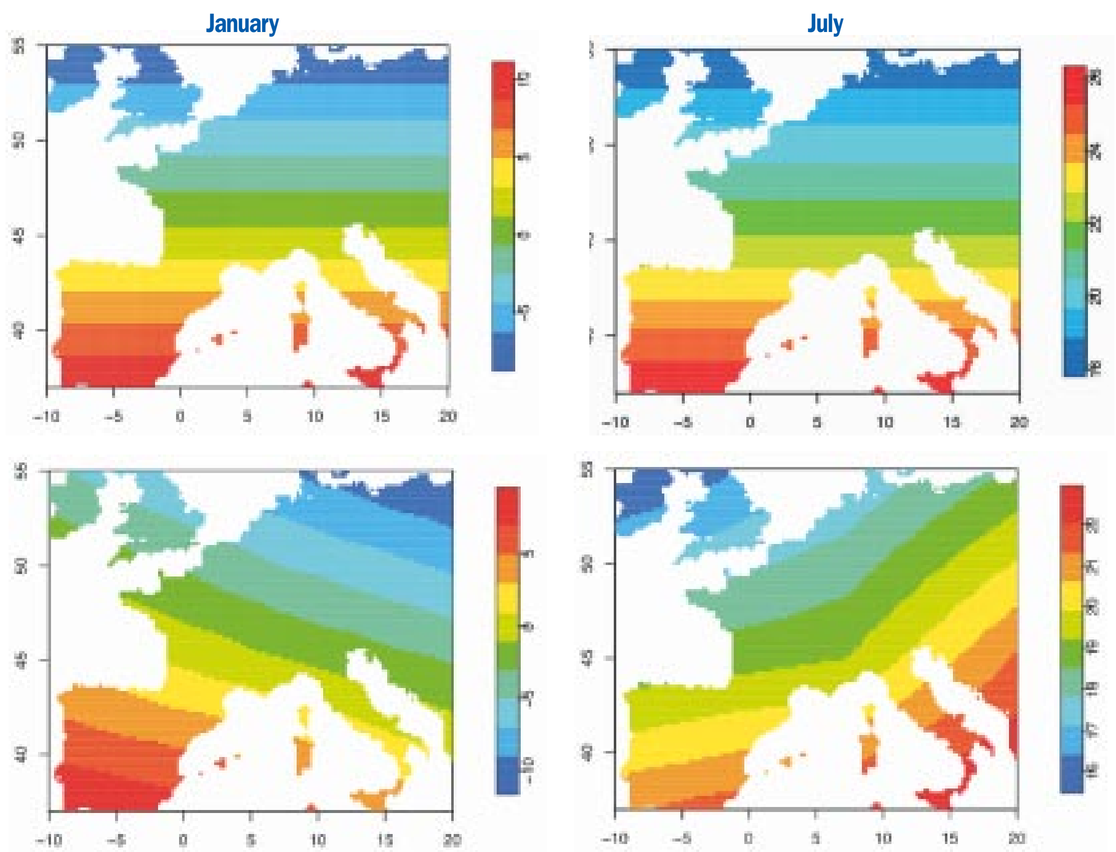


Figure 2 : *CLIMBER model surface air temperature. Top : model sector 2 only (with meridional linear interpolation). Bottom : 2D linear interpolation.*

2.2. - Physical-statistical method principles

As described above, there are much more details in the real climatology than in our model data, at various geographical scales. Some statistical approaches rely on an essentially empirical method to connect the coarse model results to high resolution variables. But these methods usually take model inputs which contain more information than what we can obtain from an EMIC such as CLIMBER. When large-scale meteorological conditions are known, these can be connected to regional patterns of precipitation and temperature on a either a statistical basis (empirical approach, see e.g. Ref.7) or a dynamical basis (model or desaggregation scheme, see e.g. Ref.4). But in the context of this climate model, we only have monthly climatological means. On the other hand, observed data of good quality on most of Europe are only available for present-day conditions. In summary we have little information on time variability at all scales, from meteorological to climate state changes.

In this context, trying to connect regional temperature and precipitation to large scale information using only statistics would have severe limitations : we don't have enough data to calibrate empirical relations in a way which could be reliably applied to climate change on long periods. Our aim is than to find "physically based" relations between regional and large scales which might supplement the statistical approach. These relations have to be robust, i.e. be independent of the climate state (past, present, future). In addition, the relations will provide insight on the climate change issue only if these involve input data for which we know the value at the desired time, such as sea-level or climate model variables.

Before going into the details of these additional physical relations, it is now necessary to introduce the statistical model. The input variables, or predictors, are the data for which climate changes value are known (either directly from the climate model or using additional "physical" hypothesis). The statistical model is thus a link (regression function) between these predictors and the desired output, or predictand - here temperature or precipitation. A quite flexible model is the Generalized Additive Model (GAM), in which the predictand is expressed as a sum of smooth (spline) functions of each predictor, including linear terms if desired :

$$Y = b_0 + b_j X_j + \sum f_j(X_j) + \varepsilon$$

where Y is the predictand, X_j are the predictors, b_o and b_j are constants, f_j are spline functions and ε is the model error.

A very simple statistical model will now illustrate the method and serve as a guide for further development :

$$T = b_0 + f(z_s) + b_T\ \Delta T_M + \overline{T}_M + \varepsilon$$

where T is the high-resolution temperature field, $f(z_s)$ is a smooth function of the land surface height z_s , T_M is the interpolated climate model surface temperature, which is decomposed in its geographical domain[1] -averaged value $\overline{T}_M$ and the deviation from this mean :

$$T_M = \overline{T}_M + \Delta T_M \qquad (3)$$

The deviation from the mean, ΔT_M , mainly represents the meridional temperature gradient from CLIMBER, because this model is very coarse and we use data from only one longitudinal sector, as shown in figure (top panels).

We are thus constructing a regression function relative to the link between land surface height and large-scale temperature gradient from the climate model, and regional temperature on the other hand. The regression function (the spline $f(z_s)$ and the coefficient b_T) is provided by the implementation of the GAM model in the R software [Ref.8].

This regression describes the geographical variability for a given month. As our final objective is climate change downscaling, the regression must also be meaningful in climate change conditions. The first step in this direction is the inclusion of the large scale

[1] The geographical domain is the "domain of interest" shown e.g. on figure 1.

gradient from the climate model : we suggest that changes in the modelled gradient have something "real", i.e. that if the model gives a larger/smaller gradient, it is reasonable that the statistical prediction also involves that change in the gradient. By doing it this way, we assume that the link between CLIMBER's gradient and the high resolution temperature is somewhat robust, i.e. that if the gradient is smaller in the reality than in the climate model, this will also be true, and possibly in the same ratio (the regression coefficient) in a changed climate. As we only have one reference climate state (the present), we have no information about the link between the domain mean temperature in the model and in the reality. Therefore, we can only decide that changes in the mean model temperature are included in the downscaling output; that's why we just add the mean temperature $\overline{T}_M$, which is thus not included in the estimated regression function.

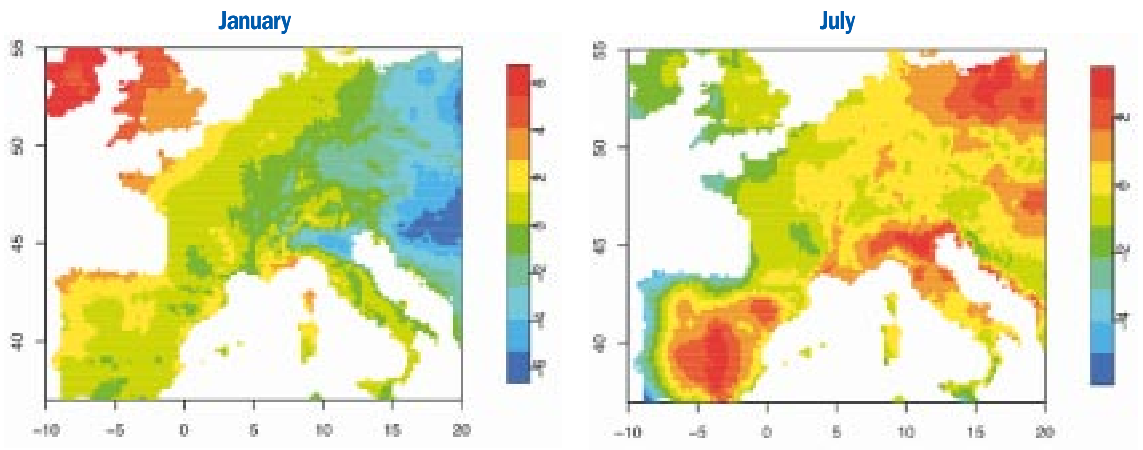


Figure 3 : *Difference between actual surface-air temperature climatology and a very simple regression based solely on topography and coarse climate model temperature.*

It is now interesting to have a look at the ability of our simple regression to represent the actual variance of temperature in the domain. Topography and north-south gradient already explain a substantial part of the geographical variability, so that our regression function produces maps which partly looks like the climatology. The difference between the regression and the actual temperature, i.e. the statistical model error ε, is plotted on figure. These maps reveal the "missing information" in the simple statistical model. The dominant "missing" feature is continentality : in winter, the map shows that to match the climatology, eastern parts of the domain should be colder while western ones should be warmer, and the contrary is seen for summer. The simple regression also lacks other effects, of which some are probably connected with secondary effects of mountain ranges (e.g. the Rhone valley, the Po plain).

2.3. - Physically based predictors

In this section, we try to define physically-sound relations between large and regional large scales to supplement the statistical approach based on climatology. These relations have to be robust, i.e. reliably apply to climate change. The obtained regional variables are meant to be used as inputs of the statistical downscaling model, or predictors.

2.3.1. - Continentality

Continentality is a major feature of geographical climate variability. Continental, eastern Europe has a larger Temperature seasonal cycle (cold winters, hot summers) than coastal regions. Broadly speaking, the temperature variability over land areas is mitigated in regions which receive maritime air more directly and frequently, in connection with cyclonic activity. This also impacts precipitation, with inner continental areas becoming dryer than those more influenced by the seas.

Predictors are computed from climate model outputs. The employed climate model variables must be selected so that these bring pertinent information about climate change, to make the predictor as useful and robust as possible. In the case of continentality computation, possible "input" variables are :

- coast line, which is influenced by sea-level, driven itself by the modelled continental ice amount.
- modelled wind, connected with arrival of air masses over the continent.

Two kinds of "continentality predictors" will be designed in this study. The first one uses the modelled wind to gain some information on how air masses come to the continent, and therefore will be called "advective continentality". As mentioned above (section 2.1.2), CLIMBER does only contain a limited representation of wind, which relates to monthly means and doesn't explicitly include cyclonic and lower scale circulations. In the model, this is supplemented by a representation of mean energy and moisture transport by the non-represented motions. A comparison of these outputs with climatological values suggested that the mean wind is quite correct. As our aim is to gain some information about how and from where air masses are coming to the continent, the "transport" model output seems less interesting, and was not used : it does not tell us much about incoming air masses (e.g. cold air coming from the North as the same effect as warm air coming from the south).

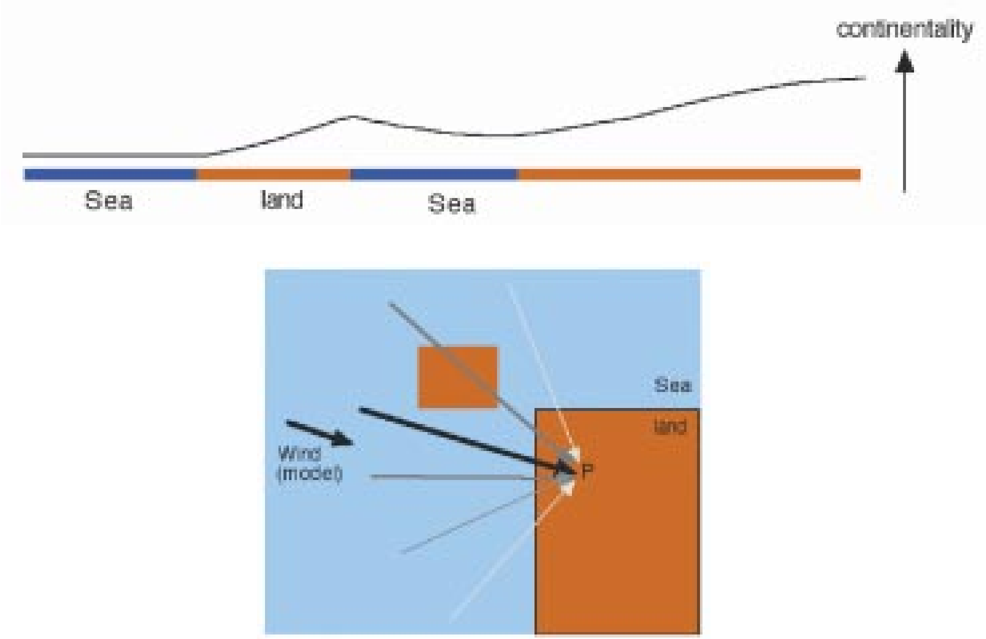


Figure 4 : Principles of continentality computation. Schematic changes in continentality for air masses travelling over sea and land areas (up); Several incoming directions are accounted for, optionally weighting their relative importance in the continentality for a given land point P according to climate model mean wind.

Consider air masses coming from several direction to the land point for which continentality is to be computed (P). Each incoming direction thus have a contribution to overall continentality at P, as sketched on figure . This contribution is calculated using the following assumption : an air mass becomes progressively continental (maritime) as it travels over land (ocean). The rate of this changes towards continental / maritime conditions is assumed to be a constant fraction (τ) per unit time, i.e. the change in continentality during *dt* time is :

$$dC = \left[-C(1-i_{co}) + (1-C)(i_{co})\right]\tau\, dt \quad (4)$$

where

C is the continentality (between 0 = sea limit, 1 = land limit),

i_{co} = 0 over sea, 1 over land

$\tau\, dt = \tau \frac{dx}{dt}\frac{1}{U}dt = \frac{dx/U}{l_0/U_0}\ln(2)$,in which dx is the element of the distance travelled by the air mass during *dt*, U is the mean wind norm (from CLIMBER), l_o/U_o is the distance / wind ratio corresponding to fractional change of 2 of the continentality predictor, currently set to

$$\frac{l_0}{U_0} = \frac{5\ 10^5 m}{5\ m/s}$$

Therefore, the wind speed enters the computation in a first way : due to the fact that the continentality change fraction is constant in time, over a given distance the continentality will change following the inverse of the wind speed (faster wind means less “residence time”, thus less “adjustment” to a given surface type). To complete the computation of continentality at a given point, we must first integrate the continentality change over each “incoming air mass path”,

$$C_d = \int_{path} dC = \int_{path} \left[-C(1-i_{co}) + (1-C)(i_{co})\right]\frac{\ln(2)/U}{l_0/U_0}dx \quad (5)$$

To complete, it is necessary to decide the respective weight of each path direction. As mentioned, we have little knowledge of the actual motion of air masses, and it seems reasonable to rely on simple assumptions, because we have no physical basis to build a more complex scheme. Minimal requirements seems to (1) give more weight to path directions which matches the direction of the mean wind, and (2) give zero weight to paths which are in opposition with the mean wind, i.e. represents an air-mass travelling against the wind (this would be inconsistent with our above assumptions for the continentality change over a given path; however, such behaviour is not impossible in practice and should be accounted for in the other continentality index). A simple way to achieve this is to use the scalar product of the mean wind $\vec{U}$ and the path direction unit vector $\hat{i}_p$ (we have integrated this over each path, but this is unimportant since the model mean wind doesn’t change much because the scale is coarse):

$$W_d = \int_{path} \max(\hat{i}_p.\vec{U}, 0)dC \quad (6)$$

The weighted average of the contributions from all paths gives the continentality at the desired point :

$$C = \frac{\sum_d W_d C_d}{\sum_d W_d} \quad (7)$$

Examples of continentality predictor maps computed with this method are given on figure.

Coming back on the results of the simple statistical model used as a starting point (figure), it can be seen that the above described “advective continentality” has some potential to explain the observed variability which was lacking in the simple regression. However, the model wind comes essentially from the West, while continentality-like effects are seen on coast which are only exposed to maritime air coming from other directions, including the East. It is also interesting to remember that the mean wind used to define the first type of continentality does only represent large-scale motions. This suggests that it is interesting to supplement the above approach by defining a second type of continentality, aimed at representing “random” atmospheric fluxes unresolved by CLIMBER. This will be called “diffusive continentality” and can be obtained by computing continentality changes along specific paths as in equation (4) again, but now without including the model wind at all. Therefore, all directions have the same weight in the final result, and the progressive gain in continentality over land will be proportional to distance, not to time. Empirical testing with various rates of continentality change with distance showed that it is interesting to use rather short scales, suggesting that most larger scale effects are represented in the "advective" continentality. This is consistent with (although not a necessary consequence of) the idea of including scales unresolved by the climate model. In this study, the distance corresponding to 50% change towards continent or sea conditions is 150 km.

The "diffusive continentality" map for present day conditions (i.e. coastline) is shown on figure. Note that only island and headlands have a very low continentality, due to the fact that other coastal regions receive maritime air from about half of the directions only. A map of the minimum distance-to-sea is also presented on figure, for comparison with the proposed "diffusive continentality". Distance-to-sea was investigated because it might have seemed simpler, involving no empirical assumptions. However, diffusive continentality seems clearly more "natural" on such a visual basis. Regression attempts using the distance to sea (not shown) also confirm that it does not represent more of the observed variance.

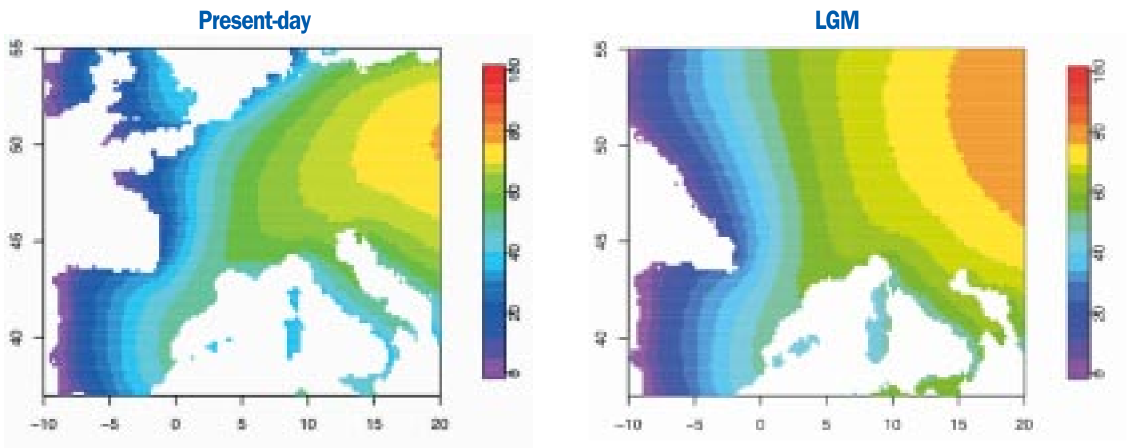


Figure 5 : *Advective continentality", for present-day and Last Glacial Maximum conditions (see text).*

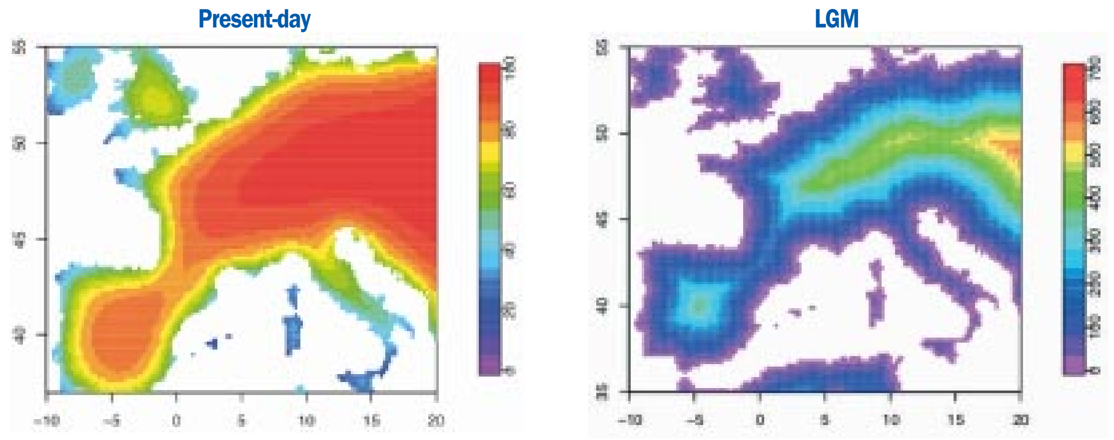


Figure 6 : *"Diffusive continentality", left panel; distance to sea, right panel (present-day conditions).*

2.3.2. - Mountains

A good deal of the European climate is connected with surface elevation. Several topography-based predictors are thus designed here. These are constructed from the ETOPO5 surface elevation map [Ref.9].

Temperature is almost directly linked to elevation itself. The quantitative link is not easy to obtain, though, specifically when it comes to finding climate change information based on CLIMBER outputs. A possibility is to re-compute near-surface temperature for several height in each (coarse) model grid box, as proposed for the coupling of CLIMBER and its ice-sheet model (see Ref.2, section 2.3.2). Another approach is the vertical temperature gradient from the free atmosphere (lapse-rate) provided by CLIMBER. The rationale behind this choice is that mountains are rather small within the grid box, and that from an empirical point of view, the impact of altitude on temperature is indeed about the same as in the free atmosphere. This second approach is used in the present work because initial tests suggested that it was more appropriate for our domain, but the first approach should remain open to investigation in any further study. In practice, the predictor is the product of the lapse-rate obtained from CLIMBER by the high resolution surface elevation, as shown for an example case on figurea.

As we are working on a grid, with a certain resolution (10 minutes, coming from the climatology), we may expect that the climate variables, specifically precipitation, are impacted by higher resolution topographical features. A potential predictor is thus the standard deviation of surface height, shown on figureb. While such variable is constant at the time scale of our study, it may explain a part of the geographical variance in our climate fields, so that its inclusion in the statistical model might be useful.

The next topography-related predictor shall be referred to as “mountain masking”. The aim is to account for the impact of mountains on the regional climate of the regions which lie downstream from the mountains with respect to the main incoming air masses. There are two possible mechanisms for this “masking” :
- part of the incoming air flow may be diverted by the mountain,
- the characteristics of air masses which went up the mountain may have changed in the process, in particular dried up due to Foehn effect.

These effects are at least partly similar to an increase of the continentality in the “masked” area (figure , top panel). In this study, the corresponding predictor is computed separately of the continentality, but in a similar way. As for continentality, several incoming air masses directions are considered, with the same weighting as before. The main change here is that the “masking index” increase only when the “hypothetical air mass” is going up. In practice, the computation is based on the difference between the height of the surface at each point along the “hypothetical air mass” track and the height of the target location. An example of the resulting maps is given on figurec.

The last predictor is connected with the lifting of air masses over topography, with a potential link to increased precipitation (figure , bottom panel). In this study, only the mean zonal wind is accounted for, and multiplied by the mean east-west slope over approximately 100 km. Only upward trends are retained, while the effect of downward mean motion is assumed to be represented by the “masking” predictor presented above. An example of the resulting maps is given on figured.

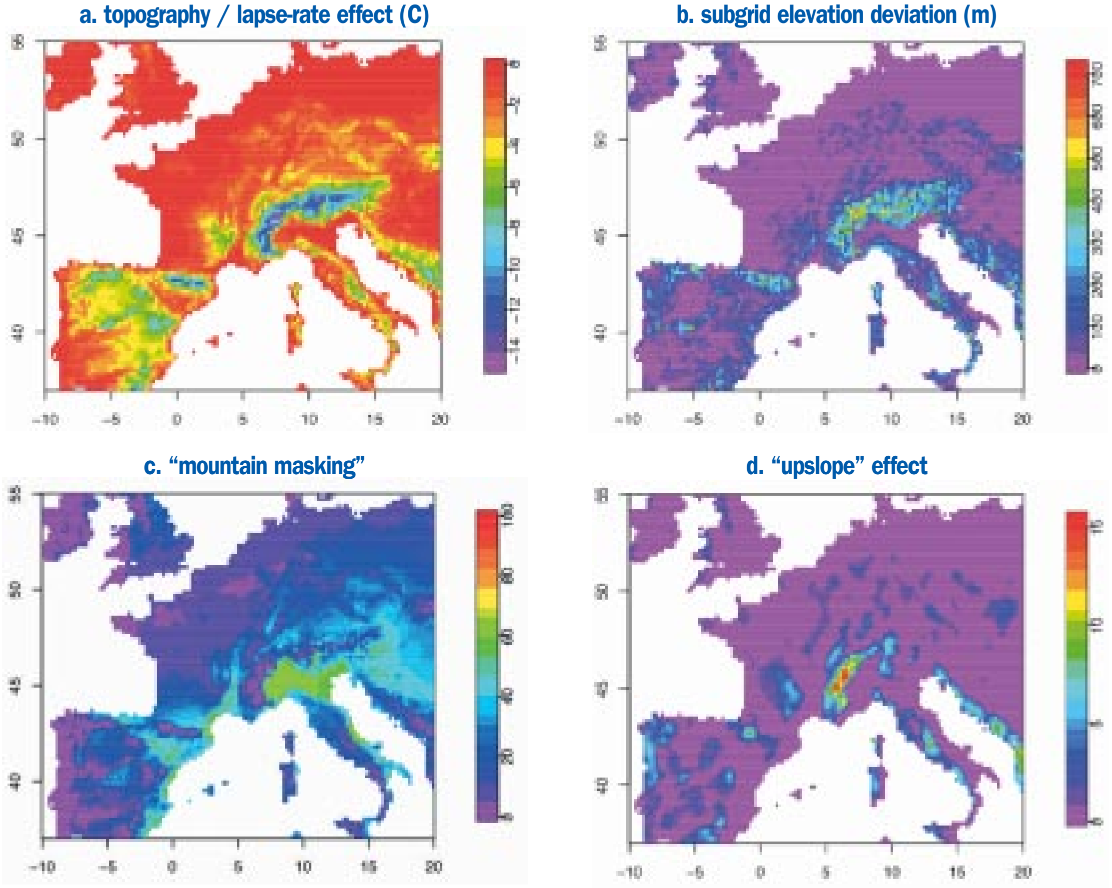


Figure 7 : Mountain-related predictors, present-day conditions (January).

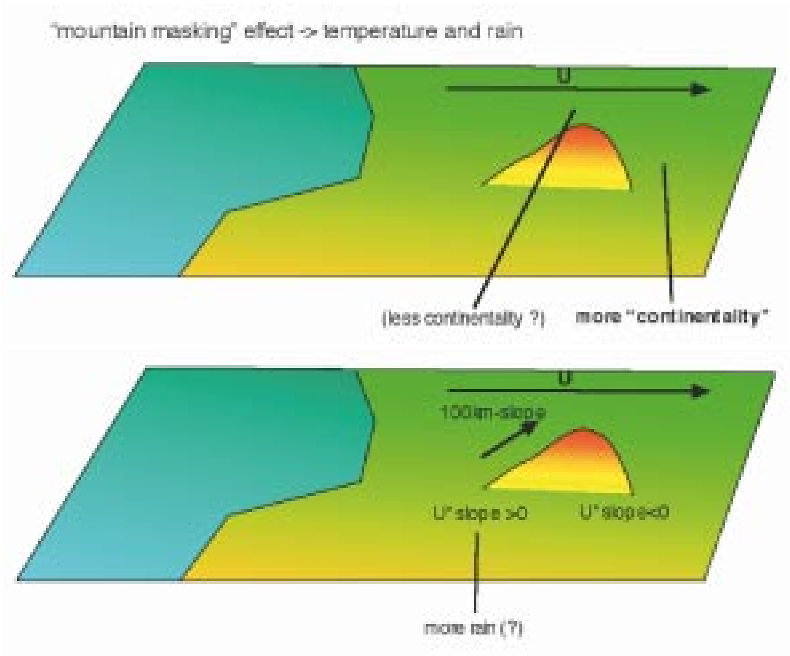


Figure 8 : Principles of the computation of predictors related to secondary mountain effects.

2.4. - Calibration of the downscaling method

Being based on a regression, the method works in two steps : first the regression function is defined as a best fit to available (present-day) data, secondly it is applied to predict high-resolution climate based on the corresponding changes in the coarse climate model. As the first step, or calibration, is based on minimizing the difference between the regression values and the present-day climatology, using corresponding input values, it needs present-day values for the predictors. These predictors being based on CLIMBER model values, a specific simulation starting from the pre-industrial conditions was run until conditions approximately matching those of the late 20th century. The end of this simulation provides the "present-day" model outputs, which are consistent with the climatology.

The statistical models used for the downscaling of temperature and precipitations will now be presented. Results for the Last Glacial Maximum (LGM, 21 kyr BP) will serve as an application example and an independent validation opportunity.

2.4.1. - Temperature

A few different sets of predictors, as well as various changes in the design of these predictors (e.g. length scales involved in the computation of continentality), where tested during this project. The following statistical model represents our best selection of predictors for the temperature field:

$$T_F = b_0 + f_{ca}(c_a) + f_{cd}(c_d) + f_\mu(\mu) + f_Y(Y) + b_T\,\Delta T_M + \overline{T}_M \quad (8)$$

in which the various terms are based on the above described predictors :

C_a advective continentality

C_d diffusive continentality

μ mountain masking effect (not included for summer months because it did not explain a significant part of the variance in that case)

Y lapse-rate effect

f_{ca} , f_{cd} , f_μ , f_Y are spline functions with only 3 knots, which results into high smoothness, i.e. the functions can not be very complex. The objective is to allow the contribution of each term to be somewhat non-linear, because it's difficult to build physical predictors which would provide a simple linear contribution to temperature or precipitation maps. However, the contributions can not be too complex, because this would introduce a kind of "overfitting" : the statistical model would not represent a link between our predictors and observations, it would just produce an arbitrary and meaningless fit to the data.

The most simple way to use the presented downscaling approach is to calibrate the statistical model using data for a single month in the year, then apply it to the same month of a climate change scenario. The regression itself relates to the geographical variability, and is thus stationary in time. In turn, the computation of the predictors is assumed to have a physical basis, and thus some robustness regarding the long-term time-variability. For example, if the coastline moves, the continentality predictor will change, and its contribution to local temperature will change accordingly (this aspect being assumed stationary). However, our current design of the predictors does not include any input related with the seasonal cycle: e.g. continentality is computed, but the impact of continentality on temperature is highly season-dependent : it might be desired to predict this link on the basis of climate model data. But using such seasonal-cycle related information from the climate model would introduce more complexity in the method, possibly bringing uncertainty. This did not appear to be desirable in the context of a first downscaling method for the CLIMBER model.

Nevertheless, some partial accounting for month-to-month changes is possible : rather than calibrating the model for 1 month, it can be calibrated using the months preceding and following the month of interest. This has two kinds of advantages:

- it provides a validation opportunity for the method. If the month of interest is not used for the calibration, it is interesting to compare the prediction of the method for this month to the actual climatology, because these data are partly independent. A good matching between these maps suggests that the method is at least making an acceptable use of the model data to make a prediction in different conditions. It doesn't suffice to validate the method in the climate change context, but it is a satisfying first test.

- some gain, possibly minor, might be expected in robustness. For climate change prediction, three months can be used at the calibration stage : the target month and its two neighbours. This may include more "diversity" in the calibration data than just one month would do. Although the regression will match the climatology of the target month less closely, it is not evidently worse: in fact more data are used, both from the model and the climatology, so that this may help cancelling random errors.

The practical implementation of this 2 or 3-months calibration is simple but not immediate: the large-scale model temperature gradient (ΔT_M) needs to be computed on the basis of the mean temperature of each month. To put it shortly, the monthly mean average temperatures do not enter the statistical model, and the final output temperature is obtained by adding the climate model mean for the target month.

Figure presents results for temperature in January. The method is calibrated using the climatology and model outputs for December and February. The temperature prediction based on equation 8 for January is reported on panel 9b, and compares favourably with the corresponding climatology on panel 9a. The explained variance is 95.2%, confirming that the designed predictors are appropriate. The difference between the climatology and regression, or model error, is presented on panel 9c. This can be compared to the error obtained with a calibration based on the month of January itself.

The corresponding maps for temperature in July are presented on figure . The explained variance is less than in January (90.7%), as shown by the comparison between climatology and model fit output (panels a, b and c).

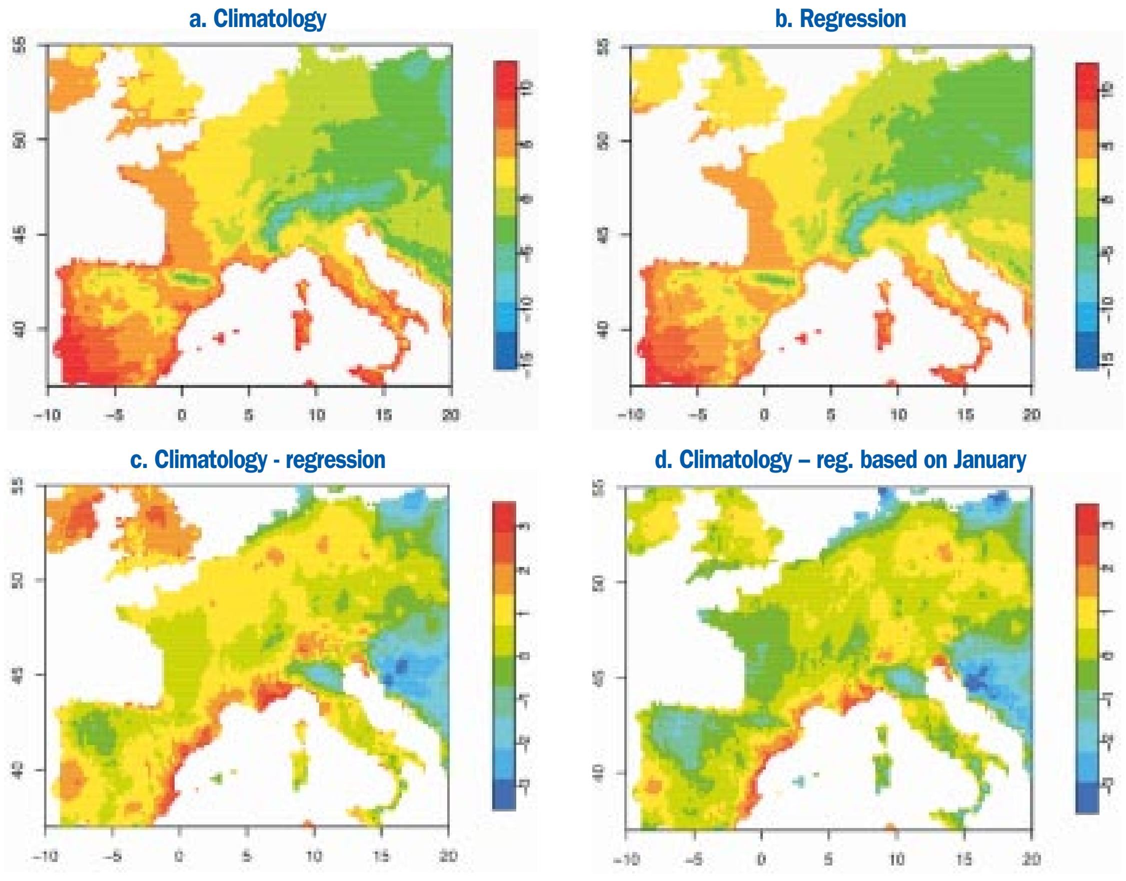


Figure 9 : Calibration and validation for temperature (°C) in January (see text).

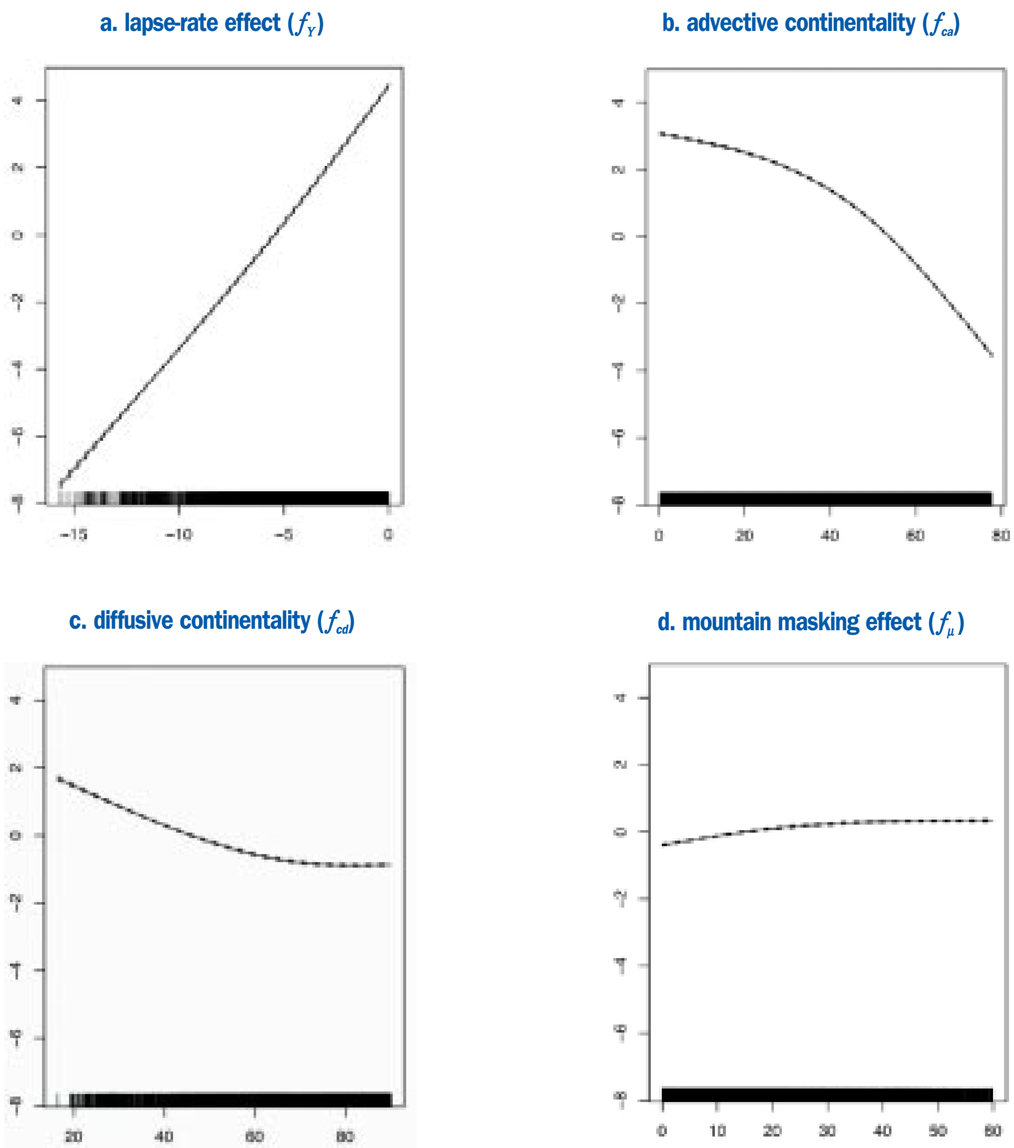


Figure 10 : *Calibration for temperature in January: contribution of each term based on spline function to the regression (additive model). Abscissa : predictor. Ordinate: contribution in Celsius (zero mean is imposed).*

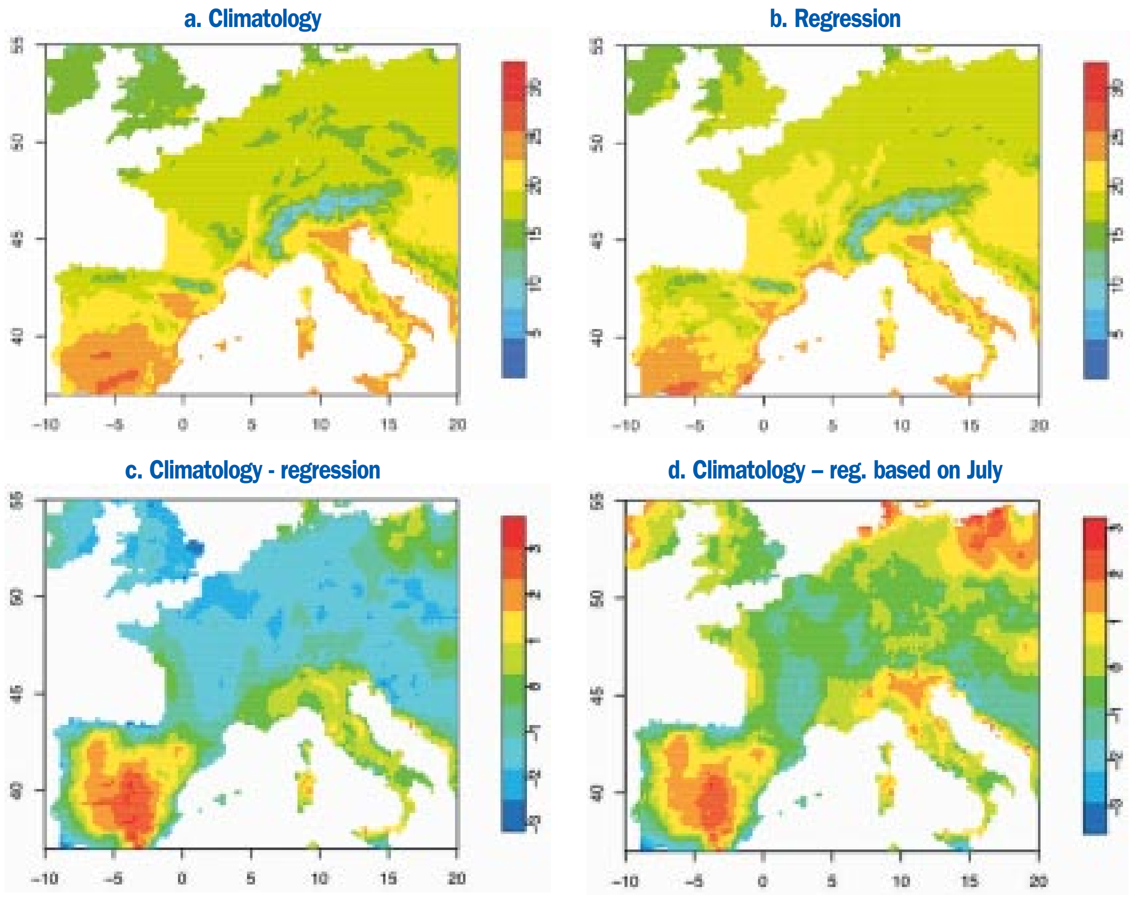


Figure 11 : Calibration and validation for temperature (°C) in July (see text; please note that the colour-temperature correspondence is not identical in the two bottom plots).

As the CLIMBER modelling and the downscaling method are aimed at providing results for widely different climates, the Last Glacial Maximum (LGM) is an interesting test period. Last Glacial Maximum surface air temperature in January is reported on figure. The first two panels (a and b) are based on the 3-month calibration explained above, and represent our best estimate for the LGM temperature and its difference to present conditions. The corresponding sea level change, due to the growth of continental ice sheets, is –128 m. Consequently, the coastline is also very different in northern Europe. Panel c shows the LGM temperature anomaly computed with CLIMBER alone (with linear interpolation). The downscaling method (panel b) provides significantly different results, in particular over England and Italy (respectively warmer and colder than CLIMBER values). The details of the downscaling method does not seem to have large impacts on the results. In particular, using a calibration on January only rather than 3 months (JJA) does almost not modify the result (panel d). Another test is to remove the diffusive continentality predictor from the regression (panel e). The result is modified in a rather expected way, with the disappearance of low distance effects of coastline changes around England. This gives some idea of the uncertainty of the method : while the results should be better when the diffusive continentality is included, this predictor clearly fails to reproduce certain details of the actual temperature change in the coastal region (see figure). It is thus interesting to see how this predictor influence the results.

Temperature reconstructions for the LGM are available, mainly on the basis of pollen data. However, the temperature is available only at certain locations and the values are still the object of research aimed at improving their reliability. The reconstruction shown here (figure 2) was used in the framework of the Paleoclimate Model Intercomparison Project (PMIP), and presented in [Ref.10]. Temperatures anomalies (LGM-present) for January over European sites range between approximately –10 and –30°C. This is clearly below all values obtained here. The downscaling does not significantly improve the comparability of simulated results to the reconstruction. However, there are only a few sites for which temperature data is provided which falls inside the BIOCLIM domain, so that no conclusions can be drawn at the moment.

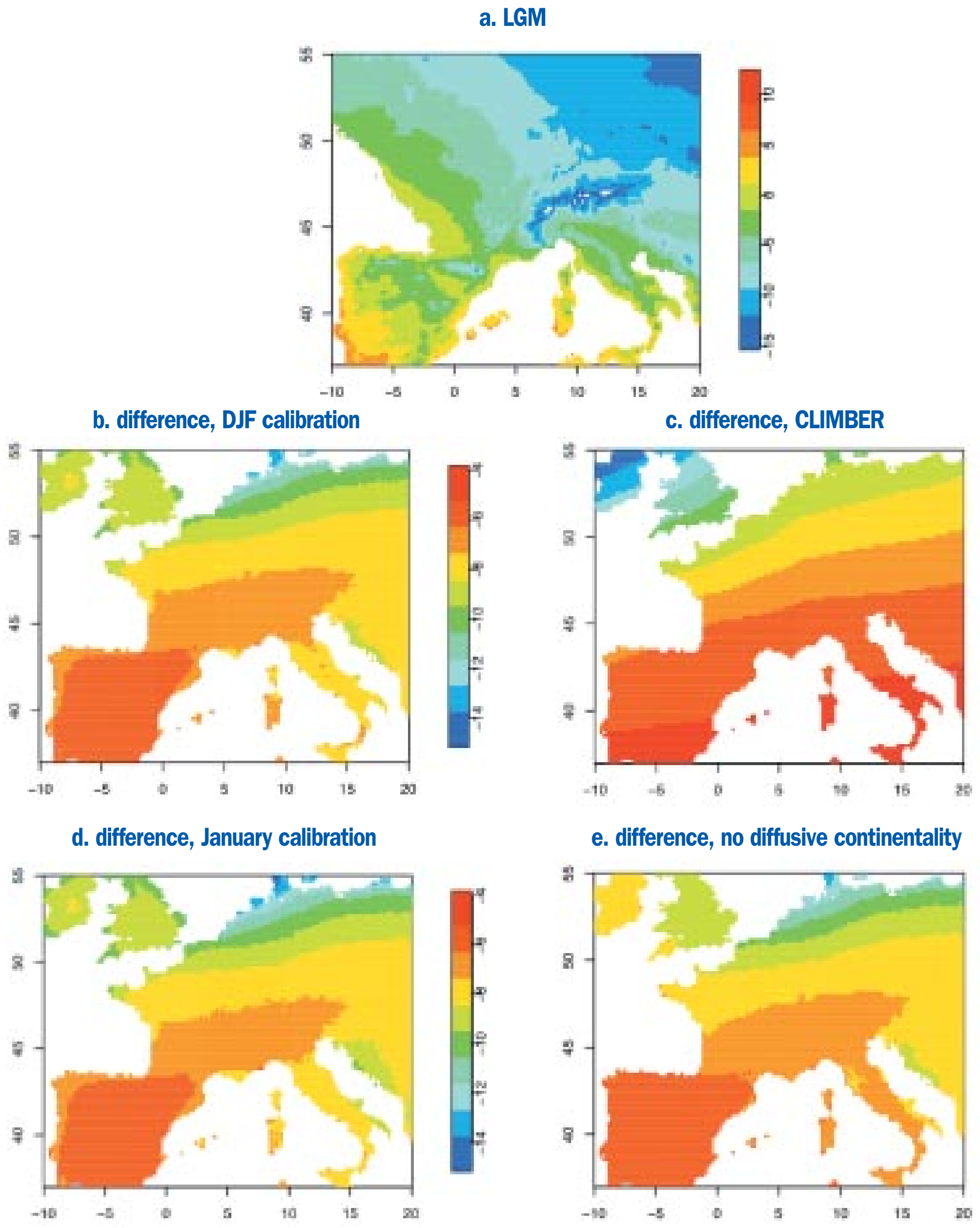


Figure 12 : *Last Glacial Maximum, January near-surface temperature (°C). a. LGM, b. predicted difference between LGM and present, c. CLIMBER interpolated, d. predicted difference when the calibration is based on January only (others use DJF). e. predicted difference when diffusive continentality is not included in the regression.*

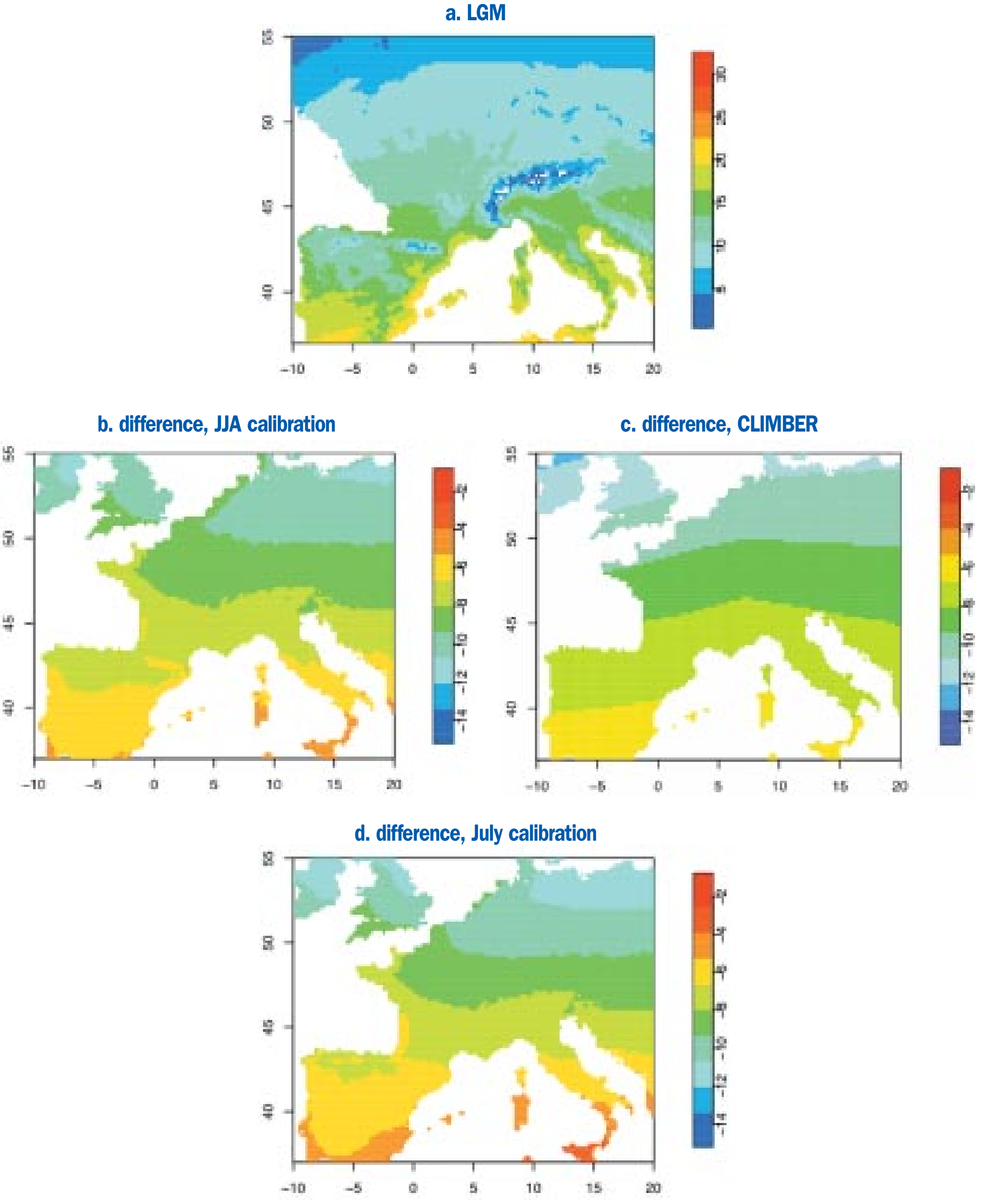


Figure 13 : *LGM-July temperature, as on figure 12*

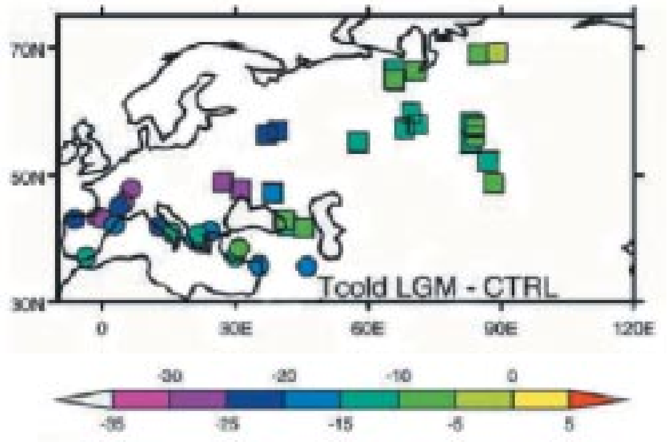


Figure 14 : *Temperature anomalies (°K), LGM-present, as reconstructed by Peyron et al.[Ref.11] (circles) and Tarasov et al. [Ref.12] (squares). Reprinted from Kageyama et. al., [Ref.10].*

2.4.2. - Precipitation

The following statistical model represents our selection of predictors for the precipitation field:

$$\Pi_p = b_0 + f_z(z) + b_\sigma \sigma + b_{ca} c_a + b_s s + b_{slp} p_{sl} + b_p \Delta\Pi_M + \overline{\Pi}_M \quad (9)$$

in which

$\Pi_M = \log(P_M)$ with P_M being the precipitation amount (mm/day) provided by the CLIMBER model and

$$\Pi_M = \Delta\Pi_M + \overline{\Pi}_M \,,\ P_p = \exp(\Pi_p)$$

is the predicted precipitation amount, and the various terms are based on the previously described predictors :

z surface eight

σ subgrid standard deviation of the surface eight

c_a advective continentality

s upslope effect

P_{sl} sea-level pressure

A prominent feature of the regression used here is that it is based on the logarithm of precipitation amount rather than precipitation itself. The basis motivation of this choice is that precipitation spans a relatively large range of magnitudes. In association with this, predictors like sea-level pressure influence precipitation in a way which is closer to exponential than linear. As a general rule, tests with the logarithmic formulation provided better regression fits than with direct introduction of precipitation (in agreement with the idea that the impact of predictors is roughly exponential).

The climatology of precipitation is more complex than that of temperature, it is more difficult to connect precipitation maps to simple physical mechanisms. We tested many combinations of our predictors, and when retaining only the physically plausible regressions, the explained variance is lower than for temperature (with the final statistical model choice, the explained variance is 59% for January and 68% for July, for calibration on these single months). The retained statistical models mainly involves linear terms. This is preferred here because test with spline functions tends to produce unrealistic results. This poor behaviour of the spline formulations is connected to the fact that part of the geographic variability can not be explained by our predictors : the functions connecting predictors to predictand becomes more complicated, but this only improves the regression with present-day values. This would represent overfitting, not improvement of a “physically sound” link. Linear terms leads to lower the explained variance, so that it must be recognised that we don’t have a complete understanding of precipitation and its change. However, this prevents the introduction of unrealistic components in the regression, which would likely be worse than the limitations of our physically based predictors. The prediction of the retained statistical model for present-day conditions is shown on b and figure 16c.

As an example of method-related uncertainty, one of the tests with another regression equation is presented here. This one is connected with the representation of precipitation peaks near the western coasts in January. The above regression underestimates this maxima (figure 15d). The alternative consists in replacing the linear advective continentality term by a more complex one based on a spline function (figure 15f).. This gives more freedom to the statistical model, which indeed better represents the coastal precipitation maximum (unfortunately, the diffusive continentality proved unsuitable for this purpose). As mentioned above, is probable that relying on complex fitted functions like this involves some “overfitting”, so that the statistical model does not entirely represent real physical links between predictors and precipitation. The practical consequence is that we regard the climate change results obtained with the “alternative” regression (figure 15g) as less reliable than the standard result (figure 15d), but more importantly, the difference between those two represents a typical uncertainty of the method.

It is interesting to note that there is theoretical risk of overfitting related to the combination of coarse model data. When two very coarse fields are used, in particular precipitation and sea-level-pressure from CLIMBER as here, the linear combination of these fields can indeed provide any requested large scale gradient (each coarse input field approximately represent a large scale gradient, and if these are not collinear, their combination gives any other gradient). In other words, any set of two model variables should explain a significant part of the domain-wide variability, so that the fact that such predictors contribute to increase the explained variance is not a proof that it forms a valuable statistical model. In the case of model precipitation and sea-level pressure, there are however good reasons to use these variable as predictors. Higher mean pressure is indeed associated with lower precipitation, connected with the presence of less low pressure systems in the area and/or air subsidence.

Last, a fraction of the unexplained variance may possibly be due to inaccuracies in the climatological data. Details of the climatology may indeed still be questioned, specifically for precipitation over mountain regions. This is shown by the difference between the 1/2 deg climatology and the new 1/6 deg CRU climatologies on figure 16 a and b: there are significant differences near the alps, at scales much larger than the grids (more detailed information over the Alps is available form the MAP project, but accessing these data was not planed in the framework of this project and is not clearly needed because no BIOCLIM sites are located in that region).

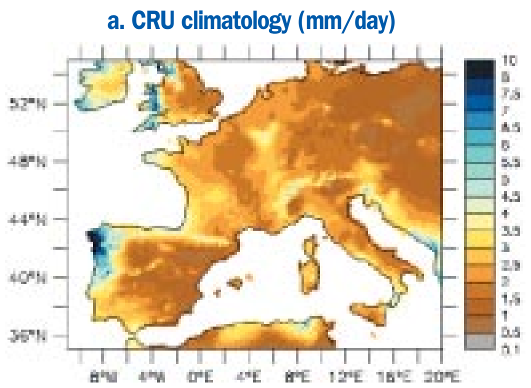
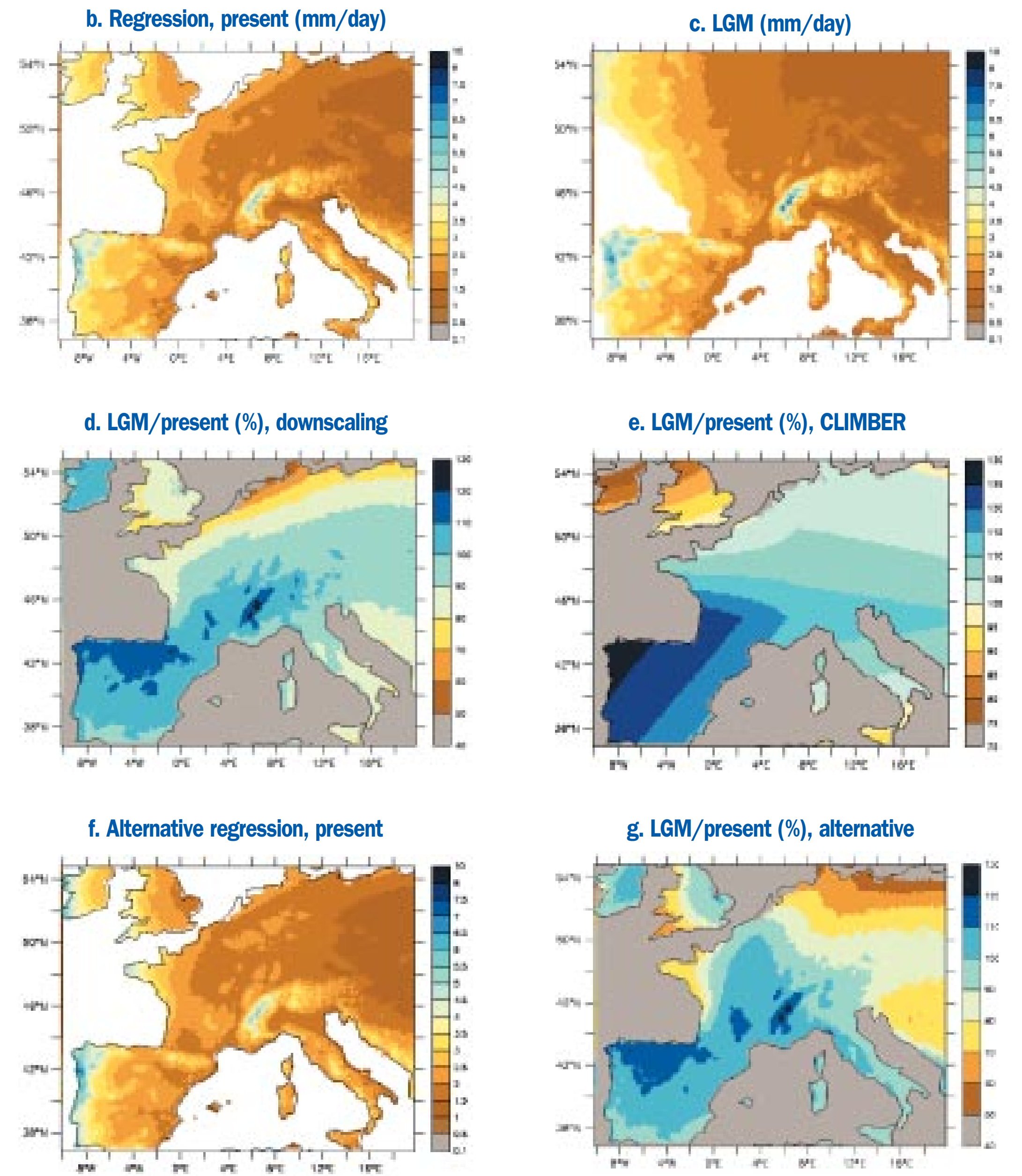


Figure 15 : *Calibration and LGM results for precipitation in January (calibration based on December-January-February)*



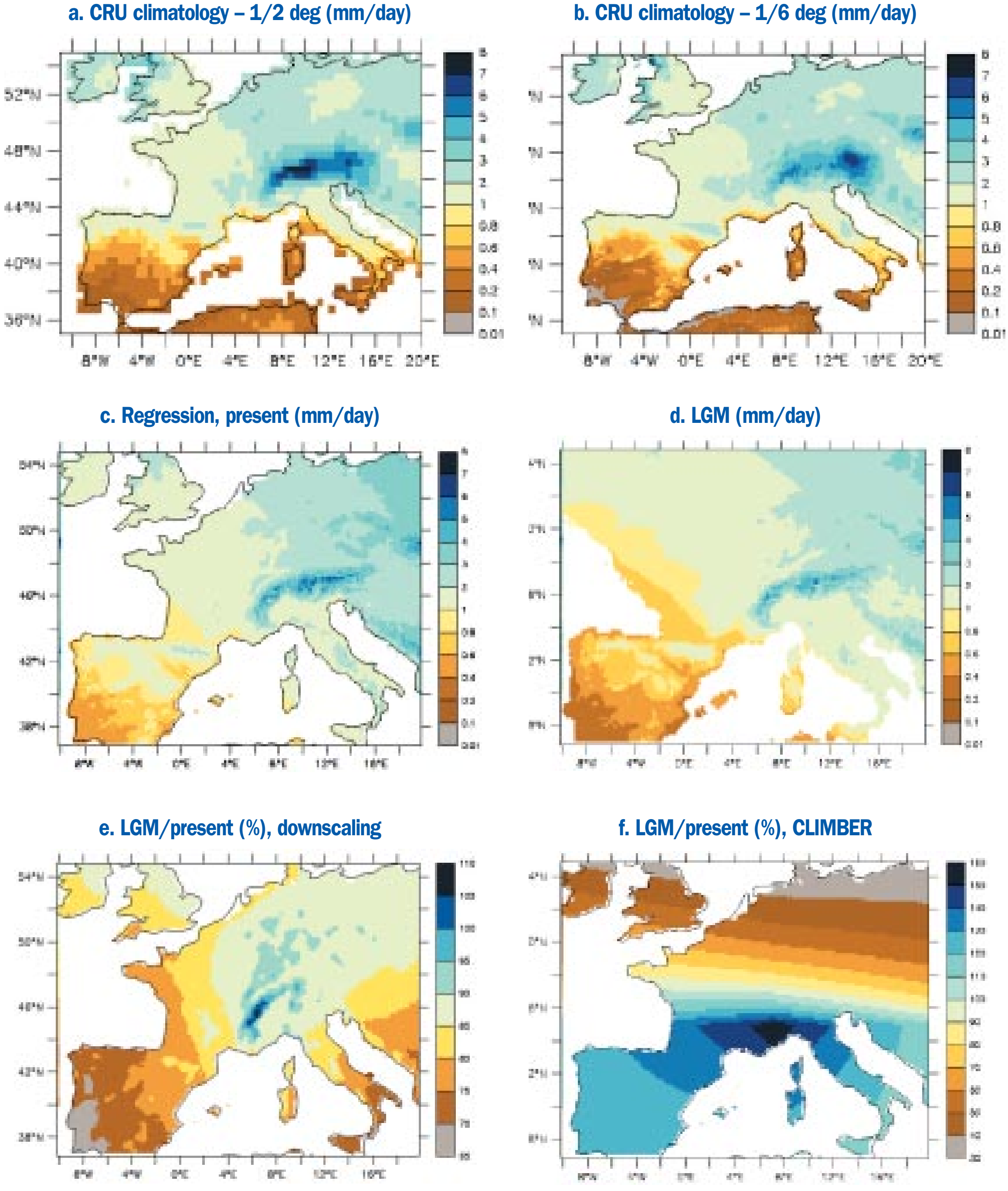


Figure 16 : Calibration and LGM results for July (calibration based on June-July-August)

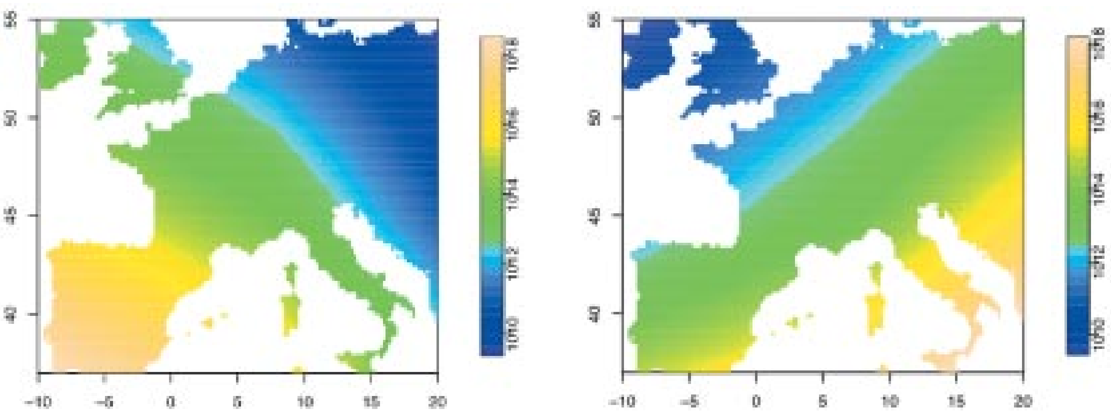


Figure 17 : *Sea-level pressure (hPa) in CLIMBER, January. Left: present-day conditions; right: LGM.*

Climate reconstructions for the LGM indicate large reductions of the annual mean precipitation over Europe, at least where data is available such as in the north of the Iberian peninsula and near the Mediterranean [Ref.10]. By contrast, the downscaling results represent moderately increased, constant, or slightly decreased precipitation in January (figure 15). Although annual precipitation was not computed here, the obtained precipitation increase is not compatible with the reconstruction data. The interpolated CLIMBER precipitation field shows even higher increases of the precipitation, and this is the main origin of the disappointing downscaling result.

At the global scale, precipitation decrease is expected at the LGM as a consequence of lower temperature and thus lower atmospheric moisture content. Over mid-latitudes, storm-track changes complicate the picture. The Atlantic storm track is believed to be shifted in the northeastward direction at the LGM [Ref.13]. This may provide more precipitation, but in the north of the continent, not in southern Europe as found here. This suggests that the present CLIMBER run does not adequately represent large-scale precipitation changes around Europe. As already mentioned, this model does not explicitly represent low pressure systems, but parametrize their effect. In the present case, this possibly fails to represent the appropriate moisture transport change. The change in the sea-level pressure field (figure 17) also seems inconsistent with the suggested storm-track shift. Over the Iberian peninsula, the decreased surface pressure contributes to increase the precipitation obtained with the downscaling method. However, precipitation over Europe is only one aspect of CLIMBER results among many others. It would be dangerous to draw conclusions about the ability of the model to represent precipitation in this area before making new experiments and specific investigations.

3. Downscaling for the BIOCLIM future scenarios

Several simulations covering the next 200 kyr were performed by two climate models, as reported in deliverable D7. In this report, we apply the presented downscaling method to the results of CLIMBER-GREMLINS. In summary, the simulations correspond to a scenario of the natural CO_2 variations (A4a), a scenario including a moderate fossil fuel contribution (B3) and a scenario including a high fossil fuel contribution (B4). The corresponding CO_2 time-series are remembered on figure 18.

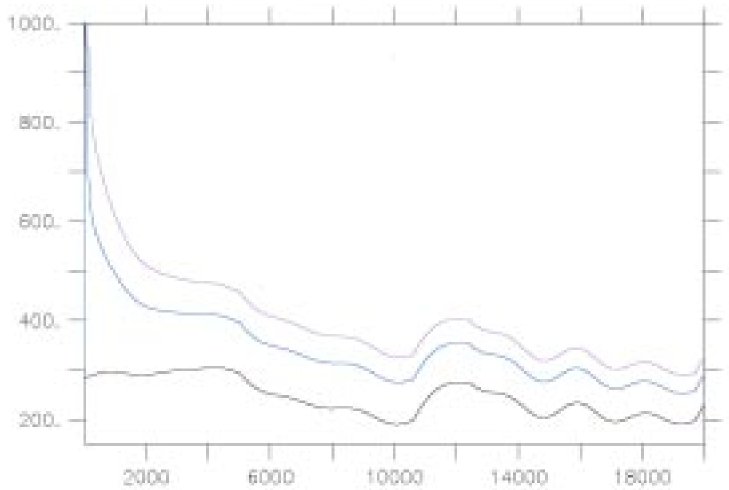


***Figure 18 :** CO_2 concentration (ppmv) as a function of time (decades). Natural scenario (A4a, black), Fossil fuel (B3, blue) and high fossil fuel (B4, purple).*

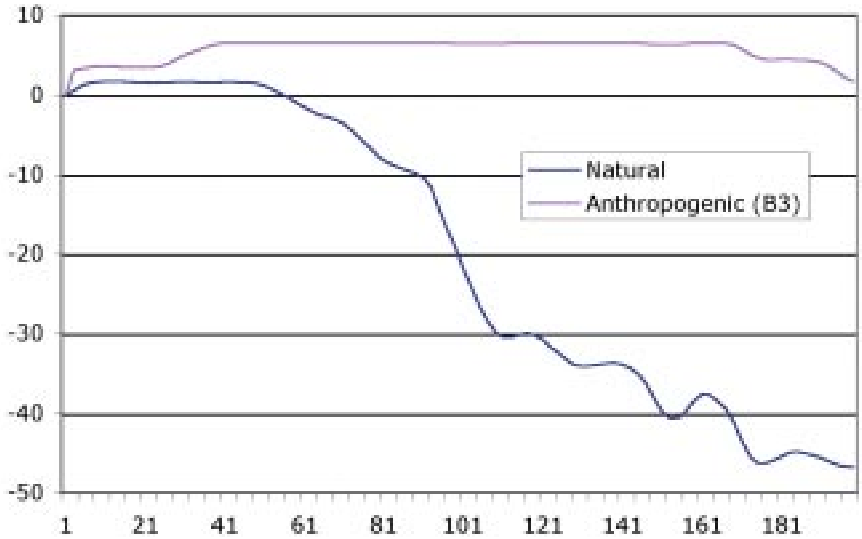


***Figure 19 :** Sea-level (m) computed for the natural (A4a) and moderate fossil fuel contribution (B3) scenarios (reference level : present-day conditions).*

The sea-level is estimated from the ice northern-hemisphere ice volume computed by CLIMBER. The changes in Antarctic ice volume are not included here because these are not modelled. However, the Antarctic component is much smaller than that of the northern hemisphere, so that the approximation is acceptable for computing the sea-level in the present context. The sea level is estimated as
(N.H. ice volume at a given time – present-day ice volume) x (2.2 m / 10^6 km^3)

This estimate gives a satisfactory value for the last glacial maximum (-129 m). The resulting sea-level height is shown on figure 19.

3.1. - Time series for the sites

The downscaling methodology was applied on the model outputs for the three 200 kyr scenarios, providing output on the 1/6 degree grid used for the downscaling (as above). This output was computed only for the points which belongs to a BIOCLIM site. The definition of the BIOCLIM sites used here is given in table 1. In this section, the results are presented as simple statistics based on the outputs on each site (site minimum, maximum, and mean).

Site No	Site name	Latitude (from – to)	Longitude (from – to)	Temperature Jan	Temperature July	Precipitation Jan	Precipitation July
1	Czech Republic	48.9 – 49.5	15.0E – 15.6E	-3.3	16.5	1.35	2.58
2	Germany	52.0 – 52.6	10.0E – 11.0E	0.3	17.3	1.60	2.22
3	France (Bure)	48.3 – 48.9	5.3E – 6.0E	0.9	17.7	2.73	2.18
4	Spain - Toledo	38.0 – 41.8	6.5W – 1.5W	5.1	23.0	1.64	0.47
5	Spain - Padul	36.7 – 37.3	4.0W – 3.4W	5.5	23.5	2.03	0.39
6	Spain - Cullar	37.3 – 37.9	2.9W – 2.3W	5.8	23.3	1.68	0.43
7	Central England	51.6 – 54.8	2.8W – 0.0	3.1	15.4	2.45	1.91

***Table 1:** Definition of the BIOCLIM sites within this report. The temperature and precipitation columns provides climatological mean values ("present-day" CRU climatology used as a reference for downscaling)*

We first present detailed results for the natural scenario, explaining how these were obtained. In a next step, summarized results are presented for the fossil-fuel scenarios.

3.1.1. - Natural scenario – model / downscaling comparison

While the initial downscaling output is available over each gridpoint (1/6 degree), we have only present mean, minimum and maximum values over the sites (however all results are available for all scenarios and site grid-points, see appendix 1).

The available results are :

- **downscaling output** ("uncorrected")
- **corrected downscaling** output, obtained as follows : For temperature, the difference between climatology and present-day downscaling output is added to the output from the downscaling for the scenario (i.e. the present-day downscaling error is removed, giving the correct value for the present climate, but this correction is maintained constant under climate change conditions while the actual model error is unknown for all future times).

For precipitation, the ratio of climatological and predicted values is used to correct the downscaling scenario, by multiplying the downscaled precipitation by the correction ratio (rather than adding a constant like for temperature). Thus if the model downscaling method predicts a 50% increase in precipitation, we just compute future precip as being 50% more than present-day climatology (not 50% more than present-day downscaling output, nor *adding* the precipitation increment from the downscaling to climatology)

- **model:** linearly interpolated CLIMBER output, provided for comparison.

- **corrected model** output. The corrected model value is the interpolated CLIMBER result with a correction done as for downscaling above: the time-mean value is corrected so that model-mean matches the climatological mean for present climate (additive correction for temp, multiplication for precipitation). This provides a fair comparison of model values to downscaling: while absolute model results do rarely reproduce the climatological mean with a high accuracy, the model is expected to provide an acceptable (large-scale) climate-*change* signal.

A selection of the results for the natural scenario (A4a) is presented in figures 20 (temperature) and 21 (precipitation). The meaning of each curve is summarised on figure 22. Site-mean values are provided for model, downscaling and corrected downscaling, as defined above. Site minimum and maximum are provided only for corrected downscaling, as this is the most important output for practical applications. The four last sites (in Spain and England) show larger differences between minimum and maximum values because the site area is larger, and sometimes because topography is more complex. While looking at the results, it is important to note that the present-day values are never plotted on the graphics : these begin with the first climate model output, that is after 1000 years from CLIMBER run start (pre-industrial). To compare future values with present day ones, the climatological values are provided in table 1 (those values are used to calibrate both the downscaling method and the "corrected values" introduced above).

For temperature, the difference between corrected downscaling mean and model mean values are quite small, not exceeding 1-2°K in both January and July.

The results for precipitation are more surprising. The results of the downscaling outputs are largely different from the model results, and the downscaling also provides a larger time variability. For present day, both the corrected model and corrected downscaling values are equal and matches the climatology. Therefore, the differences between these two time-series is only a consequence of the long-term time variability. The "correction" methodology, based on a multiplication by a constant factor as explained above, may explain some aspects of the results, but not many (uncorrected values are also shown). As a general rule, time-variability seems quite low in the model. By contrast, the variability found in the downscaling output is highly unexpected. Downscaling outputs goes up to more than 200% of the model output. In addition, there are circumstances for which the time variability shows phase oppositions between model and downscaling values. While it is unclear that the model itself is better at this scale, downscaling values should be considered very prudently. A possible origin for the large increases in the mean and variability of precipitation is the sea-level pressure term used in the downscaling. While the downscaling methodology has been developed carefully, it is only a first version of a rather new method; it still needs more validation, and this would likely suggest improvements.

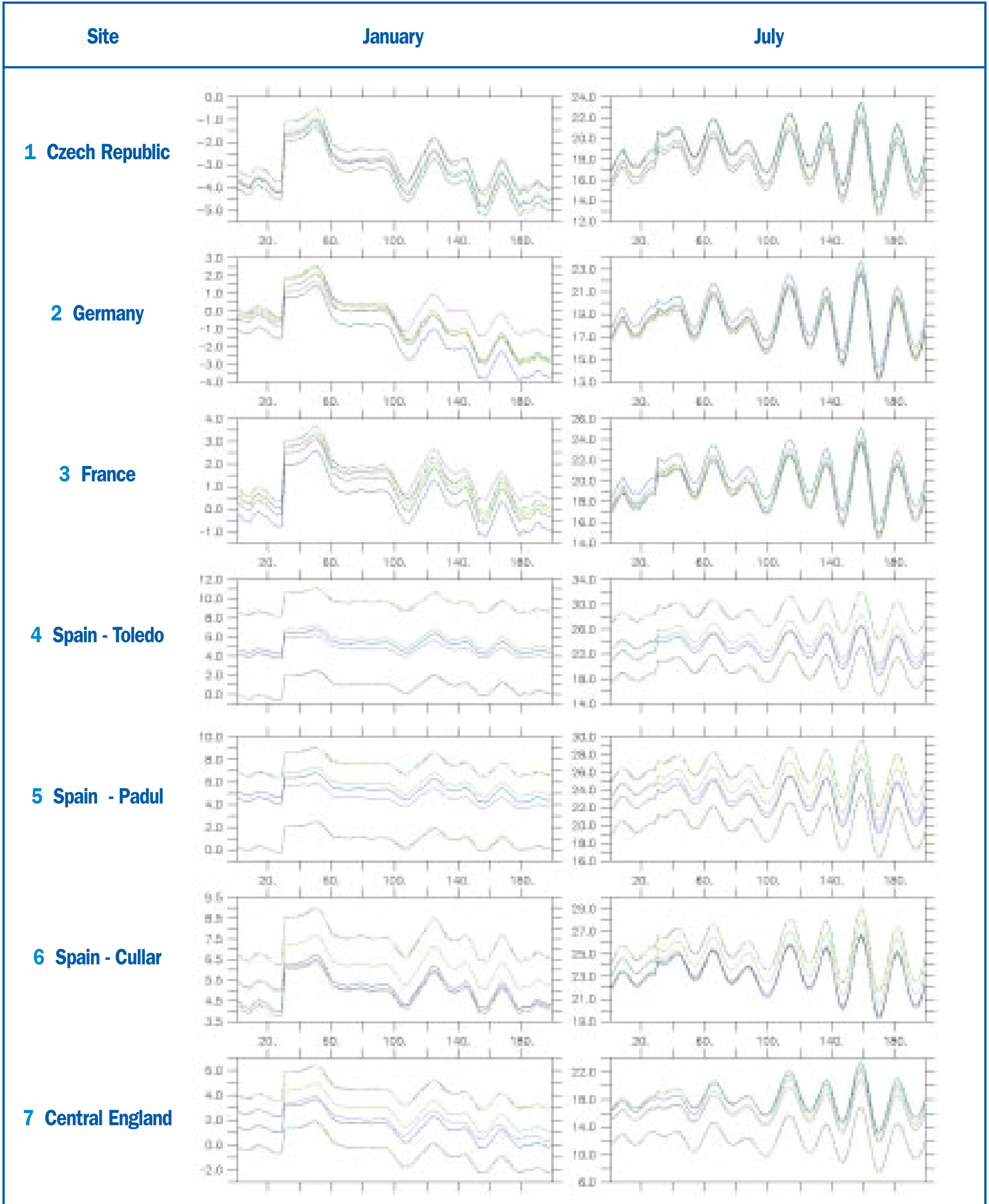


Figure 20 : *Natural scenario for the next 200 kyr – temperatures (°K). Legend is given by figure 22.*

Site	January	July
1 Czech Republic		
2 Germany		
3 France		
4 Spain - Toledo		
5 Spain - Padul		
6 Spain - Cullar		
7 Central England		

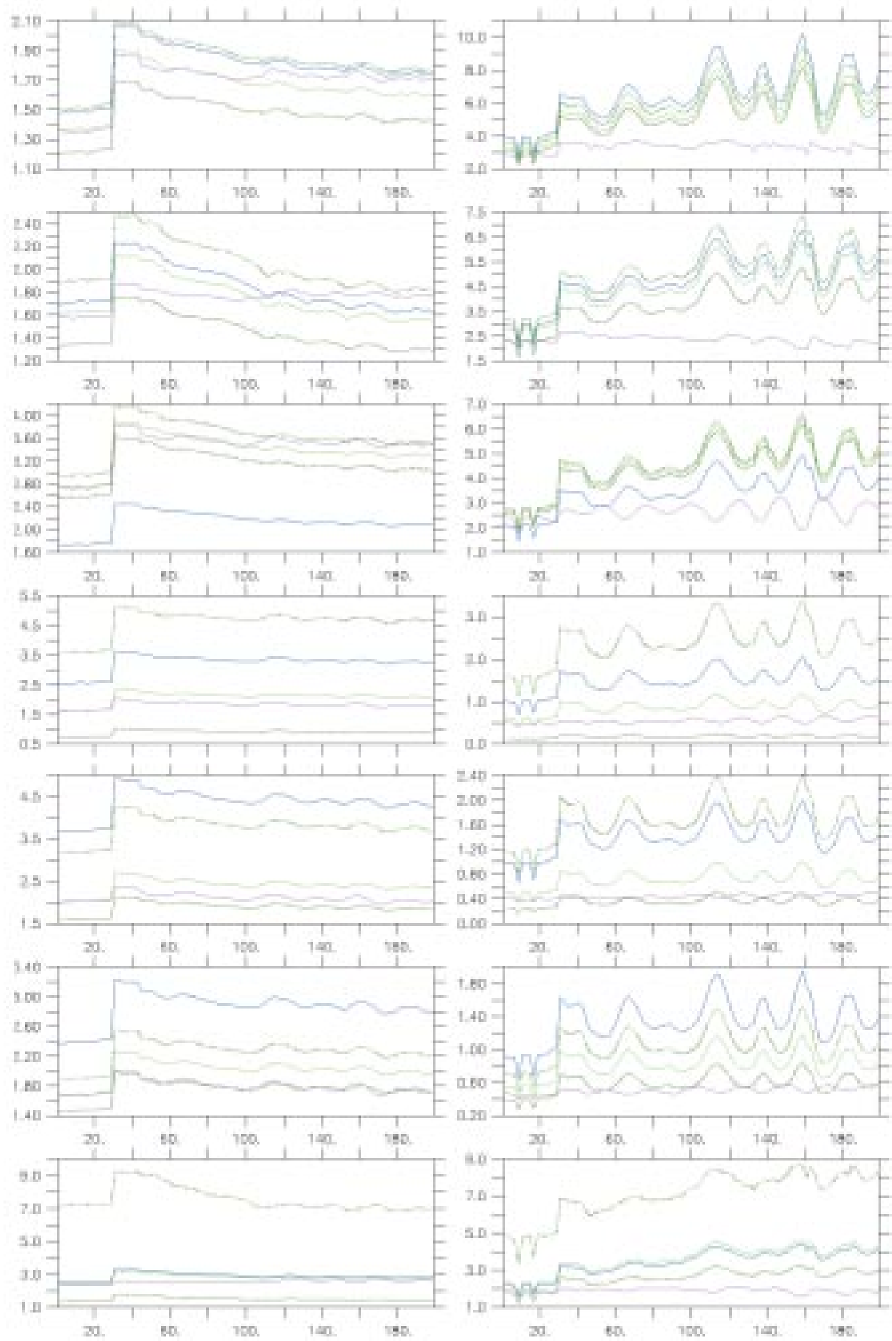


Figure 21 : *Natural scenario for the next 200 kyr : precipitation (mm/day). Legend is given by figure 22*

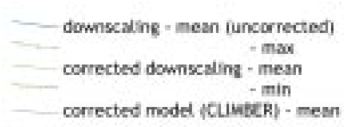


Figure 22 : *Legend for the natural scenario time series (figures 20 and 21). The data types are defined in text. Minimum/maximum/mean values refer to statistics over the site areas.*

3.1.2. *- Fossil fuel scenarios*

Figures 23 and 24 show site-mean downscaled temperature and precipitation for the three studied scenarios. As in the previous section, all graphics start after 1000 years of CLIMBER run, and the corresponding present-day value is the climatology given in table 1 (i.e. these are "corrected" downscaling outputs, as defined in the previous section).

For temperature, specifically in January, the main difference between the natural and anthropogenic (B3 and B4) scenarios is connected with an abrupt temperature increase in CLIMBER. This abrupt event does not happens at the same time in the anthropogenic and fossil fuel scenarios. The event is probably connected with changes in the thermohaline circulation (see Ref.2). There are only rather minor differences between scenarios B3 and B4 (less than 1°K, decreasing with time).

For precipitation, the reliability of the downscaling method is unclear, due to the unexpected results obtained for the natural scenario in the previous section. In January, the long-term decreasing trend found in the natural scenario (e.g. for the German site) appears as much weaker, almost suppressed, in the fossil-fuel scenarios. Thus, precipitation is much heavier for the fossil fuel cases in January. By contrast, precipitation is generally lower for the fossil fuel scenarios in July; in itself, this is not surprising for future climate experiments. However, a curious feature of these plots is that the difference between the natural and anthropogenic runs is increasing with time for several cases, e.g. German site in January or England site in July. Since the downscaling method itself is time-independent, this effect should be attributed to CLIMBER – *possibly* with an exaggerated amplification due to the downscaling methodology.

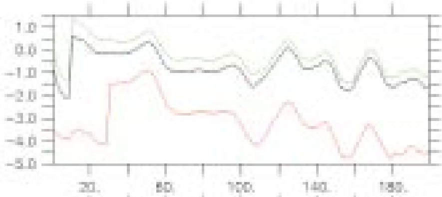
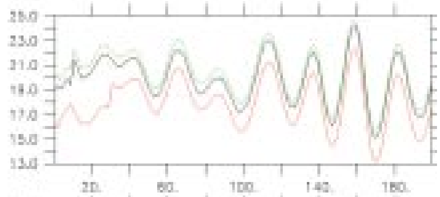
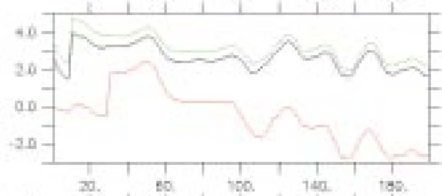
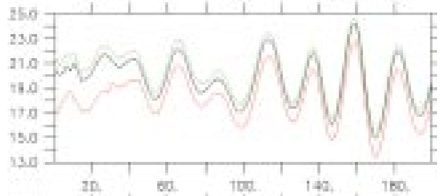
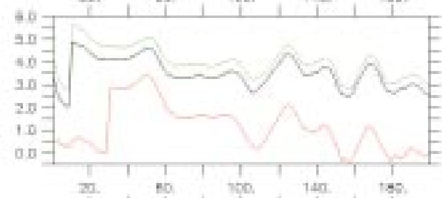
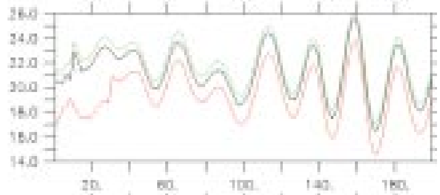
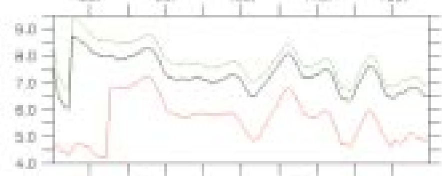
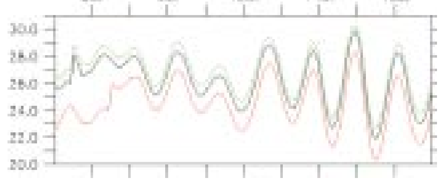
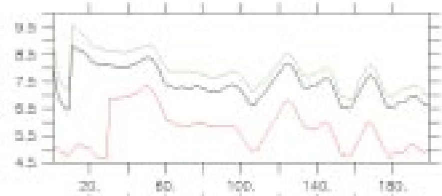
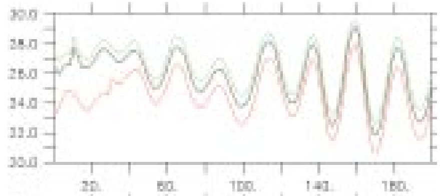
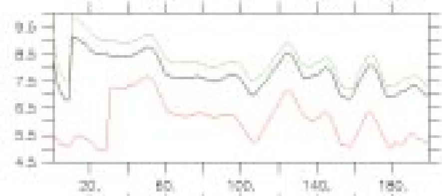
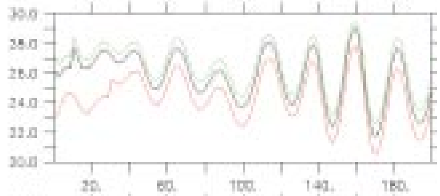
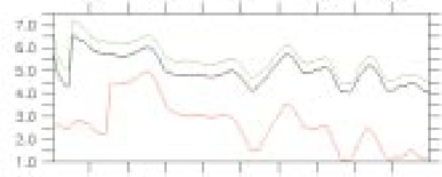
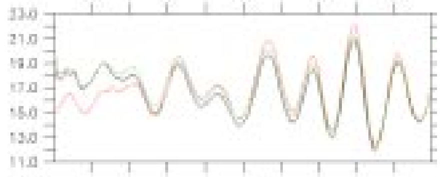
Site	January	July
1 Czech Republic		
2 Germany		
3 France		
4 Spain - Toledo		
5 Spain - Padul		
6 Spain - Cullar		
7 Central England		

Figure 23 : *Comparison of scenarios for the next 200 kyr : temperature (°K). Natural scenario (A4a, red line); fossil fuel scenario (B3, black line); high fossil fuel scenario (B4, green line)*

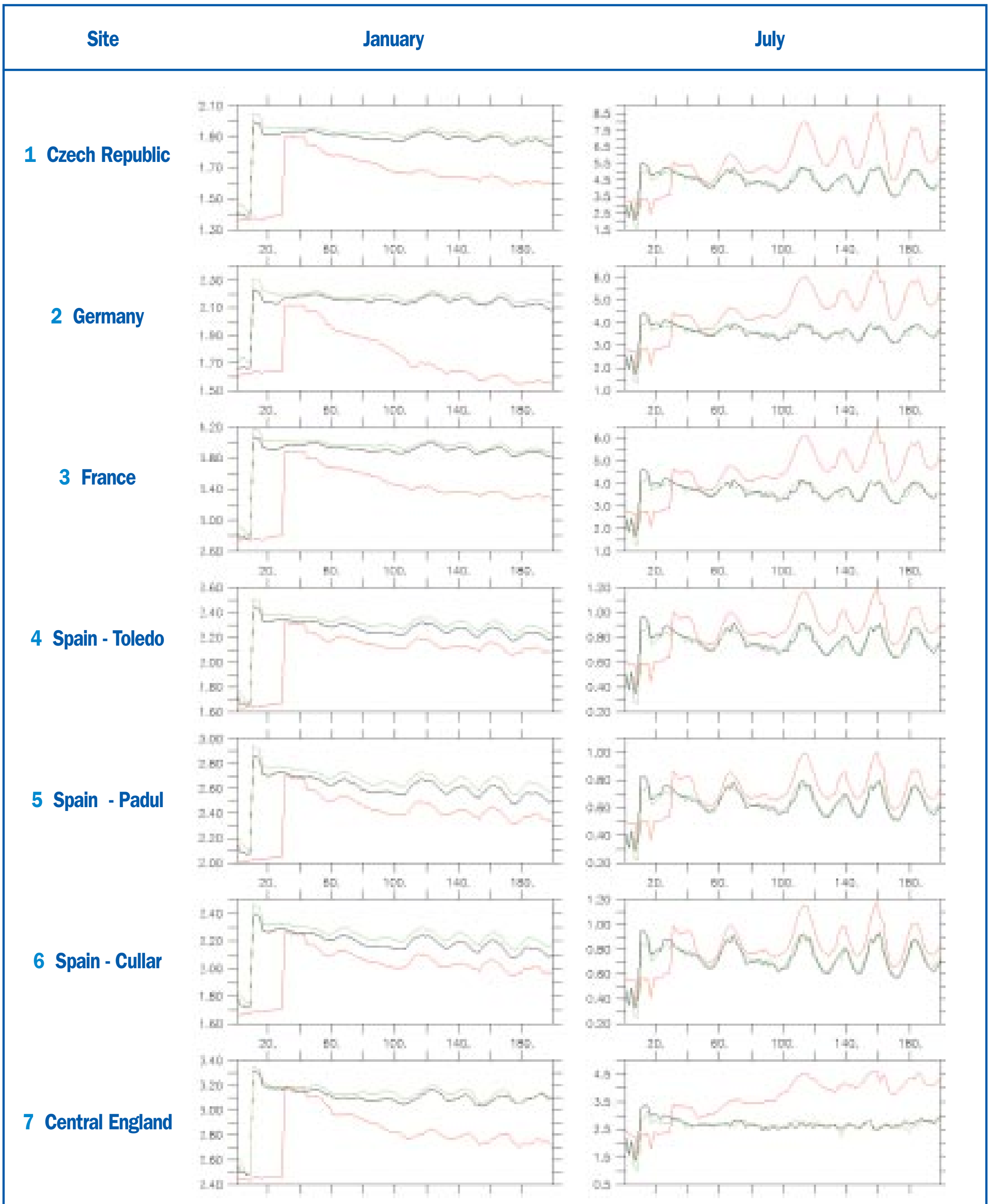


Figure 24 : *Comparison of scenarios for the next 200 kyr : precipitation (mm/day). Natural scenario (A4a, red line); fossil fuel scenario (B3, black line); high fossil fuel scenario (B4, green line).*

3.2. - Snapshots

The downscaling method was applied on all land points of the domain for two specific years selected and used in other BIOCLIM work-packages : + 67 kyr (case E) and +178 kyr (case F) from run B3. The temperature and precipitation change, found with the GCM are remembered in table 2 (values averaged over Europe, taken from [Ref.14].

Snapshot	DJF	JJA
	ΔT_{DJF} ΔP_{DJF}	ΔT_{JJA} ΔP_{JJA}
"E"	-0.024 +1.6	+2.4 -6.8
"F"	-0.87 +5.3	-0.33 +1.3

Table 2: *Summary of results from deliverable D4 – GCM simulations (IPSL_CM4_D model) which corresponds to the snapshots presented here, averaged over Europe. The values are mean temperature (K) and precipitation (%) changes for winter and summer.*

The downscaling results are presented in figures 25 (+67 kyr) and 26 (+178 kyr). There are no significant regional features in these temperature and precipitation change fields. This does not means that the downscaling method is wrong : it is accounting for the regional variations in the fields for a given time, it just did not find local effects of the climate change. The downscaling outputs are nevertheless not identical to the simple linear interpolation of CLIMBER results (not shown here), and may be more realistic. However, the near absence of regional or local details is rather disappointing. Sea level did not change much in scenario B3 (a few meters, see figure 19), so it could not have a large effect (it is probably responsible for a few "odd" points in the temperature plots, near the coasts). Mountains might have provided more interesting effects, connected with mechanisms such has "masking" or lapse rate changes (section 2.3), but such effects where at most very weak.

For precipitation, the large increase found in the time series over the sites shows again here. As explained in section 3.1.1, this increase is rather surprising and can not be given a high confidence without more research and general validation of the method. However, it is important to note that CLIMBER itself shows large precipitation increases for the present snapshots. When linear interpolation is used instead of downscaling, the precipitation change goes up to 200% but with a partly different geographical repartition and covering a smaller area (not shown).

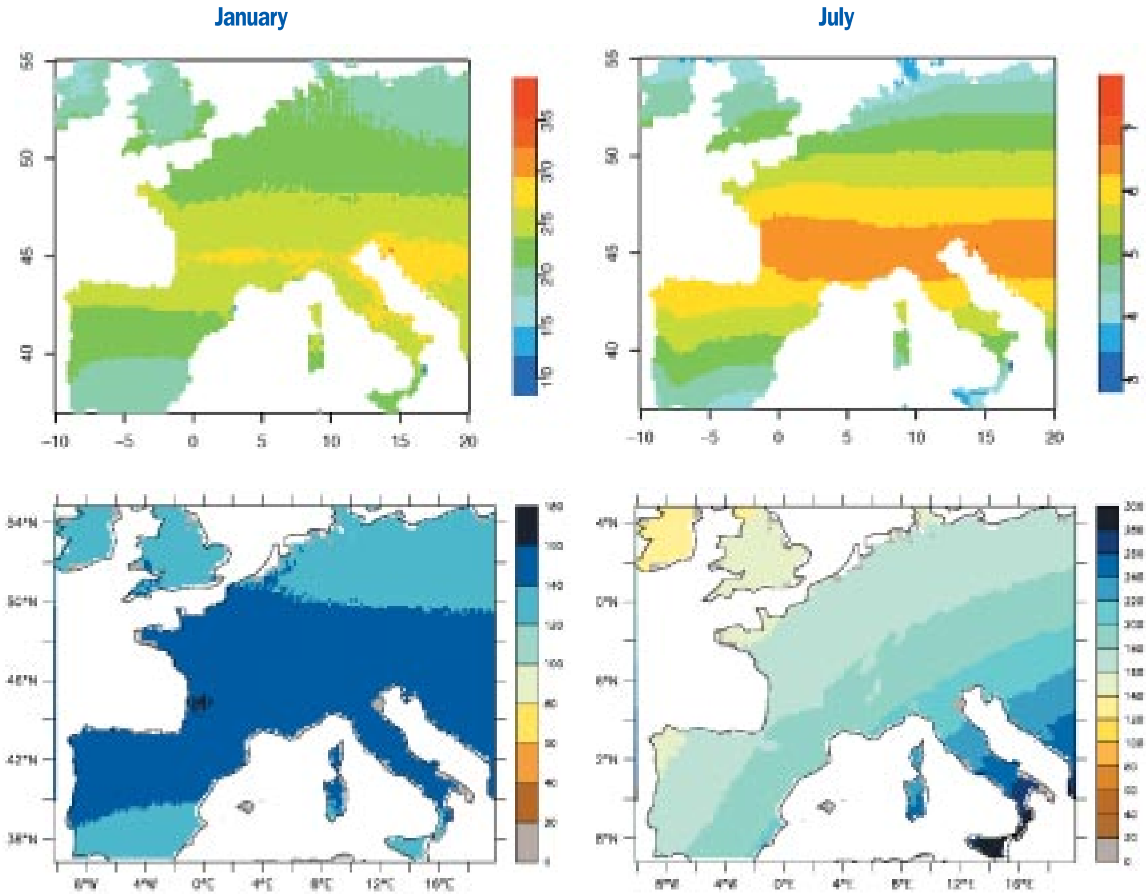


Figure 25 : *67 kyr after present.Temperature change (°K, above) and precipitation change (%, below).Changes are relative to present-day (end of the XX century). Grey areas are under sea-level at that time (and not in present day)*

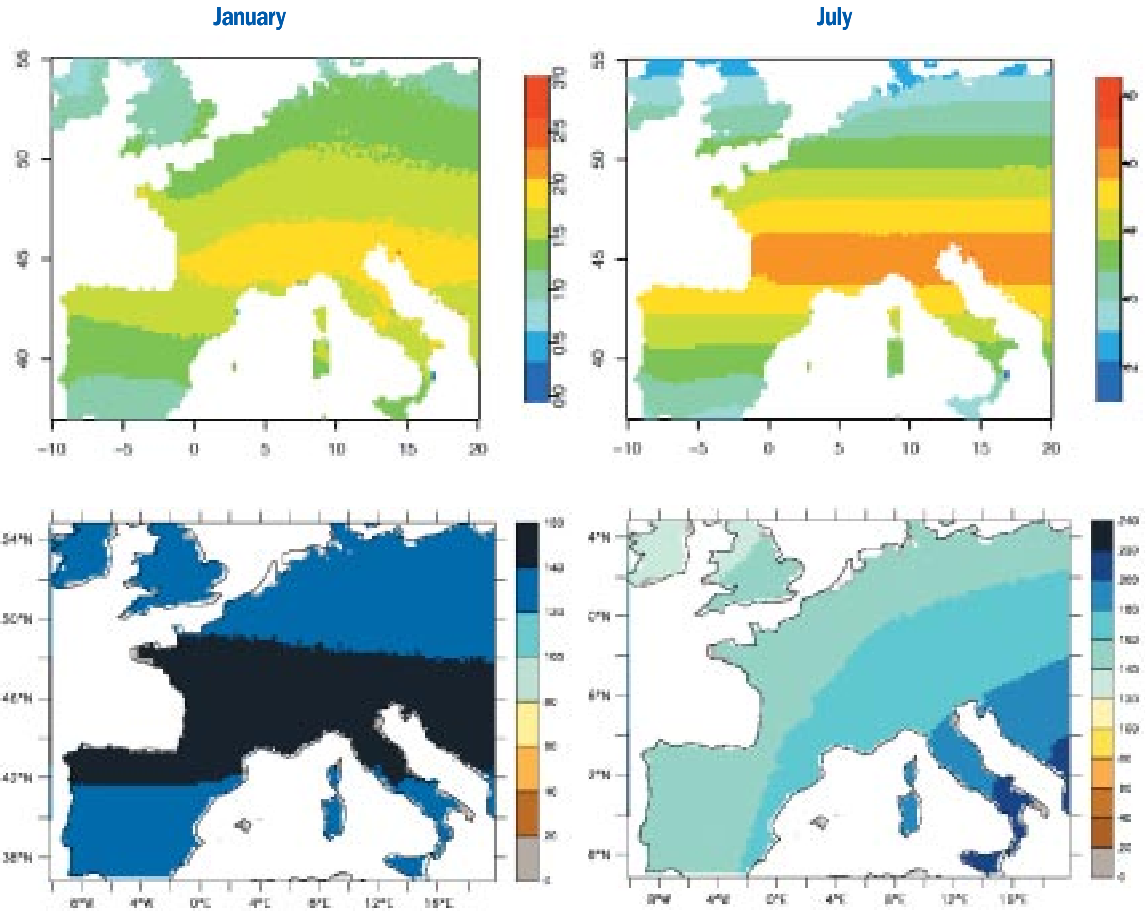


Figure 26 : *178 kyr after present. Temperature change (°K) and precipitatin change (%), as in figure 25.*

4. Conclusion

This report presents a downscaling methodology designed to provide high resolution temperature and precipitation data on the basis of outputs from the intermediate complexity model CLIMBER-GREMLINS. The method provides a link between the coarse climate model outputs and the regional (or local) climate data needed for performance assessment of radioactive waste repositories.

To obtain climate-change information at 1/6 degree resolution on the basis of the climate model outputs, the downscaling method works in 2-steps. First, physical considerations are used to define variables (predictors) which are expected to have links which climatological values; secondly, a generalized additive statistical model is used to find the links between these variables and the high-resolution climatology of temperature and precipitation. Thus the method is termed as "physical/statistical" : it involves physically based assumptions to compute predictors from model variables and then relies on statistics to find empirical links between these predictors and the climatology. These "physically based assumptions" are necessary because the climate data are provided by an intermediate complexity model, which gives only limited information about space and time variability: it provides coarse data which can not be directly linked to regional climate change by a statistical model calibrated on present-day climatology (but other downscaling strategies are also be applicable, such as in Ref.15.

The predictors which have been computed from CLIMBER outputs and physically-based assumptions are : continentality (with advective and diffusive variants), vertical temperature gradient, effects of mountains (masking, Foehn-like upslope effect).

The method is new. It has been successfully applied to CLIMBER, providing outputs for the BIOCLIM scenarios. The conception of the method was careful : many tests with different sets of predictors have been conducted (only the most interesting ones where reported here). However, further research and improvement will still be possible in the future. A potential area for improvement is the treatment of the seasonal cycle: in the current version, there is no predictor related with the seasonal cycle, while in practice the impact of continentality on temperature is highly season-dependent. In more general sense, the way continentality affects land temperature in the method also need further investigations, with a view to account for temperature contrasts between sea and land in CLIMBER. While this may seem easy, it will need a careful look at CLIMBER outputs in different climate states. Knowing which variables can be useful and how it might be used is not immediate, because due to the simplified nature of the climate model, variables such as SSTs may not have the degree of realism required for direct use in the downscaling process. The limited comparison with reconstructions for the last glacial maximum did not show advantages of the application of downscaling. This may have several origins, including the climate model and the precision of the past climate reconstructions, so that this also calls for more research in the future.

Monthly mean temperature and precipitation are presented for 3 scenarios for the next 200 kyr (natural and fossil fuel cases). These variables are mainly shown as time series of site-mean values plus maps a two specific times, while more data is available in numeric form (see appendix). For temperature, the downscaling results are expected to have some realism, and may be interesting to use for performance assessment – at least as an alternative to more direct CLIMBER-GREMLINS outputs. The downscaling results for precipitation should be considered more prudently. Large increases are shown in the future both in the model and downscaling results (up to about 200%), but the downscaling procedure provides high precipitation amounts over larger parts of Europe, as well as other surprising results. While it was interesting to obtain complete results with this new method, this clearly opens the way for further research.

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Appendix 1 : Data product

The temperature and precipitation time series (200 kyr starting from present) have been made available to the BIOCLIM community on the Buisness Collaborator web site (**http://cobweb.businesscollaborator.com/bc/bc.cgi**). The provided values are those presented in the graphics of section 3.1 in this report. Data is thus available for each BIOCLIM site, for scenario A4a and B3 (at least). A simple ASCII format is used, and can be read with commonly used software. There are two basic types of files : "raw" results contain values (temperature and precipitation) over each downscaling-grid points, and the regular output provides simple statistics on these values (e.g. site mean, max and min for the interpolated CLIMBER output, climatology, downscaling output). There is thus somewhat more data regarding the time series than shown in the report. The detailed description of the files and their organization is provided with the files.

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