Motive D 2.2. Climate and Land Use Data

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Summary
This document provides both an overview of available climate and land use change data over Europe, and it summarizes the methods used for scaling climate data from regional climate model (RCM) output to finer spatial resolution (1km and 100m).
1. Introduction

The modelling activities and subsequent integration activities in MOTIVE require consistent environmental data for assessing climate change effects on forest ecosystems through modeling forest dynamics and forest management effects. We have decided on carrying out the analyses based on a defined set of climate change scenarios prepared at a spatial resolution of 100m in each cases study region (only few deviations from this general rule exist). Deliverables D2.2 reports on the generation of the climate data sets that was generated from: (a) the Worldclim climate data base (1km spatial resolution), (b) a 90m global DEM ranging from 60°S to 60° North, and (c) IPCC-based combined GCM/RCM output available from results of the ENSEMBLES project. Additionally, the DL 2.2 also reports on the availability of land use change scenario maps at comparable spatial resolution.

The basic idea was to generate very high resolution (100m) data sets in order to complement EU wide analyses with regional studies so as to avoid the hurdles of developing regional scale data sets from scratch for each individual study area. EU-wide environmental analyses often use those data sets that are easily available at that scale. This is either the 10’ gridded data set available from the Climate Research Unit’s (CRU) website1 of the University of East Anglia (CRU13) or other similar output, such as e.g. from the ALARM EU-project. A number of such outputs exists and these primarily include projections of future climates using a suite of IPCC scenarios and global circulation models (GCM) and regional circulation models (RCM).

Current (recent) climate on the other hand is usually gridded by interpolation and regression using existing climate station records. Again such data sets are available at coarse spatial resolution (10° to 0.5°) from the same sources as mentioned above. Additionally, a global data set termed “Worldclim” (Hijmans et al. 2005) is readily available online2. This data set is available at a spatial resolution of 1km. It is based on a global analysis of a huge climate station network and the interpolation approach used consists of regression splines (Hutchinson 1995; Hutchinson 2004). The method and also the resulting climate maps compare favourably with other existing climate interpolation approaches such as DAYMET (Thornton et al. 1997) or PRISM (Daly et al. 1994).

The spatial resolution matters considerably when analyzing ecological patterns at a given extent. At an EU scale and depending on the nature of the environmental data available, a 10’ spatial resolution (~18x18km) may be far sufficient. E.g. the analysis of biodiversity patterns available in the digital version of the Atlas Flora Europaea (AFE) using 10’ gridded climate data is well doable, since AFE is only available at 50x50 km resolution. However, when environmental data is available for a comparably small plot area such as 10x10 or 100x100m, and when topographic variation is high such as in mountainous terrain, then the comparably coarse spatial resolution of 18km or larger is simply insufficient to understand ecological patterns at that fine scale. The Worldclim database is one alternative solution for analyzing finer scale patterns, and it has been successfully used in a range of studies. However, it is still too coarse for many regional studies, especially in regions with high topographic variation. Here, a 1km pixel simply averages too much of variation in elevation, slopes and aspect as to understand the nature of the biological response at the plot level of – say – 50x50 meters (see Fig.1). This is why a further downscaling of the 1km data set was envisioned.

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1 http://www.cru.uea.ac.uk/cru/data/hrg.htm
2 http://www.worldclim.org/
We distinguish two forms of downscaling (and there exist others, which we do not discuss here): (a) downscaling by simple interpolation, and (b) downscaling by combined regression and interpolation. The method (a) is used, when topographic effects such as the influence of elevation on the patterns at the finer scale upon the target variable are unimportant or unknown. If the influence of e.g. elevation on the target variable (e.g. temperature) is known and strong, then method (b) is to be used. In the data processing presented here, we used both methods. First, we downscaled the 1km Worldclim data sets to 100m. Here, we used method (b), since the finer scale topography clearly influences the values of the climate variables. Thus, we used a regression-based approach to downscaling, so as to link the climate values regionally/locally to the topography (see 2.1). On the other hand, although the anomalies from current climate as projected to the future using GCMs/RCMs may actually show clear dependencies on topography, we have no information what the dependency will be. No RCM is currently run at the spatial resolution of 100m for large scales, and thus we need to assume that the forecasted anomalies at e.g. a 0.5° spatial resolution apply to all situations inside of this pixel. At best, we can assume that if there are smooth gradients between the 0.5° cells that these gradients also apply at a finer spatial resolution. Thus for the downscaling of projected climate anomalies, we used method (a) as described in 2.2. In order to have such forecasts available at the 100m as well, we combined the downscaled anomalies with the downscaled current climate data (2.3) in order to combine the high spatial resolution of the downscaled current climate with the projected futures available through anomalies.

Figure 1: Climate mapping and spatial resolution. The figure is taken from Hijmans et al. 2005, and illustrates the importance of spatial resolution at different scales. While at the global scale a 10° spatial resolution seems sufficient to express ecological gradients, at regions with considerable mountain topography, the same is no longer true. Here, a 1km resolution (presented) or finer helps to better assess ecological patterns.
Downscaling requires the availability of very high resolution digital elevation models (DEMs). We used the only currently available source for mapping and scaling at large spatial scales, namely the global CGIAR-CSI SRTM DEM\(^3\) of a quasi 90m spatial resolution. It is available between +/-60° N/S. Because some parts of the MOTIVE project domain are not covered by this DEM, we stored all downscaling elements so that the final maps can always be easily generated regionally given the availability of specific regional DEMs.

2. Material and Methods

2.1. Downscaling of the WORLDCLIM climate maps

The climate downscaling procedure from the Worldclim 1km resolution to a resolution of 100m required three steps. First, we determined the regional dependency of climate from elevation; second, we interpolate these findings to a finer spatial resolution; and third, we combine the downscaled information with existing higher resolution DEMs. The three steps are explained below and Fig. 2 gives an illustration of this process.

The first step consists in determining how climate parameters (Tmin, Tmax, Prcp) depend on elevation regionally. The original Worldclim climate maps were originally developed by determining such dependencies from climate stations and their elevation. The mapping then consisted of applying these dependencies (in the form of regression-splines) to the global GTOPO30 DEM, which has a spatial resolution of ca. 1km. Since this DEM also contains considerable uncertainties or errors (high errors on some pixels), the resulting climate maps show high errors as well. However, the dependency of climate from elevation is still there. Thus, using regressions between climate maps and the GTOPO30 DEM in moving windows can be used to re-detect these dependencies. When doing so, we calculate this dependency e.g. in a window of – say – 15x15km (thus using 225 pixels). We then explain e.g. the precipitation of June in the Worldclim map by the elevation from the GTOPO30 map. This dependency in the form of regression parameters (ICEPT: intercept and LPSRT: lapse rate) is now valid for the situation around the center pixel of this window. If we move east-west or north-south, another set of pixels is analyzed, and the regression values change slightly. They do not change rapidly, since many pixels overlap, if we only move one row or one column. As a result, we can write all regression parameters (ICEPT, LPSRT) to the center pixel of each window position, when moving the window across the whole study area. This generates two maps of 1km spatial resolution per climate map analyzed, one containing ICEPT and one containing LPSRT. We used windows of 25x25 pixels for scaling temperature maps, and 15x15 pixels for scaling precipitation maps. On one hand, we want as small windows as possibly in order to regionalize the mapping of the elevation dependencies. On the other hand, too small windows may not show enough topographic variation to let us detect such dependencies. In preliminary studies we optimized the window sizes. The smaller number of pixels used for precipitation reflects the fact that this variable shows higher small-scale variation of the elevation dependency. Regressions were performed in moving windows by running a Fortran code on exported maps reading the GRIDASCII export format. It generates two additional files, one each for ICEPT and LPSRT in the same GRIDASCII format for later import.

The second step consists in scaling this information down to the finer spatial resolution. Since we now know the dependency on elevation, and since we now have removed the effect of topography from our maps (by simply storing the regression parameters), we can now easily scale the information by spatial interpolation. Climate may change quite abruptly from one 1km pixel to the next, but this is primarily

\(^3\) http://srtm.csi.cgiar.org/
due to large elevation differences. The resulting regression parameters from moving window regressions do not change abruptly, since the dependency explains the vast majority of the variation within the window. For this, the GRIDASCII format files of ICEPT and LSPRT are imported back to ArcInfo, and an interpolation was applied in ArcGRID. Since Worldcllim is available in a geographic projection only, we also re-projected the regression parameters to an Albers Equal Area projection (AEA) according to the INSPIRE standard. Therefore, we sampled ICEPT and LPSRT at 1km resolution (at the center of each pixel in a point format), then re-projected the points to the AEA projection, and finally used inverse distance weighted interpolations (IDW) to generate the same ICEPT and LPSRT grids again at a 1km resolution in AEA projections. In order to get from a 1km to the 100m resolution we used the RESAMPLE command with BILINEAR interpolation in ArcGRID. Note that IDW could be used to generate 100m rasters directly from point files. The two approaches give essentially the same results. We chose this way because it is the procedure implemented in a larger scaling framework coded in ArcAML, which can flexibly be used when scaling from different original resolutions.

The third step consists in re-generating climate grids at the finer resolution. In the regression model, elevation was used to “explain” the climate variable. Now the regression parameters ICEPT and LPSRT are used in combination with the fine resolution DEM to generate 100m climate grids by. In Figure 2, the above mentioned steps are illustrated with an example of scaling PRISM (Daly 1994) climate maps from ca. 4.5 km spatial resolution to 90m.

To summarize, we conclude that the procedure of scaling is doable, because we remove to a large degree the effect of the terrain from the data we want to scale. Terrain has a very strong influence upon the climate, mostly because of changes in altitude, but also through rain shadow effects. The elevation dependence is taken care of by applying regressions, and the rain shadow effects are incorporated by the moving window approach. Thus, when moving the window across a mountain, both lapse rate and intercept are adjusted.

2.2. Downscaling of climate anomalies from GCM/RCM maps

The downscaling of GCM/RCM output follows similar procedures as described under 2.1. However, we do not assume to find elevation dependencies easily in the climate signal, and rain shadow effects may or may not be visible, depending on the source resolution of the climate forecasting. The elevation dependency is certainly there, even at a comparably coarse resolution. However, there are too few pixels with too small changes in the average pixel elevation at the coarse resolution of 10’ or even larger as to accurately re-construct such elevation dependencies. Therefore, we follow a different approach here. The general procedure is explained in an overview below.

The steps for scaling GCM/RCM output foresee to “only” scale the difference between forecasted futures and present (recent) climates. We term this difference (between future and current) “climate anomalies”. By this, we can remove the topography effect to a considerable degree. When scaling anomalies, we generate grids – say for monthly temperatures – that explain how much warmer or colder the climate is expected to be in the future using one specific scenario. This information can be scaled much easier than the climate itself. In order to generate a very high-resolution futures climate map, we need however also to scale the anomalies to the same very high spatial resolution as is the current climate. Once available (see 2.1 on how to get there), the anomalies can be added to the current climate to generate future climates. The most important step here is to generate anomalies appropriately. First, we need to know the averaging period of the very high resolution climate layer. E.g. Worldcllim uses a 1950-2000 averaging of monthly values. Next, we need to generate the monthly climate anomalies for a given GCM/RCM output for a certain period. To calculate the difference between the projected future from any GCM/RCM and the current climate, we use the time series
Figure 2: Illustration of the required downscaling steps. (A) illustrates the moving window, which moves across a temperature and elevation grid, producing variable regressions (B). The regression parameters (intercept and lapse rate) are then spatially interpolated from the coarse resolution of the original DEM/climate map to the fine resolution of the target DEM (C, here 90m). Finally, the three maps of (C) are used to generate very high resolution climate maps (D) by applying the regression model to generate the climate map from the DEM, the intercept and the lapse rate maps.

Simulated model outputs for the re-analysis period of 1950-2000 from each pair of RCM/GCM. This means that we first average the modeled recent past (1950-2000), which is available for all RCM/GCM pairs we have used, to generate the proper anomalies between current (recent past) climate and future time steps. By this, we additionally avoid the projection of modeled bias in RCM/GCMs should the recent past be wrong compared to climate station measurements. We are only interested in projecting the relative difference between simulated recent past and simulated futures. Once anomalies are generated, we interpolate these anomalies to the very high resolution and add them back to existing climate maps representing the current climate.

The development of climate anomalies was done by (a) first averaging the monthly time series of Tmin, Tave, Tmax and Prcp over the period of 1951-2000 for each pair of used RCM/GCM, since these represent the same base period of Worldclim maps. Then we used GCM/RCM outputs (available at comparably coarse spatial resolutions of 10' to 0.5°) as monthly time series and calculated monthly anomalies relative to the averaged 1950-2000 period. We developed monthly anomalies by: (a) subtracting current from future climate for temperatures, and (b) by dividing future by current climate.
for precipitation. The latter results in ratios of change, which is important since negative precipitation values may be generated after downscaling if the same procedure as with temperatures would be used.

All climate anomalies are calculated at the spatial resolution of the GCM/RCM output. Figure 3 gives an example of climate anomalies of the CLM/ECHAM5 model output provided by the MPI in Hamburg using the A1B scenario by 2100.

All climate data is first scaled from the coarse spatial resolution available as RCM/GCM output (10' to 0.5' for most RCMs) to the medium resolution of 1km by a bilinear interpolation algorithm. All scaling analyses as described in Fig. 2 from coarse to medium are performed in the NETCDF format using “cdo” and other tools. This means that we first import WORLDCLIM (at 1km spatial resolution) into the NETCDF format in order to perform the required analyses. All data is stored in this medium resolution in the GEOGRAPHIC coordinate system (LAT/LON).

In order to downscale to finer spatial resolution, two different pathways were developed, the choice of which depends on the nature of the data scaled. Monthly climate series are exported first to ArcInfo grids, and then scaled to finer spatial resolution using ArcInfo AML scripts. Daily climate maps at finer spatial resolution are only are only generated for comparably small study areas. The necessary steps are all performed in NETCDF using “cdo” and other tools. Both steps are briefly described below, without going into specific detail.

**Figure 3:** Precipitation anomalies for the projected period of 2091-2100 using the A1B model output from the CLM/ECHAM5 RCM/GCM model pair (generated by MPI, Hamburg). The values are expressed as % change compared to the current (1950-2000) climate for each of the 12 months (top left to bottom right).
The scaling from medium (ca. 1km) to fine (ca. 100m) spatial resolution follows the same approach as was explained for the scaling from coarse to medium. First, monthly climate anomalies are calculated, and then interpolated to the fine spatial resolution. Once scale to the fine spatial resolution, the anomalies are added to the current climate maps of T and P available at a spatial resolution of 100m (see Fig. 2 and associated text on the derivation of 100m climate maps). By this, we do not simply smear the climate data from 1km to 100m pixels, but we rather use climate data properly scaled to 100m using the finer scale topography information instead, and we add anomalies to generate time series of future climates. Similar techniques are e.g. applied by national meteo services, if they scale RCM outputs to individual climate stations.

Daily climate maps are essentially developed in a very similar way, also including 100m scale climate maps as basis for the fine spatial resolution and scaled anomalies originating from 1km data. The major differences are as follows: (i) we generate daily time series at medium spatial resolution starting from coarse RCM resolutions; (ii) we scale daily anomalies from medium to fine, where the anomalies are those of daily values relative to the respective longer term (1950-2000) monthly mean values; (iii) all scaling from medium to fine spatial resolution is performed in the NetCDF format using “cdo” and similar tools; (iv) all daily anomalies are combined with the monthly climate maps at 100m spatial resolution.

All final grids are stored in integer format for reasons of storage efficiency. Thus, we multiply temperatures by 10 (thus storing 1/10th of degrees Celsius as integers. Precipitation is stored in mm as integers. By this, we can reduce the amount of disk space required by a factor of >10 (sometimes >50).

2.3. Generating derived climate maps from basic climate data

Additional to the basic variables of temperature and precipitation, we derive global radiation maps as driven by the continental (at 1km cell size) or regional (100m cell size) and combine these with projected future climate. We generate time series of monthly or daily actual global radiation as follows:

(i) we generate potential global radiation by using AML scripts on 1km or 100m DEMs, which generate both direct and diffuse radiation layers as influenced by topographic shading, and slope and aspect of each pixel in a DEM. The sum of both layers is the potential global topography-affected radiation.

(ii) we calculate the potential global radiation for flat surfaces (excluding the topography effects) for the same study area using the same algorithms.

(iii) we extract from an RCM the 1950-2000 mean monthly flat-surface global radiation (is available).

(iv) we calculate monthly or daily anomalies relative to this base period and scale these two the medium or fine spatial resolution, depending on data need.

(v) Finally, we add the anomalies of difference between flat-surface future relative to current radiation to the medium or fine resolution potential global topography-affected radiation.

This approach allows us to scale both potential to actual global radiation and to apply the anomalies technique to correct topography-affected radiation calculations. By this we combine several scaling techniques in order to generate more informative climate layers for ecological modeling. Notably, we now usually derive layers of potential evapotranspiration, which are driven by fine scale temperature, precipitation and actual global radiation information. Other derived climate layers include the calculation of the subtraction of potential evapotranspiration from precipitation (which we term moisture index), the derivation of degree day sum maps, or the calculation of bioclimatic variables according to the WORLDCLIM standards.
3. Available climate and land use data

3.1. Available climate data

All scenarios currently available in ArcInfo grid formats for downscaled RCM data are listed below. These contain primarily monthly mean climate time series for 2001-2100 at a spatial resolution of 1km, available in geographic projection. Depending on case study demands, these are downscaled to 100m as described above. However, daily climate variables can also be extracted from these data sets. Yet, these are not processed to ArcInfo grids. Rather, products based on daily data are specifically processed to the needs in the different case studies. Here we provide an overview of available data and scenarios. In MOTIVE, we have decided to primarily use the A1B scenario, since this is the only one widely available from RCM simulations. Other scenarios are only scarcely available right now from RCMs, and only GCMs provide these scenarios consistently. Yet, we did not consider using GCM outputs for MOTIVE, as the focus is primarily on regions, not on very large spatial scales.

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3.2. Climate model comparison

A comparison of the annual and seasonal outputs of the different scenarios has revealed clear differences between the RCM/GCM combinations processed. Early on, we have proposed that the CLM/ECHAM5 model output should be used as a basic standard dataset. This decision is important, since not all case studies and models can run all available models at due time. So below we briefly discuss how the different models and scenarios compare to the standard model. We discuss here primarily the A1B scenario, which we have decided to use in MOTIVE.

First, CLM/ECHAM5 represents an average trajectory into the future, representing a moderate warming. High warming over the 21st century are given by the HADRM3/HADCM3 and to a slightly lesser degree by the HIRHAM3/Arpège model data. These two models project a warming that is on average 1 to 1.5°C warmer than CLM/ECHAM5. On the other hand, the RCA30/CCSM3 output represents a warming that is reduced by ~1.0° by the end of the 21st century compared to the CLM/ECHAM5 model. This judgement is specifically true at the end of the 21st century, while at the beginning of the century, CLM/ECHAM5 is rather slowly heating up at the beginning, while RCA30/CCSM3 heats up faster, then stabilizes temperatures with comparably high fluctuations after 2070. An increase of climate variability is visible in all models/scenarios. Figure 4 gives an overview of the variability and trajectories of the RCM/GCM model outputs for temperature, while Fig. 5 provides similar information for precipitation. In both figures, all A1B scenarios, which build the core of MOTIVE data, are plotted in red/brown colors, while all other scenarios (A2, B1, B2) are plotted in green and blue colors. It is visible, that these other scenarios do not really exceed the variability included in the several A1B model outputs.
With respect to annual precipitation sum, we see a slightly different response. Most models predict a slight decrease in overall precipitation sum over Europe. But this is not a major concern as a whole. However, we recognize first that variability in precipitation is increasing with higher annual precipitation values in some years and increasingly more drought years on the other hand. The regional variability is huge however, which is visible from Fig. 3, where more Southern regions are projected to undergo stronger droughts in summer months than more Northern latitudes. This also means that on average, Southern regions are projected to become drier more clearly, while Northern regions might see an increase in annual precipitation.

When comparing the different RCM models, it becomes visible that the HADRM3/HADCM3 model projects a drier future than other models. The driest future with the most extreme variation is, however, projected by the HIRHAM/Arpège model. On average, the annual precipitation sum over Europe is reduced by ca. 100mm as averaged over all regions. The CLM/ECHAM5 model projects a comparably modest change over the 21st century, with only little decrease in annual precipitation sum. Also, the annual variation in precipitation does not change clearly in this model. An intermediate behavior is projected by the RCA30/CCSM3 model.
3.3. Available Land Use Scenarios

We have prepared the FP6-ECOCHANGE land use change products for use in MOTIVE. This data set is published and available for no charge and without restriction to scientists in other projects. The data originates from a downscaling (which was performed in ECOCHANGE) of the ALARM land use change scenarios. The latter was available at a comparably coarse spatial scale (10’ spatial resolution), and the information was mapped as cover fraction of different land use types. The ECOCHANGE products are available as discrete land use maps, scaled to a comparably fine spatial scale of 250m. Figure 6 provides an example of the land use change in northern Central Europe for the ALARM scenario BAMBU. The three scenarios (BAMBU, GRAS, SEGD) represent roughly three out of four IPCC scenarios and can be translated as follows: GRAS – A1B; BAMBU – A2; SEGD – B1 or B2. The land use change model is not driven by more modern climate change scenarios. But no other model that would be based on newer climate change scenarios is available for Europe. Therefore, we propose to use the one from ALARM/ECOCHANGE. One significant problem with this scenario is the fact that this model does not represent scenario data for Romania and Bulgaria. However, other than scenarios like the CLUE-S model output from P. Verburg, ALTERRA, the ALARM/ECOCHANGE product covers all of Europe, including many non-EU countries. The data distinguish rather broad land use classes (6 classes, whereof one is forest). The downscaling method is described by Dendoncker et al. 2006.
Figure 6: Land use change as modeled originally by the ALARM team and downscaled by Marc Rounsevell and colleagues from 10’ spatial resolution to a 25m raster. The model is available at four time steps: 1990, 2020, 2050, and 2080, which are presented here for the GRAS (A2) scenario for northern Central Europe.

4. References


