

Project Title: ECOPOTENTIAL: IMPROVING FUTURE ECOSYSTEM BENEFITS THROUGH EARTH OBSERVATIONS

Deliverable No. 8.1: High resolution (1-10 km) climate, land use and ocean change scenarios

This project has received funding from the *European Union's Horizon 2020 research and innovation programme* under grant agreement No 641762

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1. Executive summary

The present Deliverable illustrates the activities carried out within Task 8.1, led by CNR, in the first 30 months of the ECOPOTENTIAL project. The objective of this task is to generate high-resolution climate change and land use scenarios for the different protected areas (PAs) involved in ECOPOTENTIAL, both to describe the evolution of climatic conditions in future decades and to drive eco-hydrological, biological and impact models used in the project to estimate the future behaviour of ecosystems and their services.

The deliverable is structured as follows:

Section 2 places Task 8.1 in the general context of WP8 and introduces the main objectives of the task, also discussing eventual deviations from what was originally planned.

Section 3 presents the general scientific background behind this Task and in particular deals with (i) the problem of linking large-scale information provided by global/regional climate models to the fine-scale of the local/impact models, including the use of downscaling methods, (ii) the propagation of uncertainties along the modelling chain and the problem of cross-scale interactions, (iii) the approaches that are commonly used to correct the biases affecting large-scale information.

Section 4 outlines in more detail the future projection strategy followed in ECOPOTENTIAL. After recalling the main milestones that led to the definition of the strategy, the section describes what are the large scale climate models that have been used in ECOPOTENTIAL providing the variables to be downscaled, the bias correction techniques that have been employed, and the temperature and precipitation downscaling approaches.

Section 5 presents the downscaled data repository providing a few examples on how to access the data. Section 6 includes a basic guidance addressed to the users and practitioners of climate model outputs, indicating the good practices for dealing with the downscaled climate scenarios delivered within ECOPOTENTIAL.

Section 7 illustrates a series of (preliminary) applications on how the delivered downscaled climate data and scenarios are being (or will be) used by the project partners.

Open questions and issues are finally discussed in Section 8, while the last section concludes the deliverable.

1.1 Glossary

Climate model. A numerical representation of the climate system based on the physical, chemical and biological properties of its components, their interactions and feedback processes. The climate system can be represented by a hierarchy of models of varying complexity, from simple-process models such as Energy Balance Models to the comprehensive Global Climate Models or Earth System Models including all the climate system components with the highest possible degree of description.

Climate projection. The simulated response of the climate system to a scenario of future emission or concentration of greenhouse gases and aerosols and land-use, generally derived using climate models.

Concentration scenario. Derived from emission scenarios, concentration scenarios are used as input to a climate model to compute climate projections (extracted from IPPC 2013, AR5 WGI, Glossary).

Emission scenario. A plausible representation of the future development of emissions of substances that are potentially radiatively active (e.g., greenhouse gases, aerosols), based on a coherent and internally consistent set of assumptions about driving forces (such as demographic and socioeconomic development, technological change) and their key relationships (extracted from IPPC 2013, AR5 WGI, Glossary)

Global Climate Model (GCM). GCMs provide a representation of the climate system including many of its most important components and processes, which are described in an explicit way or by means of parameterizations. These models describe the climate using a three-dimensional grid over the globe, typically having a horizontal resolution of between 70 and 300 km in the atmosphere.

Regional Climate Model (RCM). Regional counterpart of the GCMs, RCMs are run over limited domains and with higher spatial resolution than global models and use the large scale information coming from the GCMs or from global reanalyses as input for the regional simulation.

Representative Concentration Pathways (RCPs). Scenarios that include time series of emissions and concentrations of the full set of greenhouse gases, aerosol particles, chemically and radiatively active gases, as well as land use/land cover. They provide only one of many possible scenarios that would lead to the specific radiative forcing characteristics.

1.2 Abbreviations and Acronyms

1.3 Institutions involved

2. Introduction

2.1 WP8 general framework

The overall aim of WP8 is to develop and implement a suite of methods for spatial and temporal cross-scale analysis of ecosystem indicators and services. WP8 consists of four tasks that have a methodological focus related to scaling, including (1) Downscaling, (2) Upscaling, (3) Data Assimilation/Uncertainty analysis and (4) Process-based Ecosystem Modelling across scales for selected PAs and at pan-European level. As most future projections also include cross-scale assumptions or data from beyond the regional scale of the Protected Area (e.g. GCM-based climate projections, or land use scenarios), WP8 is, in addition, dedicated to bringing together future simulations from within PAs and on the pan-European level. The present deliverable refers to the first WP8 task, Task 8.1, on "High resolution climate, land use and ocean change scenarios." This Task is specifically devoted to development and use of the methods for downscaling the climatic information from the large scales of global or regional models or coarse observational datasets to the scales of ecosystem models.

2.2 Task 8.1: objectives and deliverable

The description of Task 8.1 as defined in the Grant Agreement is as follows:

In agreement with the ECOPOTENTIAL modelling partners, the activities in Task 8.1 of WP8 concentrated on developing a suite of downscaled climate change scenarios for selected PAs. These data are desired not only to characterize the current and expected changes in climate in the various PAs of interest for ECOPOTENTIAL but also to drive the local scale ecosystem, ecological, biological and impact models developed and used in the project for estimating the future behaviour of ecosystems and of their services. The discussion about also downscaling land use scenarios showed that the advantages of individual high-resolution land use scenarios elaborated to the needs of PA managers or projected on current trends within the individual PAs, would be of higher value than systematic downscaling from existing large-scale land use scenarios. To enable ECOPOTENTIAL partners to produce trend scenarios for their particular PA based on observed land use change data, the BGU partner organised a workshop on February 7-8, 2017, in Sde Boker, Israel. Interested partners could learn and practice the use of a well-established land use extrapolation software, namely the MOLUSCE plugin for the open source GIS software QGIS, in this handson workshop.

The present document thus provides now a description of the climate downscaling carried out in Task 8.1 in the first 30 months of the project, and in particular presents:

- (i) the general background on how to bridge the scale gap between the large scales of climate model outputs and the impact scales, addressing also the problem of the propagation of uncertainties across the different scales;
- (ii) the main milestones of Task 8.1 that led to the definition of the downscaling strategy;
- (iii) the downscaling strategy including the choice of the large-scale datasets and the downscaling methods and procedures;
- (iv) the repository of the fine-scale downscaled climate outputs;
- (v) preliminary applications of the downscaled data and case studies analysed by partners as well as a plan on how the downscaled data will be used;
- (vi) criticalities and open issues as concluding remarks.

3. Background

3.1 The modelling chain connecting the large scales to the impact scales: the state of the art

Global climate models are the most comprehensive tools to explore climate processes, feedbacks and changes occurring at the global scale. The latest coordinated initiative called Coupled Model Intercomparison Project phase 5 (CMIP5, Taylor et al., 2012) produced a large ensemble of global climate simulations that has been the basis for the latest assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC, 2013). Since the former IPCC Assessment Report (AR4), global climate models have increased the number of components incorporated within them and the degree of detail in the description of the key climate processes (Stocker et al 2013). Despite there has been a tendency to increase the horizontal resolution of climate model simulations, even these most recent GCMs still operate on coarse spatial grids of 80-300 km resolution. This leads to a crude representation of some physical processes such as mid-latitude low pressure systems, convection, cloud and precipitation processes (Kang et al., 2015), and to "simplified" land surface characteristics and topography, so that mountain regions and coastal areas remain poorly resolved (e.g. Palazzi et al., 2015; Terzago et al., 2014 for mountains). All these limitations make the coarse-scale GCM output generally not adequate for studying climate change impacts at the local scale, for which information at much finer resolutions (1 km or finer) is desired. Statistical, stochastic and dynamical downscaling techniques are thus applied to increase the spatial resolution and refine the spatial information provided by the GCMs up to regional and local scales.

Dynamical downscaling employs regional climate models run over a smaller domain and at finer spatial resolution (50-10 km) than GCMs (e.g. Rummukainen, 2010). In principle this approach allows for a more detailed representation of physical and dynamical processes such as mesoscale circulation patterns and for a better representation of the processes depending on the topography, for example of orographic lifting and associated precipitation. The main advantage of the dynamical downscaling approach is that it is physically-based, many atmospheric processes are explicitly resolved and the output variables are internally (i.e., dynamically) consistent as in GCMs. One disadvantage is represented by the huge computational resources needed to run high-resolution regional climate model simulations. In addition, it is worth noting that regional simulations are driven by lateral conditions provided by GCMs, from which they can inherit fundamental errors and biases. Overall, the IPCC report that there is high confidence that downscaling adds value to the simulation of spatial climate detail in regions with highly variable topography (e.g., distinct orography, coastlines) and for mesoscale phenomena and extremes. Regional downscaling is therefore complementary to results obtained directly from global climate models (Flato et al., 2013). The Prediction of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects (PRUDENCE, Christensen and Christensen, 2007) and ENSEMBLES (van der Linden and Mitchell, 2009) projects represent two outstanding examples of coordinated initiatives on the use of dynamical downscaling to generate regional climate change scenarios at the European level and beyond. Recently a large number of CMIP5 GCMs have been downscaled in the Coordinated Regional Downscaling Experiment (CORDEX, Giorgi et al., 2009). The European branch of CORDEX, in particular, is producing a large number of regional projections over Europe of up to ~12 km horizontal resolution (0.11 degrees lon-lat) which is higher than in all previous coordinated experiments of regional modelling (e.g. Jacob et al., 2014; Vautard et al., 2013).

Statistical Downscaling (SD) techniques are based on the development of statistical relationships between largescale climate information and local climate variables. Such relationships are then applied to the large-scale model projections to simulate the local climate characteristics. Maraun et al. (2010) classified the statistical downscaling techniques into three main classes: Perfect Prognosis (PP) statistical downscaling, Model Output Statistics (MOS) and Weather Generators (WG). We briefly summarize the characteristics of the three aforementioned methods in Box 3.1. The main advantages of all SD methods are their affordable computational costs and their "easy" application. The limitations are the dependency on (the availability and reliability of) observational datasets that are used as fine-scale reference, and the assumption of stationarity in the relationships between large-scale predictors and local predictands.

Employing one downscaling technique or another often depends on the specific problem at hand and on the variable one is interested in. Surface air temperature and precipitation are important variables required by ecohydrological studies. Temperature has a more homogeneous spatial pattern than precipitation and is usually downscaled with a relatively simple adjustment based on considering the mismatch between the actual topography and its discrete representation in the models. On the contrary, precipitation is more difficult to model owing to its high spatial and temporal variability and its intermittency. In order to downscale precipitation, therefore, stochastic methods have been very often developed and used in recent decades (Deidda et al., 2006; Rebora et al., 2006; Ferraris et al., 2003; Deidda, 2000; D'Onofrio et al. 2014). For further details see Box 3.1. The main method used in ECOPOTENTIAL to downscale large scale precipitation fields is actually based on the stochastic rainfall downscaling procedure called RainFARM, as described in Sect. 4.5.2.

3.2 Future climate simulations: the RCP scenarios

Climate models are a numerical representation of a selected subset of the climate system components and processes, of their interactions and feedback mechanisms. Characterized by different degrees of complexity, climate models are used for simulating and studying the present climate and for making projections on how the climate may evolve in the future, based on "scenarios". Emission scenarios are a plausible representation of the future developments of emissions of substances that are potentially radiatively active (e.g., greenhouse gases, aerosols) based on a coherent and internally consistent set of assumptions about driving forces (such as the demographic and socioeconomic development, technological changes) (IPCC 2013 definition, see also the Glossary). The latest emission scenarios for climate change are the Representative Concentration Pathway (RCP) scenarios. "Concentration scenarios" are derived from emission scenarios and they are used as input to the climate models for producing future climate projections, like those reported in the latest assessment report of the IPCC (IPCC 2013, Glossary). RCP scenarios include time series of concentrations of the full suite of atmospheric greenhouse gases and aerosols and other chemically active gases, as well as possible changes and evolution in land use/land cover (Moss et al., 2010). The word "representative" means that each RCP provides only one of many possible scenarios that would lead to the specific radiative forcing characteristics. The term "pathway" emphasizes that not only the long-term concentration levels are dealt with, but also the trajectory taken over time to reach that outcome (Moss et al., 2010). RCPs usually refer to the portion of the concentration pathway extending up to 2100, for which Integrated Assessment Models produced ranges of corresponding emission scenarios.

Four RCPs produced from Integrated Assessment Models were selected from the published literature to be used in the latest IPCC Assessment as a basis for the climate projections:

- **RCP 2.6** is one emission pathway representative of scenarios that lead to very low greenhouse gas concentration levels. It is a "peak-and-decline" or mitigation scenario in which radiative forcing level first reaches a value of around 3 W/m² by mid-century, and returns to 2.6 W/m² by 2100. In order to reach such radiative forcing levels, greenhouse gas emissions (and indirectly emissions of air pollutants) are reduced substantially over time (van Vuuren et.al., 2011).
- **RCP 4.5** is a stabilization scenario in which radiative forcing is stabilized at 4.5 W/m² after 2100, without overshooting the long-run radiative forcing target level (Thomson et al., 2011).
- **RCP 6.0** is another stabilization scenario in which total radiative forcing is stabilized shortly at 6 W/m² after 2100, without overshoot, by the application of a range of technologies and strategies for reducing greenhouse gas emissions (Masui et al., 2011).
- **RCP 8.5** is a high pathway scenario characterized by increasing greenhouse gas emissions over time for which radiative forcing reaches greater than 8.5 W/m² by 2100 and continues to rise for some amount of time (Riahi et al. 2007). It is also known as "business as usual" scenario.

3.3 Sources of uncertainty in future climate projections

The uncertainty in future projections from climate models can be attributed to three main sources (Hawkins and Sutton, 2009): 1) the internal variability, 2) the model uncertainty and 3) the scenario uncertainty. Internal variability accounts for the natural fluctuations that arise in the absence of any change in the radiative forcing of the planet and occurs on time scales ranging from days up to years, decades, centuries or longer. The model uncertainty stems from the fact that models are always a simplification of the real world and are built using reductionist approaches, and hence they are imperfect by construction. In addition, models are not able to explicitly resolve the processes occurring at scales below their grid size, or resolution, which include radiation, convection, cloud microphysics and land surface processes. These processes are incorporated in the models by means of empirical parameterizations that are, by construction an approximation of the reality and lead to further uncertainty. Model uncertainties can be definitely separated into the following three different factors: (i) limited theoretical understanding of a given process, such as how aerosols affect cloud formation; (ii) indeterminacy/inadequacy in model parameters; (iii) model inadequacy owing to the fact that models are missing or are only approximating certain processes. The scenario uncertainty derives from the uncertainty of future demographic changes, economic development, land-use and technological changes, which, along with the environmental changes in the future climate itself, will determine future anthropogenic emissions of greenhouse gases and other pollutants. The relative importance of the scenario uncertainty grows over time within a climate simulation.

The relative importance of these sources of uncertainty varies with the variable of interest, the space and time scales involved in the climate prediction and the lead-time of the projection. For time horizons of a decade or two, the dominant sources of uncertainty on regional scales are model uncertainty and internal variability, while for time horizon of many decades or longer, the dominant sources of uncertainty at regional or larger spatial scales are model uncertainty and scenario uncertainty (Hawkins and Sutton, 2009).

The problem of exploring and quantifying uncertainty in climate model projections is partly addressed using a multimember and/or multi-model ensemble approach complemented by the use of expert judgement to assess the plausible effect of model inadequacy (IPCC 2013), a technique that is borrowed from weather forecasts. The implicit assumption is that each individual model of one ensemble can have its uncertainty and one model can reproduce better than another a certain variable or process, while another model can perform better looking at a different variable and/or process. Therefore, the whole model ensemble can provide diverse information than a single model, and higher confidence is placed on results that are common to an ensemble, although in principle all or many models of one ensemble could suffer from similar deficiencies (Knutti et al., 2010) or can have similarities that make them not truly independent.

The prevailing approach for dealing with multi-model ensemble results is model democracy, which consists in giving equal weights to all models (Knutti, 2010). This approach can be a suboptimal way of using information, yet this remains common for the lack of better and easy alternatives or consensus on what those are. A recent review considering the advantages and disadvantages of equal model weighting, and suggesting a possible weighting procedure based on both model performance and interdependence, can be found in Knutti et al. (2017). The IPCC adopt the model democracy approach and take into account the GCM uncertainties by stating headline results such as ranges of the projected change in global mean temperature only as "likely" (66%), where it is derived from a 90% model range (IPCC, 2013, Summary for Policymakers). Thus, for example, the increase of global mean surface temperatures for 2081–2100 relative to 1986–2005 is projected likely (66%) to be in the ranges derived from the concentration-driven CMIP5 model simulations (AR5 WG1 SPM pg 20), with the implication that the uncertainty ranges derived from the models are too narrow, even at global scales.

In ECOPOTENTIAL we do not deal directly with GCM outputs, so an IPCC-like approach is not applicable as-it-is. In the ECOPOTENTIAL project we build on the outcomes of the regional downscaling initiative EURO-CORDEX, which downscaled, over the European domain, 6 GCMs with a set of 7 regional climate models (EURO-CORDEX simulation

list, compiled on 19.12.2016 http://www.euro-cordex.net/imperia/md/content/csc/cordex/20161219 eurocordex-simulations.pdf). As better discussed in Section [4.2,](#page-25-0) we will use a multi-model ensemble approach consisting of the analysis of a group of 5 GCMs dynamically downscaled using a single RCM, namely the RCA4 model which is part of the CORDEX ensemble.

Since in a modelling chain regional climate models represent a further important source of uncertainty, and since already the driving models are only "likely" to describe the future, possibly even less so at the regional scale, assessing the actual uncertainty to be associated with the outputs of such a modelling chain is still a totally open issue, currently under investigation. An overall guidance on how *par*t of this uncertainty can be taken into account is provided in Section 6.

3.4 Model bias: review of state-of-the-art bias correction approaches

The intrinsic imperfection of climate model parameterizations and the errors in the model initialization are often reflected in an imperfect representation of the observed climate, which is sometimes interpretable as a simple state-dependent bias (Ehret et al., 2012). These biases must be taken into account when the climate model outputs are used in impact studies because the impacts and feedbacks can be sensitive to the absolute values and the statistical properties of the climate input. Bias correction methods are employed to remove the zero- and firstorder differences between climate model output and observed historical climate time series, in the hope that this will improve the projected time series sufficiently to make them an acceptable input data set for driving impact models. We here briefly describe the approaches that are commonly adopted to deal with biased climate model simulations, following some of the most relevant literature review papers (e.g., Cannon et al., 2015; Hempel et al 2013; Maraun 2013; Maraun et al., 2010).

Anomalies. One possible technique to deal with biased climate model simulations is to consider the anomalies of a given variable with respect to a reference period instead of its absolute values. This approach is often referred to as in-sample bias suppression. Temperature data from IPCC climate models are often presented as anomalies. This procedure removes a variation of almost 3 degrees Celsius between the IPCC's primary CMIP5 models over the 1961-1990 reference period (IPCC AR5 WG1, Figure 9.8a, page 768). This method relies on the hypothesis of linear dependence of the impacts on climate input data and thus in most cases it is not appropriate, e.g. when some processes or impacts occur when given absolute climatic thresholds are exceeded (Hempel et al., 2013). This technique is for example not suitable to correct snow-related processes, as the accuracy of the snowfall fraction and snow depth strongly depend also on the accuracy of air temperature and precipitation information and data.

Additive/Multiplicative adjustment. Basic bias correction methods include an adjustment of the mean value by adding a temporally constant offset, or by applying an associated correction factor to the simulated data. This additive or multiplicative constant quantifies the average deviation of the simulated time series from the observed one over the historical period. This method has clear advantages: first, its easy implementation in presence of a trusted reference dataset and, second, its capability of preserving the annual cycle and the linear trend in time of the variable which is analysed. Among the disadvantages of this method is the fact that it does not correct the variance and higher statistical moments of the simulated data distribution.

Quantile mapping. A generalization of the former approach is the quantile mapping that adjusts different intensities (quantiles of the distribution) individually. Bias correction algorithms based on quantile mapping have been found to outperform simpler bias correction methods that correct only the mean or the mean and variance of precipitation series (Gudmundsson et al. 2012). Recent studies, however, have highlighted potentially serious problems in using these methods for trend calculations, especially when applied to extreme statistics (e.g., Maraun et al.,2010).

All these three methods suffer from the same primary disadvantages, related to the fact that (i) they assume stationarity of the bias in time, i.e., the bias in the future is assumed to be the same as in the present (Räisänen and Räty 2013, Maraun 2013); (ii) the quality of the bias corrected data depends on the reliability of the reference dataset; and (iii) they "destroy" the physical consistency among the different climate variables (for example, after

the application of bias correction the temperature might be below the freezing point (<0°C), whereas rainfall is not converted into snowfall). With respect to this last issue, more complex methods such as the multivariate parametric quantile mapping that preserves the consistency between more than two variables (Mehrotra and Sharma, 2015) are still in their infancy.

In ECOPOTENTIAL additive and multiplicative adjustments have been adopted for bias correcting the modelled temperature and precipitation data, respectively, as better explained in Section [4.4.](#page-26-0)

4. Future projections in ECOPOTENTIAL

In this section we first recall the chronology of important actions and milestones for Task 8.1, including the meetings that were organized, the consequent decisions taken and resulting adopted strategy.

4.1 Chronology of actions and important milestones

The first important face-to-face meeting for Task 8.1 was held in September 26–28, 2016 in Pisa: the workshop on "Future projections for PAs in ECOPOTENTIAL" aimed to better discuss and define the general strategy of future projections for the ECOPOTENTIAL Protected Areas.

The discussed topics included the choice of the models to be downscaled (either GCMs or RCMs, and which ones), the application of eventual bias-correction methods to the model temperature and precipitation fields, the emission scenarios to be considered for future projections (among the internationally-agreed RCPs), the time span to be considered for projections, the downscaling methods to be applied, the adoption of reference ground-based data for bias correction and model validation purposes. Finally, the (first) data needs of individual partners concerning the various PAs were collected.

The workshop in fact led to important decisions that are summarized here below:

1. Large-scale climate model data to downscale: the RCA4 regional climate model, driven by five different global climate models, available from the CORDEX experiment (see Section [4.2](#page-25-0) for details) was selected. An overall assessment of the performances of this model against observational dataset can be found in previous studies (Kotlarsky et al., 2014), in a specific technical report (Strandberg et al., 2014) and the main results are summarized in Section 4.3. The choice of this specific model was related to the facts that (i) it was the only RCM available at that time in the CORDEX archive with both very high spatial (0.11 degrees longitude-latitude) and temporal (3 hour) resolution for the European domain (EURO-CORDEX), therefore potentially usable to drive impact models requiring sub-daily data; (ii) it provided the largest ensemble of simulations (5 complete sets of simulations, driven by 5 different GCMs and extending over both the historical period and the future in different RCP scenarios).

2. Future scenarios: the decision was to use the two representative concentration scenarios RCP4.5 and RCP8.5 (see Sectio[n 3.2](#page-12-0)) of the IPCC. The use of "what if" scenarios would eventually be taken into consideration in a second moment or for more specific applications under request (especially when dealing with changes in extreme events).

3. Time span: we opted for providing data from 1970 up to 2100, i.e. the full period of availability of the CORDEX simulations.

4. Downscaling of the temperature and precipitation variables up to 1 km resolution at least. The most appropriate downscaling solution depends on the variable and on the temporal scale of interest, as well as on the needs for a specific application. CORDEX regional climate models have a spatial resolution of ~12 km. A temperature downscaling based on orographic correction (using the atmospheric temperature lapse rate) and a stochastic downscaling for precipitation also taking into account orography, were proposed (see Sections [4.5.1](#page-29-0) and [4.5.2](#page-34-0) for details about the two downscaling techniques) to achieve spatial scales up to 1 km or less.

5. Application of bias correction schemes prior to downscaling. Climate models often have a bias (e.g., a cold and wet bias in the mountain regions in winter is commonly found in both state-of-the-art GCMs and RCMs). We agreed on correcting the bias using the station-based E-OBS reference datasets available for the European domain, since this is a well known, robust, and used dataset, regularly updated. Bias correction was carried out on the long-term climatology, and pixel by pixel, as better explained in Sectio[n 4.4.](#page-26-0)

6. Discussion about the need to generate new land use scenarios. The question arose from the awareness that there are different research groups around the world that work on land-use projections considering economic scenarios. We discussed the possibility of checking for changes in the historical dataset, e.g., in the CORINE archive (https://www.eea.europa.eu/publications/COR0) and from satellite imagery, calculating trends in land use changes using statistical methods (for example, cellular automata) and estimating/extrapolating the trends in the future. As

already explained in the Introduction, the discussion about downscaling land use scenarios showed that the advantages of individual high-resolution land use scenarios elaborated to the needs of individual PA managers or projected on current trends within the individual PAs, would be of higher value than systematic downscaling from existing large-scale land use scenarios.

Besides the decisions outlined above, other important outcomes of the Pisa workshop were the collection of the preliminary data needs from the partners who attended the workshop and the identification of the PAs for which the initial downscaling data production should be prioritized according to the partners' needs. Table 4.1 summarizes the original data requests from the ECOPOTENTIAL partners during/immediately after the Pisa workshop.

Immediately after the workshop, ISAC-CNR started the download of the agreed CORDEX datasets from the dedicated archive related to the requests received until that time. The total volume of requested data was quantified in about 20 TB. We acquired two additional hard disks, 10 TB each, for the storage of both the originally downloaded model outputs and the downscaled datasets.

During the first year of activity, besides downloading the needed model and observational datasets and making some necessary data pre-processing (e.g., cropping of the original data over the selected domains, or over the agreed time windows), we developed and tested the codes to bias-correct the precipitation and temperature model outputs and to downscale them. After the Pisa workshop, the tools were ready to start the downscaling.

A second crucial milestone for this Task was the WP8 meeting held in February 2017 in Potsdam where, besides discussing the advancements/issues/progress in this and the other WP8 Tasks, an update on the downscaling activities and on the status of the downscaled data delivery was presented. Table 4.2 resumes the status of data delivery at that time. New requests were also collected from the partners during the meeting in Potsdam.

Finally, the latest update on Task 8.1 activities and the status of the delivery of the downscaled data was presented during the ECOPOTENTIAL General Assembly held in Heraklion, Crete, in May 2017, both in the plenary and during a side meeting specifically devoted to the discussion of the upcoming WP8 deliverables. The Partners and the project coordination agreed on the structure and timeline of the deliverable that was presented at that time. On that occasion, new requests on data downscaling were also collected and discussion with project partners about the already delivered data took place.

At the beginning of August 2017, a first draft of the deliverable was circulated on Basecamp, together with a request of contribution and/or revision to all partners, especially those involved in the WP8.

Table 4.1 Climate projections data requested from ECOPOTENTIAL partners during or immediately after the Future Projections Workshop held in Pisa, September 26-28, 2016

Table 4. 2. Update of Table 4.1 with the partners' requests collected after the Pisa workshop. Green flags indicate the data delivered before the Potsdam meeting (Feb 16th, 2017), cyan flags indicate the data delivered between Potsdam meeting and the General Assembly in Crete (May 16th, 2017), magenta flags indicate the data delivered between the General Assembly and July 31st 2017.

4.2 The large-scale input: general description of the CORDEX experiment and archive

As previously mentioned, reliable, high-resolution climate change projections associated with a quantification of their inherent uncertainty are crucial for estimating future climate change impacts and for planning adaptation strategies. The WCRP Coordinated Regional Downscaling Experiment (CORDEX, http://wcrp-cordex. ipsl.jussieu.fr/; Giorgi et al. 2009) is an internationally coordinated effort aiming to harmonize the evaluation of state-of-the-art RCMs and to generate multi-model ensembles of regional climate projections for the land-regions worldwide. The EURO-CORDEX initiative [\(http://www.euro-cordex.net/\)](http://www.euro-cordex.net/), in particular, is part of the global CORDEX framework and provides regional climate projections for Europe at ~50 km (EUR-44, 0.44 degrees lon-lat) and at ~12 km (EUR-11, 0.11 degrees lon-lat) resolution, overtaking coarser resolution datasets resulting from former regional model coordinated assessments (e.g., PRUDENCE and ENSEMBLES, Jacob et al., 2014).

Within the EURO-CORDEX experiment seven regional climate models are employed to dynamically downscale the CMIP5 global climate projections (Taylor et al., 2012) using the latest greenhouse gas emission scenarios (Representative Concentration Pathways, RCPs, Moss et al., 2010; van Vuuren et al., 2011) introduced in Section [3.2.](#page-12-0)

Focusing on the European domain, the performances of the individual RCMs participating in the EURO-CORDEX experiment have been evaluated in several previous studies (e.g. Kotlarski et al., 2014, Vautard et al., 2013) aimed at quantifying the accuracy currently achievable from these regional climate models when they are driven by realistic boundary conditions, i.e. those provided by reanalysis data such as the ERA-Interim. In general, RCMs are found to be able to capture the basic features and the spatial/temporal variability of the European climate compared to observational data sets. Seasonally- and regionally-averaged temperature biases are in most cases smaller than 1.5°C while precipitation biases are typically in a ±40% range (Kotlarski et al., 2014). Nevertheless, it has been shown that RCM biases are strongly domain- and season-dependent thus they should be quantified over the specific area and season of interest. A predominant cold and wet bias in most seasons and over most parts of Europe, and a warm and dry bias in summer over southern and southeastern Europe are common to many models. Concerning climatic extremes, most models are found to overestimate summertime high temperature extremes in the Mediterranean region and to underestimate them over Scandinavia. The interannual sequence of hot summers over central/southern Europe was found to be fairly well simulated in most simulations despite an overestimation of the number of hot days (Vautard et al., 2013).

When RCMs are driven by a large-scale model, in addition to the uncertainties inherent in the specific RCM at hand, additional uncertainty is inherited from the driving GCM, which is affected by model inadequacies as well. In order to estimate this type of uncertainty, a common state-of-the-art approach consists in considering an ensemble of simulations performed with a given RCM driven by different GCMs. The spread among the RCM outputs provides an estimate of the effects of GCM diversity on the RCM simulations.

This is exactly the strategy followed in ECOPOTENTIAL where we selected all the available simulations of the RCA4 model, consisting in 5 sets of simulations driven by the following five GCMs: EC-Earth, CNRM-CM5, IPSL-CM5A-MR, HadGEM2-ES, MPI-ESM-LR. The spread of this (small) ensemble captures part of the uncertainty due to the driving GCM, i.e., the uncertainty coming from the large-scale drivers. Section 6 provides some guidelines on how to deal with this ensemble of model simulations.

4.3 The CORDEX Rossby Centre regional climate model (RCA4) and its driving GCMs

For the description of the CORDEX RCA4 model we mainly refer to the technical report by Strandberg et al. (2014). RCA4 is based on the numerical weather forecast model HIRLAM (Unden et al., 2002) and its successive modifications (Rummukainen et al., 2001; Räisänen et al., 2004; Jones et al., 2004; Kjellström et al., 2005; Samuelsson et al., 2011). The model output has been evaluated extensively by Strandberg et al. (2014) following a three steps procedure: i) validation of the ERA-Interim-driven (ERAINT) RCA4 simulations against reference datasets (both observation-based and the ERA-Interim reanalysis) in order to evaluate the model performance in

reproducing the recent/historical climate, ii) evaluation and validation of the historical simulations using several global climate models as large scale drivers and iii) evaluation of future scenarios (RCP 4.5 and RCP 8.5) forced by the same GCMs as used in the "historical" validation exercise. Here below the main results of the three step validation are summarized:

i) RCA4 is to a large extent replicating the large-scale circulation of ERAINT despite some local biases in mean sea level pressure being found. The seasonal cycles of temperature and precipitation are simulated in relatively close agreement with observations. Some biases occur, such as too much precipitation in northern Europe and too little to the south. In winter, RCA4 simulates higher precipitation amounts than observations in eastern Europe as well. Winter temperatures are generally biased toward low values in northern Europe and in the Mediterranean region while overestimated temperatures are seen in south-eastern Europe in winter and in the Mediterranean area in summer.

ii) RCA4 performs generally well when simulating the recent past climate taking boundary conditions from the GCMs rather than from ERAINT (Strandberg et al. 2014). A large part of the RCA4 simulated climate is attributed to the driving GCMs, but RCA4 creates its own climate inside the model domain and adds smaller-scale information. All nine driving GCMs have problems in their representation of the large-scale circulation in winter. This feature is inherited by RCA4 and the biases in large-scale circulation can affect the temperature and precipitation simulated by RCA4.

iii) Regarding the climate change signal in the two scenarios (RCP4.5 and RCP8.5), RCA4 projections indicate warming over Europe in the future. Warming is expected to be largest in winter in northern Europe and in summer in southern Europe. The summer maximum daily temperature is expected to increase in a way similar to summer mean temperature, slightly more in southern Europe then elsewhere. The winter minimum daily temperature in northern Europe is found to be the model parameter most sensitive to warming (Strandberg et al. 2014). The model simulates a future increase in precipitation in all seasons in northern Europe and a decrease in southern Europe. The largest amount of rainfall per day (and per seven day period) is projected to increase in almost all the European domains and in all seasons. At the same time the longest period without precipitation is expected to become even longer in southern Europe.

4.4 Bias correction

In order to bias correct the precipitation and temperature data simulated by the RCA4 RCM, we selected the observation-based E-OBS dataset (Haylock et al., 2008;

http://www.ecad.eu/download/ensembles/ensembles.php) as the reference, for the reasons outlined below:

- Availability of a long term daily precipitation and near surface air temperature climatology (from 1950 to present, regularly updated)
- Spatial coverage including all land areas in Europe and in the Mediterranean area
- Clear documentation on the methods used to derive it (interpolation techniques, underlying stations, etc.) and availability of the underlying orography (elevation data) and individual station data
- Extensive literature on the dataset, so that it can be considered a standard dataset for model evaluation over Europe.

4.4.1 The reference dataset E-OBS (1950-present): a short description

E-OBS is a European land-only daily high-resolution gridded dataset for precipitation and minimum, maximum, and mean surface air temperature, starting in 1950 and regularly updated. The dataset builds on daily observations at more than 2,000 point locations available through the European Climate Assessment and Data set portal (ECA&D; [http://eca.knmi.nl/;](http://eca.knmi.nl/) Haylock et al., 2008). Haylock et al. (2008) developed E-OBS by first interpolating the monthly precipitation totals and monthly mean temperature using three-dimensional thin-plate splines, then interpolating the daily anomalies using indicator and universal kriging for precipitation and kriging with an external drift for

temperature and, third, combining the monthly and daily estimates. A detailed evaluation of the E-OBS uncertainty can be found in Hofstra et al. (2009) and Turco et al. (2013).

E-OBS covers an area extending from 25N-75N and from 40W-75E. The data files are provided in the compressed NetCDF format, which is also the common data format for climate model outputs, and at different spatial resolutions. For our purposes the finest resolution, i.e. 0.25° lat-lon regular grid, was considered.

4.4.2 Description of the bias correction methods for temperature and precipitation

As already discussed in the introduction, the intrinsic imperfection of climate models is reflected in a deviation of the model output with respect to the observed climate. Among the most common bias correction techniques briefly summarized in Section [3.4](#page-14-0) we chose the one implying the adjustment of the mean value, either by adding a temporally constant offset (for the temperature correction) or by applying a constant correction factor (for precipitation) to the simulated data. The additive or multiplicative constant is applied to counterbalance the average deviation between the simulated and the observed time series over a historical (or baseline) period taken as the reference.

This method was chosen for its easy applicability and because it has the property of preserving the annual cycle and the linear trend in time of the original model variable, which we do not want to destroy. As discussed in Section [3.4,](#page-14-0) most bias correction methods destroy the physical consistency among the set of climate variables and, at current knowledge, multivariate approaches that preserve the consistency between more than two variables are still in their infancy. As the preservation of the seasonality, annual cycle and trends of temperature and precipitation has been recognized as a desirable characteristic of a bias correction method, we opted for the above-mentioned adjustments of the mean value, which is the less invasive method to provide absolute values of the climatic variables that are consistent with the observations.

The model values, both in the historical and future periods, are corrected using an offset or multiplicative correction factor pixel by pixel and constant over time that corrects for differences in the long-term climatology between the simulated and observed average in the historical period. The correction fields are calculated at the spatial grid of the reference dataset (E-OBS, 0.25° lon-lat resolution), which has not the same spatial resolution as the model grid (0.11° lon-lat). In order to overcome this scale mismatch we adopted the following procedure:

- the RCA4 model temperature and precipitation fields were conservatively remapped (Jones, 1999) at the same grid as E-OBS (0.25°)
- the correction factor was calculated at the E-OBS grid and then remapped at the original RCA4 grid using the nearest neighbour interpolation
- the correction factor field, now defined at the same spatial grid as the model, was applied to the raw model fields to get the bias corrected field at the original model resolution.

This procedure guarantees that the RCA4 bias corrected fields have the same long-term climatology as E-OBS at the E-OBS spatial resolution.

The correction fields for temperature and precipitation are calculated as follows:

Temperature. Being T_i the daily air temperature and \lt > the long-term average over the period 1970-2005, the additive correction factor C is calculated as:

$$
C = \langle T_i^{EOBS} \rangle - \langle T_i^{RCM} \rangle \tag{1}
$$

The bias corrected model temperature T_{bc} is then calculated as follows:

$$
Tbc_i^{RCM} = C + T_i^{RCM}
$$
\n(2)

This method supplies the most common temperature correction regularly applied in impact studies (referred to as "unbiasing method" in, e.g., Dequé, 2007). It preserves the absolute trend and the variability of the simulated data at all time scales. The temperature correction is not seasonally-dependent; at each pixel the same correction C is applied for all times of the year.

Precipitation. Being P_i the daily precipitation and \lt > the long term average over the period 1970-2005, the multiplicative factor C is calculated as:

$$
C = \frac{P_i^{EOBS} >}{\langle P_i^{RCM} \rangle} \tag{3}
$$

The bias corrected model precipitation P_i then reads:

$$
Pbc_i^{RCM} = C \times P_i^{RCM}
$$
\n(4)

Since E-OBS data exist only over land areas, in agreement with partners, we did not apply any form of bias correction for those PAs partly covered by sea. The precipitation correction is not seasonally-dependent; at each pixel the same correction C is applied for all times of the year.

An additive factor is chosen for temperature and a multiplicative factor for precipitation because

- a) temperature values at the Earth surface are far from the natural absolute zero (in Kelvin), and what the models usually display is a difference in the means and much less in the amplitude of the seasonal and/or interannual variability. Thus, an additive correction seems appropriate;
- b) precipitation has a very clearly-defined zero point (no precipitation) and a constant additive factor would result either unphysical areas of negative precipitation or implausible areas which are always raining.

Figure 4.1 shows an example of spatial maps of the correction factors calculated for EC-Earth-RCA4 simulations, for both temperature and precipitation variables.

Figure 4.1 Example of spatial maps of the correction factors for the EC-Earth-RCA4 model, for temperature (left) and precipitation (right) calculated using equations (1) and (3). For both variables the correction factors were calculated using E-OBS over the period 1970-2005 as a reference dataset.

4.5 RCA4 downscaling: from the regional to the local scale

The activities performed at ISAC-CNR during the first project year were focused on the development of downscaling tools for climate data, in particular for precipitation and air temperature, which take into account the orography. After testing the methods on a sample area, they were applied to the output of the RCA4 RCM at ~12 km spatial resolution, driven by five GCMs, as described in the previous section. This was done for all the ECOPOTENTIAL protected areas for which downscaled data were requested.

For some specific applications, the original ~12 km resolution of the RCA4 model was sufficient for the kind of study the project partners wanted to perform over a given PA. Therefore, in such cases, the RCM data were delivered at their original spatial resolution, either bias-corrected or not, depending again on the specific need or application. In the other cases we applied the downscaling methods described in sections 4.5.1 and 4.5.2, and used them to provide the downscaled climate scenarios to the other project partners. In the meanwhile, alternative downscaling techniques were explored by other project partners to be eventually used together with those presented in Sections 4.5.1 and 4.5.2 and for comparison purposes, as for example the one described in Section 4.5.3.

4.5.1 Temperature downscaling

In mountain areas, meteo-climatic features show strong spatial variability over short distances, especially along elevational gradients. Reconstructing reliable elevation gradients of the important variables based on observations is challenging because weather stations are often sparse and do not offer adequate/homogeneous coverage at high elevations (Dodson and Marks 1997).

The rate at which air cools with elevation may vary in the range between −9.8°C (1000 m)⁻¹ (i.e., the dry-air adiabatic lapse rate) for unsaturated air and −4°C (1000 m)⁻¹ (i.e., the saturated adiabatic lapse rate; Dodson and Marks 1997) for saturated air. When air is saturated the cooling rate for a rising air parcel is lower due to the release of latent heat by the condensation process. Average temperature lapse rates show strong variability in relation to the climatic zone, as well as to the season. The highest values are reached in summer, over tropical deserts; the strongest negative rates are reached in winter over Siberia, Canada, and polar regions (Barry et al., 2008). A regional study considering seasonal lapse rate from high resolution terrain-interpolated station data in the Canadian Rockies (Shea et al., 2004) found the following seasonal lapse rates (Table 4.3):

Table 4.3. A regional study considering seasonal lapse rate from high resolution terrain-interpolated station data in the Canadian Rockies (Shea et al., 2004) found the following seasonal lapse rates.

According to a study by von Hann (1906; sourced by Barry et al., 2008) focused on the Austrian Alps, the temperature decrease between Kolm Saigurn, located at 1600 m and Sonnblick, located at 3103 m, was found to be (Table 4.4):

Table 4.4 Temperature lapse rate in the Austrian Alps, from measurements between Kolm Saigurn, 1600 m, and Sonnblick, 3103 m.

A more recent and exhaustive study by Rolland et al. (2003) considered systematically 640 meteorological stations in the Austrian-Italian Alps, representative of a wide elevation range from below 100 m to above 2000 m a.s.l. This study showed yearly lapse rates ranging from −5.4° to −5.8°C (1000 m)−1, but with a remarkable seasonal pattern in monthly gradients, as shown in Figure 4.2. The highest lapse rates are found during summer for the maximum temperatures while the lowest in winter for maximum, minimum and mean temperatures.

Apart from these documented areas, in absence of more accurate lapse rate estimates based on measurements along elevational transects, average temperature gradients of −5.5° (Angot 1892), −6.0° (Dodson and Marks 1997), or −6.5°C (1000 m)−1 (Barry and Chorley 1987) are often used for application purposes. The adiabatic lapse for moist air, −6.5°C (1000 m)−1 , is the value commonly used in absence of any other local indication as representative of a "standard condition".

In order to take into account the effect of small scale orographic features in the various PAs, in ECOPOTENTIAL we adopted the common approach of using information on the air temperature lapse rate to downscale or, in other words, to further correct the large scale (0.11 degrees) RCA4 RCM fields for the mismatch between the relatively "coarse" model orography (also at 0.11 degrees spatial resolution) and the "real" orography. The latter is provided by a fine-resolution digital elevation model (DEM). In fact, the effects of the smooth model topography on air temperature fields can be circumvented by adjusting the coarse resolution air temperature fields from the model through the application of an orographic correction.

Within ECOPOTENTIAL we developed an open-source code written in the freely accessible and open-source "Julia" language (https://julialang.org/) for the downscaling of a generic coarse scale air temperature dataset. This software allows calculation of a lapse-rate correction based on the difference between the original coarse scale orography and a target DEM. The software was specifically developed during the first project year and incorporated in the RainFARM downscaling toolkit, a Julia library and set of command-line tools implementing downscaling methods for air temperature and precipitation. The complete toolkit has been published at the link <https://github.com/jhardenberg/RainFARM.jl> and it is freely downloadable and usable. A tutorial for the installation of the toolkit is available too at the same web page.

Figure 4.2 Seasonal variations of lapse rates [in °C (100 m)−1] for (top) min, (middle) mean, and (bottom) max temperatures (source: Rolland et al., 2003)

The RainFARM downscaling toolkit includes the command "rftemp" for air temperature downscaling. The usage of the command "rftemp" is illustrated in Figure 4.3. The mandatory arguments are

- orofile: a file with the fine-scale orography (in netCDF format)
- infile: a file with the coarse scale temperature fields to be downscaled (in netCDF format)
- outfile: the name of downscaled output file (in netCDF format)

```
\sim - silv
[silviat@obelix:~$
[silviat@obelix:~$ rftemp
required argument orofile was not provided
usage: rftemp [-r RADIUS] [-l LAPSE] [-v VARNAME]
               [-b COORD COORD COORD COORD] [-o OROCOARSE] orofile
               infile outfile
[silviat@obelix:~$
```
Figure 4.3 RFTEMP temperature downscaler command-line tool

Several possible options are allowed, among them:

- "-r" to specify the radius for spatial smoothing (typically half the original horizontal resolution)
- "–l" to specify the temperature lapse rate
- "-b" to specify a subdomain of interest
- "-o" to specify the coarse scale orography

For the greater alpine region we used the monthly lapse rate (in °C/1000m) from Rolland (2003), summarised in the following table:

Monthly temperature lapse rates for the Alpine region $[°C (1000m)-1]$											
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
-4.5	-5	-5.8	-6.2	-6.5	-6.5	-6.5	-6.5	-6	-5.5	-5	-4.5

Table 4. 5 Monthly temperature lapse rates for the Alpine region [°C (1000m)-1]

For the areas for which literature information on the temperature lapse rates was absent, we used the standard yearly average lapse rate of -6.5°C/1000m.

As fine-scale digital elevation model, we used one of the following, according to the spatial resolution needed by the partner:

- NOAA NGDC Globe, gridded 1 km, quality controlled global Digital Elevation Model data from the Global Land One-km Base Elevation (GLOBE) project (Hastings and Dunbar, 1999) available at <http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NGDC/.GLOBE/index.html>
- SRTM SRTM 90m Digital Elevation Database v4.1 provided by NASA [\(http://www.cgiar-csi.org/data/srtm-](http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1)[90m-digital-elevation-database-v4-1](http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1) ; Jarvis et al., 2008)

Figures 4.4, 4.5 and 4.6 summarise the steps described above to generate data downscaled at 1 km resolution from the large scale (~12 km resolution) CORDEX field, for the temperature exemplary and over the Gran Paradiso National Park PA. Figure 4.4 shows the climatological spatial maps of the temperature over the area of interest, obtained by averaging the bias-corrected data over the time period 1970-2000. Top left panel shows the temperature field from the CORDEX RCA4 model over the Gran Paradiso PA at the original resolution (~12 km) while the top right panel shows the downscaled field at 90 m resolution. The two bottom panels show the downscaled temperature fields for the RCP 4.5 (left) and RCP 8.5 (right) scenario.

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Figure 4.4 Original resolution (~12 km, top left panel) and downscaled (90 m, top right and bottom panels) tempearture fields over the Gran Paradiso National Park PA for present conditions (average over the period 1970- 2000, top) and future conditions (2070-2100 average) in the RCP4.5 (left) and RCP8.5 (right) scenario, according to the RCA4-EC-Earth regional climate model.

The "bias-corrected" and the "bias-corrected and downscaled" temperature time series have also been extracted at the position of one measurement station in the Gran Paradiso National Park PA, the Serrù Station (2260 m above sea level), in order to validate the results with ground observations and check the various steps of the procedure.

Figure 4.5 shows the results after application of the bias correction only and compares the results with the time series measured at Serrù, while Figure 4.6 shows the results after the application of the bias correction plus downscaling and extends them also to the future in the two scenarios.

Figure 4.5 Left: spatial map of the study area indicating the position of Serrù station. Right: yearly time series of the modelled surface air temperature extracted at the location of the Serrù station from the original RCA4 RCM data (orange), from the gridded E-OBS dataset (gray), and from RCA4 after bias correction (yellow). Thick red line is the observed data at the Serrù station.

Figure 4.6 Downscaled (1 km) temperature time series from the RCA4 RCM extracted at the location of the Serrù station in the historical period (yellow line is the bias-corrected RCM data while black line is the bias-corrected and downscaled data; red line indicates the observations) and the two RCP scenarios (in gray).

4.5.2 Precipitation downscaling with the RainFARM method

For the precipitation, we developed a downscaling tool based on the RainFARM stochastic precipitation downscaling method originally developed at ISAC-CNR and well documented in the literature (see Rebora et al., 2006; D'Onofrio et al., 2014 and references therein).

The stochastic precipitation downscaling method RainFARM allows us to produce, from large-scale spatio-temporal precipitation fields, ensembles of stochastic realizations at finer spatial resolution (typically 1 km or slightly less), which preserve the large-scale statistical properties of the original field and with realistic spatial and temporal correlation structures. An advantage of the method is that it has few free parameters and that it does not require further fields besides the original precipitation to downscale. It does not require, in fact, observational data for calibration as other statistical methods typically do. The small-scale correlation structure of precipitation can be estimated from the large-scale field directly. This makes the method directly applicable to the output of large-scale datasets, such as global or regional climate model outputs, or gridded observational (e.g. satellite) data available at coarse resolution, also in areas where further fine-scale information is not available. The main limitation of the "original" RainFARM procedure was that it did not take into account orographic effects at scales smaller than those resolved by the original precipitation field to downscale. As a result, the fine-scale distribution of precipitation in the downscaled fields was not dependent on fine-scale orography, and the long-term climatology at individual grid points could differ significantly from observations in areas with complex topography and particularly in mountain regions.

For applications in which the small-scale hydrological balance is of importance, such as studies of impacts on snow cover or water resources in small mountain basins, the inclusion of orographic effects is mandatory. A simple modification has then been introduced in the first project year to the original RainFARM method to integrate available information on the spatial distribution of precipitation climatology available from observations. The method is based on the availability of a reference fine-scale precipitation climatology, such as that provided by gridded observations from a dense network or high-resolution model simulations. This reference climatology allows us to derive corrective weights which are applied to the stochastic precipitation realisations generated by RainFARM, allowing us to reproduce a more realistic long-term precipitation climatology at the fine scales.

The method has been validated in a perfect model example, using daily precipitation data from long term simulations (1980-2008) with the Weather Research and Forecasting (WRF) Model run at 4 km over the Greater Alpine Region (GAR), forced with the ERA-Interim ECMWF reanalysis data (Dee et al., 2011), as described in (Pieri et al., 2015). Figure 4.7a shows the multiannual (1980-2008) mean daily precipitation as in the WRF dataset at 4 km. By aggregating the high-resolution WRF precipitation fields at 4 km we derived large-scale (64 km) precipitation fields to be downscaled (Figure 4.7b). These large-scale fields were then downscaled back to the original 4 km resolution using the standard RainFARM method and the new method that takes into account orography. The resulting climatology are reported in Figure 4.7c and Figure 4.7d respectively.

Standard RainFARM does not take into account orography inside each coarse-grid element which results in downscaled fields presenting a distribution which has no correspondence with the actual reference climatology. The fine-scale distribution simulated by standard RainFARM in each large-scale grid element is statistically almost homogeneous, and this is reflected in the smooth distributions which can be found in the climatic average. After applying the monthly map of weights, instead, the individual orographic features become clearly recognizable and there is a significantly improved correspondence between the downscaled fields and the reference climatology (Figure 4.7d). The improvement gained by the corrected procedure is clearly shown in Figures 4.7e-f showing the anomalies of the climatologies obtained with the different downscaling procedures compared to the reference climatology in Figure 4.7a. The modified RainFARM algorithm allows to remarkably reduce the positive bias in the valleys and the negative bias over the mountain ridges with respect to the reference climatology.

Figure 4.7 The "perfect model" experiment: daily average precipitation climatology (1980-2008) derived from (a) high-resolution WRF simulations at 0.04°, here considered as the "truth"; (b) WRF daily precipitation fields aggregated at 0.64° (the field, P, to be downscaled; (c) P downscaled at 0.04° using the standard RainFARM method, i.e. without the orographic correction; (d) P downscaled at 0.04° using RainFARM with the orographic correction, (e-f) anomalies of c) and d) with respect to a) respectively.

Figure 4.8 summarizes the perfect model experiment and shows in the top panel the Probability density function (PDF) of WRF precipitation data downscaled from 64 km to 4 km spatial resolution (green line) compared to the original data at 64 km (black line) and 4 km (blue line). The PDF of the downscaled dataset is in very good agreement with the PDF of the original fine-scale dataset, indicating that the method is able to reproduce the precipitation distribution with a high level of accuracy as well as the high-precipitation values which were not captured by the aggregated coarse scale WRF data (black line).

The bottom panels of Figure 4.8 show the same PDFs as before, but separating the pixels with precipitation climatology above and below a given threshold (given by the median of the long-term climatology over the domain). The bottom left (right) panel show the results using the orographic (standard) RainFARM procedure. Standard RainFARM already performs sufficiently well compared to the observations (shown with the red and green lines) but the introduction of the orographic correction allows us to better separate the pixels with high- and lowprecipitation respectively.

Figure 4.8 The "perfect model" experiment: (a) Probability density function (PDF) of WRF precipitation data downscaled from 0.64° to 0.04° spatial resolution (green line) compared to the original 0.64° and 0.04° resolution

data (black and blue lines, respectively); PDF of the WRF downscaled data when grid-points are separated between high and low precipitation gridpoints, in the case of (c) original downscaling without orographic correction and (b) new version with orographic correction.

A paper focused on the orographic modifications introduced in the RainFARM procedure and on its validation is going to be submitted to a high impact journal.

Within ECOPOTENTIAL we downscaled RCA4 precipitation datasets according to partners' requests (see Table 4.1) by applying, where necessary, the orographic downscaling method using the WORLDCLIM dataset (Hijmans et al., 2005, [http://www.worldclim.org/\)](http://www.worldclim.org/) as a reference precipitation climatology to derive the weights (see also Box 4.1). We recall that we used WorldClim because it provides climatologies at very high (1 km) resolution and because it is a global dataset, so potentially applicable also to the three non-European ECOPOTENTIAL PAs.

Box 4.1 WORLDCLIM

WorldClim (Hijmans et al., 2005) is a set of global gridded climate data based on observations with a spatial resolution of about 1 km latitude x 1 km longitude. This dataset provides a 30-year average monthly climatology of the minimum, mean, and maximum temperature and of precipitation, as well as of other bioclimatic variables, for a reference historical period (1960-1990, labelled as current climate) and for a future period (2050-2080). Monthly climatologies are obtained from various data sources through interpolation methods which use the latitude, longitude and elevation as independent variables. Assessment of uncertainties in the gridded products were made highlighting that the most uncertain estimates correspond to mountainous and poorly sampled areas. In fact, Hijmans et al. (2005) compared WorldClim data to two high-resolution datasets in the US and found significant differences particularly in high-elevation regions.

5. General description of the delivered data and the repository

All the downscaled climate model datasets requested by the partners have been produced and delivered in a suitable format according to partners' needs. The latest downscaled datasets were delivered at the end of July 2017.

In most cases we delivered the datasets in NetCDF (Network Common Data Form) format, which is the preferable option when dealing with massive array climate data. When the requests were for "point-scale" time series (i.e. extracted in selected point locations) we delivered .txt files (e.g., for the Camargue PA).

The datasets were made available through the following public repository: http://data.dta.cnr.it/ecopotential/, organizing the data in folders named according to the ECOPOTENTIAL Protected Area to which they refer. Each PA folder contains one or more subfolders, one for each variable that was requested. Two screenshots illustrating the data repository are shown in Figure 5.1.

For each data request, we collected and provided metadata through a "README" file located within each PA folder. By clicking on the README.html file the user can access information on:

- the original CORDEX-RCM datasets, including the relevant references to the CORDEX experiment, the CORDEX data archive, the RCA4 model and its output;
- the RCA4 simulations considered, i.e. the driving GCMs
- the post-processing we performed, including the cropping of the original CORDEX data over each PA domain, possible re-projections onto a different geographical reference system, temporal aggregations, bias correction, spatial downscaling. Relevant references to the employed methodologies are provided.
- the characteristics of the output datasets, eventually re-projected/bias corrected/downscaled, including the list of variables provided, units, geographical reference system, spatial and temporal resolution.

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Figure 5.1 Repository of CORDEX climate model datasets tailored for 14 ECOPOTENTIAL partners working on 12 different Protected Areas. The original data from RCA4 model have been cropped, bias corrected, and spatially downscaled according to the partners' needs. The zoom focuses on the Wadden Sea PA.

Examples of metadata are provided in Figures 5.2 and 5.3 for the Sierra Nevada and Wadden Sea PAs, respectively.

In the former case the request was for downscaled data for both air temperature and precipitation for the Sierra Nevada mountain range at 1 km spatial resolution. The original RCA4 datasets for these two variables were cropped to the domain of interest and bias corrected with the E-OBS reference dataset. Precipitation was downscaled with the RainFARM method and air temperature was adjusted applying the orographic correction using a lapse rate of 6.5°C/km at 1 km spatial resolution.

For the Wadden Sea area, the original RCA4 datasets for 8 variables in total were only cropped to the domain of interest, i.e. a large area including both land and sea surface, and delivered to the partners. Downscaling was not applied in this case because the original RCA4 spatial resolution was already sufficient for the aims of the partners, as agreed with them.

Similar information was provided for each delivered dataset and each protected area.

EURO-CORDEX SMHI-RCA4 regional climate model datasets for Sierra Nevada

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- $\begin{tabular}{ll} \textbf{6} & \textbf{EURO-CORDEX reference paper: Jacob et al., 2014}\\ \textbf{6} & \textbf{CORDER} archive specification: \underline{\text{technical reference}}\\ \textbf{7} & \textbf{Regional} {\textbf{C}}$
-
- Original Resolution: 0.11 deg curv grid, 3- or 6-hourly data
- Output Projection/Resolution: latlon, 0.0083 deg, 3h
Domain: 3.76-2.55W: 36.81-37.36N
-
- Time Period: 01.01.1970-31.12.2005 (HIST); 01.01.2006-31.12.2100 (RCP45, RCP85) • Postprocessed by: ISAC-CNR

Available variables and units:

- $•$ tas
	- o near surface air temperature
	- Frequency (units) of original data: 3h (K)
	- Frequency (units) of output data: 3n (C)

	 Brequency (units) of output data: 3n (C)

	 Bias correction: adjustment of the long term mean, additive offset derived from E-OBS climatology (0.25deg, 1970 2005)

	 Spatial
	-

 \bullet pr:

- precipitation: Frequency (units) of original data: 3h (kg m-2 s-1)
- Frequency (units) of output data: 3h (mm/day)
- ° Frequency (units) of output data: 3h (mm/day)

o Bias correction: adjustment of the long term mean, multiplicative factor derived from E-OBS climatology (0.25deg, 1970 2005)

 Spatial downscaling: RainFARM, 1 km res

*Figure 5.2 Metadata describing the datasets provided for Sierra Nevada Protected Area***.**

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Index of /ecopotential/wadden_sea

EURO-CORDEX SMHI-RCA4 regional climate model datasets at WADDEN SEA

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- EURO-CORDEX reference paper: Jacob et al., 2014
CORDEX archive specifications: <u>technical reference</u>
Regional Climate Model: <u>SMHI-RCA4</u>
Driving Global climate models: EC-Earth, CNRM-CM5, IPSL-CM5A-MR, HadGEM2-ES, MPI-ESM-
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-
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- Postprocessed by: ISAC-CNR

Available variables and units:

- \cdot tas:
	- · near surface air temperature
	- Frequency (units) of original data: 3h (K)
Frequency (units) of output data: 3h (C)
- \bullet pr:
	-
	- → precipitation:
→ Frequency (units) of original data: 3h (kg m-2 s-1)
→ Frequency (units) of output data: 3h (mm/day)
	-
- r rsds:
	- \n• Surface Downwelling Shortwave Radiation\n• Frequency (units) of original data: 3h (W m-2)\n• Frequency (units) of output data: unchanged\n
	-
- $•_u$
	- Eastward Near-Surface Wind
	- Eastward Iveal-Suriace William
• Frequency (units) of original data: 6h (m s-1)
• Frequency (units) of output data: unchanged
	-
- · vas:
	- Northward Near-Surface Wind $\ddot{\circ}$
	- Frequency (units) of original data: 6h (m s-1)
Frequency (units) of output data: unchanged λ
	-
- DS
	- **Surface Pressure**
	- Frequency (units) of original data: day (Pa)
• Frequency (units) of output data: unchanged
- $-$ hure
	- Near-Surface Relative Humidity
	- Frequency (units) of original data: day (%) • Frequency (units) of output data: unchanged
- \cdot clt:
	-
	- **Total Cloud Cover**
	- Frequency (units) of original data: day (%)
• Frequency (units) of output data: unchanged

Figure 5.3 Metadata describing the datasets provided for the Wadden Sea Protected Area.

6. Guidance for data users / practitioners

This section is intended to provide a basic guidance to the users of climate model outputs provided within the project (such as ecological modellers in ECOPOTENTIAL), indicating the good practices for dealing with the downscaled climate scenarios delivered within ECOPOTENTIAL. A more general guidance on how to deal with EURO-CORDEX climate model data is provided by Benestad et al., 2017.

We recall that, as discussed in section 4.2, the small ensemble of RCM outputs provided, can only provide a very partial measure of the actual uncertainty to be associated with future projections. Several sources of uncertainty should be accounted for, ranging from uncertainty in the driving large scale global models themselves, to further significant uncertainties introduced by the downscaling procedures. For example, the study by Kotlarsky et al (2014), over the entire EURO-CORDEX ensemble, has found for different European areas considerable biases, up to 1.5°C for temperature and even +/-40% for precipitation. Similar biases could be highly significant for ECOPOTENTIAL targets. For this reason the data provided have been bias corrected, but bias correction itself has limitations of which users should be aware, described in section 3.4.

Within ECOPOTENTIAL, we opted for selecting the simulations from a single RCM, for the reason explained in Section 4.1. For each requested variable we generally provided 5 GCM-driven RCA4 simulations (one simulation for each of the 5 driving GCMs) both over the historical period (1970-2005) and over the projection period 2006-2100.

We suggest to:

- 1. Evaluate ALL the 5 simulations provided (one for each driving GCM) and inter-compare them over the historical period using the metrics of interest for the analysis at hand (average values, variance, extremes, spatial/temporal variability, etc). This allows to quantify the *model spread* for the specific variable, area, time period and metric of interest. This is a measure of the uncertainty deriving by the GCM diversity.
- 2. Evaluate ALL the 5 simulations provided (one for each driving GCM) by comparing them (in a climatological sense) to the observations, for example in terms of BIAS, RMSE, correlation coefficients. This allows to assess the *model performance/model error* for the specific variable, area, time period and metric of interest.
- 3. In case an ensemble of stochastic downscaled precipitation realizations is delivered, assess the *uncertainty related to the stochastic downscaling* method by comparing the different realizations.
- 4. If using climate models output to drive an ecosystem model, it is good practice to run the ecosystem model over the historical period prior to its use for future projections. In particular:
	- i) a run driven by historical local observations ("reference" simulation);
	- ii) a run driven by each RCM dataset over the historical period, to evaluate the agreement with the "reference" simulation;

The output variable(s) obtained at i) and ii) should be validated against available observations. At this point the ecosystem model can be run driven by future climate projection data.

5. Evaluate the uncertainty related to different scenarios of climate change, by using the two different (RCP 4.5 and RCP8.5) simulations provided. Evaluate also how the spread among the different simulations /scenarios vary with time up to 2100.

A versatile software to handle climate models data in NetCDF format is the Climate Data Operators (CDO, 2015) software, documented and freely accessible at<https://code.mpimet.mpg.de/projects/cdo>

7. Downscaled climate scenarios applications: inputs from partners

7.1 Applying downscaled temperature and precipitation data for a model-based assessment of climate sensitivity on the vegetation structure in the Northern Negev, Israel (Shaked Park, Negev PA, partner: UP).

Kristina Steinmar (University of Potsdam) investigates the climate impact on vegetation cover for the Long-term ecological research network (LTER) site Shaked Park in the transition zone towards the Negev desert, Israel, by applying the EcoHyD (EcoHydrology in Drylands) model.

Future decline and altered distribution of precipitation is expected to have an adverse effect on the occurrence and composition of the highly adapted desert vegetation, which can lead to significant changes of this ecosystem. Especially the transition zone of the Eastern Mediterranean has been detected as a climate change "hot spot" since it is highly responsive to altered climate conditions. The northern Negev, including Shaked Park, is an ecotone which is situated between the Mediterranean climate and semi-arid climate. Changes of water amounts and distribution along with increased temperature may lead to a pronounced desertification, implying a shift of aridity further northwards within Israel. The trend of increasing dryness has already been observed during the last decades and it is assumed to continue towards the century.

METHODS: EcoHyD is an eco-hydrological vegetation model developed specifically for drylands, with strong representation of small-scale hydrological processes and vegetation responses for different plant functional types, namely annual grasses, perennial grasses and shrubs. EcoHyD runs on a spatial resolution of 5 m and outputs weekly and annual changes in the vegetation cover. The model was used to estimate the impact of the changes in climate conditions on the northern Negev vegetation structure. Climatic forcing (temperature and precipitation) was derived from the RCA4 CORDEX simulations, bias-corrected and downscaled as described in Section 4. In particular, the downscaled fields consisted of:

- temperature data at 90 m spatial resolution downscaled using an orographic lapse-rate correction
- precipitation data at 750 m spatial resolution using the RainFARM stochastic method (D'Onofrio et al., 2014), providing five different stochastic realizations for each RCA4 member

Downscaled temperature and precipitation data covered the period 1970-2100 at 3h temporal resolution.

The EcoHyD model was adapted to the local, soil and topographic conditions and validated using time series based on Rapid Eye remote sensing data. A sensitivity analysis was carried out using precipitation input data with manipulated annual sums of precipitation and rainfall distributions. Finally, the locally calibrated and validated model was used to model future vegetation cover trends forced by downscaled precipitation and temperature data. As EcoHyD requires hourly weather input, the 3-hourly downscaled values of precipitation and temperature were evenly distributed over the corresponding 1-hour intervals.

The EcoHyD simulations covered a period of 130 years, including modelled data of the historical climate (1970- 2005) and the projected climate (2006-2100) in Shaked Park. EcoHyD was run driven by each stochastic realization of each CMIP5-driven RCA4 run the two RCP4.5 and RCP8.5 climate change scenarios; the described climate data were used as an input while all further parameters were kept fixed. Subsequently, the mean annual vegetation cover of the combined plant functional types was calculated for each realization as well as a running average for the scenarios RCP4.5 and RCP8.5.

Within Shaked Park, the model was applied to a 300 m x 350 m plot, which has been selected for its hilly topography and mostly natural conditions. Vegetation on the study site consists of a shrub-steppe with small patches of dwarf shrubs.

RESULTS: The projected changes on the vegetation cover in Shaked Park (Fig. 7.1.1a, uppermost part) show a decline in vegetation cover for both RCPs. The means for all realisations and all climate models clearly indicate a decline in

vegetation cover with a decrease of 50 % and 60 % for RCP4.5 and RCP8.5, respectively. Although RCP8.5 is characterized by more extreme climate changes, the absolute decrease in mean annual vegetation cover is declining less than in RCP4.5. Shaked Park´s vegetation is dominated by shrub patches and annuals appearing during the growing season.

Figure 7.1.1: a) Simulation of past and future vegetation cover changes according to the IPCC scenarios RCP4.5 and RCP8.5 and from observed climate data. Observations are shown in red, the results of the CMIP5 multi-model ensemble for the historical period 1976-2006 (multi-model realization –MMR- of 4 CMIP5 models each with 5 stochastic realizations) are shown in gray while future scenarios for the years 2006-2099 are shown in yellow (RCP4.5) and in purple (RCP8.5). The bold lines represent the annual mean of these scenarios, respectively. Figures b) and c) show the mean precipitation input data for historical data and RCP4.5 and RCP8.5 as well as the standard deviation showing the recent trends in the period between 1990 and 2019 and future trends between 2070 and 2099.

The results of the future simulations of vegetation cover project a shift in plant distribution due to a significant decrease in perennials and shrubs in both RCP scenarios while the annuals are declining only moderately. The mean annual precipitation in RCP4.5 is expected to decrease by 15 % while the rainfall variability only slightly increases. The simulated mean vegetation cover is 12 % towards 2100. Scenario RCP8.5, on the other hand, is expected to cause a mean annual precipitation reduction of 40% with an increase in extreme rainfall events, which will lead to a mean vegetation cover of 8% at the end of this century.

Comparing the first decade with the last decade of this period, a constant decline in vegetation cover can be observed with a difference in coverage of 7 %. This downward trend continues during the whole 21st century in RCP4.5 as well as in RCP8.5. This becomes apparent when looking at the time slots 1990-2019 and 2070-2099. The mean vegetation cover is almost halved for the RCP4.5 scenario, dropping from 23 % to 12 %. The RCP8.5 scenario starts with a comparatively lower coverage of 18 % and decreases by almost 10 % towards the end of the century.

For the historic time, simulations were also carried out based on the observed climate data and added to Fig 6.1.1.a. They show a difference of about 10 % vegetation cover between simulations based on downscaled and on measured data within the area. This suggests a certain underestimation of vegetation-relevant input parameters in the downscaled data.

This is mainly affected by an altered precipitation regime. Hence, rain events will become less frequent while the intensity of these events tends to increase, in RCP8.5 more than in RCP4.5. Even though the projected temperature rise is more significant, the main driver for extreme changes in dryland vegetation is the availability of water which is a limited resource in the Negev desert.

CONCLUSION AND OUTLOOK: The results of the simulations regarding future vegetation dynamics in the northern Negev imply a significant effect of expected climate change on the vegetation cover under both RCP4.5 (stabilization) and RCP8.5 (business as usual) scenarios. These changes underline the vulnerability of these waterdependent shrublands towards further desertification. How different plant functional types perform under future scenarios is subject to current analysis.

7.2 Impact of climate changes on the functioning and services of wetlands in the Camargue and throughout the whole Mediterranean area (Camargue PA, partner: TdV)

The RCA4 regional climate model projections at 0.11 degrees made available to the project partners will be integrated into a free online software, an interactive tool to promote rational management of Mediterranean marshes [\(mar-o-sel.net/\)](http://mar-o-sel.net/).

The aim is to assess the impact of climate changes on the functioning and services of wetlands in the Camargue and throughout the whole Mediterranean area. The Mediterranean region has been identified as one of the main climate change hotspots (one of the areas most responsive to climate change) due to water scarcity, concentration of economic activities in coastal areas, and reliance on climate-sensitive agriculture. Hence, wetland managers and policy makers need projection tools to foster adaptation to water shortage and to review water allocation strategies.

By comparing wetland hydrology under different management scenarios with modeled climate data from both the past and future provided by the CORDEX RCMs, Mar-O-Sel will allow us to identify what Mediterranean regions and which wetland types will be most affected by climate changes, and how much water volume will be required to keep the services they are currently providing based on their geographic location and catchment area.

Over the last two months, scientists from the "Research Institute for the Conservation of Mediterranean wetlands" working in ECOPOTENTIAL evaluated the five realizations of the RCA4 RCM (driven by five different GCMs), biascorrected over land areas using E-OBS, for each critical variable and for 323 localities along the Mediterranean coast (see Figure 7.3.1).

Figure 7.2.1: Map of the locations considered in this study. The RCA4 RCM data were extracted at these locations and will be used for further simulations with the Mar-O-Sel tool.

Since the E-OBS correction referred to land areas only, some areas very close to the sea-land transition were not covered by E-OBS and the corresponding point locations (red dots in Figure 7.3.1) were not included in the analysis. Other areas in northern Africa were excluded as well because of the unavailability of E-OBS data over these regions. Therefore, only 263 out of 323 localities were selected and will be used for further analyses. The Mar-O-Sel software has been conceptually restructured to include these projection data. Programming of the web interface has been launched in the second week of September 2017 while simulations will be run by October 2017.

7.3 Dynamics of high-altitude environments as a life-support system to wild Reindeer (Hardangervidda National Park PA, partner: UiB)

The Hardangervidda storyline is concerned with the wild reindeer population (Rangifer tarandus) that includes this National Park as part of its range. This particular population is the southernmost in Europe, and the largest wild population on the continent. Norway therefore has a special responsibility to safeguard its survival, not only for its ecological value, but also for its economical and recreational value for hunters, hikers and landowners. Wild reindeer migrate across the Hardangervidda plateau every year in search of food and suitable calving grounds. In winter, reindeer depend greatly on lichens as a food source, which they reach by digging through the snow. In summer, they depend on good summer pastures to be able to feed their calves, but also to fatten up before the long winter. The availability and quality of winter and summer grazing pastures therefore has a great potential to affect the reindeer population.

The availability of grazing pastures is dependent on a variety of factors, both human and climatic. Climate change is expected to alter both the onset and the duration of spring. For a population whose calving time is highly synchronized with greening, in a region where the summer months are already very short, this has the potential to be a major issue. A warming climate can also increase insect harassment, which reindeer suffer from increasingly in the summer.

One of the most important climatic factors controlling reindeer populations is snow cover and quality, as snow cover strongly affects lichen biomass and lichen heath development. Reindeer are known to be able to dig through deep snow to get to their food in the winter, but are dependent on loose snow that has not been too packed or formed a crust due to thawing and re-freezing. Thus, consistent cold temperatures are very important to ensure that their food source is accessible. Under climate change, increased variability in temperature with alternating warm and cold periods is therefore of particular concern, particularly in the spring.

The reindeer population on the Hardangervidda plateau is at the southern end of its European range. Studying the changes in environmental attributes of this region, particularly those which are expected to change the most under climate change, are therefore of particular interest when considering future projections for this population. We are using a climate time series of 20 years (from met.no), along with reindeer population and movement data, to see to what extent climatic variables control the location of the animals, and to help us to make projections about how these variables can affect population fluctuations. The projected climate data will be used in the coming months in much the same way, and should help us to make projections as to how future changes in climate have the potential to affect both the population itself, and its movements across the plateau.

Figure 7.3.1 Left: lichens, an important food source for reindeer in winter. Climate, grazing and human disturbance affect lichen biomass and its accessibility to reindeer. Right: wild reindeer migrate over the whole Hardangervidda plateau in search of summer and winter grazing pastures all year round (Photographer Anders Mossing).

7.4 Usage of meteo-climatic data to force hydrodynamic models in the Curonian Lagoon (Curonian Lagoon PA, partner: CNR)

Type of data

Data has been made available from various climate models. The period covered is the control run from 1970-2005 and two scenarios (RCP4.5 and RCP8.5) described in the IPCC 5th Assessment Report for the period 2006-2100. The climate models used to produce the results were the models CNRM-CM5, ICHEC, IPSL-CM5, HadGEM2-ES, MPI-ESM. The parameters that have been extracted were atmospheric pressure, wind velocity (2 components), solar radiation, air temperature, relative humidity, cloud cover and precipitation.

Areal coverage

The area that has been extracted corresponds in the west to the extension of the Lithuanian Exclusive Economic Zone, and in the other three directions it covers the complete Nemunas drainage basin. Inside this area is also situated the Curonian Lagoon (CL) and the Vistula Lagoon (VL), making it possible to run simulations for both lagoons and the available drainage basin model.

Data preparation

Data preparation has already started and it is still in progress. There are no particular problems reading the netcdf files. However, in analyzing the first files some problems have surfaced that are described here:

- Hydrodynamic models very often combine parameters in one file. E.g., forcing for hydrodynamics consists in atmospheric pressure and wind velocity, and these are normally written in one file. In any case, at least both wind components are normally found in one file. This means that before usage these parameters first have to be combined in other files, only then can the model data be used.
- Comparable parameters that are normally used together to force hydrodynamic models do not have the same temporal resolution. This is true for atmospheric pressure (24 hours of resolution) and wind speed (6 hours of resolution). This makes combining both parameters in one file difficult. In order to be used, pressure must first be interpolated on 6 hour intervals, and then the parameters can be written in one file together with the wind velocity.

Data usage

After the data preparation has been finished, it will then be used in various projects:

- Climatological runs, to study the effect of climate change, will be carried out. Main parameters in the simulations will be the number of storms acting on the Curonian Lagoon and the high water events that affect the Klaipeda harbour. Driven by these water level variations also the change in saltwater intrusion events will be computed. Finally, temperature variations will be studied. IPCC estimates of sea level rise will be used to carry out these simulations.
- A comparison study between Curonian Lagoon and Vistula Lagoon will be carried out. This will be possible, because the grid with the atmospheric forcing is big enough to cover both lagoons. Their behaviour in the future under climate change will be investigated, and similarities and differences of their behavior can be distinguished.
- The climatic meteo data will also be used for the available drainage basin model of the Nemunas River. This river discharges directly into the Curonian Lagoon and is therefore an important driver of the hydrodynamics of the lagoon. The forcing data will allow quantifying the discharge changes of the Nemunas. This information is extremely important, because the average salinity and the renewal time will depend crucially on this discharge.
- In a later moment the drainage basin model, forced with climatic scenarios, will also be used to compute the variations in sediment load and biogeochemical parameters that will affect the ecosystem in the Curonian Lagoon. This information, together with the ecological model outputs, will give an indication on changing conditions and ecosystem services in the Curonian Lagoon.

7.5 Assessing water and sediment related Ecosystem Services from hydrological modelling for future climate scenarios (Sierra Nevada PA, partner: UGR)

The University of Granada/IISTA group is working to improve the integration of ecological and hydrological models within Sierra Nevada in order to quantify ecological functions and services. Within this work, we have already analysed the effect of land use changes, and the existing trade-offs between provisioning, regulating and cultural services for different past scenarios from 1950 to present. Climate effects are included in the studio since we use real data of precipitation and temperature available at several weather stations throughout Sierra Nevada. Since late 1990s data from wind, relative humidity and solar radiation can also be included in the study.

In this work, the assessment of the different ecosystem services related to water and sediment relies on hydrological modelling, since there is no data to evaluate some of these services in the past, nor even in the present. Sierra Nevada is an alpine mountain range that reaches 3500 m above sea level at a latitude of 37ºN. Its hydrology is dominated by the snow-related processes modified by a Mediterranean semiarid climate. This causes a high heterogeneity in all physical properties of the basin due to the topographical influence. The abrupt change in altitude, the steep slopes and different slope aspects causes heterogeneity to dominate in the patterns of rainfall/snowfall, accumulated snow, soil moisture, or vegetation type and density. To handle this variability from a hydrological point of view, we simulate water and sediment cycles with a distributed and physically-based model called WiMMed [\(www.ugr.es/local/herrero/wimmed\)](http://www.ugr.es/local/herrero/wimmed) capable of dealing, to a certain extent, with this variability.

Figure 7.5.1. Mean annual precipitation (left) and temperature (right) for Sierra Nevada and surrounding area at 90x90 m resolution. Meteorological interpolation was made using WiMMed with all the available data from weather stations for 2000 to 2015. They were produced using daily maximum and minimum temperature data and daily and 1-hourly precipitation data.

With this same modelling scheme, we will use WiMMed in combination with the high-resolution climate change scenarios generated by ISAC-CNR within ECOPOTENTIAL to assess the expected Ecosystem Services given some climatic and land use land cover scenarios. ISAC-CNR has provided datasets of surface temperature and precipitation for Sierra Nevada generated with the regional climate model RCA4 driven by 5 different driving Global Climate Models and for two greenhouse gas concentration scenarios (RCP45 and RCP85), and then further downscaled to a spatial resolution of 1km and a temporal resolution of 3 hours.

7.6 Planned use of downscaled data in the Doñana PA (Doñana PA, partner: CSIC)

At Doñana PA the temporal dynamics of the different wetlands using earth observation data is studied. Instantaneous flooding maps for the last 40 years have been derived from Landsat images, and from these maps annual hydroperiods have been estimated both for the marshes (Diaz-Delgado et al. 2016) and for the temporary ponds on the aeolian sands (Bustamante et al 2016). Current work is done to improve the estimation of hydroperiods using Sentinel-2 images and estimating marsh vegetation biomass (Lumbierres et al. 2017).

The different ESS provided by Doñana wetlands depend on the hydrological dynamic of this seasonal fresh-water marsh and on the biomass production of aquatic vegetation. Hydroperiod and aquatic vegetation determine the habitat available for waterbirds and the carrying capacity of the marshes for cattle ranging. Hydroperiod and annual biomass at the pixel level are very variable, and depend on rainfall and temperature patterns.

Statistical models that relate hydroperiod and biomass production to precipitation and temperature are being built. Downscaled climate scenarios will be used to estimate how hydroperiod and biomass production will change in the future in this PA and what the spatial patterns of these changes will be. This will allow us to estimate annual carrying capacity of the marshes for cattle ranging, and trends in carrying capacity under climate change scenarios. Spatially explicit models will provide tools to PA managers to adjust grazing load in the different areas into which the PA is divided.

Species distribution models (SDM) for waterbirds in Doñana PA and surrounding wetlands (Figure 7.6.1) have been developed as well, using as predictors hydrological variables measured on site (Ramírez et al. submitted). We plan to expand the models to use hydrological predictors derived from EO data (hydroperiod duration, water depth, vegetation communities, biomass, wetland type, wetland size). In-situ variables dependent on rainfall and temperature have a large influence on habitat suitability for different species of water birds. We have simulated how different guilds of waterbirds will respond under different climate change scenarios. Downscaled climatic scenarios will be used to estimate the available habitat for different species of waterbirds in Doñana PA and surrounding wetlands in spatially explicit models. This will allow us to forecast the habitat availability for different species, and which management options to maintain waterbird diversity and the ESS provided by waterbirds will be available.

Figure 7.6.1. Change in waterbird habitat suitability estimated by GAMs and BRTs in the Doñana PA under different climate change scenarios (Ramírez et al. submitted). We show the effect estimated for three different scenarios encompassing changes of 10%, 30% and 50% in main environmental predictors affected by rainfall and temperature. Colours denote the guild and ellipses summarize the distribution of species per guild by considering the variance/covariance matrix. In particular, we have represented the Standard Ellipses corrected for small sample sizes (SEAc) using the R-package SIAR.

local landscape features.

7.7 Downscaled temperature data as drivers of a metapopulation model to assess climate change impact on the distribution of mountainous species (Gran Paradiso National Park PA, partner: EPFL)

The foreseen increase in temperatures due to the ongoing global climate change is among the main environmental factors that will impact species distributions in mountainous landscapes during the next century. The spatially-explicit metapopulation model developed at the ECHO lab (EPFL) following the work by Hanski (1998) and Bertuzzo et al. (2016) provides possible dynamics of the landscape occupancy of a selected species due to changing environmental features, such as temperature, soil cover, irradiation. The model consists of local colonization and extinction events that randomly occur in space and time. The probability of occurrence of these events on a particular grid cell depends on the global species occupancy and on the fitness of the species to the

In a preliminary study (Giezendanner et al., to be submitted), elevation has been considered as a proxy for temperature, with the species fitness represented by a Gaussian function having the maximum at the species optimal elevation and the deviation describing the niche width. Species characterized by different dispersal, optimal elevation, and niche width have been compared on different mountainous topographies: geometrical landscapes (cone, pyramid, roof), realistic fluvial landscapes (Optimal Channel Networks, OCNs), and real landscapes (Gran Paradiso National Park). For each species, an ensemble of 100 model solutions is evaluated to assess the probability of occupancy, thus differentiating among suitable and unsuitable species to a given topography under the current climatic conditions. Suitable species are defined as native species (Figure 7.7.1, Initial Phase). The impact of raising temperatures due to climate change (4° in 100 years) is then simulated by an upward shift of the optimal elevations with a constant velocity (6 m per year). In this way, the model is able to differentiate among species able and unable to track climate change (Figure 7.7.1, Climate Change). A final modeling step assesses the species distribution under the new climatic conditions, recognizing the species that will increase or decrease their occupancy, and the species doomed to extinction (extinction debt, see Figure 7.7.1, Post-Climate Change). Our results show that the fate of species characterized by a small niche width (specialists) are highly conditioned by the local landscape features, which might not allow them to track future changes in temperature.

The forthcoming research step consists in the application of the metapopulation model in a real scenario, in particular for modelling the distribution of the species that have been monitored at the Gran Paradiso National Park (Coleoptera Staphylinidae, Coleoptera Carabida, see Viterbi et al. 2013). In this context, it is fundamental to consider an accurate spatio-temporal description of the environmental features characterizing the species niche, at a scale that could be easily compared with the size of the plots used to collect the data (about 200 m). In fact, the fitness function has to include the particular landscape and climatic features that are relevant for each species (for example NDVI, Land Cover, Land Surface Temperature/Irradiation, in addition to downscaled monthly climatologies of temperature and precipitation) and the model parameters need to be calibrated against the available data of presence/absence.

To achieve this goal, CNR provided downscaled temperature data at a resolution of 90 m and daily frequency over a period of 10 years (2005–2010). This high spatial and temporal resolution will be especially important in catching sudden fluctuations in species presence due to extreme temperature events during the modeling process.

Two strategies will be explored to integrate these landscape features within the model:

- 1) Direct inclusion of the relevant RS data into the fitness function, e.g. considering a multivariate Gaussian fitness. The main difficulty associated with this approach is the model calibration, as two parameters (mean and deviation) require to be defined for each feature, and for each species.
- 2) Use climatological and RS data as predictors of statistical species distribution models (e.g. MaxEnt), and then adapt the fitness function to the computed probability distributions.

Figure 7.7.1 Digital elevation models (a) of four landscapes (three OCNs and the Gran Paradiso National Park) used in the experiment and their respective elevational area frequency distribution (b); (c) shows the three phases of the experiment: initial phase to sort out non-native species, climate change phase characterized by an upward shift of species' optimal elevations, and post-climate change phase and the different fates the species can undergo.

7.8 Population dynamics of a mountain ungulate (Alpine chamois, Rupicapra rupicapra) in the Gran Paradiso National Park, Italy (Gran Paradiso National Park PA, partner: CNR)

Long-term climatic changes are significantly affecting natural ecosystems and their impacts are expected to be particularly strong in extreme environments. Mountain areas offer a unique opportunity to investigate potential impacts of climate change on the biotic components of ecosystems.

To understand factors driving wildlife abundance fluctuations, recent studies on population dynamics have emphasised the need to investigate the interactions between extrinsic (e.g. climate) and intrinsic factors such as density-dependent food limitation and demographic structure. In this respect, mountain ungulates represent an interesting taxon, given their different age- and sex-dependent allocation of resources at different times of the year, and the predictable – yet highly variable – seasonality of their habitats. We therefore took advantage of a long-term series of 56 years (1956-2012) of count data of the protected Alpine chamois population of the Gran Paradiso National Park (hereafter GPNP, western Italian Alps), to investigate the effects of intrinsic and extrinsic factors over the past decades on the demographic parameters of this bovid.

Figure 7.8.1 Chamois in the Gran Paradiso National Park

Furthermore, disentangling the intrinsic and extrinsic mechanism underlying the demographic response of wildlife populations is necessary to robustly project numerical changes in future years. When trying to estimate future demographic changes based on climatic projections, however, it is necessary to take into account the intrinsic uncertainty associated with climatic projections. The assessment of climate impact on animal populations at local scale thus requires the availability of high-resolution climate change scenarios, and this is especially important in mountain areas, where small-scale variability in elevation and slope make it difficult to characterise climatic processes, in particular precipitation and snow depth.

We then aim to estimate the response of the study population to the expected climate change, by projecting its dynamics under the future climatic conditions as in the state-of-the-art climate models up to the year 2100. We relied on the time series of meteorological variables (temperature, precipitation, and snow depth) generated by the climate projections produced by the Coordinated Regional Climate Downscaling Experiment (CORDEX) for the RCP4.5 and RCP8.5 scenarios in the period 2013-2100. We selected the finest resolution available to date for the European domain (EURO-CORDEX), that is 0.11° on a curvilinear grid. At this resolution, the output of five regional climate models, driven by as many CMIP5 global climate models, have been produced (one run for each: CNRM-CERFACS-CNRM-CM5, ICHEC-EC-EARTH, IPSL-IPSL-CM5A-MR, MOHC-HadGEM2-ES, MPI-M-MPI-ESM-LR). Datasets were handled with the raster package in R, and the daily values averaged for the whole GPNP area (weighted with the fraction of each cell that is covered by the polygon) were extracted. To standardize the model's meteorological variables for subsequent analyses, all CORDEX time series were scaled (bias-corrected) to have the same mean and variance – in the period 1970-2005 – of the observed series recorded by one meteorological station inside GPNP ("Serrù" station, 2240 m above sea level; data available since the year 1962).

Figure 7.8.2 Projection of chamois population in the Gran Paradiso National Park, according to the output of 5 CMIP5 climate models in the framework of the CORDEX program for the RCP4.5 scenario.

7.9 Dynamics of savanna in Kruger National Park, South Africa (Kruger National Park PA, partners: CSIR, CNR)

Kruger National Park is a savanna ecosystem where grasses and trees are in balance, maintained by droughts, fires and herbivores. We aim at modelling the pattern of change of grass biomass taking into account temperature, precipitation, frequency of fire and herbivore abundance through time. This will help us understand how grass biomass will change in the next decades.

Herbaceous biomass (g/m²) has been estimated using empirical model based on *in situ* leaf area index (LAI) and MODIS data for the period Jan 2001 - Dec 2016. For the same period, we use the yearly burnt area (estimated by MODIS images) and CRU near surface air temperature downscaled at 1 km. Then, we selected 4 freely-available, high-resolution gridded datasets on precipitation (based on both meteorological stations and satellite data) and compared them with precipitation time series of 25 meteorological stations inside Kruger. The product that best correlates with stations (CHIRPS, 0.5° spatial resolution) has been selected for subsequent analyses.

Figure 7.9.1: (left) Savanna in the Kruger National Park. (right) Rainfall intensity (in 01/01/2001) as estimated by the CHIRPS gridded dataset; Kruger area (in gray), national borders (blue lines) and rainfall stations (points) are also shown.

Future projections of grass biomass dynamics will rely on CORDEX data: near surface air temperature, bias corrected and downscaled at 1 km; precipitation, bias corrected and downscaled at 1 km; near surface wind speed at 0.5° spatial resolution.

7.10 Simulating small-scale rainfall fields conditioned by weather state and elevation: A data-driven approach based on rainfall radar images (partner: BGU)

Rainfall spatial patterns generated by similar weather conditions can be extremely diverse. This variability can have a significant impact on hydrological processes.

The quantification of rainfall spatial distribution is critical for distributed hydrological modeling.

Stochastic simulation allows generating multiple realizations of spatial rainfall or filling missing data. The simulated data can then be used as input for numerical models to study the uncertainty on hydrological predictions.

This contribution is based on the use of an alternative rainfall downscaling method (other than RainFARM) based on a Direct Sampling (DS) technique, belonging to the multiple-point statistics family.

The direct sampling is employed to generate stochastic simulations of high-resolution (1-km) daily rainfall fields, conditioned by elevation and weather state. The technique associates historical radar estimates to variables describing the daily weather conditions, such as the rainfall type and mean intensity, and selects radar images accordingly to form a conditional training image set of each day.

Rainfall fields are then generated by resampling pixels from these images. The simulation at each location is conditioned by neighbor patterns of rainfall amount and elevation. The technique is tested on the simulation of daily rainfall amount for the eastern Mediterranean. The results show that it can generate realistic rainfall fields for different weather types, preserving the temporal weather pattern, the spatial features, and the complex relation with elevation (Oriani et al., 2017).

The concept of conditional training image provides added value to multiple-point simulation techniques dealing with extremely non-stationary heterogeneities and extensive datasets.

Figure 7.10.1: Sketch of the direct sampling iterative workflow in the two-dimensional simulation of a continuous variable, illustrating the generation of one value in the simulation grid (SG) by resampling from the training image (TI). See also Fig. 7.10.2 showing an example of application of the procedure.

Figure 7.10.2: One example of daily spatial variable used in step 2 of the simulation technique: elevation M(x) (a); daily rainfall amount K (b); and dry/wet/extreme categorical pattern W (c). The circular zone indicated by the arrow in c is a missing data region surrounding the radar station.

7.11 Temperature and precipitation downscaling with the GeoMMstats method (CREAF)

An auxiliary method has been developed for research and comparison purposes at CREAF.

This method is going to be applied to a subset of the temperatures and precipitation databases in two selected protected areas: the Doñana National Park and Sierra Nevada PAs. The proposed model is applied to both PAs in a unique processing and, at the end, the result is clipped to the corresponding PA.

This method combines the extrapolation of time series of in-situ observations from gauge meteorological stations with the geostatistical interpolation of the residual values obtained between the continuous modelling of the insitu observations and the RCA4 RCM datasets.

The generation of downscaled temperature and precipitation fields follows the methodology presented by Ninyerola et al. (2006, 2007) with some geostatistical improvements in the residual interpolation. This methodology includes topography (elevation) and other geographical variables (latitude, radiation, continentality, etc, see Figure 7.11.1) in a first multilinear regression step.

GeoMMStats has been implemented under C programming language, building upon the previous software by Pesquer et al (2007). The repository of the source code developed for the ECOPOTENTIAL project, [https://github.com/grumets/ECOPotential/tree/master/GeoMMStats,](https://github.com/grumets/ECOPotential/tree/master/GeoMMStats) is currently under construction.

Figure 7.11.1 Top: maps of the independent variables of the multilinear regression used in the GeoMMStats method. Bottom: spatial distribution of the meteorological stations and map of the Andalucía region that includes the Doñana and Sierra Nevada PAs.

8. Open questions and issues

In the last few decades, the reliability of climate models (both global and regional) and downscaling techniques has improved quite a lot (e.g. Rahmstorf et al., 2007) and some applications exist in which the downscaled model outputs have been used in impact studies, e.g. to drive hydrological models and estimate changes in water resources availability (see, among others, Chenoweth et al., 2011). The cascade of uncertainty from climate to local/impact/ecosystem modelling across the downscaling chain, however, has still not yet been taken into account in a systematic way and some questions still do not have clear or definite answers, for example:

- How do uncertainties propagate across the chain and how to estimate the final uncertainty?

- Do the uncertainties associated with small-scale dynamics at the surface, soil and vegetation feed back on to the atmosphere and effect larger scales?

- Can methodologies be developed to reduce uncertainties?
- What is the role of the observations/ data assimilation along the chain?

Uncertainties inherent in the climate models, and those inherent in the local-scale models, either hydrological or ecosystem or impact models in general, can be in part reduced by increasing our knowledge of the functioning of the system, which can be achieved using different strategies depending upon the model type and the process at hand. In some cases, uncertainties can be reduced using models coupled with field-scale measurements. The observations, in fact, are important elements in many (if not all) steps of the chain: for calibrations, verification, testing, and for validation purposes. For example, the GCM/RCM outputs and their downscaled fields on historical periods can be compared with the available in-situ or satellite measurements, in order to evaluate the performances of the large-scale models and of the downscaling procedures, and then used in local-scale simulations for validation against measured data in order to validate the modelling chain.

Future developments will also consider the "vulnerability approach" to future projections, namely, the identification of the ranges of driving parameters for which a "dangerous" behaviour of the system under study is obtained. Subsequently, the probability of occurrence of such range of parameter values is estimated from the (possibly downscaled) climate projections.

9. Conclusions

This Deliverable has presented the activities carried out within Task 8.1 of WP8 that led to the production and delivery of the downscaled climate data for the different ECOPOTENTIAL PAs. We also provided some guidelines to manage and use the data and assess, at least in part, the big issue of quantifying uncertainty in future projections.

The large-scale model data to be downscaled as well as the downscaling methodologies were discussed with the other project partners and the project coordination during two important meetings: in Pisa (September 2016) and in Potsdam (February 2017). These workshops were extremely useful to provide a direction and set a common downscaling strategy, as we have outlined in the present document.

For most PAs, we downscaled precipitation and temperature data simulated by the CORDEX regional climate model RCA4 driven by different global climate models. The characteristics of this specific model and its drivers as well as of the CORDEX coordinated experiment have been described in Sections 4.2 and 4.3. To downscale the RCA4 model precipitation and temperature we used existing methods already developed at CNR, but improved with the implementation of orographic corrections, to make them more suitable also for applications to mountainous and complex areas. We plan to submit the paper describing the new precipitation downscaling methods to a highimpact journal. In some cases, we provided the RCA4 RCM variables, including temperature, precipitation (with no further downscaling), snow, wind, radiation, potential evapotranspiration, following partners' requests.

The delivered data are already being used and will be used (see section 7) in the coming months by the project partners to perform ecosystem modelling studies in the different PAs.

Since the latest downscaled data were delivered at the end of July 2017, however, we expect that the partners will be able to handle and use the data during the next few months. We will continue to collect new eventual downscaling requests from partners in the coming months and provide support in the data pre-processing and analysis should specific requests come from the project partners.

We remind readers that both the downscaling software and the downscaled data are available to the project community respectively at the following links:

<https://github.com/jhardenberg/RainFARM.jl>

<http://data.dta.cnr.it/ecopotential/>

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