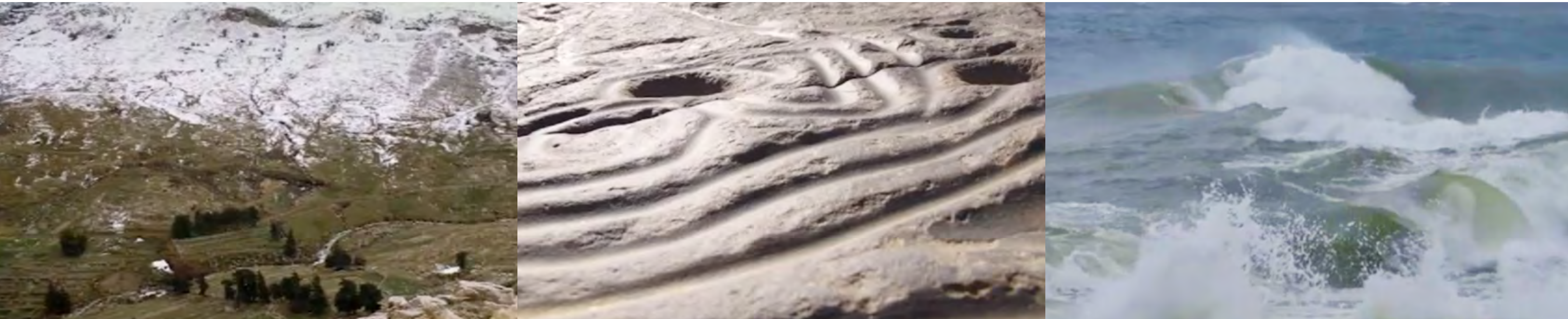
HANDBOOK N°6
Seminar held in Lecce, Italy
9 - 20 March 2015

Euro South Mediterranean Initiative:
Climate Resilient Societies
Supported by Low Carbon Economies



Downscaling Climate Modelling for High-Resolution Climate Information and Impact Assessment

Project funded by the European Union

Project implemented by
AGRICONSULTING CONSORTIUM
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d'Appolonia Pescares Typsa Sviluppo Globale

DISCLAIMER

The content of the report is based on presentations delivered by speakers at the seminars and discussions triggered by participants.

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FOREWORD

The Mediterranean region has been identified as a climate change hotspot by the Intergovernmental Panel on Climate Change (IPCC). Most countries in the region are already experiencing rising temperature, increasing water scarcity, rising frequency of droughts and forest fires, as well as growing rates of desertification. A common understanding is thus emerging in the region that fighting climate change is essential, by employing both mitigation and adaptation measures. These may also open new opportunities for further economic development, particularly those associated with low carbon options.

The EU-funded ClimaSouth project supports climate change mitigation and adaptation in nine Southern Mediterranean partner countries: Algeria, Egypt, Israel, Jordan, Lebanon, Libya, Morocco, Palestine and Tunisia. The project assists partner countries and their administrations in transitioning towards low carbon societies while building climate resilience and promoting opportunities for sustainable economic growth and employment. The project also supports South-South cooperation and information sharing on climate change issues within the region as well as closer dialogue and partnership with the European Union.

As part of its efforts to enhance climate change strategic planning, the ClimaSouth project is producing a series of handbooks tailored to the needs of the South Mediterranean region. The key users targeted include relevant government departments at operational and policy levels, climate change units and committees, decision makers, meteorological services, and members of local government, the private sector and civil society. The ClimaSouth handbooks are based on peer-to-peer seminars and training sessions held by the project, which are designed to support national administrations in the development and implementation of climate change policy; they further help stakeholders in the region to engage more effectively in the global climate change framework.

This sixth handbook builds on the previous ClimaSouth E-handbook N.2 "Improving Climate Information", by focussing on the process of downscaling and translating climate knowledge into actionable climate information that may support on-the-ground adaptation. Material on climate change downscaling is primarily illustrated in the context of dynamical downscaling, while seasonal forecasts are illustrated with reference to the suite of techniques available in statistical downscaling. Both dynamical and statistical approaches, are illustrated through various examples. We hope this handbook will contribute to enhancing capacity for the downscaling of seasonal forecasts and global change scenarios in the South Mediterranean region.

May your reading be informative and interesting.

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CLIMASOUTH HANDBOOKS

Handbook N. 1: Building Capacity & Mainstreaming Climate Change Policy
Handbook N. 2: Improving Climate Information
Handbook N. 3: An Introduction to Greenhouse Gas Inventories and MRV
Handbook N. 4: Long-range Energy Alternatives Planning System (LEAP) & Greenhouse Gas (GHG) Modelling
Handbook N. 5: Low-Emission Development Strategy (LEDS)
Handbook N. 6: Downscaling Climate Modelling for High-Resolution Climate Information and Impact Assessment
Handbook N. 7: Connecting Downscaling, Impacts and Adaptation: A Summary

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LIST OF SELECTED ACRONYMS

AR4	IPCC Assessment Report 4
AR5	IPCC Assessment Report 5
CDO	Climate Data Operators
CDF	Cumulative Density Function
CMCC	Euro-Mediterranean Center on Climate Change
COSMO-CLM	Consortium for Small-scale Modeling - Climate Limited-Area Modeling
CORDEX	Coordinated Regional Climate Downscaling Experiment
CPT	Climate Predictability Tool
DGVM	Dynamic Global Vegetation Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA	ECMWF Reanalysis
EURO-CORDEX	Europe - CORDEX
GCM	General Circulation Model
GHG	Greenhouse Gas
IAM-Bari	Istituto Agronomico Mediterraneo di Bari
IPCC	Intergovernmental Panel on Climate Change
MED-CORDEX	Mediterranean - CORDEX
MENA-CORDEX	Middle East North Africa - CORDEX
MOS	Model Output Statistics
PCR	Principle Component Regression
PDF	Probability Density Function

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RCM	Regional Climate Model
RCP	Representative Concentration Pathway
SIMETAW	Simulation of Evapotranspiration of Applied Water
SMHI	Swedish Meteorological and Hydrological Institute
SST	Sea-surface Temperature
WCRP	World Climate Research Programme
WL	Web Link

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1. INTRODUCTION

ClimaSouth organized a workshop in Lecce, Italy (March 9 - 20, 2015) in collaboration with the Euro- Mediterranean Center on Climate Change (CMCC). The aim of the workshop wasto advance capacity in downscaling climate modelling for the purpose of high-resolution climate impact assessment in support of adaptation actions. This was achieved through an intense first phase of the workshop (1.5 weeks), concentrating on climate downscaling concepts and implementation, followed by a second phase (3 days) discussing concepts and providing illustrative examples in the use of high-resolution climate information for impact assessment and adaptation. One climate participant from each country was invited to attend the complete 2 week workshop and one sectoral participant from each country was invited to join the workshop for the final three days, when the focus was on impacts. The workshop concentrated on the agriculture/forestry and water sectors.

The overall initiative originated following discussions at the ClimaSouth Regional Workshop on Improving Climate Information held in April 2014 (see ClimaSouth E-Handbook N.2[WL1]). Capacity for the creation of downscaled climate information had been recognized as an important gap in the process of translating climate knowledge into actionable climate information that could support onthe-ground adaptation. At the 2014 workshop it ws concluded that enhanced adaptive management could be better empowered by a range of downscaled climate information such as real-time monitoring, seasonal forecasts and global change scenarios. Enhancing capacity in the ClimaSouth region for the downscaling of seasonal forecasts and global change scenarios was considered especially critical. In response to this, the 2015 workshop on downscaling climate modelling reported on herein addressed both these

timescales (in this handbook, see Climate Change Scenarios in Section 2 and Seasonal Forecasts in Section 3). The 2014 workshop also recognized that dynamical and statistical approaches to downscaling both had important roles to play. To provide balance in presenting the material, climate change downscaling (Section 2) is primarily illustrated in the context of dynamical downscaling (and bias correction), while seasonal forecasts (Section 3) are primarily discussed in the context of the suite of techniques available in statistical downscaling. Nonetheless, as the discussion in these sections describes, dynamical and statistical approaches can be effectively applied in the context of both global change and seasonal forecast information. Section 4 captures some of the concepts and examples discussed in the impacts module of the workshop.

The initiative contributes to the ClimaSouth project structure by improving and analysing climate data relevant for adaptation (Project Activity 3.1.1), while also focusing on the use of the downscaled information for case study impacts and discussing adaptation options (Project Activity 3.1.3). The workshop was structured in a way that increases regional cooperation, through joint training and the sharing of experiences and practical exercises in the form of case studies. This handbook is primarily intended for technical professionals and technically informed policy makers in the ClimaSouth countries. The aim is to facilitate discussion and action on the improvement of highresolution climate information in each country in order to support the enhancement of national adaptation strategies.

The ClimaSouth programme team is grateful to the speakers who contributed to the success of the workshop, in particular the experts of the CMCC (Climate experts E. Bucchignani, M. Montesarchio, A. Zollo, and impact experts G. Rianna, N. Mancosu, V. Bacciu) and invited agricultural impact expert M. Todorovic (IAM-Bari). The learning achieved at the workshop through practical exercises was, in addition to the above-mentioned science experts, made possible by the careful attention and support of the CMCC computer staff.

2. DOWNSCALING CLIMATE CHANGE SCENARIOS

2.1 Introduction and dynamical downscaling concepts

The warming of the climate system in recent decades is evident from observations and is mainly related to the increase of anthropogenic greenhouse gas (GHG) concentrations (IPCC 2013). As a consequence, precipitation will also be altered, partly because a warmer atmosphere will hold more water vapour, resulting in heavier rains. In addition, processes will be engaged to increase droughts in some locations, due in part to larger water absorption from soil and vegetation. The main tool for providing insights into possible future climate changes is *climate modelling*. Climate models are mathematical models that simulate the behaviour of Earth systems based on the fundamental laws of physics. More specifically, general circulation models (GCMs) simulate planet-wide climate dynamics, representing a powerful instrument for simulating the response of the global climate system to external forcing (Giorgi 2005).

However, GCMs are generally unsuitable for simulating local climate, since they are currently characterized by resolutions generally around or coarser than 100 km, while many important phenomena occur at spatial scales less than 10 km. Moreover, GCMs do not adequately account for vegetation variations, complex topography and coastlines, which are important aspects of the physical response governing the regional/local climate change signal. Thus, downscaling techniques have been developed which take the large-scale predictions provided by a GCM and apply methods to extract implied climate change information at more regional/local scales.

Downscaling methods can be divided into two main categories: *statistical methods*, which apply transformations to the GCM output, based on relationships calculated with high-resolution observations; *dynamical methods*, which explicitly solve the process-based physical dynamics of the regional climate system at high spatial resolution, when driven by the large-scale low-

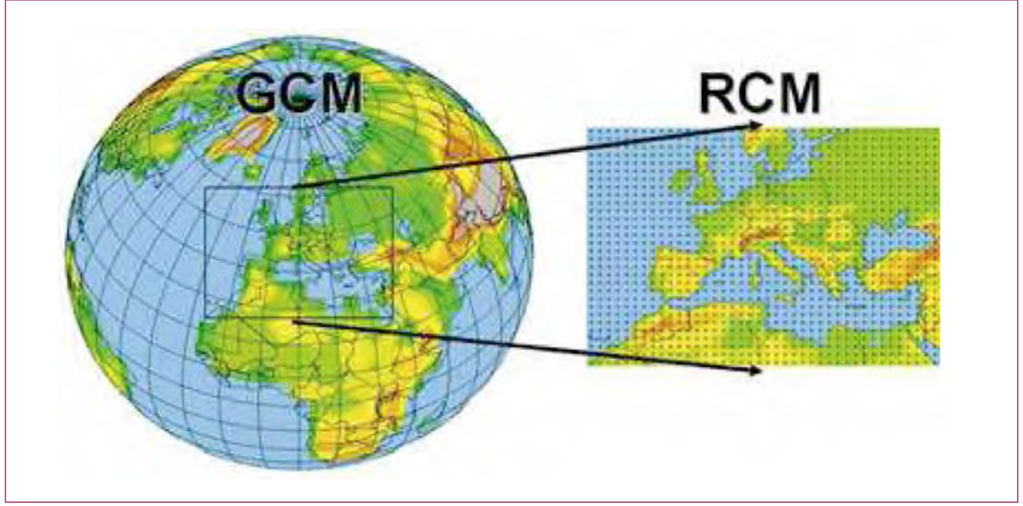

Figure 1. A schematic representation of the dynamical downscaling technique.

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resolution forcing of the GCM. One of the most effective tools, providing high-resolution climate analysis through dynamical downscaling, is the regional climate model (RCM) (Giorgi and Mearns 1991). RCMs are often able to provide an accurate description of climate variability on local scales (Figure 1). Moreover, RCMs show the capability to provide a detailed description of climate extremes, including the statistics of extreme weather events (Rummukainen 2010).

The capabilities of the current generation of RCMs have been assessed in the framework of several international projects. In recent years, the WCRP Coordinated Regional Climate Downscaling Experiment (CORDEX[WL2]) project (Giorgi et al. 2009), has been established to provide global coordination of regional climate downscaling for improved climate-change adaptation policy and impact assessment. Of course, dynamical downscaling also has some drawbacks; for example, dynamical downscaling is computationally expensive, needing large computing resources, and is strongly dependent on the boundary conditions that are provided by GCMs (if the large-scale GCM simulation is in error, this will transfer to the output of the RCM: a concept often referred to as "garbage in–garbage out"). Also, RCMs (like GCMs) contain semi-empirical parameterization schemes such as for convection; it must be assumed that these parameterization schemes are still valid in a future climate. A further constraint is that the spatial resolution of most current-generation models is limited to about 1 km, especially for the huge amount of computational resources required by finer grids, but also due to the lack of suitable numerical models for some processes with such resolution values.

RCMs must be validated against observational data sets in order to evaluate the capability of the model to reproduce current climate conditions. This in turn allows to define its deficiencies originating from various modelling assumptions and their related uncertainties. Two different kinds of data can be used as initial and boundary conditions of an RCM to evaluate its ability to simulate current climate: (i) *Reanalysis* and (ii) *GCMs that were driven with currently observed GHG forcing*. The reanalyses most commonly used to perform RCM simulations are the ERA-Interim[WL3], the latest global atmospheric reanalyses produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). Reanalyses represent our best estimate of the large-scale observed climate at every time point across recent decades, since reanalyses are informed by actual observations of the climate system. The ERA-Interim is available from 1979 and the reanalyses are continuously updated in real-time. The usage of reanalysis as initial and boundary conditions of RCMs allows the assessment of RCM capability in reproducing the most important climate features of a specific region of interest. GCMs (with current GHG forcing) are not constrained by atmospheric observations during their integration, and so may develop systematic errors (drift) which can contribute to errors in the RCMs that they drive. Nonetheless, these experiments are important, since they provide a base against which to compare RCM experiments that are driven by GCM climate change projections (IPCC scenarios), and in this way, RCMs generate high-resolution estimates of climate change projections.

A major source of the uncertainty in RCMs arises from the large number of parameterized physical processes within the climate model and the associated unconfined model parameters. Several studies have demonstrated the importance of this "parameter uncertainty" for the simulation of present and future climates, by perturbing single and multiple model parameters within plausible parameter ranges determined by expert judgment (Giorgi and Mearns 1991). Since uncertain model parameters are responsible for a large part of modelling errors, the parameter uncertainty is typically constrained by calibration or tuning methods to improve the agreement between the climate model and the available observations. This tuning process is one of the aspects that requires highly skilled technical human resources in order to effectively implement and run the RCM.

2.2 Climate Change Projections over the ClimaSouth Domain

The ClimaSouth domain is located in a transition zone between the arid climates of the Saharan North Africa/ Middle East region and the temperate climates of central Europe; it is affected by interactions between mid-latitude and tropical processes. Anticipating climate change in the region is further complicated by the existence of a major enclosed sea (the Mediterranean) with very active regional thermohaline circulation, and linkage to the Atlantic Ocean through the Strait of Gibraltar. However, it is already very clear that the broader Mediterranean region is very sensitive to climate changes induced by increases in GHG concentrations and it has been identified as a

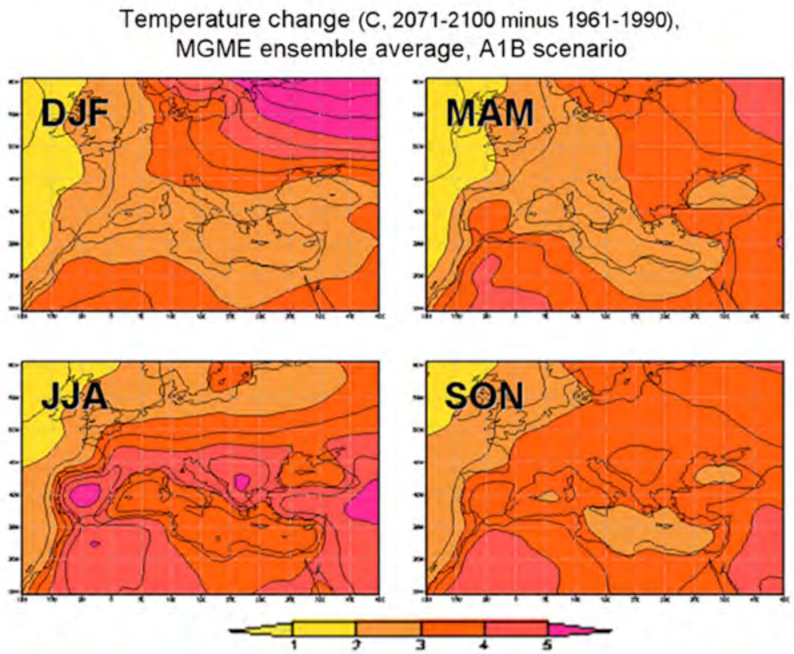

Figure 2. Temperature change for the four seasons (2071-2100 minus 1961-1990), ensemble average, A1B scenario (from Giorgi and Lionello 2008)

"Hotspot" for future climate change. Major impacts on society are expected, including on agriculture, tourism and water resources.

Many GCM climate-change projections have been analysed for the Mediterranean under different GHG forcing scenarios, and many of the projections are freely available[WL4, WL5]. A generally consistent picture has emerged over recent IPCC assessments, culminating in the recent AR5 (IPCC 2013). Overall, increasingly drier and warmer conditions are projected: these conditions are particularly evident in summer. As a summary of temperatures from AR4, Fig.

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2 shows the ensemble average as constructed by Giorgi and Lionello (2008). These then, represent the type of GCM integrations that are subsequently used to drive RCMs to assess patterns of climate change at higher spatial resolution.

2.3 Illustration of dynamically downscaled results

Downscaling is particularly important for assessing regional climate change for the broader Mediterranean area, which is characterized by high space variability and many climate types. Strong land-sea contrasts, land-atmosphere feedbacks, intense air-sea couplings and aerosol-radiation interactions, are among the challenging regional characteristics to take into account when dealing with high-resolution climate modelling of the region.

There are several coordinated ensembles of high-resolution regional climate simulations that are relevant for countries targeted by the ClimaSouth project. One example is based on a grid size down to 25 km and on the previous generation of emission scenarios (the ENSEMBLES project, Hewitt 2005). The recent CORDEX[WL2] project archives many relevant simulations considering the new RCP emission scenarios (van Vuuren et al. 2011). Relevant domains are MED-CORDEX, EURO-CORDEX (covering much of the ClimaSouth domain at very high resolution) and MENA-CORDEX (see next section for more details). Analysis of multiple models and ensembles of the same model (run with small changes in initial conditions) are important to building an impression of uncertainty, which is a significant component for arriving at appropriate adaptation actions (e.g., Vermeulen et al. 2013).

At the CMCC, high-resolution climate projections (about 14 km) over the Euro-Mediterranean area (also including the Black Sea) have been performed with the regional climate model COSMO-CLM[WL6] (Rockel et al. 2008). Specifically, two simulations driven by the global model CMCC-CM (Scoccimarro et al. 2011) were carried out over the 1971-2100 period, employing the IPCC RCP4.5 and RCP8.5 emission scenarios (van Vuuren et al. 2011), chosen as representative of a world with less (RCP4.5) or more (RCP8.5) pronounced global emissions. To illustrate the results, Fig. 3 shows the temperature change projections

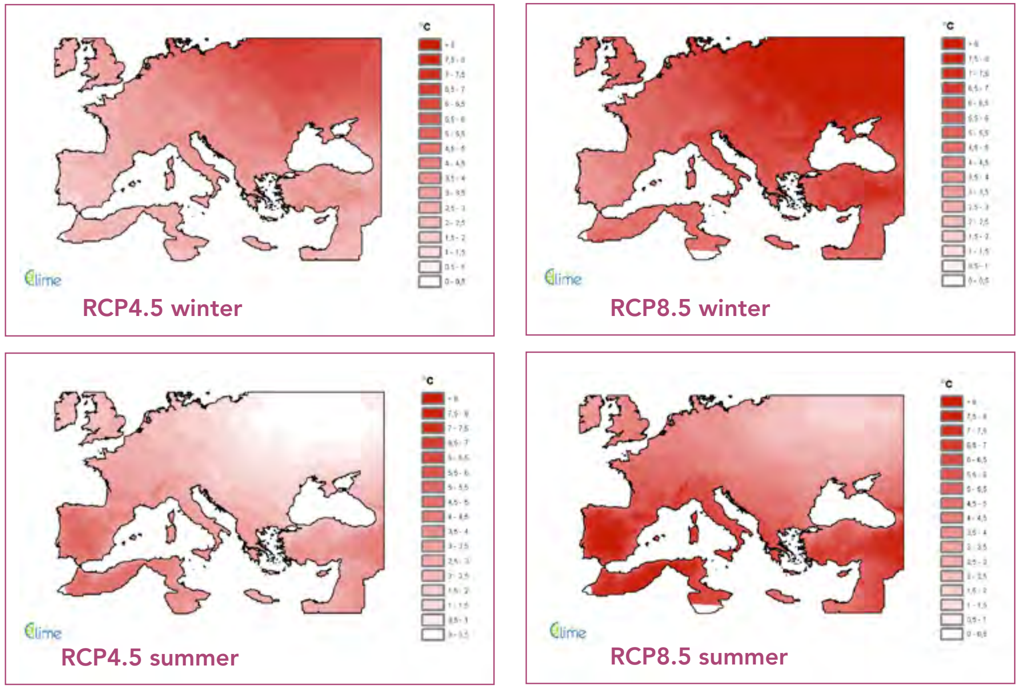

Figure 3. Temperature change for winter and summer (2071-2100 minus 1971-2000) projected with COSMO-CLM.

for the period 2071-2100 compared to 1971-2000 for both scenarios.[1] Considering the RCP4.5 scenario, a general increase in temperature is projected for all seasons. The increase is more pronounced in winter, while in summer the northeast part of the domain is characterized by negligible variations. Considering the RCP8.5 scenario, distribution anomalies similar to those observed for RCP4.5 are found, but with larger increases in temperature: peaks of 8° C are registered in winter. These climate projections are associated with substantial precipitation changes (not shown).

2.4 Dynamical downscaling practical exercises

The COSMO-CLM (as used for Fig. 3) is applicable to downscaling in all regions of the world and to most of the global climate simulations available. It is characterised by a non-hydrostatic formulation, a key feature at high resolutions, allowing better representation of convective phenomena and subgrid- scale physical processes.

Running of the COSMO-CLM (as used to produce the results in Fig. 3) was demonstrated to participants, including an illustration of the computing operating system, the fixed boundary forcing datasets, the datasets containing the driving GCM data, and the parameterization choices that need to be made.

[1] Surface temperature is here (and throughout the handbook) focused upon to illustrate the downscaling concept. The RCM delivers projections of all climate variables, some of which are judged more confident than others. Surface temperature is one of the more confident variables.

The RCM COSMO-CLM has been widely adopted in several international projects, such as PRUDENCE (Christensen et al. 2007) and CORDEX (Giorgi et al. 2009), showing good capability in reproducing the mean climate features of the analysed areas. The CORDEX[WL2] initiative (introduced in the previous section) was established to produce coordinated sets of regional downscaled projections useful for better understanding relevant climate phenomena and for assessing climate change impacts. In this framework, different institutions make available RCM simulations, using as forcing both ERA-Interim Reanalysis and global models. Thirteen domains were considered for the regional model integrations, including EURO-CORDEX (with model runs at 0.11° and 0.44° of horizontal resolution) and MENA-CORDEX (at 0.22° and 0.44° horizontal resolution). It is noteworthy that the output of the CORDEX simulations follows particular specifications regarding, for example, the file format, the coordinate grid, the variable names and attributes and the time frequency.

The workshop introduced one of the post-processing tools useful for managing regional model output and, in particular, netCDF (Network Common Data Format) files, the standard file format of the CORDEX simulations. The processing tool introduced was CDO[WL7] (Climate Data Operators), a collection of command line operators used to manipulate and analyse climate model data. Several operators were illustrated and made available for hands-on practice, highlighting also the main features of netCDF files.

In the practical exercises, CDO commands were used to evaluate the error of a regional simulation with respect to observations: annual cycles and seasonal bias maps were computed. For this, EOBS [WL8] (Haylock et al. 2008) and

CRU[WL9] (Harris et al. 2014) observational gridded datasets were used to validate EURO-CORDEX and MENA-CORDEX simulations respectively. Furthermore, the climate projections were analysed, producing seasonal maps of projections for the 2071-2100 period compared to the 1981-2010 period, considering the IPCC RCP4.5 scenario. Figure 4 illustrates some of the practical exercises undertaken with the CORDEX data.

Figure 4. Illustrations of the dynamical downscaling practical exercise analyses undertaken at the workshop.

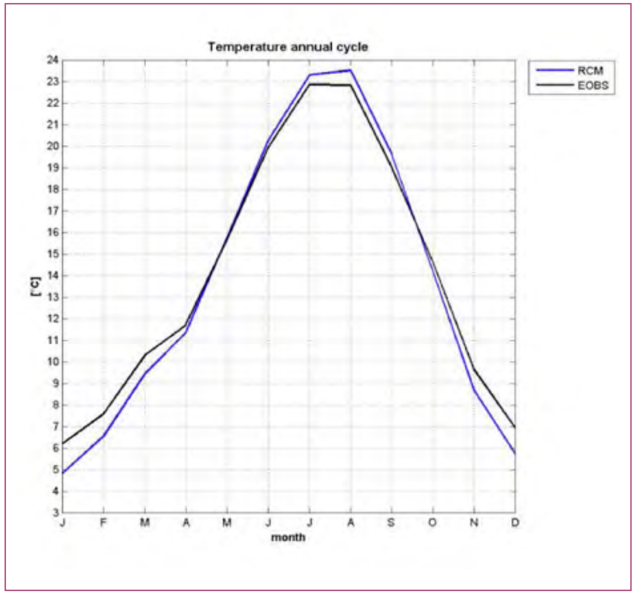

Figure 4 (a)

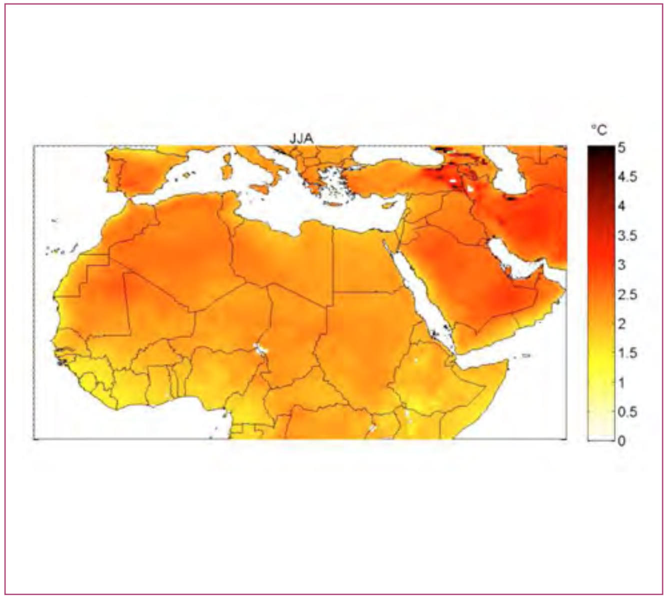

Figure 4 (b)

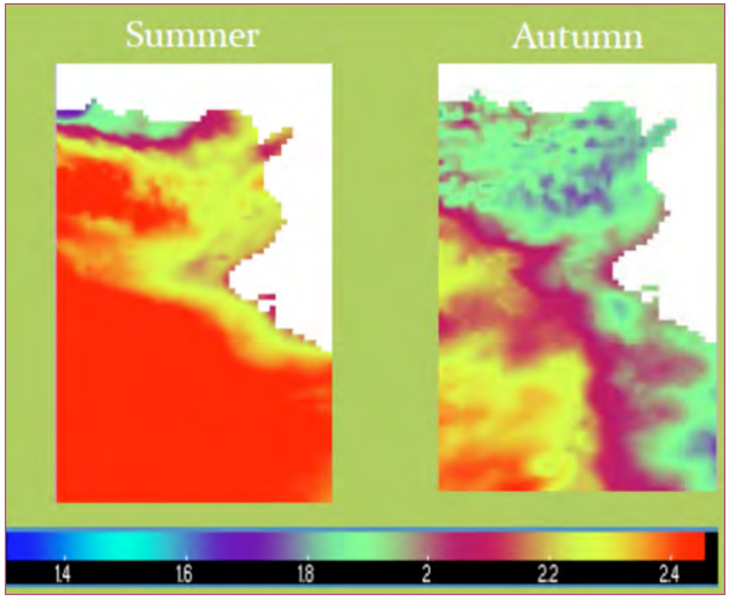

Figure 4 (c)

Figure 4 (a): Evaluating the ability of a Euro-CORDEX experiment driven by ERA reanalysis to simulate current climatology. The graphs show the temperature annual cycles of E-OBS data and of a EURO-CORDEX simulation at 0.11° of resolution (simulation provided by the Danish Meteorological Institute (DMI) and carried out with the RCM HIRHAM5 forced by ERA-Interim) for the 1989-2010 period over the Iberian Peninsula.

Figure 4 (b): summer (June-July-August, JJA) difference in temperature between the 2071-2100 and 1981-2010 periods, considering the IPCC RCP4.5 scenario, for a MENA-CORDEX simulation at 0.44° of resolution (simulation provided by SMHI and carried out with the RCM RCA4 using as forcing the GCM CNRM-CM5).

Figure 4 (c): Focused plot over Tunisia of EURO-CORDEX (at 0.11° of resolution) for surface temperature change (degrees Celsius) 2071-2100 minus 1981-2010 (produced during practical exercise analysis by workshop Tunisia participants). For the full list of CORDEX simulations available, and details of the different contributing institutions and models used, see the CORDEX website[WL2].

2.5 Statistical downscaling of regional change scenarios for impact assessment

Methodological discussion

GCM outputs usually cannot be directly used for regional/local impact studies, since there are two main problems: they are biased with respect to observations and their spatial scale is too coarse. Statistical downscaling of the GCM output is one response to the problem (the range of possible approaches is discussed in Section 3 in relation to seasonal forecasts). Alternatively, RCMs can be applied to dynamically downscale the outputs of GCMs (Section 2.4). RCMs provide time series of climatic variables on a smaller scale, giving detailed information at the regional scale. However the direct use of RCM simulations in impact studies is still challenging: indeed, impact models typically require a higher spatial resolution than that delivered by a RCM, so further downscaling is often necessary. Furthermore, RCM outputs are also biased and often do not provide realistic control conditions. In order to bridge the gap between the information necessary for the impacts community and the available RCM data, hybrid downscaling methods can be introduced, merging dynamical and statistical approaches, using both RCM and statistical techniques in a complementary fashion. The combined use of these approaches allows, at least to some extent, to combine their advantages (Zollo et al. 2015). Such a modelling chain that has been adopted in impact studies is illustrated in Fig. 5.

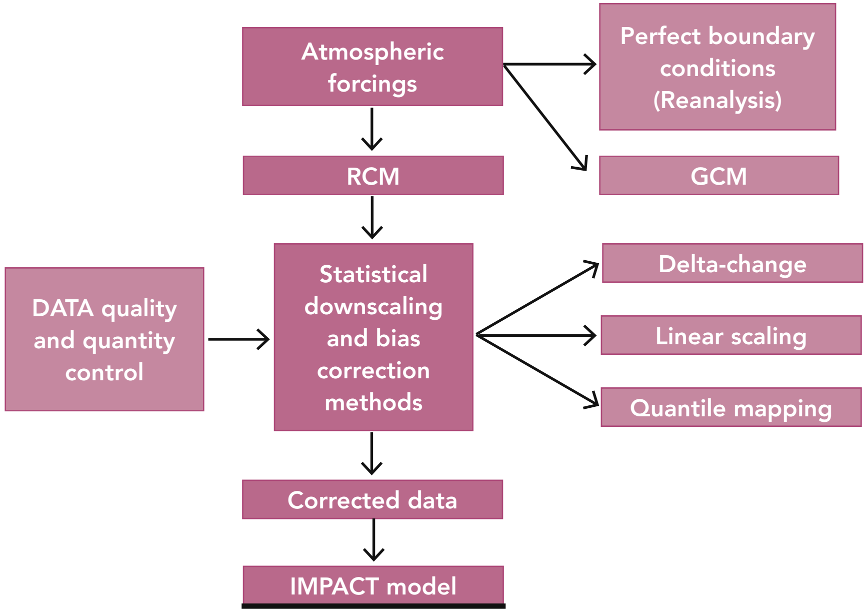

Figure 5. A hybrid dynamical-statistical climate modelling flowchart for impact studies.

Corrected downscaled data are in most cases products for "end users" (Maraun et al. 2010). Different kinds of statistical downscaling/bias correction techniques exist, with different characteristics to meet the specific needs of different targeted end users. As a first step in developing high-resolution regional climate scenarios for climate change impact studies, it is necessary to carefully analyze long observation datasets (Turco et al. 2013). These are needed both for the validation of the RCM itself (i.e., to verify the reliability of the simulated data), and for the calibration of RCM outputs, through statistical downscaling or bias correction methods. Therefore the preliminary step is data quality and quantity control. Observed meteorological data may be provided by weather stations. However a direct comparison between climate model output and point measurement is challenging, as they have different characteristics since measurements are representative for a point and not for the grid cell (area-weighted average). An alternative is provided by gridded datasets obtained by interpolating station measurements. A gridded dataset represents a more appropriate tool for model validation since they are both areal-averaged data.

However, gridded observations are affected by some problems such as: uncertainties introduced by the interpolation method employed; irregularly spaced stations; and incomplete and inhomogeneous time series. These issues should always be considered when applying gridded datasets for model validation.

Implementation of downscaling bias correction methods (including practical exercise + illustration)

Bias correction methods operate by comparing a model output grid-box time-series to a corresponding observed time-series. The basic idea of bias correction techniques is to correct the model output using observed data. Of course the quality and the general characteristics of the available data affect the quality and character of the correction performed. Given the importance of the observed data in the process, a good practice could be the analysis of different datasets over the area of interest (if available) in order to choose the most reliable and suitable dataset. Moreover, it should be considered that the correction performed using a specific observed dataset also involves an implicit downscaling to the same scale as the observational data.

Bias correction methods are based on the strong assumption that biases between observations and model are constant and therefore independent of the control period (stationarity assumption). Thus, it is assumed that the same correction algorithm applies to both current and future climate conditions (an assumption that pervades all statistical downscaling approaches).

Some of the commonly used bias correction methods are: Delta-change approach, linear scaling and quantile mapping. The basic idea of the *Delta-change method* is to take the RCM anomalies (e.g., scenario minus base-period) and apply these to the base-period observed data. The correction is usually done on a monthly basis with a multiplicative correction for precipitation and an additive correction for temperature (Teutschbein and Seibert 2012). The *linear-scaling approach*, on the contrary, operates with monthly correction values based on the differences between observed and simulated values in the base period. By definition, corrected RCM simulations in the base period will perfectly agree in their monthly mean values with the observations. Precipitation is corrected with a factor calculated as the ratio of observed and simulated monthly mean data, while temperature is corrected with an additive term calculated as the difference between observed and simulated monthly mean data. The applied correction factors and addends are assumed to remain unvaried, even for future conditions (Teutschbein and Seibert 2012). Finally, *quantile mapping correction* tries to adjust all the moments of the probability distribution function (PDF) of the simulated climate variable. It estimates the corrected value as a function of the original variable, using a transfer function calculated forcing equality between the CDF (cumulative distribution function) of the observed and simulated variables in the base period (Piani et al. 2010). The corrected variable is then obtained using the following equation:

$$X^* = F^{-1}_{obs}(F_{rcm}(X_{rcm}))$$

where F_{rcm} and F_{obs} are, respectively, the CDF of the simulated and observed data and X represents the climate variable (temperature or precipitation). Different kinds of quantile mapping methods exist (Gudmundsson et al. 2012): (1) distribution derived transformations, (2) nonparametric transformations (empirical quantiles) and (3) parametric transformations. In the case of a distribution derived method, the statistical transformations are achieved by using theoretical distributions; the most commonly used distribution for representing the PDF is the Gamma distribution for precipitation, and the Gaussian distribution for temperature (Teutschbein and Seibert 2012). On the contrary, the empirical method does not make any a priori assumptions about data distribution. The empirical CDFs are approximated using tables of empirical percentiles which can be used to calculate the corrected value for the variable (Berg et al. 2012). Finally, the quantile– quantile relation can be modelled directly using parametric transformations; a review of different kinds of available parametric transformations is illustrated in Gudmundsson et al. (2012). Furthermore, they developed a freely available R-package (qmap[WL10]), which implements, in the R language, all the quantile mapping methods mentioned above.

In order to use these techniques to downscale future scenarios, it is also important to assess their robustness in climate change conditions. One check that can be applied is to analyze the consistency of the climate change signals in the bias-corrected data and the original RCM data. Bias correction should not substantially alter the RCM's climate change signal (the aim is rather to arrive at a more realistic daily weather sequence). Indeed, Zollo et al. (2015) found that generally, these postprocessing techniques are able to preserve the climate-change signal of the RCM. These results suggest that the proposed hybrid downscaling techniques may be very useful tools for climate change impact studies, where users require high-resolution data in which systematic errors are minimized.

In the practical session, some exercises on bias correction and downscaling to point stations were introduced using the linear scaling method (implemented in software R). The exercises showed (1) how to compare observed and simulated data, (2) how to compute the correction of the simulated data using linear scaling, saving the result in an excel file; and, finally, (3) how to check if the result is correct. Figure 6 represents an example of results obtained in this session. In addition, the linear scaling of data was applied to a climate change scenario. The climate change signals, before and after application of the bias correction technique, were compared in order to evaluate the ability of this method to preserve the climate change signal of the RCM.

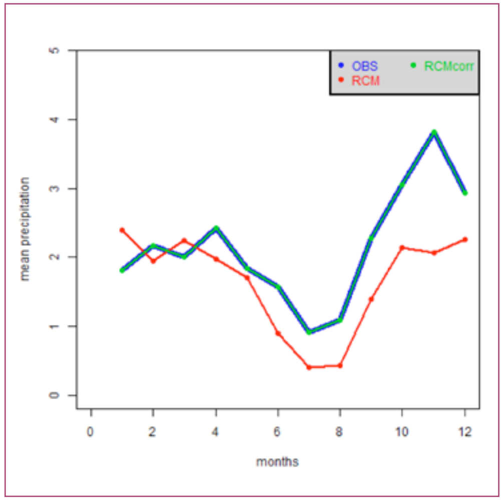

Figure 6. Examples of results obtained in the practical session: observed base-period seasonal cycle of simulated RCM data and RCM data corrected using linear scaling. Note how the corrected data (green dots) now have monthly mean values identical to the mean values of the observed base period (blue line).

3. DOWNSCALING OF SEASONAL CLIMATE FORECAST INFORMATION

3.1 Introduction to seasonal climate forecasts and downscaling approaches

Information on climate anomalies expected to occur in the short-term (e.g., the risk of a major drought) can be helpful in many of society's adaptive management problems. Such climate information is typically referred to as a "seasonal climate forecast". It is possible to make skilful predictions in such cases because the atmospheric climate anomalies averaged over one or several months may be influenced by predictable large-scale climate system drivers, such as sea-surface temperature (SST), persistent soil moisture anomalies or persistent snow cover anomalies.

To make a dynamical seasonal prediction, the climate variables observed just before the forecast (known as "initial conditions") are input to a GCM, which then projects the climate system forward in time, typically 1-6 months at most operational forecast centres (a discussion of operational prediction initiatives, both national and regional, is contained in ClimaSouth E-Handbook N.2[WL1], Section 5). Skilful forecasts are only possible if the initial conditions lead the GCM to successfully predict large-scale anomalous features over the subsequent months (e.g., El Niño), which in turn drive regional atmospheric climate anomalies. Predicting large-scale tropical SST anomalies is especially important, because these exert strong control over the tropical atmosphere, which in turn can drive anomalies in mid-latitudes as well. Although the domain covered by the ClimaSouth project has often been at the southern periphery of many studies, leaving room for further investigation. The available evidence nonetheless suggests that El Niño and other tropical SST patterns have been found to exert only a minor influence on seasonal atmospheric anomalies (e.g., see Rodo et al. 1997; Mariotti et al. 2002; Bolle 2003; Cassou and Terray 2001; Cassou et al. 2005; Kushnir et al. 2006; Shaman and Tziperman 2011; Black et al.,2010). Local SSTs (nearby local North Atlantic and Mediterranean) may in some situations add some local predictability for precipitation and, especially, land surface temperature, a skill which can also be enhanced by more global-scale temperature variations (both inter-annual variations and longer-term trends). Local soil moisture anomalies may also enhance skill in some situations (Paolino et al. 2012; Materia et al. 2014). Some information may also be derived from persistent anomalies in the stratosphere related to the Quasi- Biennial Oscillation (e.g., Fereday et al. 2012).

Thus, some useful information for the domain covered by the ClimaSouth project may be present in seasonal forecasts at certain times and in some locations. The skill to expect can be estimated by running forecast systems over many past years (typically at least about 20 years), and verifying the accuracy achieved in the past at each location (concept illustrated in Fig. 7b). This is then assumed to reflect the degree of skill to expect in real-time forecasts.

High-resolution seasonal climate forecasts may be generated through a range of approaches:

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(i) High-Resolution GCM. If computing power is available, and a suitable global model available for seasonal prediction, then GCMs may generate seasonal forecasts at a spatial resolution that is adequate for some (but still far from all) impact assessments. Indeed, quite widely for seasonal forecasts (less so for global change scenarios), relatively high-resolution GCMs are being run to generate seasonal forecasts. For example, ECMWF seasonal forecasts[WL11] are currently run at about 80 km resolution. One important disadvantage is that parameterizations must usually be constant over the global domain: for example, in RCMs, the convection scheme can be tuned to the target region domain, whereas this is not the case for a global model.

(ii) Dynamical downscaling of a low-resolution GCM. The process is exactly analogous to that applied to global change projections (see Section 2.1). The GCM creates a large-scale seasonal forecast, and the output of the GCM is used to drive an RCM over the target domain. The RCM can also be driven with reanalysis boundary conditions for a given year to assess the general performance of the RCM and the maximum potential predictability of the seasonal climate anomaly. A good estimate of the true uncertainty in predictions can also be assessed by running RCM forecasts for many past years and verifying the forecasts – assuming that comparable highresolution observations are available (however, available observations for verification constitute an important constraint in assessing the expected skill of high-resolution seasonal forecasts).

(iii) Statistical downscaling of GCM forecasts. Statistical downscaling of GCMs is often more precisely referred to as statistical transformation of GCM forecasts. A statistical transformation is applied to extract more useful information from the GCM forecast, usually with an eye to being able to better assess likely impacts (e.g., on agriculture production, Hansen et al. 2006). Thus, a simple transformation may be to correct a systematic bias in the GCM (e.g., removing an overall dry bias), while more complex transformations may improve the useful spatial and temporal resolution of information (such a transformation more obviously matching the downscaling terminology). Statistical downscaling of seasonal forecasts may apply the "perfect prognosis" or "model output statistics" approach, whereas all global-change downscaled scenarios must adopt the "perfect prognosis" approach.

Model Output Statistics (MOS) approach: Statistical relationships are calculated between GCM seasonal forecasts for past years and the target high-resolution verifying observations (e.g., station observations). These relationships are applied to real-time seasonal forecasts to create MOS downscaled forecasts.

Perfect Prognosis approach: Statistical relationships are calculated between observed large-scale fields (e.g., reanalysis fields) and the target high-resolution verifying observations (e.g., station observations). These relationships are applied to real-time seasonal forecasts to create perfect-prognosis downscaled forecasts. These relationships are almost always inevitably good (because large-scale observed circulation has a strong relationship with the simultaneously observed target station observations). The strength of the relationship does not indicate the level of skill to expect from a downscaled seasonal forecast. In contrast, the skill achieved through MOS can be considered a good estimate of the skill to expect in real-time application.

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(iv) Direct information from candidate predictors. The application of GCM/RCM may be completely substituted by statistical systems that directly relate the source of predictability (such as SST in a given region) to the target high-resolution variable (such as station precipitation). Such approaches require basic computing power, but also require careful application to ensure genuine predictability in the climate system being captured by the statistical relationships. Usually, prior identification of these relationships in historical GCM/RCM experiments will provide important justification for the application of the simplified statistical system.

3.2 Overview of statistical downscaling concepts and application to seasonal forecasts

A range of statistical transformations/downscaling methods have been widely applied to seasonal forecasts in order to improve their utility. Seasonal forecasts from GCMs may inherently have poor spatial resolution. Assessing the impact of a seasonal forecast on crop production at a given location may therefore require transformation of the GCM information to the implied climate for a given nearby station-point location (i.e., to statistically downscaling the GCM forecast to the station location). In terms of temporal resolution, GCMs may implicitly output information at a high temporal frequency (e.g., every 15 minutes), yet their ability to reproduce statistics for weather such as dry spells or extreme storms is often very limited and requires statistical approaches to improve the information for impact assessment.

Bias Correction and Weather Generators.

In seasonal forecasting, a range of bias correction approaches have been applied, analogous to the techniques described for regional change scenarios in Section 2.5 (for seasonal forecasting contexts, see Ines and Hanson 2005; Piani et al. 2010). Quantile mapping approaches may be effective at transforming a seasonal forecast into daily information suitable to drive crop models. If the seasonal forecast contains useful information about the timing of rainfall through a season, quantile mapping will preserve this information. However, it does rely on the GCM's containing the appropriate statistical temporal structure of rainfall through the season. For example, if the GCM fails to produce realistic sequences of wet spells and dry spells, the PDF transformation will not solve this issue. One approach to producing the appropriate temporal structure is to apply weather generators (Wilks and Wilby 1999). First, statistical models describing the observed temporal structure of rainfall are fitted. Then, these models are applied, based on the seasonal rainfall total predicted by the GCM (thus, a daily rainfall sequence for the season is generated, that is both consistent with the historical observed temporal structure of daily rainfall, and which also sums over the season to the GCM prediction). The weather generator approach may be better able to reproduce the statistical structure of the weather through the season.

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Spatial pattern, regression-based approaches: overview

The above techniques apply individually to each grid-box time-series of the GCM output. An alternative approach is to take into consideration the larger-scale regional patterns simulated by the GCM, and use these to provide information about the target high-resolution information. These approaches are often initially applied to the monthly or seasonal time averages of the GCM output to generate high-resolution monthly or seasonal climate variables across the target region. The approaches were applied in some of the earliest downscaling studies (von Storch et al. 1993), and correctly reflect the original concept of downscaling, which assumed that large-scale climate fields have repeatable statistical expression at high spatial resolution in key climate variables like seasonal mean rainfall and temperature.

Examples using Principle Component Regression

Principle Component Regression (PCR) techniques form part of the above family of spatial pattern regression-based downscaling tools (e.g., see the categorization of statistical downscaling tools in Fowler et al., 2007). PCR can be used in a variety of contexts for the downscaling of seasonal climate forecasts. The freely available Climate Predictability Tool[WL12] (CPT, from the IRI, Columbia University) may be utilized to relate large-scale predictor fields (GCM fields or fields of observations such as SSTs) to an analyst's target set of climate variables (such as gridded observed fields of precipitation, or a user's set of target station observations). The principle component method identifies the leading spatial patterns of variation in a dataset, and calculates accompanying indices that measure the time-variation of each principle component. Principle component regression (PCR) uses these indices (the principle components, PCs) as candidate regression predictors. A related approach available in CPT is canonical correlation analysis (CCA) where optimal modes of both the predictor and the predictand are used to construct prediction equations. Sample contexts for the application of the tool (here focusing on the use of the simpler PCR method) include the following:

i) Perfect prognosis: providing a diagnosis and basis for downscaled predictions

In this setting, relationships similar to those in some of the original formulations of statistical downscaling may be assessed (e.g., von Storch et al. 1993). For example, atmospheric reanalysis of sea level pressure over the North Atlantic may be related to high-resolution observed precipitation fields over North Africa. The leading pattern of atmospheric variation is the North Atlantic Oscillation (NAO), which many studies (e.g., Lamb and Peppler 1987; Metha et al. 2000) have shown to have a strong relation with simultaneous rainfall observed over North Africa (e.g., January SLP is related to January station precipitation). Principle component regression for a given rainfall station may relate January NAO (as represented by North Atlantic SLP PC1) through a simple regression equation:

$$\boxed{\text{January Precipitation Total} = a_0 + a_1(\text{NAO January Value})}$$

Typically for sub-tropical North Africa, the correlation fit of such a model is about r=0.5, and the fit is increased with

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the addition of other lower-order PCs (which capture other modes of atmospheric variation, such as the East Atlantic pattern). The increase in fit with additional predictors must be estimated using approaches like cross-validation to avoid overfitting (see CPT manual[WL13]). The PCR models provide useful diagnostic information. They may also be applied to generate a downscaled forecast for January precipitation, inserting the GCM-predicted NAO value into the above equation. However, since GCMs typically have low skill in predicting the January value of the NAO (and other North Atlantic/Euro-Mediterranean circulation patterns), the actual downscaled seasonal forecast skill typically achieved using the above approach is low, although recent work suggests that GCMs may achieve some useful NAO skill in certain situations (Scaife et al. 2014; Athanasiadis et al. 2014). Similar results hold when other months of the year are studied.

ii) Model output statistics (MOS) for downscaled predictions

In an MOS approach, the model in the above equation would not use the observed January value of the NAO, but instead, the GCM-predicted value of the January NAO. The regression fit of the model will be low, because the GCM has low skill in predicting the observed NAO at all lead times. In other settings, where the GCM does have good skill in predicting a large-scale feature (such as in many settings in the tropics), the MOS downscaling approach provides a sound basis for both estimating the expected skill of downscaled forecasts and providing a method for making forecasts (as used in some Regional Climate Outlook Forums; these forums are described in Section 5 of ClimaSouth EHandbook N.2[WL1]). In some situations for the domain covered by the ClimaSouth project, the MOS approach may provide some useful information, although for land surface temperature, it is not clear that the MOS is adding substantial additional information compared to that from direct GCM output, such as from ECMWF seasonal forecasts (A. Kamga, ACMAD, personal communication, 2015).

iii) Direct high-resolution information from candidate predictors

In this setting, the predictor dataset contains fields of a variable believed to be a direct driver of seasonal climate anomalies over the target domain. To illustrate this concept, practical exercises during the workshop used SST data[WL14] (Smith and Reynolds 2003) as the predictor. For the predictand (for illustration purposes), models used high-resolution gridded datasets of precipitation (25km resolution, TRMM[WL15], Huffman et al. 2007) or estimates of observed land surface temperature from the ERA reanalysis[WL3]. An illustrative analysis is shown in Fig. 7, where January SST in the Eastern Mediterranean is related to nearby precipitation over land areas. It was previously hypothesised that positive (negative) SST anomalies over this domain may be associated with positive (negative) rainfall anomalies in some situations (M. Wehaibe, Director, Lebanese Meteorological Department, personal communication, 2015). The result shown represents a promising first step at quantifying this effect, and needs to be assessed more comprehensively with longer station series of rainfall, as well as diagnosed in high-resolution dynamical models. Furthermore, this relation appears confined to particular times of the annual cycle. Nonetheless, it illustrates the concept of an emerging capacity to anticipate some climate anomalies over the region on monthly/seasonal timescales. Often, for agricultural application, the potential daily distribution of rainfall is needed to assess implications for water balance and crop stress. When applying the PCR approach to generate a monthly rainfall total, this may be combined with the daily weather generator approach to simulate a daily rainfall series consistent with the monthly rainfall prediction (e.g., Hanson and Indeje 2004; Vezzoli et al. 2013).

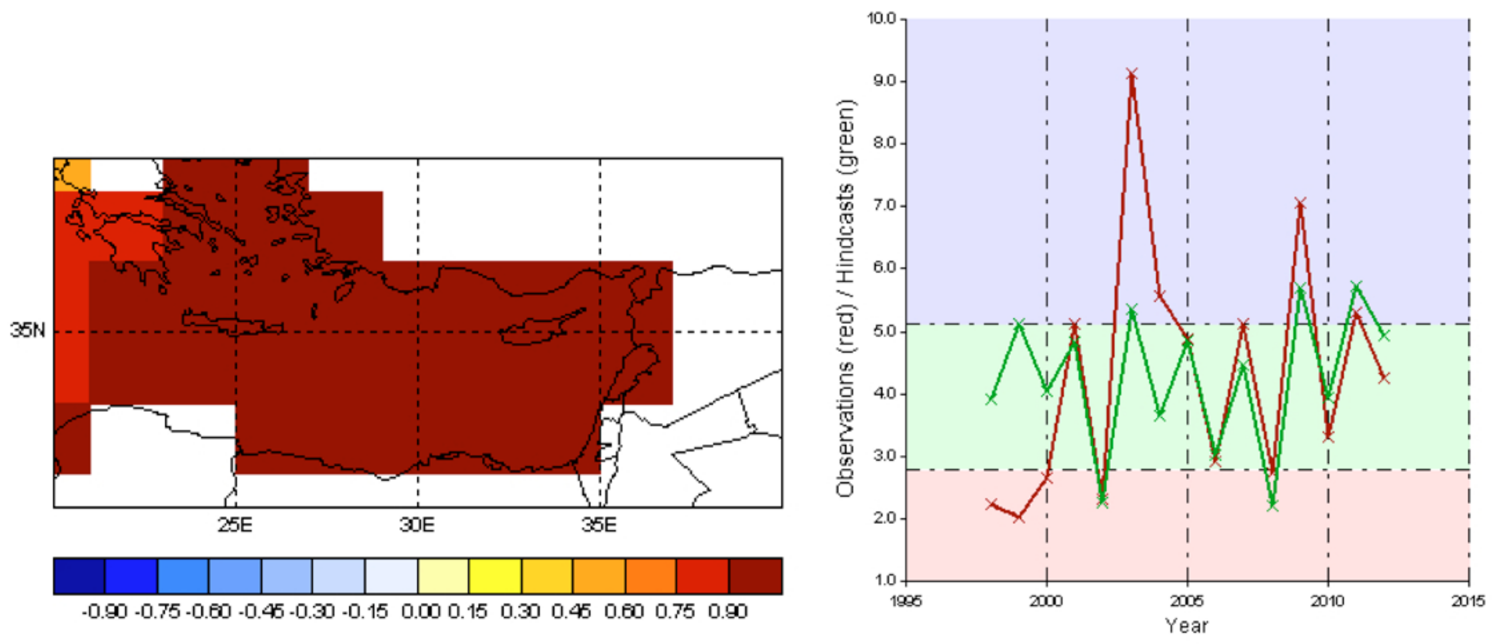

Figure 7. Predicting February rainfall using a January East Mediterranean SST. The first principal component of the January SST ((a), left panel) contributes to cross-validated predictions of February precipitation (mm/day) at a grid box close to Tal Amara, Lebanon **((b), right panel).** The sign of the relationship is such that positive SST anomalies generally indicate above-normal rainfall. The model yielded a cross-validated correlation skill of r>0.45 at almost all grid-boxes over Lebanon. Results produced during practical exercise work with CPT software by Lebanon and Palestine participants during the workshop.

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4. CONCEPTS AND EXAMPLES IN USING HIGH-RESOLUTION (DOWNSCALED) CLIMATE INFORMATION FOR IMPACT ASSESSMENT

4.1 Challenges in assessing high-resolution climate impacts

Local and regional-scale knowledge of climate is of utmost importance in order to accurately model ecosystem responses, assess vulnerabilities, identify potential threats, and formulate effective adaptation strategies (an increasing priority for government and environmental agencies). Credible, high-quality and high-resolution climate data are needed, regardless of which time scale is taken into consideration, from short-term weather forecasts up to climate change projections, especially when the results and the potential application are intended for stakeholders and policy-makers.

Researchers have for a long time recognized the spatial scale issue; impact studies, especially those applied in regions of complex topography, often require field-scale climate observation and are extremely sensitive to fine-scale variations (Wilby et al. 2004). To date, many efforts have been made to achieve reliable climate data, but many challenges in selecting and using high-resolution data for assessing climate impacts still need to be addressed.

Dynamical and statistical approaches to improving data resolution were presented earlier, yet, as noted in Section 2.5 (and see Boberg and Christensen 2012), even RCM output still often requires statistical correction. Such approaches require *high-quality observational data* for model calibration and verification. As pointed out by Vezzoli et al. (2013), in the absence of large amounts of observations, statistical downscaling cannot be performed and the validity of the relationships between variables to be scaled and climate model variables is limited to the calibration data. Such a data constraint may be an abstract limit to an ideal analysis from the meteorological perspective, but becomes a fundamental obstacle to the end goal in the context of impact assessment.

Moreover, a recognized need in impact assessment is represented by the consideration of *relationships, feedback, and domino effects* between climate and non-climate factors, such as volcanic eruption, ocean heat uptake, or human activities. Dynamical downscaling approaches can reflect these underlying human-land-surface controls and feedbacks, but this implies one of the main drawbacks, namely their *high computational demand*. On the other hand, one of the primary advantages of statistical downscaling approaches is that they are computationally inexpensive. But they must assume constant statistical relationships over time, with a low ability to represent responses to different external forcing.

Finally, along with improvements in computing power, there has been a parallel increase in the awareness of the importance of assessing *uncertainty*. Indeed, increased resolution does not equal increased confidence in projections (Wilby et al. 2004) and a number of papers have recognized

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the added value of multi-model simulations, allowing the characterization of model uncertainties and encouraging scientists to attach likelihoods to climate projections (Wilby et al. 2009). This, in turn, allows better estimates of the likelihood of different impacts, with potential to lead to adaptation actions that best match the true status of climate knowledge.

4.2 Uses of high-resolution climate change information for adaptation planning and actions

Since most impacts of climate variability and climate change will be manifested locally, the attention of climatologist and policy makers is now focused on risk consideration and its management from the local to the national level (IPCC 2014). Furthermore, local stakeholders, policy makers and the private sector are increasingly becoming critical actors in the process of adaptation and risk management. This implies also that the requirements of a territory have to be taken into consideration during the development of adaptation strategies, through a shift from a top-down to a bottom-up approach. That is, the choice of climate scenario must be embedded in the foreseen application, taking into consideration local constraints such as time, resources and human capacity (Wilby et al. 2009). Smith et al. (2000) and Wilby et al. (2009) provided a classification of adaptation activities requiring different types of climate data information (see Table 1).

One of the most studied impact types, spanning from the field scale to the global one, is related to resource management. As highlighted by a number of authors, there

Table 1. High-resolution climate data classified according to their resource needs, scale of application, input requirements, and adaptation activities. The table is adapted from Wilby et al. (2009).

METHODS	COMPUTATIONAL DEMAND	SPATIAL APPLICATION	INPUT REQUIREMENTS	ADAPTATION PLANNING APPLICATIONS
Dynamical	High	Local-regionalglobal	Host GCM, high-quality observational climate data	Communication, financial, behavioural, resource management, new infrastructure
Statistical	Limited-modest	Local-Regional	Observed climate data	Retrofitting, behavioural, resource management, communication, institutional, sectoral

New infrastructure = cost-benefit analysis; Resource management = assessment of natural resource availability; Retrofit = scoping assessment to identify risks and reduce exposure; Behavioural = measures that optimize scheduling of performances of existing infrastructures; Institutional = regulation, monitoring, and reporting; Sectoral = economic planning, sector restructuring, guidance and standards; Communication = communication risks to stakeholders and planning; Financial = service to transfer risk, incentives and insurance

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are also variations in relevant time scale, from a few hours or days up to seasons and decades, and this also implies changes in adaptation responses. The resulting adjustment or mitigation of risks and exposure to extreme events and climate changes (e.g., Salis et al. 2012) is another example of an adaptation activity, called retrofitting by Wilby et al. (2009). Within this framework, a challenge is still represented by the modelization of extreme events and their integration in adaptation planning and disaster risk management. Another aspect of this issue is represented by behavioral adaptation measures that involve all the operational approaches to optimizing the performances of existing assets or activities. This measure is quite common within the agricultural sector (e.g., Mancosu et al. 2013), and requires high resolution and reliable data in terms of both time and space scales.

4.3 Examples of high-resolution climate change impact assessments

Agricultural sector

Based on many studies covering a broad range of regions and crops, the IPCC (2014) reports that negative impacts of climate change on crop yields have been more common than positive impacts. The agro-system will be subject, among others, to decreased productivity for major crops (e.g., Mereu et al. 2015), shifts in crop-growing areas (e.g., Ciscar et al. 2011), and a decrease in water resources and soil quality (Mancosu et al. 2015a). Furthermore, due also to world population growth, more food will be necessary in future, and many studies are now addressing this issue in order to be ready to cope with future food needs, especially in developing countries (e.g., Mereu et al. 2014).

At the CMCC, an ensemble of high-resolution climate projections (derived from the high-resolution COSMO-CLM simulation and its five "perturbations") were used to assess climate change impacts on crop productivity in Sub-Saharan Africa, also taking into account uncertainty (Mereu et al. 2015). DSSAT[WL16] software was used, considering multiple combinations of crops, soils, crop varieties and crop management. Results showed that, over the medium-term period, even if precipitation is projected to increase, the crop yield (especially cereal crops) is still likely to decrease due to the increase in temperatures. On the other hand, it seems that the short-term effects (2020) are more uncertain, with a likely increase in cassava and millet yields. Furthermore, the authors highlighted that, overall, the direct effect of increased carbon dioxide (CO_2) will only partially mitigate yield reductions (Fig. 8).

Recently, in the context of the CLIMAFRICA project, the CMCC used three GCMs (CanESM2, GFDLESM2M and MIROC5) downscaled with both statistical (SOMD - Self-Organizing Maps Downscaling, Hewitson and Crane (2006)) and dynamical (SMHI-RCM) approaches to force the soil water

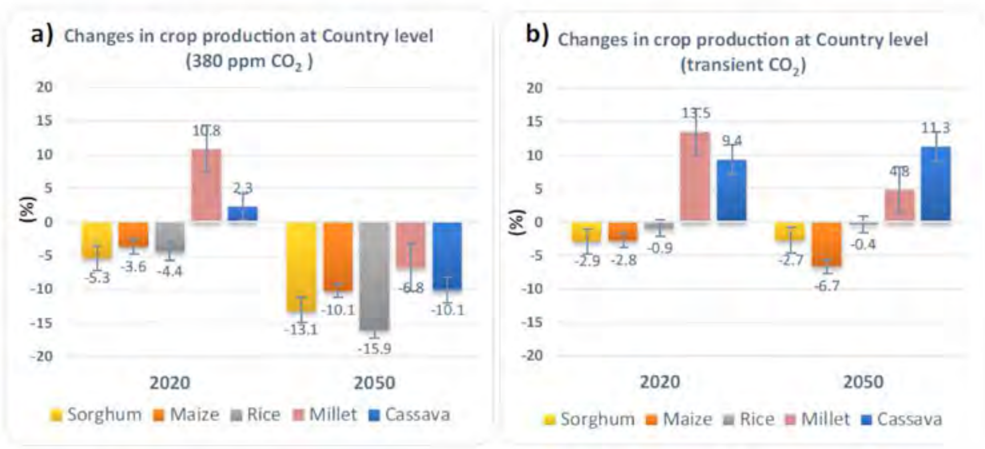

Figure 8. Changes in crop yield aggregated across Nigeria for 2020 and 2050, compared to the baseline (1990) with constant (a) and increased (b) $C0_2$ atmospheric concentration.
Source: Mereu et al. (2015).

balance model SIMETAW#[WL17] (Simulation of Evapotranspiration of Applied Water, Snyder et al. (2004), see Fig. 9). The goal was to predict climate change impacts on actual evapotranspiration (ETc & ETa), irrigation requirements (ETaw) and crop productivity (reduction of yield relative to full irrigated conditions) during the growing season for the main crops in 6 case study countries of Africa.

The analysis highlighted large differences in model results depending on GCM and downscaling method, with sometimes opposite crop signals occurring according to the climate projections considered. Among the case study areas, Kenya showed the highest irrigation requirements, or Evapotranspiration of Applied Water (ETaw) values, followed by Malawi, Togo, and Ghana. In addition, Kenya showed an increase of ETaw due to projected climate change for both statistically and dynamically downscaled data, while other countries showed very little change or no impact in terms of irrigation requirements. Overall, higher irrigation demand was derived in simulation with dynamically downscaled data (Fig. 10).

The results highlight the importance of considering multiple climate models and downscaling approaches, to make progress in assessing uncertainty in expected impacts. Participants at the workshop expressed interest in applying soil water balance models such as the SIMETAW# one used in this study in order to assess high-resolution climate change impacts on agriculture.

Forestry sector

Climate change and forests interact strongly. On the one hand, air temperature, solar radiation, rainfall, and atmos-

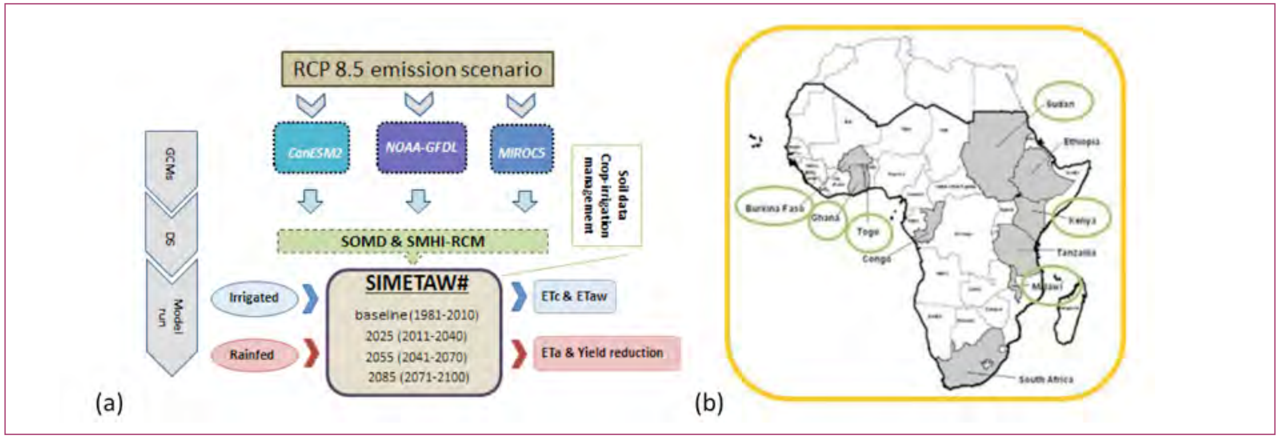

Figure 9. Work Flow (a) applied in the CLIMAFRICA project to assess impact and evaluate adaptation measures in 6 case studies of Sub-Saharan Africa (b). Output, inputs and temporal scales of the applied model are specified.
Source: Mancosu et al. (2015b).

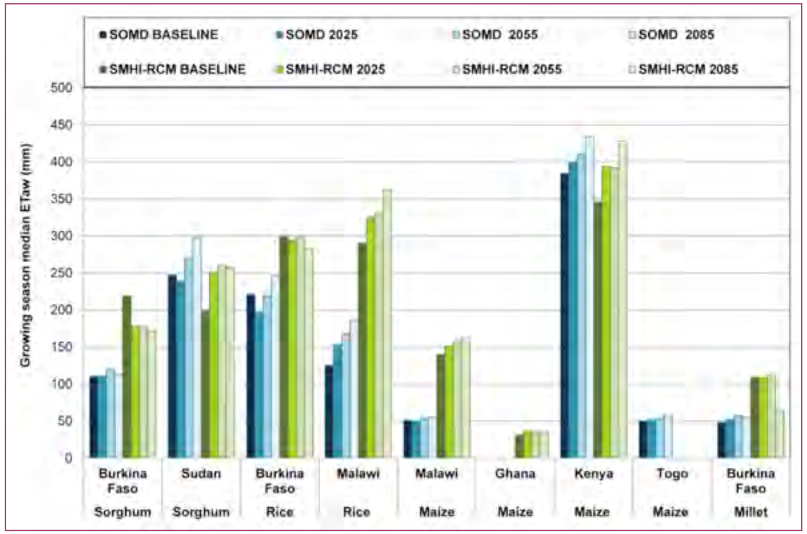

Figure 10. Summary of crop irrigation requirements, assuming full efficiency (ETaw , mm) during the growing season for the baseline and three future periods (2025, 2055, and 2085), and two downscaling methods (SOMD and SMHI-RCM) in each case study.
Source: Mancosu et al. (2015b).

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pheric CO_2 concentrations are major drivers of forest productivity and forest dynamics. On the other hand, climate is also controlled by forests through a number of features, such as the forest's role as a carbon sink or source (that is, removing or releasing C from the atmosphere), cooling through evapotranspiration, etc. Fires play an important role in driving forest dynamics in many parts of the world, but due to the recent and projected changes (such as increased numbers of high-fire-danger days, fire season length, and fire frequency and severity), greater losses and escalating firefighting costs are also projected. Therefore, a number of studies have explored the potential of future fire activities, at different time scales, in the context of a changing environment.

At the CMCC, three main categories of tools have been used to estimate fire danger, risk, activity and related features: fire danger systems; fire spread and behaviour; and the Dynamic Global Vegetation Model (DGVM).

Fire danger systems, combining relevant weather variables into suitable indices, are usually valuable tools for identifying potentially dangerous conditions (fire intensity, large fires), and for helping forest fire services to effectively prevent and respond to forecasted danger. Recently, the highresolution COSMO-CLM simulation under the A1B emission scenario was used to assess fire danger impacts (through the FWI – Fire Weather Index) over the Euro-Mediterranean area (Fig. 11). FWI projections showed an increase in the annual mean fire danger, especially in southwestern Europe. Furthermore, the increase in extreme events was also evaluated through the computation of the 75° FWI percentile. The results (not shown) highlighted broader variability, with a marked increase in extreme fire danger events during the spring and summer seasons.

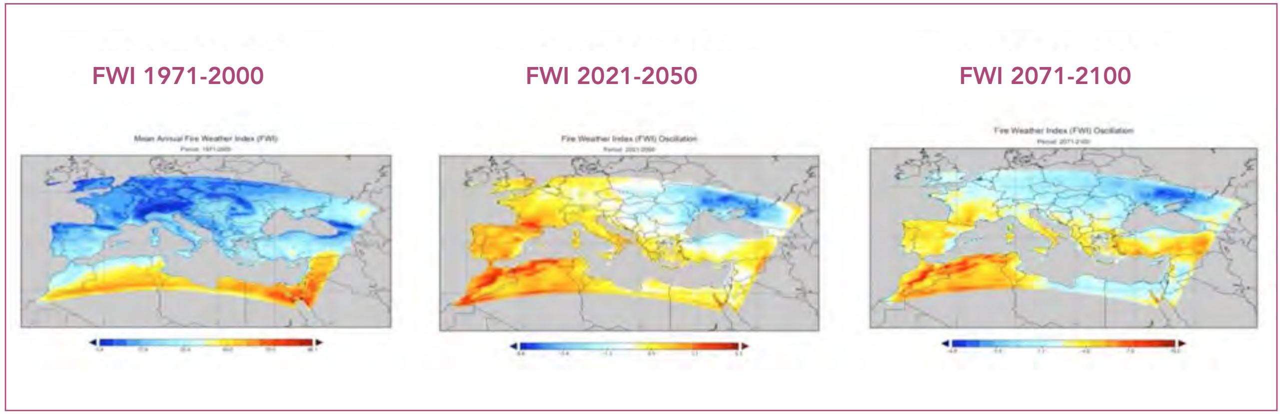

Figure 11. Mean annual values of FWI under current climate (1971-2000) conditions and future periods (2021-2050 and 2071-2100).
Source: Sirca et al. (2013).

Multi-model ensemble climate projections were used by Santini et al. (2014) through the application of LPJ-DGVM-WL18 (Sitch et al. 2003) to investigate uncertainties in predictions of future Euro- Mediterranean fire impacts. In particular, twenty simulations from the past to the future were run, based on combinations of different climate inputs (obtained from five different climate projections performed for the CIRCE project under 20C3M (Meehl et al. 2007) and A1b (Gualdi et al. 2013), as well as different vegetation model parameterizations, and configurations. The results, evaluated by associating a likelihood degree in accordance with the most recent IPCC terminology, showed that almost two-thirds of the Euro-Mediterranean domain was expected to suffer from an increase in fire occurrence (Fig. 12).

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4.4 Assessing the high-resolution impact implications of a seasonal forecast

Recently, several research groups have been investing much effort into developing seasonal prediction systems coupled with impact assessment. In a forest fire context, predicting the influence of weather on fire ignition and spread is an operational requirement (Roads et al. 2010) that could help inform medium-term fire and fuel management strategies at the local/regional scale. One of the first works on this topic (Roads et al. 2005) suggested that fire danger indices could be dynamically forecast with an experimental global-to-regional seasonal prediction model (an earlier version of the NCEP, National Centers for Environmental Prediction, model). Such a seasonal forecast system would deliver continuous data availability, in all terrain situations, with complete spatial coverage. A challenge is that seasonal climatic forecasts are burdened by systematic errors (model deficiencies, boundary conditions, terrain elevation, etc.), aspects discussed in earlier sections in the context of climate change projections, bias correction therefore being a challenge for impact assessment with seasonal forecasts as well.

Since 2013, the JRC (European Joint Research Center) has developed an experimental long-term fire weather forecast system[WL19], using ECMWF (European Centre for Medium-Range Weather Forecasts) seasonal forecasts named S4 (Spessa et al. 2015). In parallel, the CMCC started to assess the capability of the CMCC-SPS (CMCC Seasonal Prediction System, a newer version of the system described in Alessandri et al. (2010) and then in Borrelli et al. (2012) in predicting fire danger outlooks. Sirca et al. (2010) evaluated the forecast system response at the yearly and monthly scales, revealing promising skill.

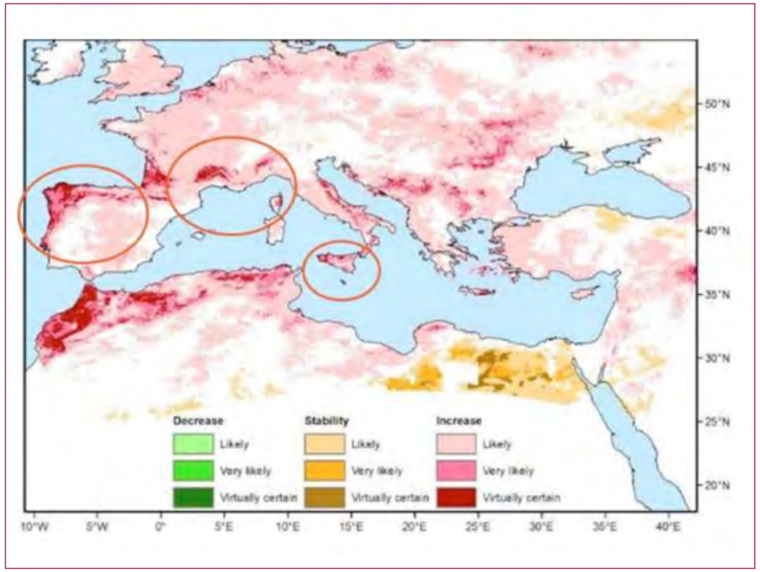

Figure 12. The map shows agreement among simulations in predicting trends (increase, decrease, and stability) in changes in fire frequency from 1971-2000 to 2021-2050. Note that trends are reported only for those map units with acceptable likelihood (likely, very likely, virtually certain; i.e., high agreement).
Source: Santini et al. (2014).

5. CONCLUSIONS

Downscaling is a concept with multiple dimensions and interpretations. At one level, there exists a scientific concept: the downscaling goal is to extract the high-resolution local climate expression from the large-scale regional circulation regimes (e.g., von Storch et al. 1993). At another level, there exists a motivational definition: to extract the most useful climate information possible from climate models to inform impact assessment. The first scientific definition delivers partly, but not completely, on the motivational definition. The workshop covered both approaches. Lectures and practical exercises exposed participants to classic concepts and methods of dynamical and statistical downscaling. In addition, there was emphasis on the extraction of the best information to inform impact assessments and adaptation; even high-resolution RCM dynamically downscaled output was shown to benefit greatly from further statistical transformation/calibration, if it is to be optimally used for driving impact models and underpinning impact assessments.

The workshop exposed participants to the existence of high-resolution climate change scenario products that can be accessed and that can be very useful for impact assessment across the domain covered by the ClimaSouth project. Furthermore, techniques were demonstrated that permit analysts to further transform these products using calibration station data available in each country. Equally, the potential to utilise national climate data to build high-resolution seasonal climate forecast information systems was shared during the workshop. In addition, it is clear that there can still be demand for implementation of the highly computer-intensive and human-skill-intensive dynamical downscaling models to address specific national domain and sector problem questions. Participants learned how such models are run, along with the datasets, scientific judgements, and computer capacities that are needed. Climate participants wanted more time to carry out practical exercises to master skills in dynamical and statistical downscaling. Impact participants requested more exposure to climate and downscaling modelling, to gain sufficient understanding to accurately interpret climate information that feeds impact models and impact assessments, and which can better underpin adaptation actions.

6. WEB LINKS TO FURTHER RELEVANT MATERIAL

CLIMATE CHANGE DYNAMICAL DOWNSCALING AND VALIDATION

[WL2]CORDEX information and RCM data: http://www.cordex.org/

[WL4]IPCC AR4 data: http://www.ipcc-data.org/sim/gcm_monthly/SRES_AR4/index.html

[WL5]IPCC AR5 data: http://www.ipcc-data.org/sim/gcm_monthly/AR5/index.html

[WL6]COSMO-CLM climate model and community information: http://www.clmcommunity. eu/index.php?menuid=1

[WL7]CDO home page: https://code.zmaw.de/projects/cdo

CDO users guide: https://code.zmaw.de/projects/cdo/embedded/cdo.pdf

CDO reference card: https://code.zmaw.de/projects/cdo/embedded/cdo_refcard.pdf

[WL8]High-resolution gridded observed precipitation and temperature E-OBS data: http://www.ecad.eu/download/ensembles/ensembles.php

[WL9]High-resolution gridded observed CRU data: http://www.cru.uea.ac.uk/cru/data/hrg/

[WL10]R-software package qmap: https://cran.r-project.org/web/packages/qmap/index.html

R-software (freely available) for statistical computing: https://www.r-project.org/

SEASONAL FORECAST AND DOWNSCALING

[WL11]ECMWF seasonal forecast: http://www.ecmwf.int/en/forecasts/documentation-and-support

[WL12]CPT: http://iri.columbia.edu/our-expertise/climate/tools/cpt/

[WL13]CPT Tutorial in English (including discussion of PCR and CCA): http://iri.columbia.edu/wpcontent/ uploads/2013/07/CPT_Tutorial.pdf

CPT Tutorial in French (including discussion of PCR and CCA): http://iri.columbia.edu/wpcontent/ uploads/2013/07/CPT_Tutorial_French.pdf

[WL14]SST data for CPT (can be downloaded in format ready to use in CPT): http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCDC/.ERSST/.version3b/.anom/

[WL15]TRMM NASA precipitation (25km resolution): http://disc.sci.gsfc.nasa.gov/precipitation/documentation/TRMM_README/TRMM_3B43_readme.s html

The NASA next-generation global observations of rain and snow (GPM): http://pmm.nasa.gov/gpm

[WL19]Forest fire seasonal forecast: http://forest.jrc.ec.europa.eu/effis/applications/long-termforecast/

IMPACT MODELS

[WL16]DSSAT model: http://dssat.net/

[WL17]SIMETAW# model: http://www.water.ca.gov/landwateruse/models.cfm

[WL18]LPJ model: https://www.pik-potsdam.de/research/projects/activities/biosphere-watermodelling/lpjml

OTHER BACKGROUND INFORMATION

[WL1]ClimaSouth E-Handbook N.2, Improving Climate Information: http://www.climasouth.eu/en/node/116

[WL3]Reanalysis data from ECMWF: http://www.ecmwf.int/en/research/climate-reanalysis/era-interim

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