

# *Working paper on the need for downscaling of seasonal-to- decadal integrations within the EU-funded ENSEMBLES project*



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# **Working paper on the need for downscaling of seasonal-to-decadal integrations within the EU-funded ENSEMBLES project**

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## **Abstract**

This working paper arises from cross-research theme discussions which took place during the early months of the ENSEMBLES project. ENSEMBLES provides a unique opportunity to bring together research on both climate change (i.e., projections up to the end of the 21<sup>st</sup> century) and seasonal-to-decadal (i.e., predictions of seasonal, annual and multi-annual averages) timescales which traditionally has been undertaken separately. This working paper is an attempt to introduce to scientists performing downscaling of climate information (in ENSEMBLES RT2B), generally much more familiar with downscaling data related to climate change experiments, to the specific problems of ensemble seasonal-to-decadal prediction (being undertaken in ENSEMBLES RT1/RT2A and applied in RT6). The rationale for using a multi-model approach to address forecast error is outlined, before explaining the need for downscaling and summarising the downscaling approaches available. It is shown that sufficient datasets are available for ENSEMBLES partners interested in downscaling seasonal-to-decadal predictions. Some of the major issues and problems which need to be addressed both with respect to statistical and dynamical downscaling approaches are identified. Finally, the opportunities and advantages offered by addressing both climate change and seasonal-to-decadal downscaling together are considered. The possibility of verifying the downscaled predictions is, for example, one of the main interests and motivations for testing downscaling methods for seasonal-to-decadal predictions.

## **Introduction**

The ENSEMBLES project aims to provide probabilistic estimates of climatic risk through ensemble integrations of Earth system models in which the uncertainties are explicitly incorporated. The exploitation of the results will be maximised by linking the output of the ensemble prediction system, which includes both global (Research Theme 2A) and regional (Research Theme 2B) modelling components, to a wide range of applications, such as agriculture and health, within the framework of the end-to-end concept (Buizer et al., 2000; Sarewitz et al., 2000). In fact, one of the main objectives of the project consists in maximising the exploitation of the results by linking the outputs of the ensemble prediction system to a range of applications, including agriculture, health, food security, energy, water resources, insurance, and weather risk management. In turn, feedback from these impact areas to the climate system will be used to improve both the model system and cross-disciplinary communication.

ENSEMBLES focuses on both climate change (i.e., projections up to the end of the 21<sup>st</sup> century) and seasonal-to-decadal (i.e., predictions of seasonal, annual and multi-annual averages, henceforth s2d) timescales. The research undertaken to perform predictions for these different time scales has tended to be separated with little or no sharing of

expertise or results. ENSEMBLES provides a unique opportunity to overcome this separation. It is, for example, by closely collaborating with partners in Research Theme 6 to increase the use of climate predictions by end users and to understand their specific needs in an attempt to bridge the gap between users and climate scientists, that the communities working in the climate change and s2d prediction problems will also be able to share experiences and results.

This working paper is an attempt to introduce to scientists performing downscaling of climate information, generally much more familiar with downscaling data related to climate change experiments, to the specific problems of ensemble s2d prediction.

## **ENSEMBLES and prediction uncertainties**

In a nonlinear system such as the climate, small-scale circulation systems can influence the development of larger-scale circulation systems and vice versa. The inability to perfectly observe the climate system and computational constraints that limit climate-model complexity both introduce uncertainties in weather and climate simulations. Initial condition and model uncertainties cause the simulations to differ from what is actually observed, also known as forecast error.

Ensemble prediction has been developed to tackle the initial condition uncertainty problem, which is due to unavoidable errors in initial conditions of the atmosphere and the ocean. In ensemble prediction, a set of simulations that verify at the same time is carried out using slightly different initial conditions. Additional contributions to forecast error come from model uncertainty, due to the necessary approximations used in modelling the climate system. Even using the same initial conditions, two different models of the climate system will provide different outcomes. Different approaches have been devised to deal with the model uncertainty problem (see e.g. Palmer et al., 2005): multi-model, stochastic physics and perturbed parameter approaches.

The multi-model approach consists in performing simulations with different prediction models. It is a pragmatic solution to the problem that can be combined with the ensemble method to perform multi-model ensemble simulations. This system produces more skilful and reliable probabilistic estimates of future states of the atmosphere and the ocean than any single model (Palmer et al., 2004). In the stochastic physics approach, individual simulations of an ensemble are perturbed with the introduction of some form of stochastic term that represents the effect of the small-scale processes not resolved by the model. The stochastic physics approach has already proven beneficial for medium-range weather forecasts. The perturbed parameter approach perturbs poorly constrained parameters in a given model over ranges of uncertainty proposed by experts with the purpose of running a number of experiments. As in the case of the multi-model approach, it can be combined with the ensemble method to perform large ensemble simulations

An important aim of the ENSEMBLES project consists in the assessment of the benefits of these methods to minimise forecast error in seasonal, decadal and longer timescale predictions. This objective will be achieved by carrying out global simulations for both climate change and s2d timescales.

## **The need for downscaling**

Several end-user applications of seasonal climate prediction, including crop yield prediction and prediction of tropical disease (Cantelaube and Terres, 2005; Challinor et al., 2005; Marletto et al., 2005; Morse et al., 2005), have been developed recently in Europe, many as part of the EU-funded DEMETER project. Although skilful predictions can be obtained in tropical areas several months in advance using ensembles of simulations from global circulation models (Palmer et al., 2004), most of these application models require meteorological surface variables on a spatial scale much finer than that of present-day global dynamical climate prediction models (~100 km at best). In addition to inaccuracies associated with the lack of horizontal resolution, coupled ocean/atmosphere models suffer from a substantial drift away from the observed climate (Palmer et al., 2004), a drift that also needs to be corrected. Therefore, there is an obvious need for high-resolution, calibrated predictions of surface variables, such as precipitation or temperature, to force the end-user models. To bridge the gap between the low-resolution global ensemble predictions and the high-resolution probabilistic end-user requirements, downscaling techniques allow the mapping of the low-resolution global predictions to a high-resolution set of forecasts for a network of stations over an area of interest. This requirement is common to global simulations at every time scale.

## **Downscaling approaches**

Both statistical/empirical methods and dynamical regional climate models can be applied for downscaling purposes. In the statistical/empirical methods, a mapping (e.g., based on regression methods, analogue techniques, or neural networks) is derived from one or more large-scale fields to the fine scale required by the application models. The statistical methods are relatively straightforward to apply and computationally cheap compared with the dynamical approach. Previous work (Feddersen et al., 1999) has shown that seasonal prediction skill, notably for precipitation, can be improved using statistical techniques to correct the global model output. Feddersen and Andersen (2005) show how statistical correction using the leading modes of a singular value decomposition analysis could improve the skill of seasonal precipitation simulations from global coupled models.

Statistical downscaling makes use of relationships that are derived between observed (or re-analysed) predictors and predictand fields, e.g., the 700 hPa height field and precipitation, respectively. However, predictions based on this perfect prognosis (perfect prog) approach (Wilks, 1995), which tends to be widely applied in climate change studies, are sensitive to model errors in the predictor field. Drift and other types of systematic errors are common among global coupled model simulations. If, instead, the predictor is chosen to be a model field, model systematic errors in the predictions may be accounted for, and hopefully corrected, in the downscaling process. This approach, known as Model Output Statistics or MOS (Wilks, 1995), is widely applied to short and medium-range weather forecasts to obtain station predictions. The major drawback of MOS is the need for a long series of predictions or hindcasts in order to derive robust MOS relationships that take into account the systematic errors of the dynamical model. These hindcasts are systematically computed in s2d predictions. For this purpose, a 40-year long set of s2d multi-model hindcasts will be performed in ENSEMBLES within Research Theme 2A. In addition to the hindcasts, both approaches to

statistical/empirical downscaling require the existence of a long predictand dataset. As in the case of the model hindcasts (for MOS) or the re-analysis fields and station data (for perfect prog), the predictand dataset needs to be of sufficient length to estimate robust relationships between predictor and predictand.

In addition to spatial downscaling, some s2d end-user applications have also required from statistical/empirical methods a downscaling in time, i.e. time series at a higher temporal resolution specified from seasonal or monthly averages (Goddard et al., 2001). Most crop yield models, for example, require daily weather input. Synthetic daily time series can be generated using a stochastic weather generator, for example, which could be conditioned on the time-averaged data.

As a second type of downscaling approach, dynamical models can also be used. Dynamical downscaling has the potential to outperform statistical/empirical methods, and is the only possible approach for areas where observed data required to train statistical/empirical models are not available. In particular, the lack of observational data to develop statistical/empirical downscaling methods is a major problem for tropical regions, which happen to be those where the s2d forecast quality is the highest. However, the use of regional models also presents outstanding problems, including the propagation of systematic biases from the global to the regional model (Giorgi and Mearns, 1999). In addition, the computational expense of running a high-resolution regional climate model can be comparable to that of running a global seasonal prediction model. And, still, a minimum set of observational data is required for validation purposes.

There is only limited experience with downscaling of s2d predictions (Misra et al., 2003; Díez et al., 2005; Feddersen and Andersen, 2005; Pavan et al., 2005), whereas in climate change studies, both dynamical and statistical approaches to downscaling have been applied extensively. Good examples of such climate change applications, focusing on the daily resolution and extreme events, are the results from the EU-funded FP5 PRUDENCE and STARDEX projects (Christensen, 2005; Christensen et al., 2006; Goodess, 2003; Goodess et al. 2006).

## **Data available to perform s2d downscaling**

Those ENSEMBLES partners interested in downscaling s2d data have a unique opportunity to benefit from comprehensive sets of observed, analysed and hindcast data, all available online.

Detailed information about the s2d integrations that will be carried out in ENSEMBLES during the first 18 months in Research Theme 1 and of those intended for the third and fourth year of the project within Research Theme 2 can be obtained from:

[http://www.ecmwf.int/research/EU\\_projects/ENSEMBLES/news/index.html](http://www.ecmwf.int/research/EU_projects/ENSEMBLES/news/index.html)

A significant number of these integrations will archive 6-hourly model-level data required as boundary conditions to perform dynamical downscaling with regional models. In particular, within the first 18 months of the ENSEMBLES project, boundary conditions will be available from the coupled models IFS/HOPE, ARPEGE/OPA and GloSea (Palmer et al., 2004). These boundary conditions (6-hourly model-level data for temperature, winds, humidity, cloud liquid water content, plus the corresponding surface parameters) will be made available for 9-member ensembles seasonal (7-month long runs) hindcasts. Two start dates per year, 1<sup>st</sup> of May and 1<sup>st</sup> of November will allow dynamical downscaling of both boreal winters and of summer conditions, of interest for

downscaling exercises over monsoonal tropical regions. The 7-month hindcasts will be carried out over a period of 11 years of hindcasts (1991-2001). Downscaling partners interested in using these experiments have the possibility of either using the model-level data or use a script that will be provided to convert the model-level data into pressure-level data. The data is expected to be available on ECMWF's mass storage system (MARS) in GRIB format some time around September 2005.

Pressure level data, as required by the statistical/empirical downscaling methods, will be available from all the integrations, as described here:

[http://www.ecmwf.int/research/EU\\_projects/ENSEMBLES/news/common\\_variables.htm](http://www.ecmwf.int/research/EU_projects/ENSEMBLES/news/common_variables.htm)  
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These data will be in a common standardised format, with the same units for all models and experiments, and will have undergone a basic quality control process. As a large-scale reference dataset, the ERA-40 re-analyses can be publicly obtained from:

<http://data.ecmwf.int/data/>

However, large-scale variables from the global models are only part of the datasets required for statistical downscaling. To offer a simple and complete setup to all partners using statistical/empirical downscaling methods, the Joint Research Centre (JRC) of the European Commission in Ispra (Italy), one of the end-user partners in ENSEMBLES, has made available a European-wide gridded dataset of daily near-surface meteorological parameters. The dataset, starting in 1975, has been obtained gathering meteorological observed variables at station level using a network of more than 6000 inventoried stations. The data have been interpolated over Europe using a grid of 50x50 km. To facilitate access to the dataset, JRC has created a web application through which users can register, select the parameters, areas and years of interest and download the data directly. The data distribution and use conditions are clarified in the following web site:

<http://agrifish.jrc.it/marsstat/datadistribution/>

JRC is happy to collaborate with ENSEMBLES partners interested in using this dataset for downscaling s2d predictions. Any suitable downscaled output will be used to force the JRC crop growth model to create probabilistic predictions for several crop yields.

## **Issues to be addressed in downscaling s2d simulations**

Downscaling s2d ensemble global predictions implies that complex problems need to be addressed. These problems depend on the downscaling approach. For statistical downscaling, the major challenges are how to:

- Correct the systematic bias of the predictions from realistic coupled ocean/atmosphere forecasting systems and obtain reliable (i.e., with statistical properties similar to the observed data) probabilistic predictions.
- Deal with full ensembles, not a deterministic prediction or the ensemble mean.
- Consider the benefits of dealing with model uncertainty after statistical downscaling has been applied individually to each ensemble member of each single model or model version.
- Generate daily time series of surface variables using stochastic weather generators conditioned on downscaled monthly or seasonal time-averaged predictions (an approach conventionally used for s2d downscaling) or adapt

other statistical methods for the construction of daily time series (e.g., methods developed in the STARDEX project).

- Obtain robust estimates using what are likely to be short (i.e., 15 to 30 years) training samples.

In the case of dynamical downscaling, some of the problems to be taken into account are how to:

- Assess the reliability of the downscaled ensemble predictions, which requires the existence of a long enough high-resolution observational dataset.
- Deal with full ensembles, some of them produced with different global models or versions of a single model, not a deterministic prediction or the ensemble mean.
- Maximise the number of regional model integrations, as is already done in the COSMO/LEPS system (Montani et al., 2003) for ensemble medium-range forecasts, taking into account that there is a large number of ensemble members and years of hindcasts in an s2d ensemble.

Both approaches will need to address the problems of integrating the information provided by large ensembles and assessing the forecast quality of the results. Inevitably, the results obtained with statistical and dynamical downscaling techniques will have to be compared to determine the best method(s) for a specific problem. In addition to this, an interesting and novel option consists in putting together the results obtained with dynamical and statistical downscaling methods, which could help to increase the forecast quality of the predictions.

Although there are some obvious similarities between downscaling applied to climate changes at the s2d and centennial time scale, the two problems have a fundamentally different nature: global change predictions (and subsequent downscaling) cannot be verified in the same manner as s2d predictions can. This implies that downscaled s2d predictions forcing end-user models can be used to measure the reliability and skill of the whole end-to-end ensemble prediction system and to design shorter-term policies and mitigation strategies that will increase the capacity for adaptation to longer-term climate changes. The possibility of verifying the downscaled predictions is one of the main interests and motivations for testing downscaling methods for s2d predictions.

## **Final remarks**

There is a clear need for downscaled information from s2d simulations from the ENSEMBLES Research Theme 6 user groups. In addition, it is considered that downscaling of s2d simulations offers the climate change downscaling community the following opportunities and advantages, which reflect the potential synergies of addressing both timescales together:

- The chance to transfer information from the s2d forecast quality estimates to climate change experiments carried out with the same models.

- An opportunity to learn, develop and apply validation and evaluation concepts (Jolliffe and Stephenson, 2003) not usually applied to climate change simulations (e.g., comprehensive assessment of forecast quality of non-deterministic predictions in terms of skill and reliability using Brier and ROC scores).
- A chance to work with larger ensembles than tend to be available for climate change simulations.
- A chance to test and verify downscaling methods in very different areas, i.e., tropical regions where s2d forecast quality tends to be higher.
- The potential to incorporate successful downscaling methods into operational prediction systems.

Any ENSEMBLES partners potentially interested in applying statistical/empirical and/or dynamical downscaling methods to s2d integrations are encouraged to discuss this possibility with Francisco Doblas-Reyes at ECMWF. ECMWF will be able to provide advice about the regions and seasons where such integrations are likely to have the greatest skill and hence are worth focusing on, together with advice about the end-user needs for such information. Clare Goodess can provide advice about how to integrate any such work with the climate change downscaling work being undertaken in Research Theme 2B.

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## Relevant links

DEMETER: <http://www.ecmwf.int/research/demeter>

PRUDENCE: <http://prudence.dmi.dk/>

STARDEX: <http://www.cru.uea.ac.uk/cru/projects/stardex/>

ENSEMBLES: <http://ensembles-eu.metoffice.com/index.html>

ECMWF public data server: <http://data.ecmwf.int/data/>

JRC meteorological data: <http://agrifish.jrc.it/marsstat/datadistribution/>