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Climate service development, delivery and use in Europe at monthly to inter-annual timescales

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ABSTRACT

Climate services have become the focus of major international coordination activities over the past few years. In 2012 the Global Framework for Climate Services (GFCS) was approved and will be led by several United Nations Agencies, to strengthen and coordinate existing initiatives and develop new infrastructure where needed to meet society's climate-related challenges. At European level the European Commission has allocated almost 27 million Euros from 2012 to 2016 towards the science behind seasonal and decadal climate services effectively putting Europe at the forefront of the international effort in developing this field.

One of the main challenges climate service will face is the bridging of the so called valley of death: the divide still existing between climate science and decision-makers. Managing the multiple boundaries between producers and users of climate information is now of crucial importance. The concept of codesign and more generally of co-generation of knowledge is key to success of the new generation of climate services which need to be perceived as being not only credible scientifically but also salient and legitimate. In order to improve on the current setup it is essential for researchers to work on topics which could directly impact on the decision making process.

The paper presents some of the key challenges and open questions climate service science will face in the coming years.

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Climate services have become the focus of major international coordination and development activities over the past few years. In 2009 the World Climate Conference-3 brought together heads of states, government ministers, industry representatives, and scientific and technical experts who laid out the clear need for climate services. In 2012 the Global Framework for Climate Services (GFCS) was approved by governments worldwide at the Extraordinary World Meteorological Congress. In parallel to the GFCS, climate service providers, users and funders are collaborating through an informal Climate Services Partnership, to further ensure climate services are effectively developed, delivered and used (see Vaughan and Dessai, 2014 for a recent review).

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Building upon such international efforts, there are major research projects underway to improve the underpinning climate science, promote the development of new applications and actively engage with users of climate services. Here we present some of the key challenges and open questions climate service science will face in the coming years.

Improved scientific knowledge of the processes controlling climate predictability has the potential to improve climate-influenced decisions. Whilst it is essential to improve our understanding of the climate and its impact on our activities, this cannot occur in isolation and should instead ensure that users and producers of climate information effectively work together. Bridging the so-called 'valley of death' between users and providers is recognised as a key priority for climate services but currently there is limited understanding on how this should be done (Cash et al., 2006). Empirical research has shown that a range of contextual and intrinsic factors affect the use of information in decision making, e.g., informal and formal institutional barriers, decision and policy goals, spatial and temporal resolution, quality-level required to utilise the information and the level of trust between information producers and users.

One challenge is that climate scientists are often motivated by curiosity and a desire for a deeper understanding of the processes controlling weather and climate and their variability, whilst the majority of decision makers require the minimum amount of, or easiest to obtain, knowledge to sufficiently inform their decisions. This motivational divide can create a disconnection between real and perceived needs of decision makers.

Working on the interactions between providers and users of climate information is thus of crucial importance. Identifying effective ways to co-design and co-generate climate services with the users is becoming one of the most important challenges that climate service science needs to tackle (Lemos and Morehouse, 2005; McNie, 2008). The co-design process is needed to develop knowledge that is scientifically credible, trustworthy, relevant and actionable (Cash et al., 2003).

The current situation can be improved by researchers prioritising work on topics which directly impact on decision-making processes; for example focusing research effort on the parameters, timescales, and spatial scales that are most relevant to users. Rather than undermining the need for fundamental research, this shift in priority should be seen as an attempt to focus some of the international research effort on user-relevant science (Stokes, 1997). This can in turn help making some essential observational and modelling activities more visible and attractive to a wider community. In order to be effective in addressing specific problems the development of scientific knowledge needs to become more flexible, iterative and interactive (Kirchhoff et al., 2013).

There are a number of challenges climate science is facing in the generation of reliable and skilful predictions on decision-relevant time horizons. Climate simulations try to represent the future, and past, evolution of the climate system over timescales that range from a few weeks, through seasons, years, decades and centuries. For many climate-influenced decisions, prediction times of months to a decade are likely to be the most important. Making predictions with such lead times largely relies on the existence of relatively slow, and hence predictable, variations in quantities such as the moisture in the soil, snow cover, sea-ice and ocean temperatures (Shukla and Kinter, 2006), and how the atmosphere interacts with and is affected by these conditions. In addition, the observed evolution of temperature and other climate variables at the seasonal and longer timescales can also be considered as externally forced low-frequency variability due to human-induced changes in greenhouse gas (GHG) and aerosol concentrations, land-use changes as well as natural variations in solar activity and volcanic eruptions, superimposed on the natural variability of the system.

At seasonal timescales, the El Niño-Southern Oscillation (ENSO; Chang et al., 2006) is the main process that contributes to the forecast quality on seasonal timescales (van Oldenborgh et al., 2005) and its understanding and modelling has been the main target of the scientific community. Efforts to formulate forecasts at the sub-seasonal timescale have only recently begun with the development of a Madden–Julian Oscillation (MJO) prediction metric and a common approach to its application amongst a number of international forecast centres (e.g., Gottschalck et al., 2010) and operational dynamical forecast systems that target predictions of both intra-seasonal tropical variability (Rashid et al., 2010), tropical cyclones (Elsberry et al., 2009) and extra-tropical weather types (Vitart and Molteni, 2010). The recently created Sub-seasonal-to-Seasonal Prediction Research Project[1] aims to create a multi-model operational system for climate prediction at those timescales.

Timescales beyond a few months have also been considered in dynamical predictions (e.g., Smith et al., 2007; Doblas-Reyes et al., 2013a). These efforts bridge the timescales between seasonal and multi-decadal forecasting problems, and show that other modes of variability, particularly in the North Atlantic, have skill with respect to simple benchmarks beyond the first forecast year.

Two types of prediction methods are typically used, those based on either statistical-empirical approaches or on process-based dynamical systems. Scientists developing each method might feel tempted to compete to demonstrate which one is best, but both types are complementary because advances in statistical prediction are often associated with enhanced understanding, which usually leads to improved dynamical prediction, and vice versa (Doblas-Reyes et al., 2013b; Kirtman et al., 2013). This collaborative approach should be favoured for the users' benefit.

Due to the chaotic nature of the climate system and the inadequacy of current forecast systems, quantifying forecast uncertainty plays an important role in climate forecasting (Palmer, 2000). This is because a priori estimates of the uncertainty can be used as predictors of the forecast error, a fundamental element of a forecast when making informed decisions. Two of the main sources of uncertainty in dynamical climate prediction are the lack of perfect knowledge of the initial conditions of the climate system and the inability to perfectly model this system (Slingo and Palmer, 2011).

[1] http://www.wmo.int/pages/prog/arep/wwrp/new/thorpex_new.html

Table 1
The long-term challenges that climate science faces and the potential benefits climate services would see when these challenges are addressed.

Challenges	Potential benefits
Achieve an exhaustive evaluation of both predictability and current forecast quality	Provide the users with a: • clear understanding of the factors limiting predictive capability • set of tools to compare the merits of different forecasts
Understand the role of tropical and extra tropical atmosphere–ocean coupling	Better use of the computational resources that would maximise the forecast's usefulness to users
Test and assess new hypotheses using a process-based verification approach	Improved skill of large-scale climate predictions
Identify new methodologies to model the mechanisms responsible for high-impact events	
Use multidimensional observational data of the atmosphere–ocean–cryosphere–land system as sources of initial conditions	
Improve our understanding of the initial-condition uncertainties	
Increase the spatial resolution of the global forecast systems	Improved forecast quality at regional scales
Assess alternatives to characterise the uncertainties that better describe forecast errors	Produce reliable and accurate local-to-regional predictions
Combine and calibrate the information from different sources	

The unavoidable uncertainty in climate prediction forces climate forecasts to be formulated in a probabilistic way (Tippett and Barnston, 2008). Besides the different aspects associated with forecast accuracy the probabilistic formulation requires an appropriate assessment of how reliable (i.e., whether the forecast uncertainty estimate is accurate) the forecasts are (Slingo and Palmer, 2011), a concept absolutely fundamental for an appropriate use of the climate information.

Global forecast systems are often unable to provide information at the spatial scale required for (or perceived to be needed by) many end users. Although there are both empirical and dynamical approaches to downscaling, local-scale seasonal predictions focus on the empirical/statistical methods due to the enormous amount of re-forecasts that have to be downscaled to estimate both the model systematic error and the necessary forecast quality (Frías et al., 2010). The merits of empirical/statistical downscaling consist mainly in providing climate information for specific locations and with much reduced systematic error (Charles et al., 2013), but with a marginal increase, when not a degradation, of the skill. Whilst dynamical downscaling climate predictions could be justifiable given the importance of local feedbacks between, for example, soil moisture, clouds and precipitation, until now, no clear advantages in terms of forecast quality of dynamically downscaled predictions have been found (Diro et al., 2012). Hence, users need to be made aware that at the moment increasing the spatial resolution of the climate predictions they are interested in might provide no benefit and it could even degrade the quality of the information with respect to what is found for larger spatial scales.

Apart from the regionalisation to increase the spatial resolution of the predictions, a post-processing method known as calibration is needed to prevent climate information suffering from unavoidable systematic errors present in all forecast systems. In addition, as different sources of information are available, such as different dynamical forecast systems (as in the multi-model approach), several complementary statistical predictions (Hawkins et al., 2011) and climatology estimates, robust combination methods are needed. Both calibration and combination have been explored in research and operational seasonal prediction but still require a substantial amount of attention to adapt the methods to the requirements expressed by the users.

Based on the above, climate prediction needs to address a long list of challenges to produce climate information that responds to the users' expectations.

A list of longer-term challenges being considered by climate scientists is provided in Table 1. In addition to a large set of international coordinated initiatives and operational activities, the EU-funded project SPECS[2] offers unique opportunities to address some of these issues.

These challenges are already being tackled but if we want to maximise the societal impact of climate knowledge it is essential we illustrate to policy-makers, stakeholders and the public the usefulness and relevance of these improvements. We need to greatly improve the interface between the scientific understanding of the predictions and the decision-making processes. The need for such a translation from science to users has long been identified as a critical priority. The same, perhaps, cannot be said for the opposite and very few have yet recognised the importance of formally mapping the societal need into the research agenda.

The climate community is just beginning to realise that research projects should not engage with stakeholders at the end of the project in an attempt to 'sell' the newly acquired knowledge. Instead, key to the development of successful climate services is the co-design which implies a continuous interaction between users and producers throughout the life of the project. A good example of this co-design is the Climate Science Research Partnership,[3] a project funded by the UK's Department for International Development looking at how to improve the usefulness of seasonal predictions in tropical Africa (Vellinga et al., 2013). Working closely with the stakeholders, it made clear that rather than providing information on the average summer

[2] http://www.specs-fp7.eu.
[3] http://www.metoffice.gov.uk/csrp.

rainfall the users would value more an assessment of and improvement in the prediction of the onset of the rainy season. This allowed the project to inform the research agenda and focus more attention on the phenomena that matter in controlling the monsoon onset which, in turn, led to an improvement in the relevant model performance.

The interaction with the users can also lead to unexpected results. Working on malaria outbreak in Botswana, Thomson et al. (2006) found that the third rather than the top rainfall quartile category was the one showing the highest skill. This came as a surprise because the inner categories do not usually receive as much attention as the outer categories. Exposing the users of climate information to the limits of our climate understanding is probably as important as it is for the research community to understand what the most relevant challenges are for the decision-makers.

The interaction between providers and users can be daunting at first. Often users' requirements are perceived as unachievable by the scientists whilst the available products are often considered sub-optimal by the users. Whilst this may sound challenging, it actually provides a good starting point for the necessary dialogue between both parties.

It has recently been re-emphasised (Weaver et al., 2013) that focusing on the two-way communication process is a better approach of interaction between producers and users of climate information than a one-way model. Researchers developing climate services should put sufficient effort into actively improving their interface with decision makers. Unfortunately this typically requires a detailed understanding of users needs and the decision-making process, something that is not commonly found amongst scientists.

EUPORIAS (http://www.euporias.eu), an EC-funded project on climate services science, addresses this through the inclusion in the project consortium of several social scientists, design specialists, communicators and artists. This led to the development of a protocol of interaction between the project and the stakeholders early on.

To address some of these aspects, the EUPORIAS project is being developed around the needs and involvement of stakeholders from a variety of climate-sensitive sectors, and it is being shaped to embrace the concept of co-design. The stakeholders have been closely involved since before the project started and play a pivotal role throughout in defining the research priorities and in selecting case studies for more detailed study. The main outcome of the project will be the delivery of a few semi-operational prototypes working on the seasonal (and possibly inter-annual) timescale drawing on the case studies.

A post-normal science approach (Funtowicz and Ravetz, 2003) to the co-production of actionable knowledge is likely to become an integral part of climate service science. At this stage the standard paradigm is still largely based on the translation of science output onto the impact user-relevant space. Whilst such a solution can potentially make the information more usable and actionable the full potential of the available climate knowledge cannot be obtained without a significant paradigm shift. An important example is confidence in climate predictions. Climate science strives to identify the boundaries of knowledge. These boundaries can reside, for instance, around forecast uncertainty, which lies in the climate model formulation, the initial conditions or other forms of uncertainty. The providers of climate information typically offer a mapping of this uncertainty onto the impacts with minimal understanding of how this information has fed into the decision-making chain. This clearly results in a sub-optimal sampling of forecast uncertainty from a user point of view.

We argue that much more should be done to map specific decisions onto our knowledge (or lack thereof) of the future climate state. We have often tried to characterise our ignorance of the future state of the system through a number of techniques (such as empirical models, an ensemble of initial conditions, perturbed physics ensemble, etc). With a few noticeable exceptions such as representative concentration pathways of atmospheric composition (Meinshausen et al., 2011), these approaches start from the climate scientist's knowledge and map it into a decision-relevant space. To some decision makers the only part of the prediction space that matters is the one that maps in the surroundings of a specific decision threshold (Thomson et al., 2006). Effort should be put into inverting the relationship linking climate information to climate-sensitive decisions as this would help the user understand which part of our ignorance is more relevant to them.

The fact that at present such an inverse mapping may prove difficult or unfeasible should not prevent us from trying. Many of the recent advancements in science would have been unconceivable only a few decades ago. We are proposing here that gaining this sort of understanding would be very useful in informing the research agenda.

The benefit of such a paradigm shift would be twofold. Firstly, it could provide new visibility and relevance to specific areas of science which, despite their potential relevance for the decision-maker, have not managed to attract sufficient attention and funding. Secondly, such an approach could lead to the identification of a new class of scientific challenges that may have been overlooked by scientists.The key challenges climate services face can be summarised as follows:

1- Develop and promote novel dialogue mechanisms and fora to ensure users and providers of climate information work together and co-design actionable knowledge.
2- Promote a non-hierarchical, heterogeneously organised multidisciplinary approach to service-development which should build upon the knowledge and skill sets of different communities.
3- Give visibility amongst users to the needs for a significant investment in the science that underpins climate services.

These big challenges are unlikely to be tackled by one single project. International research efforts are starting to show an appetite for user-driven initiatives, which in time should enable the provision of guidance of how climate service projects should be structured and run.

The SPECS–EUPORIAS experience is likely to represent only one of the many attempts that will be needed to understand how to best structure the interaction between users and providers of climate information so that the societal benefit can be maximised. Overcoming the limitations of normal science–user interaction will be challenging as the solution will probably imply a multidisciplinary user-driven approach to the applied science. We encourage both the climate community as a whole and the funding agencies to be brave in exploring novel user–provider interactions.

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