BAMS Article

Towards Useful Decadal Climate Services

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ABSTRACT: The decadal time scale (~1–10 years) bridges the gap between seasonal predictions and longer-term climate projections. It is a key planning time scale for users in many sectors as they seek to adapt to our rapidly changing climate. While significant advances in using initialized climate models to make skillful decadal predictions have been made in the last decades, including coordinated international experiments and multimodel forecast exchanges, few user-focused decadal climate services have been developed. Here we highlight the potential of decadal climate services using four case studies from a project led by four institutions that produce real-time decadal climate predictions. Working in co-development with users in agriculture, energy, infrastructure, and insurance sectors, four prototype climate service products were developed. This study describes the challenge of trying to match user needs with the current scientific capability. For example, the use of large ensembles (achieved via a multisystem approach) and skillfully predicted large-scale environmental conditions, are found to improve regional predictions, particularly in midlatitudes. For each climate service, a two-page "product sheet" template was developed that provides users with both a concise probabilistic forecast and information on retrospective performance. We describe the development cycle, where valuable feedback was obtained from a "showcase event" where a wider group of sector users were engaged. We conclude that for society to take full and rapid advantage of useful decadal climate services, easier and more timely access to decadal climate prediction data are required, along with building wider community expertise in their use.

KEYWORDS: Climate prediction; Ensembles; Hindcasts; Decadal variability; Interannual variability; Climate services

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Near-term climate prediction on the interannual to decadal time scale is a quickly maturing field of climate science that has the potential to provide key climate services that support government and industry sector users to make decisions in our rapidly changing climate. By initializing latest-generation coupled general circulation models (GCMs) with observational estimates of atmosphere, ocean, and sea ice conditions, skillful climate predictions have been recently demonstrated for both global and regional scales (e.g., Smith et al. 2019; Athanasiadis et al. 2020). Coordinated multimodel decadal prediction experiments (e.g., Boer et al. 2016), involving retrospective 10-yr-long forecasts (hindcasts) starting every year from 1960, have now been performed in both the fifth and sixth Coupled Model Intercomparison Projects (CMIP5/6), in order to assess the predictability of global climate on interannual to decadal (1–10-yr) time scales.

To date, most work on decadal climate prediction has focused on exploring the skill for global and large-scale modes of decadal climate variability. We give two such examples here, starting with the Atlantic multidecadal variability (AMV), which is the leading mode of decadal variability in North Atlantic sea surface temperature (SST) and is associated with climate impacts over the surrounding continents (e.g., Sutton and Dong 2012; Ruprich-Robert et al. 2018). Initialized multimodel decadal climate predictions have shown high levels of skill in predicting the AMV (e.g., Doblas-Reyes et al. 2013; Hermanson et al. 2014; Smith et al. 2019), which has been linked to both dynamical variability in the deep ocean Atlantic meridional overturning circulation (Robson et al. 2012; Yeager and Robson 2017) and changes in external forcings (e.g., Booth et al. 2012). Skillful AMV hindcasts have been linked to skillful predictions of climate variability in many regions, particularly in boreal summer, including Atlantic tropical storm frequency (e.g., Smith et al. 2010; Caron et al. 2018) and drought over the African Sahel region (e.g., Sheen et al. 2017). Real-time decadal forecasts for a recent cooling of AMV (Hermanson et al. 2014) have also verified well.

More recently, decadal predictions of the winter North Atlantic Oscillation (NAO), the dominant mode of low-frequency atmospheric variability impacting western Europe and eastern North America, have also been shown to be skillful (Smith et al. 2020; Athanasiadis et al. 2020). This follows on from NAO skill found on seasonal (Scaife et al. 2014; Athanasiadis et al. 2017) and interannual (Dunstone et al. 2016) time scales. Importantly, current climate models underrepresent the observed NAO predictable signals (commonly referred to as the "signal-to-noise paradox"; Dunstone et al. 2016; Scaife and Smith 2018) and hence very large ensembles are required to predict the observed NAO variability. However, once the predictable signal for the decadal NAO is estimated via the ensemble mean variability, the former can be used to skillfully predict surface winter climate variability that is associated to the NAO over parts of Europe (Smith et al. 2020). An example application of this methodology is given later in the energy sector prototype climate service.

An informal annual international exchange of near-real-time decadal forecasts was started by the Met Office in 2010 (Smith et al. 2013). This led to the establishment of the World Meteorological Organization (WMO) Lead Centre for Annual to Decadal Climate Predictions (ADCP) in 2018. Every year the Met Office, as ADCP Lead Centre, collates global decadal predictions covering the next 5–10 years from 12 contributing centers (in 2020) and publishes forecast anomaly maps and time series on a dedicated website.[1] Using the collected real-time decadal forecasts, a Global Annual to Decadal Climate Update (GADCU) is now produced annually (Hermanson et al. 2022). This shows annual and 5-yr-mean forecast anomaly maps of surface variables such as temperature, precipitation, and mean sea level pressure. Key modes of decadal variability such as the AMV are also presented as time series. The GADCU includes predictions of global mean surface temperature, a key metric for monitoring our changing climate and how fast (Smith et al. 2018) we are approaching the 2015 Paris Agreement (UNFCCC 2015) aim to limit global surface temperature rise to "well below 2°C above preindustrial levels."

[1] www.wmolc-adcp.org/

While prediction of such key global and large-scale indices is useful to scientists and policy-makers, there are few sector end-users who can make direct use of this information in their operations. Instead, end-users in different sectors typically require more regionally focused climate predictions of relevant variables, usually for a specific forecast range, period and/or season (e.g., Solaraju-Murali et al. 2019). To date, there are very few examples of decadal climate services (tailored forecast products) for sector users. This is despite the skill now demonstrated by retrospective decadal predictions and the clear need of sector users for operational near-term climate predictions (e.g., Kushnir et al. 2019) delivered in the format of useful climate services (e.g., Hewitt et al. 2020a).

The C3S_34c contract of the European Union funded Climate Copernicus Climate Change Service (C3S) set out to start addressing this challenge by co-developing prototype decadal climate services with and for sector users. Here we briefly describe the resulting co-development process for the four prototype decadal climate services, but we note that full details of each case study are described in separate publications. This paper focuses on discussing some of the key lessons learned in the process of co-developing decadal climate services using the four climate services as examples. All four case studies are available to view on the C3S website.[2]

[2] https://climate.copernicus.eu/sectoral-applications-decadal-predictions

Bridging the gap between user needs and current capability

The project consortium comprised national meteorological and climate centers from four European countries: the Deutscher Wetterdienst (DWD, Germany), the Barcelona Supercomputing Center (BSC, Spain), the Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC, Italy), and the Met Office (United Kingdom). All four institutions produce decadal climate predictions using global climate models on supercomputing facilities and all have contributed to the Decadal Climate Prediction Project (DCPP) (Boer et al. 2016) of CMIP6. DCPP is a coordinated set of decadal predictions, with 5- or 10-yr forecasts starting every year from 1960, using historical natural and anthropogenic forcings until 2014 and then followed by the RCP4.5 emissions scenario thereafter (including real-time forecasts). The ~40-member ensemble made from combining these four decadal prediction systems is used here in designing the climate services. Each of the four institutions focused on a different sector to develop a prototype decadal climate service for agriculture (BSC), energy (CMCC), infrastructure (DWD), and insurance (Met Office).

Given that this project was led by decadal climate prediction scientists at these institutions, we were starting from the position of deep knowledge of the current decadal climate prediction capability, but in many cases somewhat limited knowledge of how this could be applied to address user needs in different sectors. Nevertheless, all four institutes partnered with sector users and regular meetings were setup to co-develop the decadal climate services. Such co-development of climate services is essential to guarantee that the developed products will be useful to the user. A timeline overview of the decadal climate service development is shown in Fig. 1. The first hurdle was to bridge the gap between scientific capabilities and user needs. This was a challenge as the current level of decadal climate prediction skill varies strongly by climate variable, geographic region, calendar season, and forecast lead time/period. Communicating current capability was also hindered by the current relatively low level of experience/awareness of initialized decadal climate predictions among sector users. Therefore, it was important that time was taken to establish a common "language" so that both climate scientists and sector users could effectively communicate their requirements and current capabilities in a way understandable to both. For example, terms related to reference forecasts and skill assessment can have quite different meanings for sector users (Solaraju-Murali et al. 2022).

Most users already had an established way of making decisions at the interannual-to-decadal climate time scale. For example, users often based such decisions on a long historical period of observations (an observed climatology), on conditions experienced in recent years (persistence forecast), or a combination of the two, such as projecting recent observed trends into the near-term future. Alternatively, some users had prior experience in using probability density functions from standard (uninitialized) climate projection ensembles and examining these for the present or near future. Thus, the challenge was to—where possible—demonstrate to users that initialized decadal climate predictions can provide additional value over these existing methods. When discussing the potential of initialized decadal climate predictions, those users who had previous experience of using seasonal climate predictions were best placed to quickly appreciate the possible advantages. Finally, if a user need based on a combination of variables, temporal, or spatial scales cannot be fulfilled due to a lack of prediction skill, some kind of "compromise solution" might be successful, e.g., analyzing longer time periods, larger regions, or slightly different variables. Such decisions need to be taken together with the users within the co-development process (represented by the green loops in Fig. 1).

The prototype agriculture climate service is a good example of how the user requirements led to the development of a sector-specific forecast product and full details are given in Solaraju-Murali et al. (2021). The BSC co-developed, with the EU Joint Research Centre (JRC), an agriculture climate service for global wheat production. To give a global 5-yr forecast for the wheat-producing regions, the local harvest month needs to be taken into account (as shown in Fig. 2a). It is the conditions

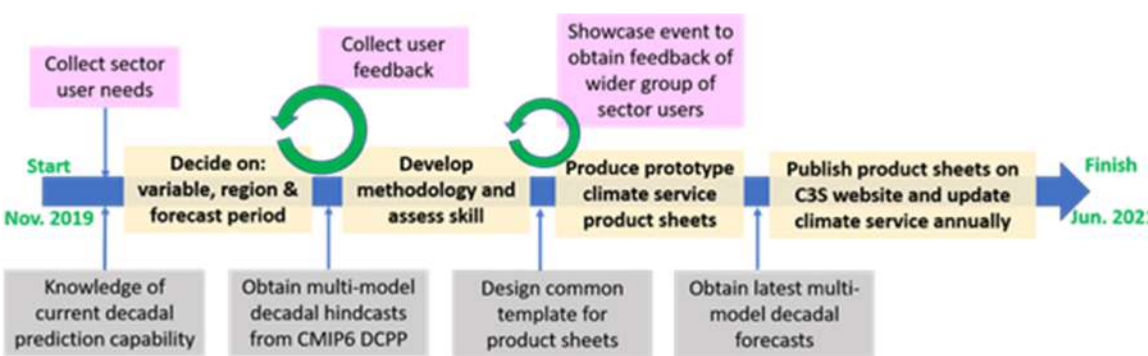

Fig. 1. Schematic of decadal climate service prototype development during this 20-month project. Input from users is shown in the purple boxes, input from scientists is shown in the bottom gray boxes, and the middle beige boxes show the main co-development activities. Green loops show where the key iterations during the co-development occurred.

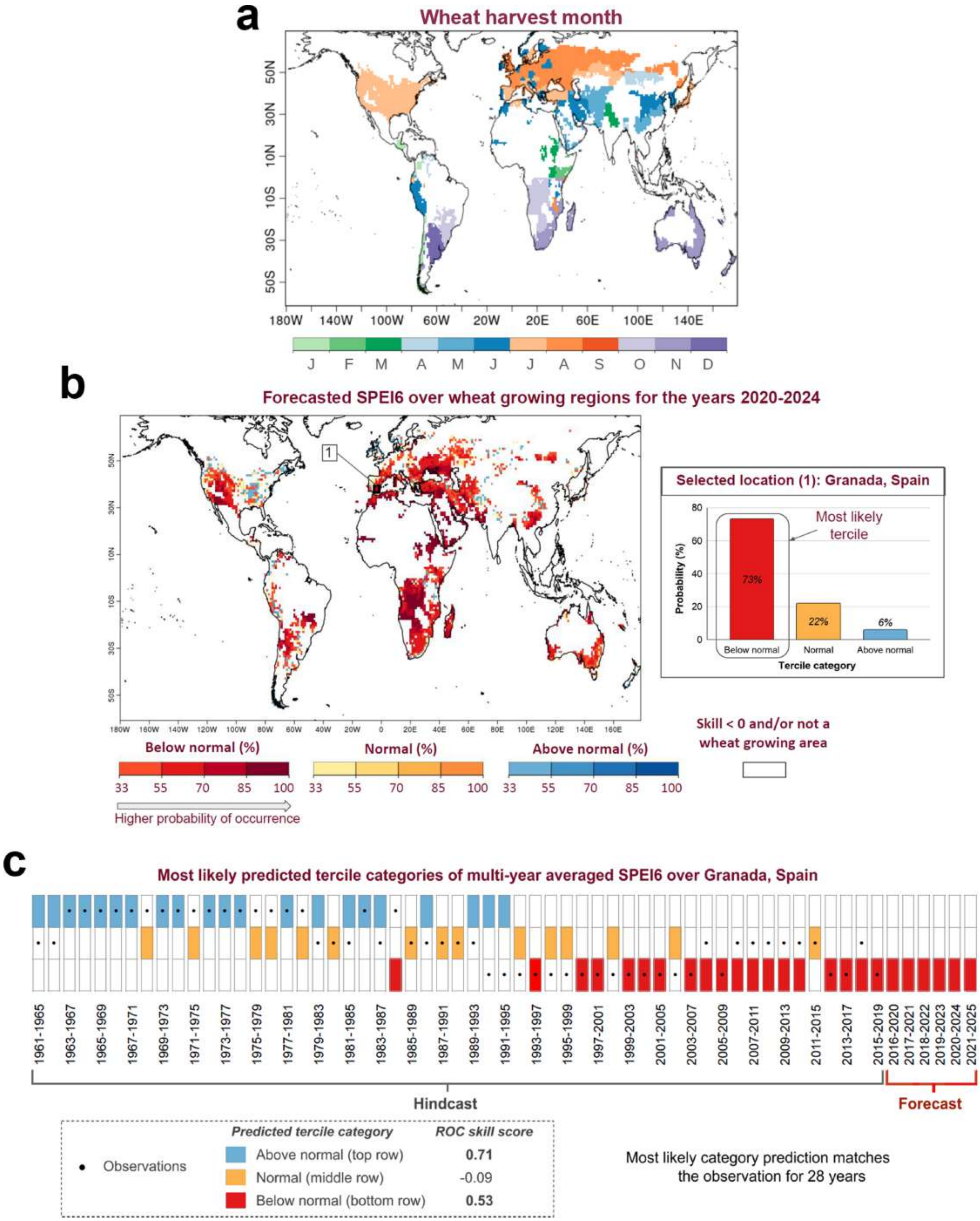

Fig. 2. Agriculture climate service. (a) Wheat harvest month required to calculate the preceding 6-month SPEI. (b) Forecasts of multiyear-averaged SPEI over 2020–24 for regions of positive skill; small box labeled "1" shows the location of Granada, Spain. (c) Time series showing the most likely tercile over the hindcast period for Granada, along with that observed (black dots) and the forecasts shown for recent 5-yr periods.

experienced during the half-year growing season leading up to the local harvest month that ultimately influences the wheat harvest yield/quality. Hence the 6-month Standardized Precipitation Evapotranspiration Index (SPEI6) was chosen as the key forecast climate variable. This resulting bespoke spatiotemporal user-focused forecast is quite different from the standard generic assessment of decadal predictions which typically focus either on annual means, or a multiyear prediction for a single season at all locations. As shown in Fig. 2b, the resulting prototype of the agriculture decadal climate service developed with the 2019 predictions presents a 2020–24 global forecast of SPEI6, for regions with positive hindcast correlation skill. This reveals that drought conditions (the "below-normal" SPEI6 tercile) are the most probable outcome in most global wheat-producing regions for this forecast period. Granada in southern Spain is used in Fig. 2c as an example of how additional information can be extracted for a specific region. Here, the most likely predicted SPEI6 tercile is identified for each 5-yr hindcast from 1960 to the present and the corresponding observed verification data are shown (black dots), which allows users to visually assess the skill and reliability of the forecasts. A quantitative analysis of this is also provided by the relative operating characteristic (ROC) probabilistic skill scores, revealing significant skill in the above- and below-normal terciles.

Maximizing regional skill over user-focused areas

The users in the energy, infrastructure, and insurance decadal climate services required climate predictions for a particular region. To achieve this none of the three prototype services used direct "local" output from the decadal prediction data to make predictions. Instead, information on the larger-scale environmental conditions that drive regional climate variability is used. Using predictions of larger-scale environment conditions has been demonstrated to be beneficial for seasonal forecast climate services (e.g., Karpechko et al. 2015; Palin et al. 2016; Clark et al. 2017; Thornton et al. 2019). This approach is motivated by the fact that the large scale is sometimes more skillfully predicted than the regional or local scale by the global models used in decadal climate predictions. However, there are many potential ways to produce regional predictions and the following three case studies below explore some of these methods and focus on progressively more local-scale decadal predictions.

We first discuss the climate service developed for the insurance sector that was led by the Met Office. Here, decadal predictions of Atlantic hurricane activity, and ultimately insured losses, were of interest to the Willis Research Network who work with (re)insurers of assets over the East Coast of the United States of America. We built upon previously published work showing that skillful decadal predictions of North Atlantic hurricane activity are possible (Smith et al. 2010; Caron et al. 2015), and we focused on predicting the Accumulated Cyclone Energy (ACE) index. The ACE index gives an overall measure of hurricane activity within the North Atlantic basin and reflects the frequency, duration, and intensity of tropical storms. After testing several possible approaches to predicting ACE, a simple temperature difference index was used, namely, MDR-TROP (Villarini and Vecchi 2012), which is the temperature of the Atlantic Main Development Region (MDR, 10°–20°N, 90°W–0°) minus the temperature of the whole tropics (TROP, 20°S–20°N). As shown in previous studies (e.g., Vecchi et al. 2011; Dunstone et al. 2013; Caron et al. 2014), the MDR-TROP index is related to the physical environmental conditions that drive North Atlantic hurricane variability (such as SST, vertical wind shear, and atmospheric stability). We built an empirical statistical relationship between the observed hurricane activity (ACE) and the hindcast MDR-TROP index directly, which implicitly applies bias correction in the predicted MDR-TROP from the models. This captures the decadal variability in historical hurricane activity (Fig. 3b), as shown by both a high rank correlation skill score (0.78, $p < 0.05$) and the Brier skill score (0.66) when using persistence as the reference forecast and based on predicting above- or below-average ACE

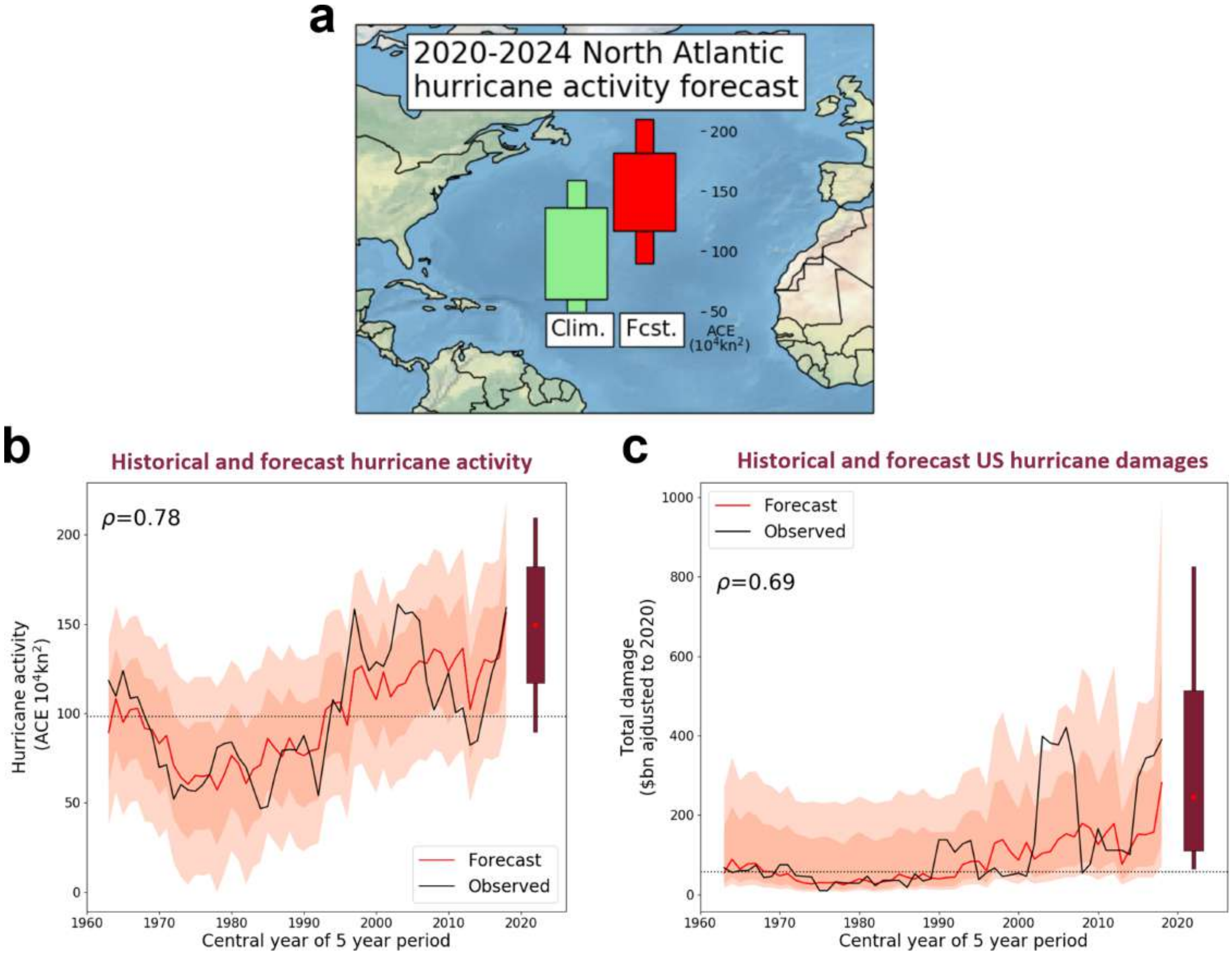

Fig. 3. Insurance decadal climate service. (a) Graphical summary of decadal prediction (red) of North Atlantic hurricane activity (ACE index) relative to climatology (green). (b) Time series of observed (black line) and hindcast (red line) 5-yr-mean hurricane activity. The 2020–24 forecast is also shown on the right side of as a red box-and-whisker plot. (c) As in (b), but the 5-yr running total of U.S. hurricane damage is shown, with damages adjusted to 2020. The horizontal dotted line shows the long-term average (median) 5-yr total hurricane damage calculated over 1960–2020. The darker and lighter shading in (b) and (c) correspond to the 75% and 95% prediction intervals of past forecasts, respectively. The box-and-whisker plot shows the 75% and 95% prediction intervals for the 2020–24 forecast. The ρ refers to the rank correlation coefficient.

values. The decadal forecast for 2020–24 shows an increased likelihood for active North Atlantic tropical storm activity.

For the insurance case study, we also co-developed a more user-relevant service by predicting the total financial losses expected from tropical cyclone–related damages over the U.S. East Coast. U.S. hurricane damages, including both insured and uninsured losses, were used and adjusted for changes in population, wealth, and inflation (following Pielke and Landsea 1998) to give loss in current U.S. dollars (USD). Although the forecast MDR-TROP index was also found to have a significant correlation with total damages, the relationship is nonlinear and hence we model the logarithm of losses. The inclusion of two individual extreme loss events—Hurricanes Andrew in 1992 and Katrina in 2005—produced seemingly unrealistically large prediction intervals in our statistical model for large MDR-TROP values (the 95% confidence value was ~3 trillion USD, equivalent of 14 Hurricane Katrinas in a single 5-yr period). Extreme loss events are caused by major hurricanes either tracking directly over population centers and/or causing storm surges that breach coastal flood defenses increasing associated damage. Such events were therefore treated as random and unpredictable, and these two events were removed before fitting the statistical relationship. The probabilities of extreme losses were then reinstated, assuming that such events could happen in any year (i.e., independent of the MDR-TROP predictor). The resulting loss predictions and confidence intervals are shown in Fig. 3c and again predict an increased chance for high losses in the 2020–24 forecast. This example highlights some of the challenges of attempting to go beyond the meteorology to provide a climate service closer to the end-user variable of interest. Full details of the insurance case study can be found on the C3S website.

Our next case study is the CMCC-led energy decadal climate service, which provides decadal predictions (forecast years 1–10) of precipitation to address the needs of the hydropower industry. The Enel Green Power group requires predictions of precipitation in three large European drainage basins: Guadalquivir and Ebro in Spain and Po in northern Italy (see Fig. 4a) to aid long-term planning of potential hydropower energy production. The focus is on the extended cold-season precipitation (November–March) when most of the recharge of the reservoirs occurs. Using the multisystem decadal climate predictions (40 members), we

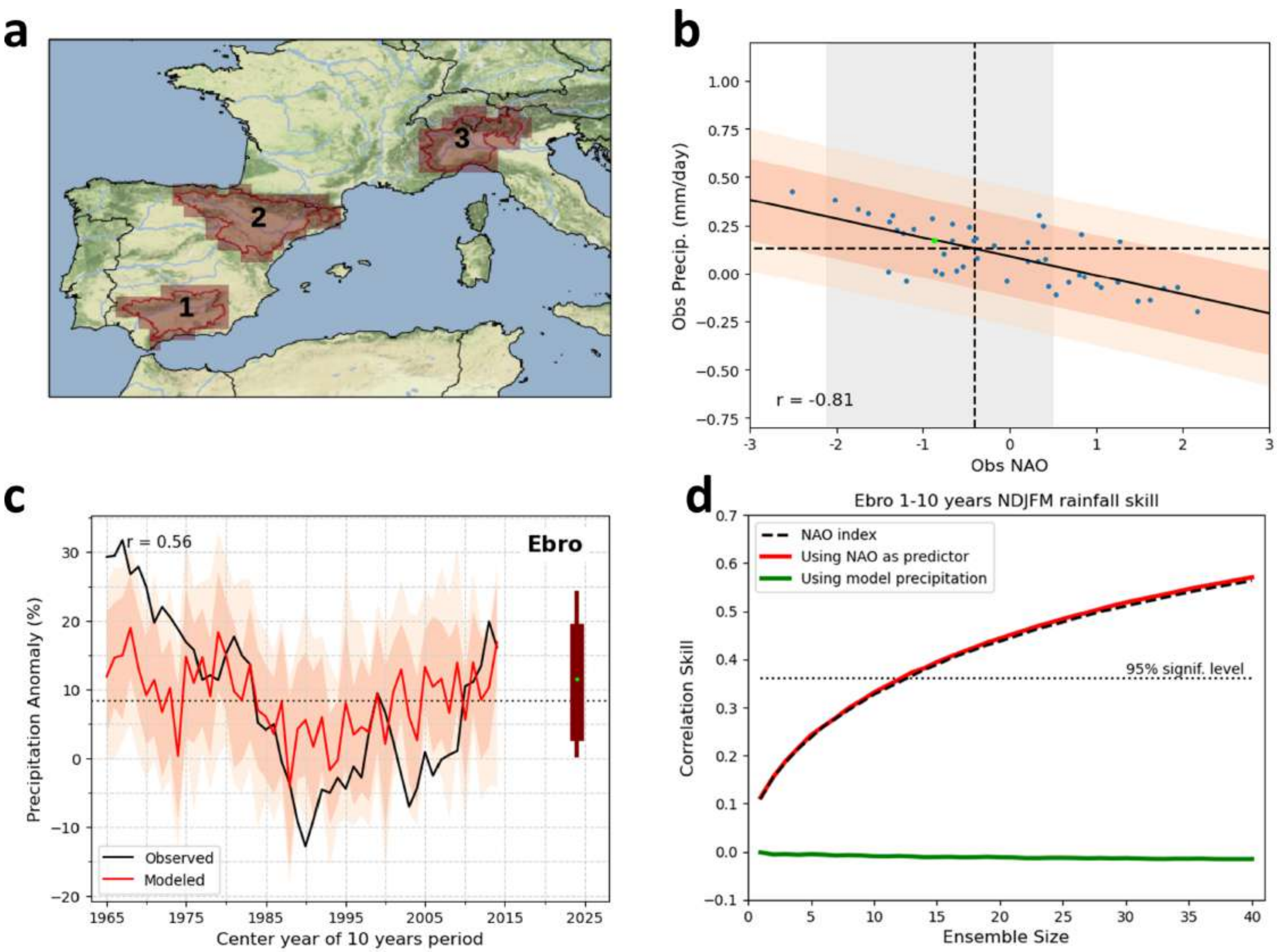

Fig. 4. **Energy climate service. (a) Identifying the three rainfall basins of interest for hydropower production: 1) Guadalquivir, 2) Ebro, and 3) Po. (b) Example observed decadal relationship between the NAO and precipitation over the Ebro basin. (c) Time series of decadal observed (black) and predicted (red) precipitation anomalies over the Ebro basin with 2020–29 forecast shown. (d) Correlation skill as a function of ensemble size for predicting decadal Ebro precipitation using gridpoint model output (green) and the NAO as statistical predictor (red). Also shown is the skill of predicting the NAO itself (black dashed line).**

first examined the skill of predictions using the local ensemble-mean precipitation output over each of the three basins. This did not yield statistically significant skill in all basins (as shown by the green line in Fig. 4d for the Ebro basin) and so a different approach was needed.

As discussed earlier, skillful predictions of decadal winter NAO variability have been developed in recent studies (Smith et al. 2020; Athanasiadis et al. 2020) and these could potentially be used to give skillful decadal forecasts of surface variables over European regions affected by this teleconnection. The multisystem decadal winter NAO skill of the four systems used here, assessed for year 1–10 hindcasts that start in years 1960–2009, is $r = 0.56$ ($p < 0.01$, see dashed black line in Fig. 4d), which suggests that there is potential to use the model-forecasted NAO as a statistical predictor. However, first we need to determine the observed relationship between decadal NAO variability and rainfall in each of the basins. We found strong negative correlations of $r = -0.83$, -0.81, and -0.61 (for Guadalquivir, Ebro, and Po, respectively); it should be noted that the negative correlations between winter NAO and rainfall are as expected for southern Europe regions (see Fig. 4b for Ebro example) due to the latitudinal shifts in the North Atlantic jet associated with the NAO. By using the forecast NAO index (with variance adjusted to account for the spuriously weak model predictable signal), and the observed linear regression relationship shown in Fig. 4b, we can obtain a calibrated precipitation forecast. The result of doing this for each forecast start date is shown in the time series in Fig. 4c for the Ebro basin: a skillful hindcast prediction ($r = 0.56$) is obtained using the forecast NAO as a statistical predictor of local rainfall. This is a key example of where a skillfully predicted pattern of large-scale circulation can be used to give skillful forecast information on the regional scale that cannot be achieved using the direct model output (see also Simpson et al. 2019). This point is further illustrated in Fig. 4d, where the skill as a function of ensemble size is shown for both methods, using the NAO as a predictor (red line) and using the direct model regional rainfall output (green line). This figure also illustrates the importance of ensemble size for this hybrid prediction, noting that the skill is still increasing at the ensemble size (40 members) used here. If only 10 members are used (typical ensemble size of an individual decadal prediction system) then no statistically significant skill is found. Athanasiadis et al. (2020) clearly demonstrate this point using a single prediction system. Full details of the energy case study can be found on the C3S website.

Our final prototype is the DWD led infrastructure case study that approached the challenging task of providing a high-spatial-resolution climate service to stay close to user needs of German water managers. Here decadal predictions of drought indices for water management in the Wupper catchment in western Germany were co-developed with the Wupper catchment water board. The Wupper catchment water board manages 14 dams in a catchment area of 813 km^2 and specified a need for high-spatial-resolution decadal climate information over this catchment (see Fig. 5a). An empirical–statistical downscaling (ESD) methodology called EPISODES (Kreienkamp et al. 2019) was used to give high-resolution predictions on an ~11-km spatial scale which is significantly higher resolution than the ~50–200-km global models used in decadal prediction. This ESD requires GCM decadal prediction daily output (of geopotential height, temperature, and relative humidity at 1000, 850, 700, and 500 hPa) over a large region of northern Europe (~38°–60°N, 5°W–25°E). Each model day for each member is mapped onto the most similar days from observed reanalysis and statistical relationships based on observed historical data are used to go from the large scale to the 11-km local scale. Therefore, in principle EPISODES provides a high-resolution dataset that is physically consistent across different variables.

The daily data required by EPISODES were not available for three of the decadal prediction systems thus only 16 members of the MPI-ESM1-2-LR system could be used. Using only one model is a shortcoming of this case study because it does not fully exploit potential skill over Europe that can be gained from a large ensemble. However, in the future, more decadal prediction systems might provide the daily data required by the EPISODES method. Statistical recalibration was used that adjusts the bias, drift, conditional bias, and ensemble spread of the model output toward observed statistics (Pasternack et al. 2018). Based on this recalibrated EPISODES model output, the SPI (Standard Precipitation Index; McKee et al. 1993) of 3-yr precipitation means for forecast years 1–3 has been computed at each ~11-km grid box and compared to observations from the early 1960s to 2020 (Fig. 5c). The chosen focus area includes the Wupper catchment as well as northern and western Germany to also cover similar user needs of neighboring water managers. The November 2020 fore cast product gives a forecast for 2021–23, as shown in Fig. 5b, indicating an increased risk of dryer than usual conditions over the period. We refer to Paxian et al. (2022) for further details on the infrastructure case study.

Creating climate services from decadal predictions is a work in progress and many useful lessons were learned when the DWD decadal prediction system was changed to a new system for the November 2020 forecast. The previous prediction system (MPI-ESM-HR) was used during most of the development and for the earlier November 2019 infrastructure decadal climate service prototype (available on the C3S website). This forecast had been designed to predict the high-resolution SPEI of the February–April season of the forecast years 1–3 (hence only a quarter of the data that were used for SPI annual means above). It was hence closer to the original requirements of the Wupper catchment water board, as they wanted predictions of the SPEI computed applying the Penman–Monteith parameterization for potential evapotranspiration. However, when the new MPI-ESM1-2-LR hindcast was analyzed the February–April year

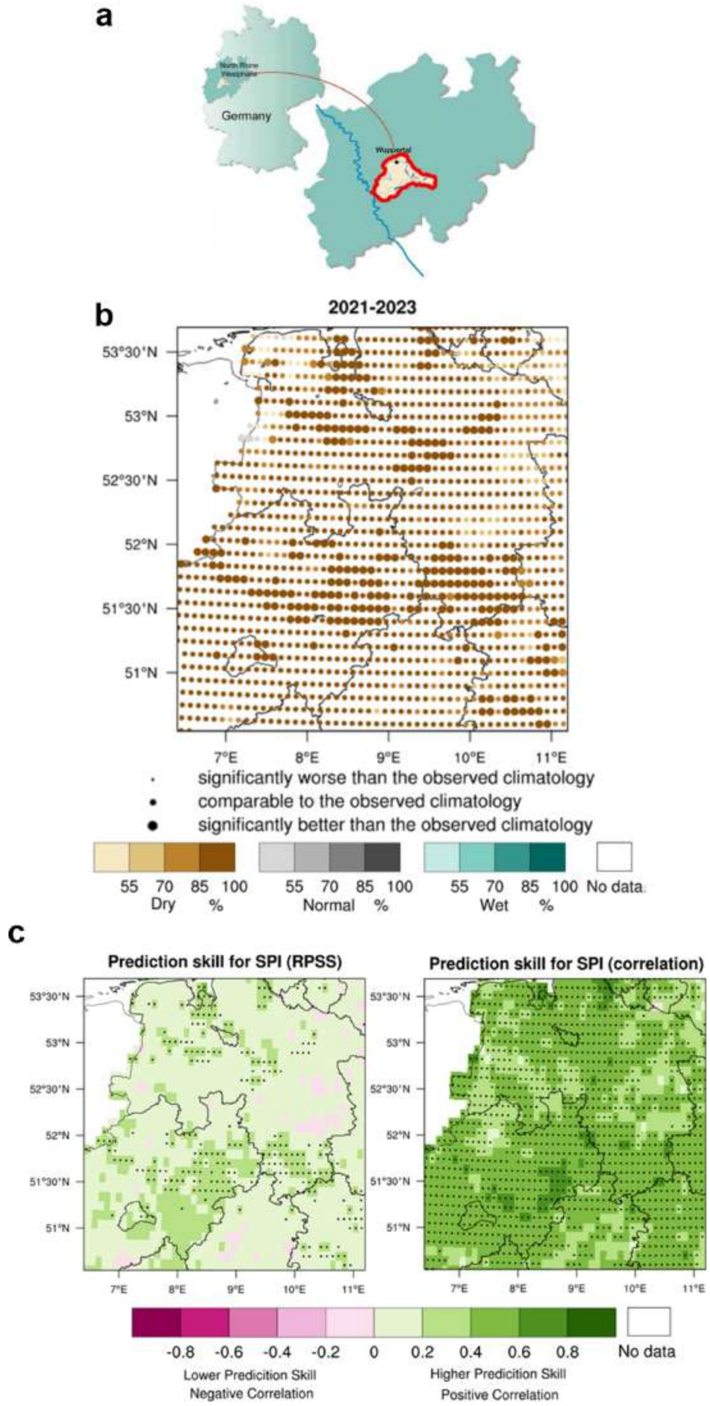

Fig. 5. Infrastructure decadal climate service. (a) Identifying the location of the Wupper catchment in western Germany. (b) Probabilistic forecast of SPI for the 3-yr (annual mean) period of 2021–23. The color represents the most probable category (dry, normal, wet) relative to the 1981–2020 climatology. Note that the size of the dots provide an indication of the prediction skill relative to climatology. (c) Prediction skill for SPI as measured by the (left) ranked probability skill score (RPSS) and (right) correlation. Dots indicate significant skill at the 95% level.

1–3 SPEI was no longer skillfully predicted. One confounding problem here was that the necessary high-resolution wind and radiation observations in Germany, needed to verify the SPEI forecasts, were only available for the relatively short verification period of 1995–2012. Such short verification periods are more vulnerable to fluctuations in skill than using a longer period (e.g., one starting in the 1960s as for SPI). Furthermore, the lack of skill when changing model system highlights the potential dangers of relying on a single prediction system in a climate service and the use of a multisystem ensemble is recommended to ensure robust skill assessment. Many of the methodological choices made in the infrastructure case study were aimed at meeting the user requirement for high-spatial-resolution decadal climate information; however, the impacts of the model change showed the limits of current scientific capability and the need for robust statistics. Thus, this case study highlights that a compromise solution, here applying a slightly different index and time period, can still be of use to the user even if the original user needs cannot be fulfilled.

Climate service product design and user feedback

A common template was adopted for presenting the four prototype decadal climate services. The design was inspired from a product first developed for a seasonal climate service providing predictions for Chinese Yangtze River summer rainfall (Golding et al. 2017; Bett et al. 2020), which was subsequently also adapted for a seasonal prediction service of landfalling East Asian tropical cyclone frequency (Hewitt et al. 2020b). An example of the two-page "product sheet" design prepared for the insurance case study is illustrated in Fig. 6. A summary box at the top provides a brief overview of the probabilistic forecast for the predicted time period and graphically identifies the forecast region. The remainder of the first page shows the time series of retrospective predictions, which helps to put this forecast in a historical context and allows a visual evaluation of hindcast performance. The second page of the product sheet

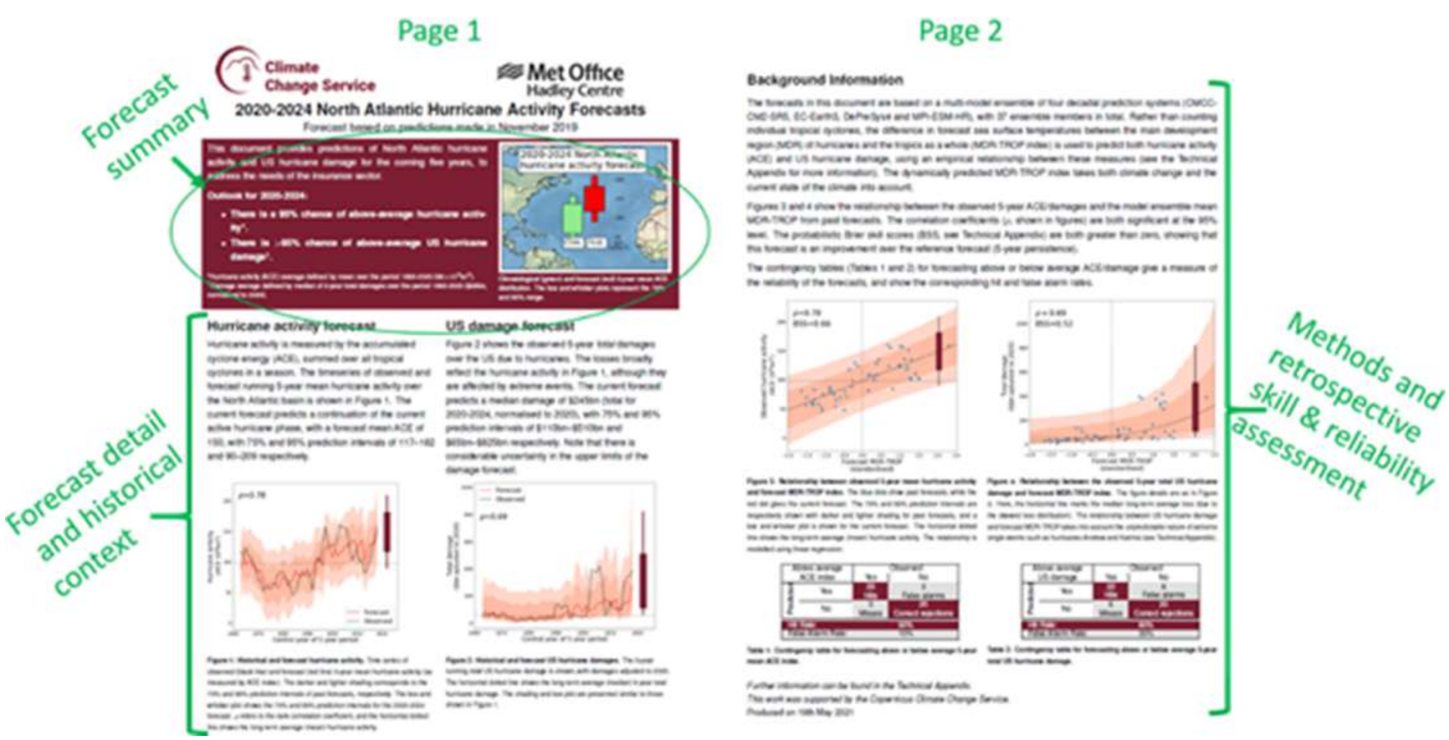

Fig. 6. Common two-page climate service product sheet format used across all four prototype decadal climate services. Note that all four product sheets are available to view on the C3S website (https://climate.copernicus.eu/sectoral-applications-decadal-predictions). This figure is only to illustrate the format and structure of the product sheet. Green text is to annotate main sections of product sheet.

includes basic methodological information about how the forecast was made, including verification skill scores for the hindcast performance. A contingency table is also included at the end of the product sheet, which was found from user feedback to communicate in a simple but effective way the probabilistic skill and reliability of the forecast. Each of the four prototype services tailored this template according to the needs of their sector users, but most of the key information and formatting was retained.

We recognize that providing the decadal climate service as a two-page product sheet might not satisfy all user requirements from a climate service. For example, many users require quantitative climate prediction data to drive their own downstream impacts and prediction models to make forecasts of end-user variables. However, the common two-page format ensured that the key information was included in the provided product, and it was useful within the framework of this project to showcase these four prototype decadal climate services to users in a coherent way and receive feedback. It should be noted that a technical appendix containing the full methodological details required to replicate the climate service is also provided on the C3S webpages.

Although each of the four sectoral decadal climate services was co-developed with a user from that sector, the project was also keen to engage a wider group of sector users. This was done by hosting a “showcase event” where many European users from each of the four sectors were invited. During this event, the four prototype climate service product sheets were presented, and valuable feedback was obtained for each. For example, there were requests to change the forecast unit, e.g., from a standardized value to USD in the case of direct losses from hurricanes in the insurance product, and from actual rainfall in millimeters per day to a percentage rainfall anomaly in the energy product—in both cases, this helped to improve the relevance of the information to the end-user. A brief interactive survey was also undertaken to solicit views on the potential of decadal prediction services for sector users. For example, in answer to the question “Do you think that decadal prediction products like those shown can be used in your sector or cover your needs?”, 79% of responses were “Yes, with some modifications”—giving us confidence that the prototype services at least demonstrated potential for many sector users.

Outlook

The four prototypes developed in this project have highlighted the potential and need for decadal climate services to aid decision-making in several sectors. The decadal time scale is becoming an increasingly important one, as illustrated by the Glasgow Climate Pact agreed at the 26th United Nations Climate Change Conference (COP26) meeting in November 2021. This calls on nations, and hence different sectors, to rapidly reduce their greenhouse gas emissions by 2030 in order to limit global warming. However, the near-term results of these efforts, especially regionally, will not necessarily be those expected based on longer-term climate projections, due to the relatively large internal variability on the decadal time scale. Hence, decadal climate services that are based on initialized predictions and capture some of the internal variability, as well as refining the model responses to external forcings, will become increasingly important to sector users.

In this study, we have shown that skillful decadal predictions of regional user-relevant surface climate variables are possible, although careful consideration is needed to develop the best services. In particular, we found that using skillful information from the large-scale environment rather than direct gridpoint model output can be key to making skillful regional climate predictions for services. This is especially important in the extratropics, e.g., for European rainfall predictions in the energy case study, where predictable atmospheric dynamical signals are spuriously small in the current generation of climate models, and very large ensembles are needed to skillfully predict climate variability patterns such as the NAO. The added complexity of first needing to understand how dynamical model errors impact regional climate prediction currently requires specialist scientific expertise for developing decadal climate services. However, we envisage that further examples of useful decadal climate services will emerge in the coming years and that these will help stimulate applied climate scientists and environmental consultants to continue developing services on this important time scale.

In parallel to developing further decadal climate services, there is clear scope for further scientific developments to improve our prediction systems. As global coupled climate models increase in spatial resolution, utilizing increasingly larger supercomputer facilities, we can expect to resolve more of the small-scale physical processes. These have the potential to feedback onto the large-scale circulation, and hence give increased predictive skill on decadal time scales. For example, there is tentative evidence that increased spatial resolution may lead to increased eddy feedback that could strengthen the weak model signals in predictions of the NAO (Scaife et al. 2019). Other studies point to higher-resolution simulations leading to improvements such as reduced SST biases (Roberts et al. 2019), improved ocean–atmosphere interactions (Ma et al. 2016; Bellucci et al. 2021), and elements of the hydrological cycle (Vannière et al. 2019). We should also strive to make climate predictions, and hence future climate services, more seamless across time scales. For example, intermediate between seasonal and decadal is the interannual time scale (e.g., from ~6 months to 2 years), which has received relatively little attention to date (Dunstone et al. 2020) and was highlighted by many users during this project as being of particular interest to their operations.

Based on our engagement with sector users, we are encouraged that most see the potential benefit of decadal climate services to their operations and planning. To enable growth of decadal climate services, we need to make sure that decadal climate prediction data (both hindcasts and forecasts) are readily accessible to users in a timely manner. At present, the most publicly available decadal climate prediction hindcast data are in the CMIP archives hosted by the Earth System Grid Federation.[3] While this is an excellent resource for decadal prediction scientists, it is not designed to serve operational forecasts in real time. The WMO ADCP hosted by the Met Office collects multimodel forecasts and provides forecast data on request. However, in the long-term a web portal will likely be required that can serve both the hindcast and forecast data, including more user-focused variables, e.g., multiyear seasonal averages. In addition, the provision of an online "toolbox" would allow users to build workflows and applications suited to their needs without having to locally download vast amounts of decadal prediction data. The C3S Climate Data Store (CDS)[4] for seasonal climate predictions is a good example of such a platform. Ultimately, it is only by stimulating the production of real-time decadal climate services for sector users, and those users then finding them useful in their decision-making, that user trust will slowly be built and decadal services further developed.

[3] https://esgf.llnl.gov/

[4] https://cds.climate.copernicus.eu/

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Data availability statement. Hindcast data used here can be obtained from the Earth System Grid Federation website for CMIP6 (https://esgf-node.llnl.gov/projects/cmip6/) by searching for the DCPP activity experiment dccpA-hindcast. Some forecasts are available in the same place under experiment dccpB-forecast and forecasts can also be obtained from the WMO Lead Centre website (http://www.wmolc-adcp.org).

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