BAMS Article

WMO Global Annual to Decadal Climate Update

A Prediction for 2021–25

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ABSTRACT: As climate change accelerates, societies and climate-sensitive socioeconomic sectors cannot continue to rely on the past as a guide to possible future climate hazards. Operational decadal predictions offer the potential to inform current adaptation and increase resilience by filling the important gap between seasonal forecasts and climate projections. The World Meteorological Organization (WMO) has recognized this and in 2017 established the WMO Lead Centre for Annual to Decadal Climate Predictions (shortened to "Lead Centre" below), which annually provides a large multimodel ensemble of predictions covering the next 5 years. This international collaboration produces a prediction that is more skillful and useful than any single center can achieve. One of the main outputs of the Lead Centre is the Global Annual to Decadal Climate Update (GADCU), a consensus forecast based on these predictions. This update includes maps showing key variables, discussion on forecast skill, and predictions of climate indices such as the global mean near-surface temperature and Atlantic multidecadal variability. it also estimates the probability of the global mean temperature exceeding 1.5°C above preindustrial levels for at least 1 year in the next 5 years, which helps policy-makers understand how closely the world is approaching this goal of the Paris Agreement. This paper, written by the authors of the GADCU, introduces the GADCU, presents its key outputs, and briefly discusses its role in providing vital climate information for society now and in the future.

KEYWORDS: Adaptation; Climate prediction; Climate services; Decadal variability; Policy

https://doi.org/10.1175/BAMS-D-20-0311.1
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In final form 23 December 2021

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As Earth's climate changes rapidly due to anthropogenic activity, predictive climate information has become increasingly crucial to help society prepare for these changes and attendant worsening of weather and climate extremes. Such information has been available from internationally coordinated sources in the form of seasonal to multiseasonal predictions issued monthly, and long-term climate projections to 2100 and beyond. The latter encompass the current epoch but do not constrain the timing of naturally occurring climate variability. Lacking until recently has been an authoritative source of predictive climate information for intermediate time scales from a year to a decade that considers near-term climate predictability, especially one that is updated more frequently than the approximately 7-yr interval between Intergovernmental Panel on Climate Change (IPCC) Assessment Reports.

Decadal predictions were developed to fill the gap between the time scales of seasonal forecasts and climate change projections in order to predict climate over the next few years, out to 10 years (and sometimes longer). On these time scales initial conditions (mainly those in the ocean) are important as well as external climate forcings, including greenhouse gases, solar variability, tropical volcanoes, and anthropogenic aerosol (Kushnir et al. 2019). Hence initialized climate predictions are designed to provide climate information for the coming decade, while climate projections are designed for longer time scales (Meehl et al. 2014; Smith et al. 2019). Decadal predictions are able to skillfully predict many aspects of climate including global temperature (Doblas-Reyes et al. 2013; Smith et al. 2018), Atlantic variability (Hermanson et al. 2014; Yeager and Robson 2017), Atlantic hurricane frequency (Smith et al.

2010; Caron et al. 2018), Sahel drought (Sheen et al. 2017), Arctic sea ice extent (Yeager et al. 2015), and wildfire in North America (Chikamoto et al. 2017).

Such demonstrations of the skill of decadal predictions provided strong motivation for developing operational predictions for the time range between operational seasonal predictions and climate projections. A strong impetus for international coordination was provided by prior demonstrations that multimodel ensemble forecasts are generally more skillful and reliable in predicting past climate than such forecasts from a single model (Hagedorn et al. 2005; Kirtman et al. 2014; Choudhury et al. 2017). Experience from seasonal and decadal predictions also shows that the current generation of models underestimate important climate signals (Eade et al. 2014; Scaife and Smith 2018; Smith et al. 2020). Large ensembles are needed to capture the predictable signal in such cases, although the signal will still be too small in amplitude. As a step toward creating an operational multimodel decadal prediction ensemble, an informal exchange of decadal predictions among modeling centers around the world was started at the Met Office in 2010 (Smith et al. 2013) to produce a large multimodel ensemble of real-time decadal forecasts.

Building on this informal exchange, the World Meteorological Organization (WMO) established the operational Lead Centre for Annual to Decadal Climate Predictions (LC-ADCP) in 2017 (WMO 2019). The LC-ADCP issues annually updated predictions out to 5 years ahead that are based on a large multimodel ensemble (more than 100 members) and are published on its website (www.wmolc-adcp.org, accessed November 2021). As a means to encapsulate and disseminate these predictions, the World Climate Research Programme's Grand Challenge on Near Term Climate Prediction (www.wcrp-climate.org/gc-near-term-climate-prediction, accessed November 2021) recommended the initiation of an annually issued decadal climate outlook along the lines of the WMO's Global Seasonal Climate Update (https://public.wmo.int/en/our-mandate/climate/global-seasonal-climate-update, accessed November 2021). Following this recommendation, the LC-ADCP in 2020, and again in 2021, released a Global Annual to Decadal Climate Update (GADCU) which summarizes its predictions issued in those years. The GADCU provides an Executive Summary, a description of the observed climate of the last 5 years to provide context, and maps showing predictions for key climate variables together with explanatory text highlighting important aspects of the predictions and noting where they are skillful. In addition, predictions of key climate indices such as the global mean near-surface temperature and Atlantic multidecadal variability are provided.

An additional function of the GADCU is to frame the predicted evolution of annual mean global temperature over the coming 5 years in relation to the 1.5°C threshold of warming from preindustrial levels (reference period 1850–1900) that is a focus under the Paris Agreement. This is achieved by providing an annually updated probability that at least one of the next 5 years will exceed the threshold, emphasizing that such exceedances are expected, initially at least, to be temporary as a consequence of interannual variability superimposed on the warming trend. The increase of these probabilities from year to year provide a warning that 1.5°C warming of the mean climate is being approached.

The broader importance of the GADCU and operational decadal predictions in general stems from the vulnerability of societies and ecosystems especially in less developed regions to negative aspects of climate variability and change, which include increased drought frequency, heatwave intensity, wildfires, floods, epidemics, and agricultural pests, as well as energy demand and risk of conflict. Decadal predictions are highly relevant for planners and policy-makers to develop strategies for adaptation and increased resilience (Kushnir et al. 2019), for supporting the UN Sustainable Development Goals by giving advance warning of potential climate hazards, and for developing climate services that can be used to reduce exposure to natural hazards and increase prosperity (Hewitt et al. 2020).

In this paper, we, the authors who developed the GADCU and provide the forecasts that inform it, highlight the key outputs from the GADCU (which is available on the LC-ADCP website) as a source of annually updated decadal prediction information for societal applications. Predictions for the 5-yr period 2021–25 are first described, emphasizing historical skill and hence confidence levels of the forecasts. We next evaluate a past real-time forecast for 2016–20 produced using similar methodologies to forecasts in the GADCU. Finally, we summarize the prospects for the GADCU and how it can inform decision making and climate research in the years to come.

Initialized climate predictions

The data used at the WMO LC-ADCP and for the GADCU come from the Global Producing Centres (GPCs) and the Contributing Centres. The GPCs are approved by the WMO and contribute a forecast every year. These are currently Barcelona Supercomputing Center, Canadian Centre for Climate Modelling and Analysis, Commonwealth Science and Industrial Research Organisation, Deutscher Wetterdienst, and Met Office. The Contributing Centres contribute data to the multimodel ensemble when priorities and funding allow. For the forecast shown here these were Bjerknes Centre for Climate Research, Centro Euro-Mediterraneo sui Cambiamenti Climatici, Danish Meteorological Institute partnered with Swedish Meteorological and Hydrological Institute, Geophysical Fluid Dynamics Laboratory, Japan Agency for Marine-Earth Science and Technology partnered with the University of Tokyo/National Institute for Environmental Studies, Meteorological Research Institute, and Naval Research Laboratory. This gives an ensemble size of well over 100 members. All centers, except the Naval Research Laboratory, have also provided retrospective forecasts (hindcasts) for skill evaluation. The predictions were initialized and started at the end of 2020 and the forecast anomalies shown are from a climatology covering the years 1981–2010. Biases are reduced by calculating the anomalies from a lead-time-dependent climatology calculated separately for each model (see appendix E of Boer et al. 2016).

We start by presenting predictions for two important climate indices included in the GADCU. The first is annual global mean near-surface temperature, which is closely monitored by the WMO as it is the primary indicator of climate change. The prediction shown in Fig. 1a indicates that the annual global mean near-surface temperature is likely to be at least 0.3°C above the 1981–2010 average in each of the coming 5 years, which is about 1°C warmer than preindustrial levels (defined as the average over the period 1850–1900). On the right of Fig. 1a we show skill scores for global mean near-surface temperature ensemble mean (top panel, calculated as in Goddard et al. 2013) and the contingency table for the probabilistic forecast (bottom panel). Our confidence in forecasts of global mean temperature is high since hindcasts show high skill in all measures.

The histogram inset in Fig. 1a, which refers to the brown right-hand axis shows that there is approximately a 40% chance that at least 1 of the next 5 years will be more than 1.5°C warmer than preindustrial levels. Furthermore, it shows that this chance is increasing with time. The preindustrial conditions are estimated to be 0.68°C cooler than the 1981–2010 reference. This offset is nevertheless uncertain and varies between 0.61° and 0.75°C depending on the observational datasets used so that the chance of 1 year exceeding 1.5°C above preindustrial levels is between 25% and 65%, with 40% being the current best estimate.

The chance of at least 1 year exceeding the current warmest year, 2016, in the next 5 years is 90% and the chance of the 5-yr mean for 2021–25 being higher than the last 5 years is 80%. These exceedance probabilities are better constrained as they refer to recent years when observations are of higher quality, greater coverage, and increased spatial resolution as compared to earlier historical periods.

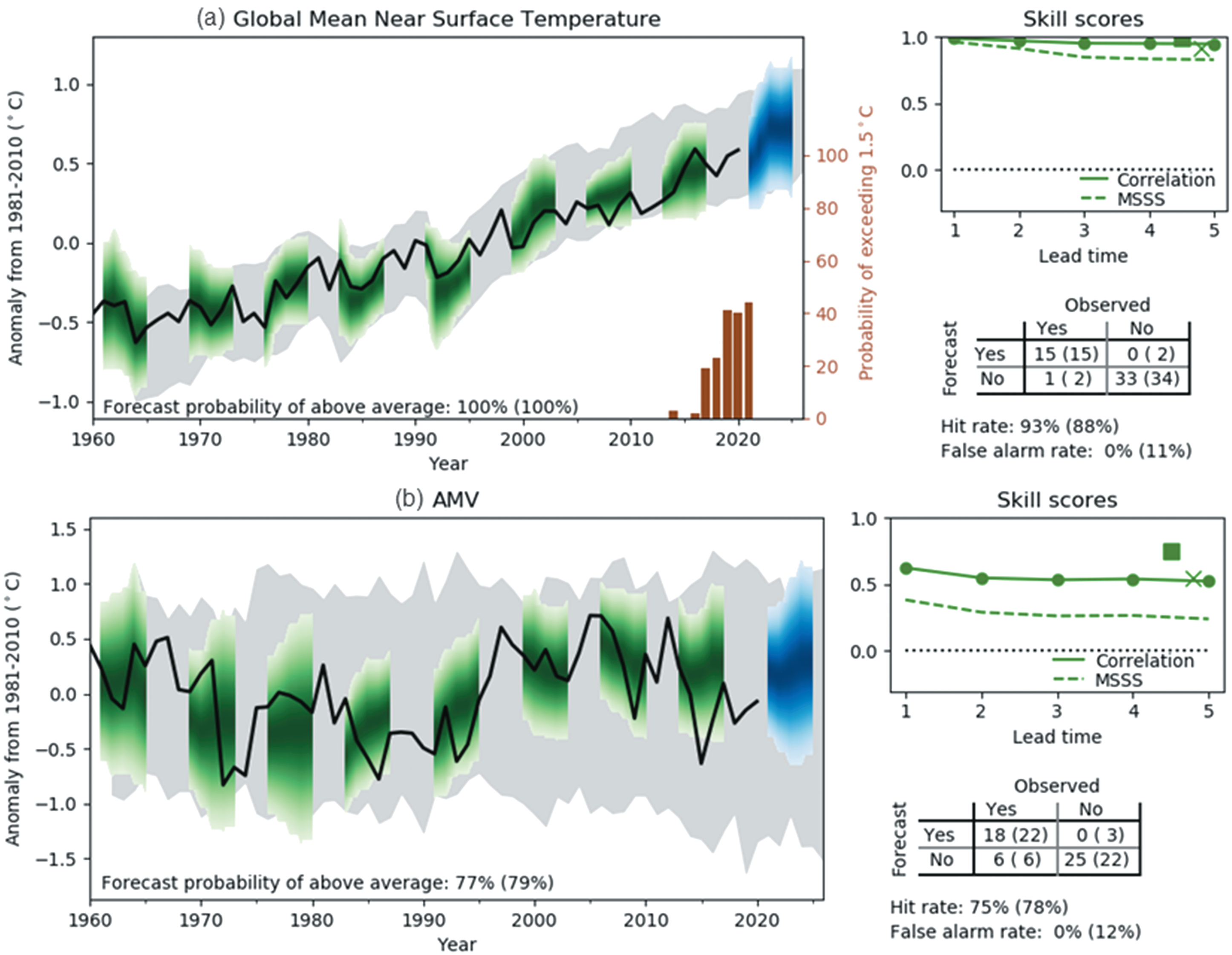

Fig. 1. Multiannual predictions of annual mean (a) global mean near-surface temperature and (b) Atlantic multidecadal variability (AMV) relative to 1981–2010. Annual mean observations are in black, the forecast is in blue, hindcasts are in green, and uninitialized simulations are in gray. The shading indicates the 90% confidence range. The probability for above average (compared to 1981–2010) in the 5-yr mean of the forecast is written at the bottom of the main panel (in parentheses the probability for above average in the next year). Hindcast skill scores are shown in the top-right panel, with the square and the cross showing the correlation skill and mean square skill score (MSSS) for 5-yr means, respectively. Significant correlation skill (at the 5% confidence level) is indicated by solid circles and square. The contingency table for the prediction of above average 5-yr means is shown in the bottom-right panel (in parentheses values for above average in the next year). For (a), inset in the main panel, referring to the right-hand axis, is the probability of global temperature exceeding 1.5°C above preindustrial levels for at least 1 year during the 5 years starting in the year indicated (brown bars). This probability is calculated as in Smith et al. (2018) by counting the proportion of ensemble members that predict at least 1 year above 1.5°C. Observed temperature is an average of three observational datasets: HadCRUT5 (Morice et al. 2021, updated), NASA GISS (Hansen et al. 2010, updated), and NCDC (Karl et al. 2015, updated). The AMV in (b) is the difference between two regions: 45°–60°N, 60°W–0° minus 45°S–0°, 30°W–10°E, closely related to the index used in Roberts et al. (2013), but adapted to not cover land areas, as we use near-surface temperature (since we do not have sea surface temperature data).

The second index we consider is the Atlantic multidecadal variability (AMV), which measures interdecadal changes of basin-wide warming and cooling in the North Atlantic (Sutton et al. 2018). This variability has impacts on temperature and rainfall over land surrounding the North Atlantic Ocean, particularly in summer, and modulates the number of hurricanes (Trenberth and Shea 2006; Sutton and Dong 2012; Martin and Thorncroft 2014; O'Reilly et al. 2017). Predictions in Fig. 1b indicate a 77% probability that AMV will be positive (relative to the 1981–2010 climatology) when averaged over the next 5 years. However, AMV is likely to be lower than recent peak values seen in the 2000s. As can be seen on the right side of Fig. 1b, skill for the AMV is lower than that of global mean near-surface temperature, but is still high both for single years and the 5-yr mean with a high hit rate for the probabilistic forecast of above average. We therefore have medium to high confidence in this prediction.

An important part of the GADCU are maps of predicted fields, which are useful for understanding the features of regional climate. In Fig. 2 we show predictions for 2021 regional temperature, mean sea level pressure, and precipitation, the ensemble mean prediction in the left column and the probability of exceeding the 1981–2010 average in the right column. Deterministic skill of the multimodel ensemble mean is assessed in the left column of Fig. 3 using the Pearson correlation. In the right column, the skill of the probabilistic forecast for above-average conditions is assessed using the area under the receiver operating characteristic curve (ROC). For both measures, red shows areas of high skill and pale or blue areas have

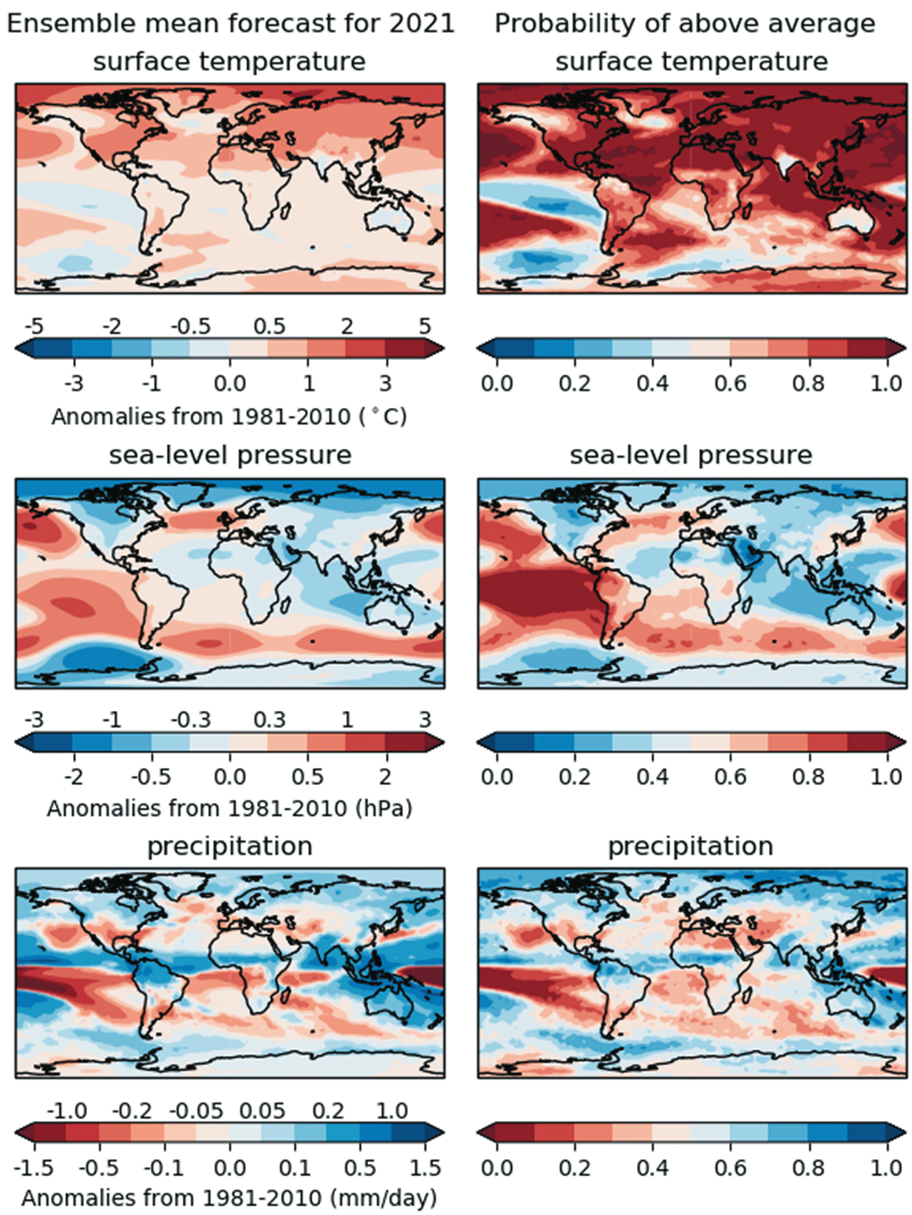

Fig. 2. **Annual mean anomaly predictions for 2021 relative to 1981–2010. (left) Ensemble mean for temperature (top, °C), sea level pressure (middle, hPa), and precipitation (bottom, mm day^{-1}) and (right) probability of above average for the same three variables. As this is a two-category forecast, the probability for below average is one minus the probability shown in the right column.**

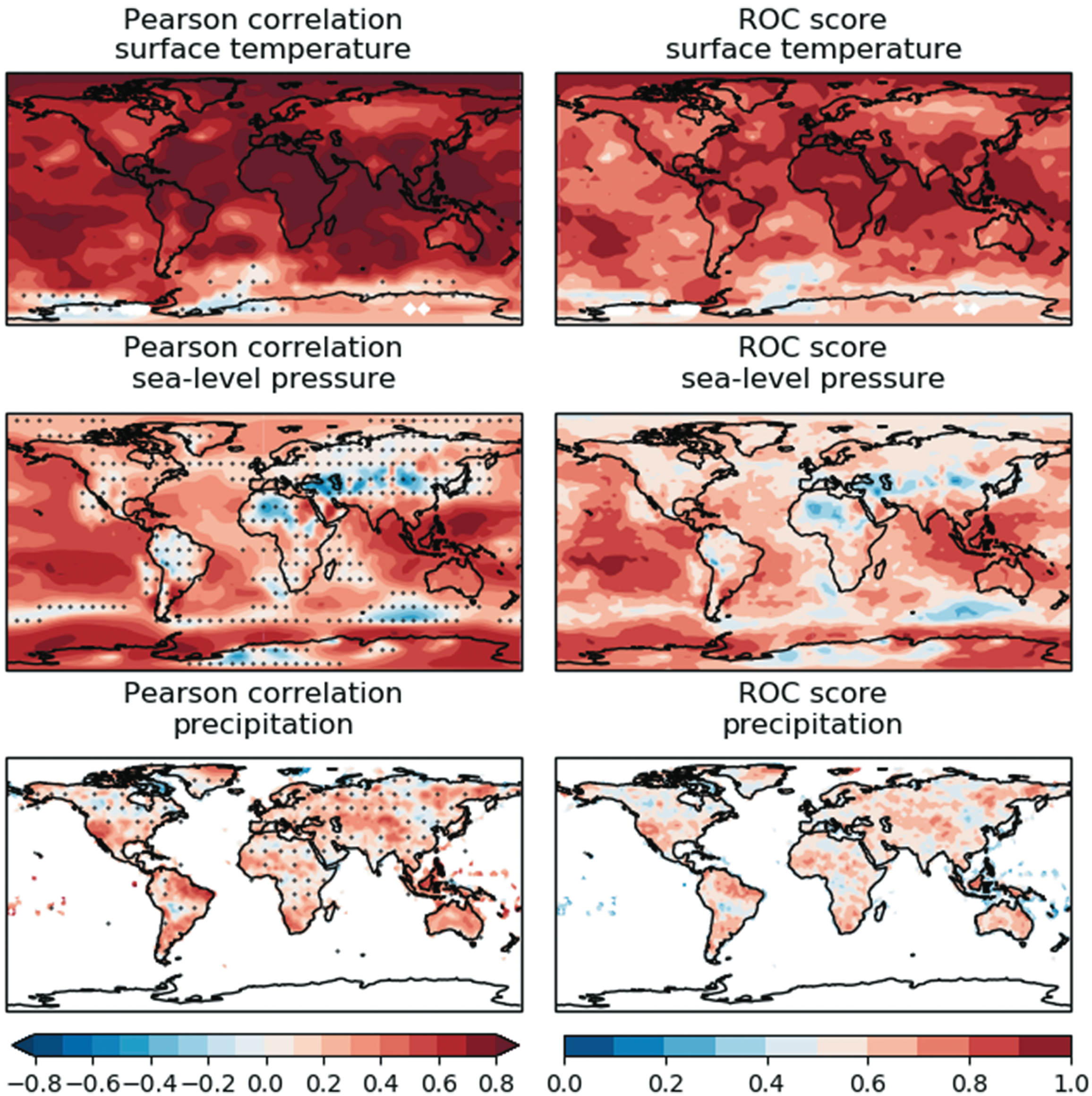

Fig. 3. Prediction skill of annual mean hindcasts. (left) Pearson correlation and (right) ROC score (the area under the ROC) for predictions of above-average conditions. For correlation, stippling shows where skill is not significant (at the 5% level) using the beta function to give a two-sided *p* value. The hindcast skill was evaluated over the period for which we had hindcasts with all models, 1961–2018, using the same surface temperature dataset as in Fig. 1, sea level pressure using HadSLP2r (Allan and Ansell 2006), and precipitation using GPCP (Adler et al. 2003).

low or no skill. Note that using past predictions to assess the skill of a forecast can only ever be an estimate as the forecast may encounter previously unseen climate states. We find that skill is very similar to that found in large ensembles and other multimodel ensembles and in many cases the sources of skill are known (Yeager et al. 2018; Smith et al. 2019).

Temperatures in 2021 are predicted to be higher than the 1981–2010 average in almost all regions except parts of the Southern Ocean and the tropical and southeast Pacific. Temperature has high skill for both the deterministic and probabilistic prediction in most regions for near-surface temperature, so we estimate medium to high confidence in this prediction. Sea level pressure predictions suggest anomalous low pressure over the Arctic and high pressure over the Pacific and Atlantic consistent with stronger winds between these regions. Skill is moderate but significant for sea level pressure in both measures, giving us medium confidence in the prediction. Predicted precipitation patterns suggest an increased chance of drier conditions over southwestern Europe and southwestern North America and wetter conditions in northern Europe, the Sahel, and Australia. There is moderate skill in both types of prediction for Europe, parts of North America, Australia, and the Sahel, giving us low to medium confidence for these regions.[1]

The GADCU also gives regional climate predictions averaged over the 5-yr period 2021–25; these are shown in Fig. 4. The predictions are for enhanced warming at high northern latitudes and over land compared to ocean, consistent with what is expected from climate change. The Arctic (north of 60°N) anomaly is more than twice as large as the global mean anomaly. As deterministic skill for near surface temperature, which

[1] These predictions are for 2021 and can now be verified against observations. A side-by-side comparison of predictions and observations can be found on the LC-ADCP website: www.wmolc-adcp.org.

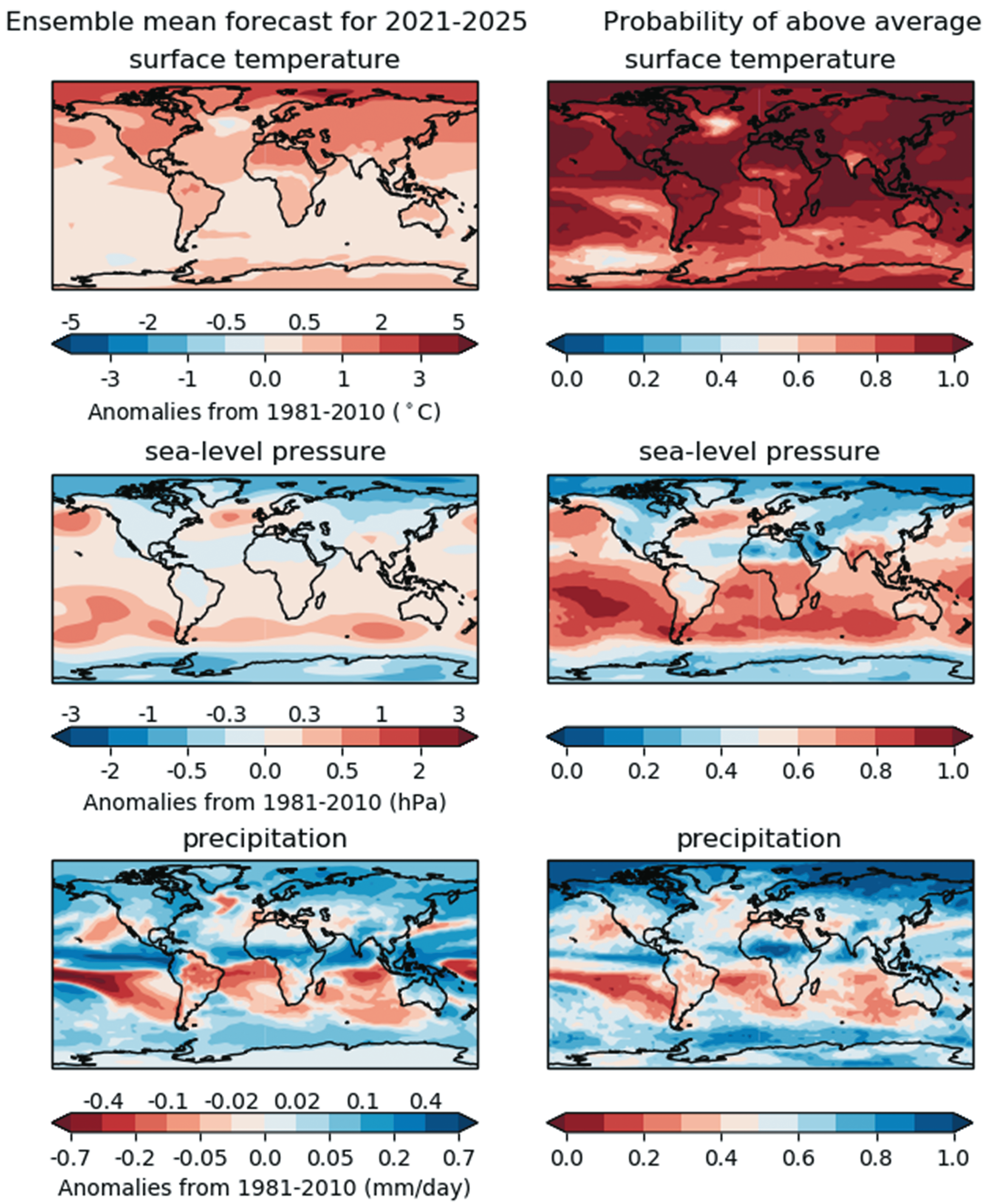

Fig. 4. Predictions for 2021–25 anomalies relative to 1981–2010. (left) Ensemble mean for (top) temperature (°C), (middle) sea level pressure (hPa), and (bottom) precipitation (mm day^{-1}) and (right) probability of above average for the same three variables. As this is a two-category forecast, the probability for below average is one minus the probability shown in the right column.

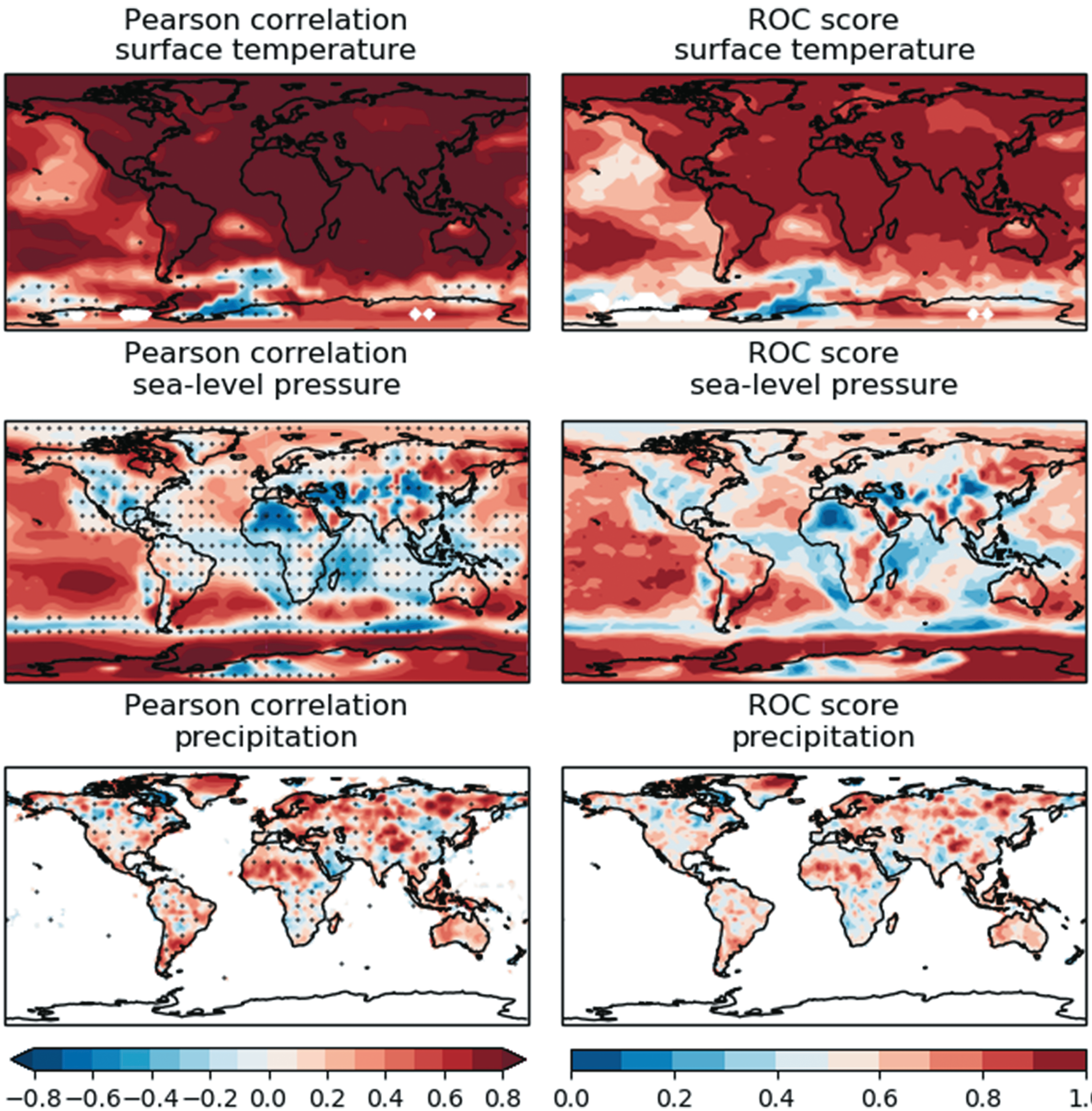

Fig. 5. Prediction skill of 5-yr means from hindcasts. (left) Pearson correlation and (right) ROC score for predictions of above-average conditions. For correlation, stippling shows where skill is not significantly positive (at the 5% level) using the beta function to give a two-sided *p* value. The hindcast skill was evaluated over the period for which we had hindcasts with all models, 1961–2018, using the same datasets as in Fig. 3.

is shown in Fig. 5, is high in all regions apart from the eastern Pacific and the Southern Ocean, we have high confidence in this prediction.

Both the ensemble mean and the probabilistic prediction indicate that sea level pressure is likely to be below average over both poles and above average in the midlatitudes. Such a pressure gradient indicates stronger westerly winds in the regions between these two anomalies. Skill is good over the southern polar region, but is low to moderate over the northern polar region and the midlatitudes. This means we have low to medium confidence in our prediction. In the northern North Atlantic the sea level pressure prediction shows an increased north–south pressure gradient, which means there is an increased chance of extratropical storms and rainfall, especially for parts of northern Europe and eastern North America. Skill for pressure in the relevant regions is moderate, so we have low to medium confidence.

The predictions show above-average precipitation over the Sahel and across northern Europe and Eurasia. There is moderate but significant skill for the ensemble mean over the

Sahel and across northern Europe and Eurasia, giving us medium confidence in the forecast for an increased chance of higher precipitation in these regions.

The predictions for the tropical Atlantic show above-average temperatures, below-average sea level pressure, and above-average precipitation, which together with a northward-shifted intertropical convergence zone indicates that the number of tropical cyclones could be higher than normal (Caron et al. 2018). This is also indicated by the predicted positive AMV index discussed above. The skill for temperature is high, but the skill for sea level pressure is moderate, so we have medium confidence in this prediction.

Evaluation of a past forecast

The skill of predictions is assessed from hindcasts (retrospective forecasts), but the strongest test of a prediction system is how well its predictions perform. Unfortunately for decadal prediction, few forecasts can be verified as forecasts with no knowledge of the future have only been made since the early 2000s. Instead, in the GADCU we make a simple evaluation, which gives an indication of performance. The WMO Lead Centre website (www.wmolc-adcp.org, accessed November 2021) displays past real-time predictions and one of them is evaluated here.

Figure 6 shows a prediction made in late 2015 for 2016–20 using the models available at that time. The left column shows the ensemble mean prediction and the right-hand column shows the corresponding observations. The observed pattern including very warm conditions over the Arctic and Eurasia, and anomalously cool conditions in the Southern Ocean, northern North Atlantic, and tropical Pacific are reproduced by the forecast. However, the anomalies are often smaller than observed and stippling indicates where the observations are outside the ensemble 90% range. Observed cooler conditions in parts of North America and eastern Indian Ocean were not predicted and polar temperatures were higher than predicted despite high skill in the region. The predicted pattern of sea level pressure anomalies is good where skill is high (Fig. 5), but the forecast signals are small and observations are outside the forecast range in many regions even when the ensemble mean shows the correct sign. Precipitation patterns show reasonable agreement with observations, including wetter conditions across much of Eurasia and central Africa, and drier conditions in southern North America, west Asia, northeast Brazil, and southern Africa. Dry conditions in western Canada, Australia, and western Europe were not predicted.

Outlook

Operational decadal climate predictions fill an important gap between seasonal predictions and climate projections and provide policy relevant information with substantial lead time. The WMO Global Annual to Decadal Climate Update (GADCU) is an important step in providing science-based real-time climate predictions for the next 5 years, a time scale important for governments and many social and economic sectors (Vera et al. 2010). There are already examples of climate services based on decadal predictions being explored in the water sector (Towler et al. 2018) and the agricultural sector (Solaraju-Murali et al. 2019).

The GADCU was issued for the second time in 2021 and will continue to be issued annually in early May on the Lead Centre website: www.wmolc-adcp.org. The core of this service are the five Global Producing Centres, who have committed to providing forecasts at the beginning of each year. The forecasts from the Contributing Centres are important to increase the ensemble size and with it the skill. Changes in priorities and funding mean that these can be different each year, pointing to the need for a secure source of funding to ensure these contributions can continue. There has been an increase in the number of contributors in the last few years and this reflects the growing importance of decadal predictions and its prominence in World Climate Research Programme (WCRP) research plans.

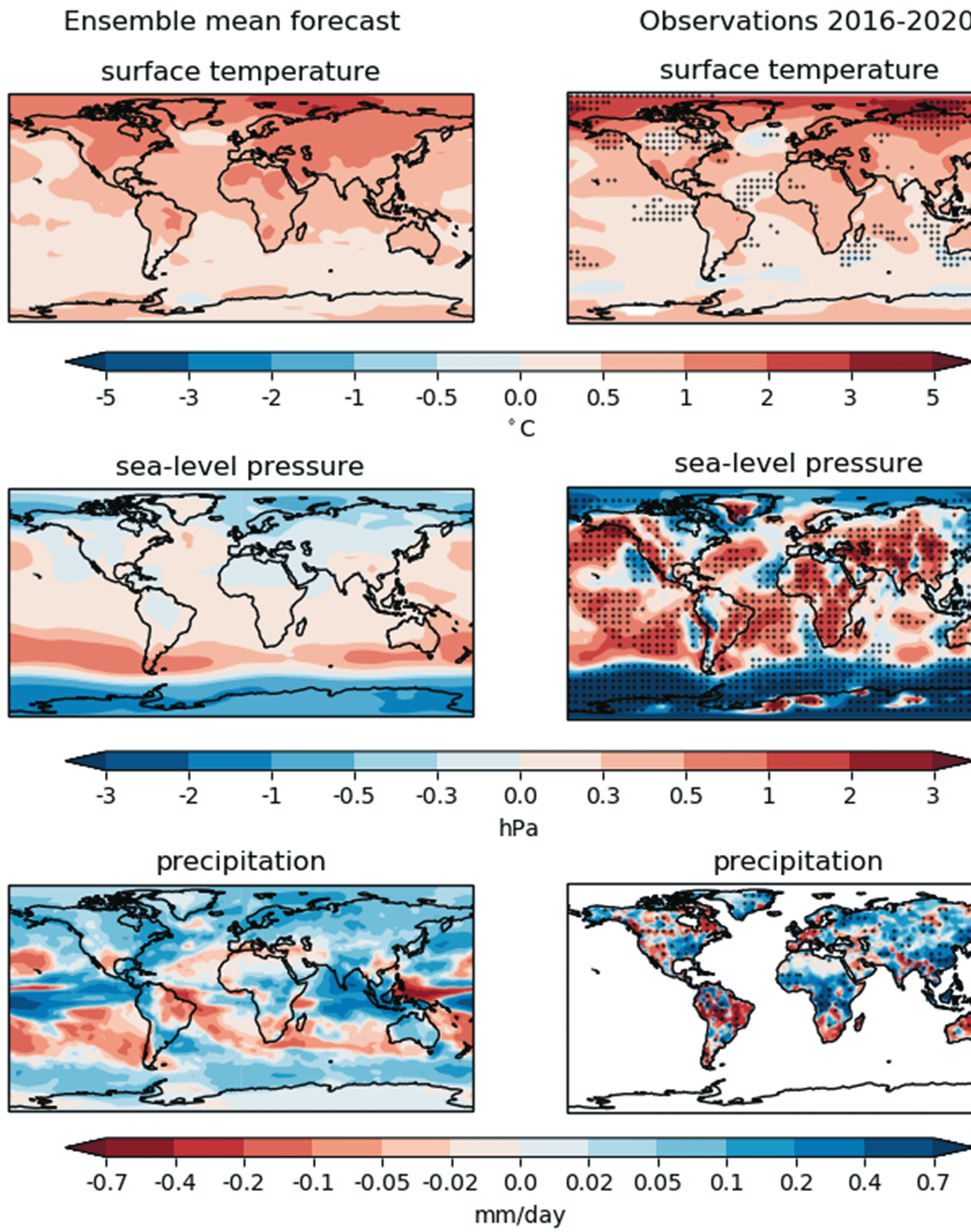

Fig. 6. Evaluation of the 5-yr forecast for 2016–20 relative to 1971–2000. (left) Ensemble mean forecast and (right) observed anomalies. Stippling shows where the observations fall outside of the 90% range of the forecast ensemble. Observations are as in Fig. 3.

The WCRP has programs to organize its work toward key priorities, so-called lighthouse activities, which will lead to improvements of the GADCU. The "Explaining and Predicting Earth System Change" activity will provide an improved understanding of the drivers of decadal variability, thereby improving the confidence in the predictions. The "My Climate Risk" activity will explore methodologies to provide better regional information to support the development of climate services.

The WMO Lead Centre for Annual to Decadal Prediction publishes prediction skill information on its website as well as in the GADCU. It is important that model performance is monitored and the information is fed back to model developers so that model problems relevant to decadal prediction, such as the signal-to-noise paradox (Eade et al. 2014;

Scaife and Smith 2018), are prioritized. At the moment, only annual means are used in the figures for the Lead Centre and the GADCU. The capability to use seasonal means is currently being developed which will lead to even more relevant predictions, including for El Niño–Southern Oscillation and seasonal rainfall, including monsoons. There are also plans to expand the predictions to give more detailed regional information.

The WMO Lead Centre data contribute to an important core function of the Climate Services Information System, a foundational pillar of the Global Framework for Climate Services. WMO Regional Climate Centres, already active users of seasonal forecasts in support of National Meteorological and Hydrological Services to provide early warnings to reduce the impact of climate hazards, are considering decadal predictions as part of their highly recommended functions. As the use of climate prediction information increases and applications are developed, the WMO Lead Centre for Annual to Decadal Climate Prediction multimodel ensemble will benefit many people and communities.

Acknowledgments. LH and AS were supported by the EUCP project funded by the European Commission's Horizon 2020 programme, Grant Agreement 776613 and supported by the U.K.–China Research and Innovation Partnership Fund through the Met Office Climate Science for Service Partnership (CSSP) China as part of the Newton Fund. AS, DS, and MS were supported by the Met Office Hadley Centre Climate Programme funded by BEIS and Defra. The EC-Earth simulations at SMHI were performed on resources provided by the Swedish National Infrastructure for Computing (SNIC) at PDC and NSC and have been performed as part of the NordForsk-funded Nordic Centre of Excellence project (Award 76654) Arctic Climate Predictions: Pathways to Resilient, Sustainable Societies (ARCPATH). SY and TT were supported by the ARCPATH (NordForsk Award 76654) and the Danish state-funded National Centre for Climate Research [Nationalt Center for Klimaforskning (NCFK)]. SY was also partly supported by the EUCP project (Horizon 2020 Grant Agreement 776613). The EC-Earth simulations at BSC were performed using resources from the Red Española de Supercomputación. HP and WM received funding from the German Federal Ministry of Education and Research (BMBF) project MiKlip (FKZ 01LP1519A). Takahito Kataoka and Hiroaki Tatebe were supported by the Integrated Research Program for Advancing Climate Models (TOUGOU) Grant JPMXD0717935457 from the Ministry of Education, Culture, Sports, Science and Technology (MEXT), Japan. MIROC simulations were performed on the Earth Simulator at JAMSTEC. NK, YW, FC, and IB were supported by the Trond Mohn Foundation (Grant BFS2018TMT01; Bjerknes Climate Prediction Unit).

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 (www.wmolc-adcp.org). New forecasts initialized at the beginning of the year are available every April.

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