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The DWD climate predictions website: Towards a seamless outlook based on subseasonal, seasonal and decadal predictions

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HIGHLIGHTS

- Consistent climate outlook based on subseasonal, seasonal and decadal predictions.
- Basic and expert predictions offer two levels of complexity for different users.
- Statistical downscaling provides high-resolution predictions for Germany.
- Predictions are displayed in conjunction with a user-oriented skill traffic light.
- Climate service was developed in close user cooperation via surveys and workshops.

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ABSTRACT

The climate predictions website of the Deutscher Wetterdienst (DWD, https://www.dwd.de/climatepredictions) presents a consistent operational outlook for the coming weeks, months and years, focusing on the needs of German users. At global scale, subseasonal predictions from the European Centre of Medium-Range Weather Forecasts as well as seasonal and decadal predictions from the DWD are used. Statistical downscaling is applied to achieve high resolution over Germany. Lead-time dependent bias correction is performed on all time scales. Additionally, decadal predictions are recalibrated.

The website offers ensemble mean and probabilistic predictions for temperature and precipitation combined with their skill (mean squared error skill score, ranked probability skill score). Two levels of complexity are offered: basic climate predictions display simple, regionally averaged information for Germany, German regions and cities as maps, time series and tables. The skill is presented as traffic light. Expert climate predictions show complex, gridded predictions for Germany (at high resolution), Europe and the world as maps and time series. The skill is displayed as the size of dots. Their color is related to the signal in the prediction.

The website was developed in cooperation with users from different sectors via surveys, workshops and meetings to guarantee its understandability and usability. The users realize the potential of climate predictions, but some need advice in using probabilistic predictions and skill. Future activities will include the further development of predictions to improve skill (multi-model ensembles, teleconnections), the introduction of additional products (data provision, extremes) and the further clarification of the information (interactivity, video clips).

Practical implications

The climate predictions website of the Deutscher Wetterdienst (DWD, https://www.dwd.de/climatepredictions) offers operational climate predictions on the subseasonal, seasonal and decadal climate timescales. The subseasonal predictions cover the

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next 2-5 weeks, the seasonal predictions regard the months 1-6 and the decadal predictions consider the years 1-10. Since the website uses different models, observations and separate products across time scales, it is not fully seamless but provides a consistent 'one-stop-shopping' outlook for the coming weeks, months and years on a single platform.

The global subseasonal predictions are taken from the European Centre of Medium-Range Weather Forecasts (ECMWF), whereas the global seasonal and decadal predictions are produced by the Deutscher Wetterdienst (DWD). Since this climate service is focused on German data users, all climate predictions are transformed to a higher spatial resolution in Germany, applying statistical relationships between large scale and small scale from observations. For each model, a prediction ensemble is calculated consisting of several slightly different simulations. The ensemble spread describes the prediction uncertainty.

The subseasonal predictions are presented as weekly means for week 2, 3, 4 and 5, whereas the seasonal predictions are displayed as 3-month means for months 1-3, 2-4, 3-5 and 4-6. Finally, the decadal predictions are offered as 1- or 5-year means for years 1, 1-5, 3-7 and 6-10. All predictions include information on future temperature and precipitation for the whole world, Europe, Germany and four German regions (north, south, east, west). For seasonal and decadal predictions, information is also available for the 16 capital cities of the German federal states and the pilot city Aschaffenburg. This city-scale information was not yet implemented for subseasonal predictions due to high computing times in the context of short operational time slots. In addition, the publication of subseasonal predictions for Europe and the world was in preparation at the time this manuscript was written.

Two different types of predictions are considered, enabling different kinds of future outlooks: the ensemble mean prediction describes the mean of the prediction ensemble compared to the long-term mean of a reference period (e.g. "The next year will be 0.5 °C warmer than the reference period of 1991–2020."). Based on the distribution of the ensemble, the probabilistic prediction estimates the probability of the three categories 'below normal', 'normal' and 'above normal' which are defined based on the climate characteristics of the reference period (e.g. "The probability that the temperature of the next year will be above normal compared to the reference period of 1991–2020 is 80 %."). Additionally, the quality of this prediction of the future state is assessed based on the verification of retrospective predictions, which have been started from points in time in the past, with observations. If the prediction model reproduces well the past observations, it is assumed that it also predicts well the future state.

The climate predictions are presented on a web platform with two levels of complexity: basic climate predictions present simple and regionally averaged predictions for Germany, German regions or cities as maps, time series or tables. The quality of the prediction is described as a traffic light. The expert climate predictions describe complex, gridded predictions for Germany (at high resolution), Europe and the world as maps and time series. The prediction quality defines the size of the dots (large dots denote high quality and small dots denote low quality), whereas the color describes the prediction. The concept and design of this website was developed in cooperation with users at workshops, in surveys and in individual meetings and proved to be mostly understandable and usable in their working routines. Additionally, the global prediction data can be downloaded for further modelling in climate impact studies. The regional prediction data will be available soon.

Discussions with users from different sectors disclosed their needs in terms of climate predictions and revealed many different possible applications of the DWD climate predictions website. Indeed, some users already use these predictions or plan to use them soon: in the water sector, they can help in the operational and long-term management of dams, rivers and ground water in the context of droughts and heavy rainfall. In the agriculture and forestry sectors, climate predictions can be used to manage the time of planting and the kind of species to plant as well as cope with possible threats due to pest infestation. In the energy sector, future potentials of solar and water energy can be estimated to plan operational energy distribution and long-term structure work. In the health sector, adaptation measures for long heat waves and the spread of vector diseases can be planned and implemented. In the insurance sector, the occurrence of extreme events such as heavy rainfall and corresponding flooding can be assessed to adjust insurance rates. Finally, the disaster risk reduction sector may strongly benefit from climate predictions across different time scales using the cascading prediction approach: if decadal predictions show a drying tendency for the next five years, first low-cost measures like long-term planning actions can be taken. If seasonal predictions display dryness for the next months, more intensive measures can be planned like planting dry-resistant crops. If subseasonal predictions confirm a drought, final actions can be taken to be better prepared for an emergency event.

Finally, this website will be further enhanced to improve the understandability and usability of the climate service products offered. The climate prediction models will be further refined to improve the prediction quality. Further user-oriented products will be offered to extend the range of possible applications: wind, extreme events such as droughts, heat waves or storms and multi-annual seasonal means like five-year summer means. Additionally, regional prediction data for Germany will be provided for impact modelling activities. Understandability will be enhanced in improving the communication of complex issues via video clips, like already done for the prediction quality. The basic climate predictions will be made more attractive via interactive tools. Finally, a time series across all climate time scales including past observations, climate predictions for the next weeks to years and long-term climate projections will be developed to enable the next step towards a seamless future outlook at a glance.

Data availability

Data will be made available on request.

Introduction

For many years future climate outlooks for Germany focused on long climate change projections analyzing the impacts of future scenarios of natural and anthropogenic forcings to advise governments and decision-makers, like in the latest assessment report of the Intergovernmental Panel on Climate Change (IPCC, 2021) based on coordinated multi-model simulations of the Coupled Model Intercomparison Projects (e.g. CMIP Phase 6, Eyring et al., 2016). However, surveys, user workshops and individual user meetings at Deutscher Wetterdienst (DWD) reveal that climate data users from different German user groups, like the society, economy, government policy or climate impact research, need further information on short to medium-term climate variability to implement appropriate operational management and adaptation activities. Such user needs were stated e.g. in the agriculture (Solaraju-Murali et al., 2021), water management (Paxian et al., 2022), energy (Ostermöller et al., 2021) or insurance sectors (C3S, 2022a). Information on climate variability for the coming weeks, months and years can be derived from climate predictions on the subseasonal, seasonal and decadal timescales, respectively. They close the gap between weather predictions for the next days and climate projections for the next tens of years, combining the initialization of various components of the climate system, like ocean (Matei et al., 2012) or land surface (Bellucci et al., 2015), with external forcings from aerosols and greenhouse gases (Van Oldenborgh et al., 2012). A few years ago the Global Framework for Climate Services highlighted the development of climate information for society in interaction with users to manage hazards, opportunities and adaptation activities concerning both long-term climate change and short-term climate variability (Hewitt et al., 2012).

In the international community, seasonal climate predictions based on coupled models such as System 1 of the European Centre of Medium-Range Weather Forecasts (ECMWF, 2022a) are operational since over 20 years, and climate services based on seasonal climate predictions are developed and disseminated: for example the Lead Centre for Long-range forecast multi-model ensemble (KMA, 2022) of the World Meteorological Organization (WMO) collects seasonal forecasts of different global producing centers (recently 14) for more than ten years. It offers deterministic and probabilistic multi-model prediction plots and issues regular Global Seasonal Climate Updates (Graham et al., 2011). The Copernicus Climate Change Service (C3S, 2022b) provides seasonal forecasts from eight prediction systems and sector-specific applications in its Sectoral Information System (Buontempo et al., 2020). It offers operational services for the water management (C3S, 2022c) and energy sectors (C3S, 2022d) applying seasonal forecasts.

For several years the ECMWF publishes subseasonal predictions of different variables twice a week on its website. The current version of these 'Extended forecast graphical products' can be found on ECMWF (2022b). Subseasonal and seasonal temperature and rainfall forecasts are issued operationally in the 'Climate and forecasts products' section of the International Research Institute for Climate and Society (IRI, 2022) and the 'Climate outlooks – weeks, months and seasons' section of the Australian Bureau of Meteorology (BOM, 2022). Applications of subseasonal forecasts were analyzed in 12 sectoral case studies, e.g. on health, agriculture or water management (White et al., 2021), and case studies on the subseasonal predictability of extreme events such as heatwaves, heavy precipitation and cyclones were performed (Domeisen et al., 2022) to plan preparedness and emergency measures.

Only a few years ago, one of the first websites on decadal predictions was developed in the MiKlip project (Hettrich et al., 2021), showing ensemble mean and probabilistic temperature predictions of the German decadal prediction system for Europe and the world. The WMO Lead Centre for Annual to Decadal Climate Predictions (Met Office, 2022) publishes forecasts from five global producing and 14 contributing centers and provides the Global Annual to Decadal Climate Update (Hermanson et al., 2022). A C3S demonstrator service presents prototype decadal climate prediction products (Dunstone et al., 2022) for the agriculture (Solaraju-Murali et al., 2021), energy (C3S, 2022e), insurance (C3S, 2022a) and infrastructure sectors (Paxian et al., 2022).

Two surveys of the MiKlip project on decadal predictions reveal the needs of German data users: mainly predictions of temperature and precipitation (but also wind, heat and droughts) for Germany and German regions accompanied by information on the ensemble spread and quality of the prediction. The usability of the MiKlip decadal predictions website (Hettrich et al., 2021) is limited because it is too complex for basic users and high resolution for Germany is missing. Generally, a climate service should be tailored to user requirements, e.g. providing different layers of complexity for different user groups, and delivered in data formats compatible with user working routines to guarantee its usability (Bruno Soares et al., 2018; Rössler et al., 2019). To set up a successful user-oriented climate service, users should be involved in the development process, and feedback should be regularly considered (Buontempo et al., 2018). Interacting with sector-specific intermediate users helps to bridge the gap between providers of climate predictions and different user groups (Buontempo et al., 2020). Additionally, the emerging possibilities to create climate services based on subseasonal, seasonal and decadal predictions enable the development of a seamless range of climate prediction products for the consistent planning of adaptation activities for the next weeks, months and years (Kushnir et al., 2019). The WMO expanded the original definition of 'seamless' describing predictions across different time scales (Palmer et al., 2008) to include different models, observations, space and time scales and Earth system components as well as requirements of users and decision-makers in a value cycle approach to enable a co-design of climate services (Ruti et al., 2020). According to our state of knowledge no such operational seamless climate prediction service exists until now although needed by different sectors, e.g. in Germany.

The objective of this manuscript is to present and describe the design of the DWD climate predictions website developed to cover the needs of different user groups in Germany: a user-oriented operational climate prediction product on subseasonal, seasonal and decadal timescales for Germany, German regions and cities, Europe and the world. The publication of subseasonal predictions for Europe and the world was in preparation at the time this paper was written. The website is not fully seamless because some boundaries cannot be overcome, i.e. the usage of different model systems and observations leading to separate products with different reference periods across time scales. However, it provides a 'one-stop-shopping' of prediction products of consistent evaluation and presentation across different time scales on a single platform. Two information layers are presented: the simple, spatially averaged basic climate predictions and the complex, gridded expert climate predictions. The predictions are displayed combined with the corresponding skill, e.g. via a skill traffic light. The website was developed in cooperation with intermediate and end users, and several feedback loops were considered. Thus, Section "Data and methods" of this article introduces the prediction models and observations used and the methods applied, like the statistical downscaling, bias correction and recalibration, calculation and kind of presentation of climate predictions and their skill and the process of user interaction. Section "Results" presents the resulting structure of the website, examples to show the display of the ensemble mean and probabilistic basic and expert climate predictions and their skill for different timescales and how user feedback helped to shape the products. Lastly, Section "Discussion" summarizes the design and development of the DWD climate predictions website and draws major conclusions motivating future activities in the outlook. Please note that the manuscript describes the current state of the website at the time of writing. Since it is an operational climate service, the structure or presentation of products might change in the future.

Data and methods

This section describes the global climate predictions at subseasonal, seasonal and decadal timescales and the high-resolution predictions statistically downscaled in Germany applied in the development of this website and the observations used to evaluate the prediction skill globally and in Germany. Furthermore, the methods used are presented: the bias correction and recalibration procedure, the temporal and spatial aggregation, the computation of ensemble mean and probabilistic predictions, the assessment of prediction skill, the display of prediction products and the process of user interaction to evaluate and shape the products.

Global subseasonal climate predictions

Since DWD does not operate an own subseasonal climate prediction system until now, the extended-range (monthly) forecasts of the ECMWF (2022c) are applied as global subseasonal climate predictions (week 2 to 5 after prediction start, see Section "Temporal and spatial aggregation"). The Integrated Forecasting system (IFS) CY47R3 (ECMWF, 2021, since 10/2021) employs a horizontal resolution of 36 km for days 15–46, extending the Ensemble forecasts (ENS) for days 1–14 at 18 km. It is coupled to the NEMO ocean model in the ORCA025 configuration, i.e. at approximately 0.25° horizontal resolution (ECMWF, 2021). In the atmosphere, ERA5 reanalyses (Hersbach et al., 2020) and the operational analysis with 4D-Var are applied for initializing hindcasts and real-time forecasts, respectively. In the ocean, data from the Ocean ReAnalysis System 5 (ORAS5, Zou et al., 2017) and the near-real-time component of the operational ocean analysis (NEMOVAR, Mogensen et al., 2012) are used. Ensemble members are generated by different initial conditions using the singular vector method (Leutbecher and Palmer, 2008), ensemble data assimilation (EDA, Buizza et al., 2008) and the Stochastically Perturbed Parametrization Tendency scheme (SPPT, Leutbecher et al., 2017). The real-time ENS/monthly forecasts include 51 ensemble members, started twice weekly every Monday and Thursday. The 11 hindcast members are initialized on the equivalent day and month in the hindcast period of the last 20 years, e.g. 2002–2021 for prediction start in 2022. The subseasonal predictions are available at ECMWF (2022d), depending on the data access rights.

Global seasonal climate predictions

Global seasonal predictions are taken from the German Climate Forecast System (GCFS, Fröhlich et al., 2020), currently Version 2.1 (DWD, 2022a). It uses the Max Planck Institute for Meteorology Earth System Model High Resolution (MPI-ESM-HR, Mauritsen et al., 2018; Müller et al., 2018) with a horizontal resolution of ~70 km at 50° N and 95 levels in the vertical in the atmosphere as well as 0.4° resolution and 40 levels in the ocean. The assimilation applies continuous nudging (Baehr et al., 2015) of ERA5 reanalyses (Hersbach et al., 2020) for hindcasts and near real-time ERA5T data for operational forecasts in the atmosphere as well as ORAS5 reanalyses (Zou et al., 2017) for ocean and sea ice. The ensemble generation uses bred vectors in all ocean levels (Baehr and Piontek, 2014) and a perturbation of the diffusion at the uppermost atmospheric level. Thirty hindcast ensemble members are started on the first day of all months in the hindcast period 1990–2019 for a simulation period of six months. Fifty forecast members are initialized from 2020 on. As both data sets are based on the same analysis systems, we use the first 30 forecast members of 2020 to extend the hindcast period to cover the full reference period of 1991–2020. External CMIP6 forcing uses historical data until 2014 and SSP245 (Shared Socioeconomic Pathways, Fricko et al., 2017) scenario data afterwards. Since DWD provides seasonal forecasts to C3S, the operational predictions are available at the C3S Climate Data Store (CDS; C3S, 2022f).

Global decadal climate predictions

The MPI-ESM Low Resolution Version 1.2 (MPI-ESM-LR, Mauritsen et al., 2018) is applied as global decadal prediction system. Forty levels in the vertical at ~1.5° horizontal resolution are considered in its oceanic component MPIOM and 47 levels at a ~200 km grid in its atmospheric component ECHAM6 (Jungclaus et al., 2013; Pohlmann et al., 2013; Stevens et al., 2013). The ocean is initialized applying an Ensemble Kalman filter (Brune et al., 2015) to assimilate observed anomalies of temperature and salinity from EN4 (Good et al., 2013). In the atmosphere, full-fields of ERA40 (Uppala et al., 2005) and ERA5 reanalyses (Hersbach et al., 2020) are nudged before 1978 and after, respectively. This concatenation of different reanalyses was chosen because the ERA40 driven spin-up run was more stable than the one using the ERA5-preliminary-backextension data before 1979 revealing a questionable quality of that particular dataset for nudging purposes. Ten-year long decadal predictions are started on 1 November annually in the hindcast period of 1960–2020 from this assimilation run. Predictions are started from 2021 on applying the same setup as the hindcasts. Sixteen ensemble members are initialized with various oceanic conditions resulting from different states of the Ensemble Kalman filter. Observations and the SSP245 scenario were applied as external CMIP6 forcing before 2015 and after, respectively. The decadal predictions are accessible from DWD's ESGF (Earth System Grid Federation, DWD-ESGF, 2022) node.

Statistical downscaling

To achieve a high spatial resolution in Germany the global predictions are downscaled by the empirical–statistical downscaling procedure EPISODES (Kreienkamp et al., 2018; Kreienkamp et al., 2020). Subseasonal, seasonal and decadal climate predictions at ~5 km resolution are computed for Germany. This output is used to construct prediction products for German cities (see Section "Temporal and spatial aggregation") on seasonal and decadal timescales and aggregated to a ~20 km resolution to provide prediction products for Germany on all timescales to be displayed on the DWD climate predictions website (DWD, 2022b). The procedure builds statistical relationships between large-scale NCEP/NCAR reanalyses (Kalnay et al., 1996) and small-scale HYRAS observations (Rauthe et al., 2013; Frick et al., 2014) in Germany which are transferred to global predictions.

First, a 'perfect prognosis' approach (Klein et al., 1959; San-Martín et al., 2017) is applied. For each predicted day of the model the 35 most similar reanalysis days (analogue days) are selected (for each prediction ensemble member separately). For this, geopotential height, relative humidity and temperature fields at various levels (1000, 850, 700, and 500 hPa) are interpolated to a 100 km grid, and from those additional fields are derived (e.g., vorticity). The values of two of those fields in a radius of two grid rows with respect to each target point (i.e. an area of 400 km × 400 km) are considered for the selection of the analogue days. Linear regressions between regional means of local observations of precipitation or temperature and large-scale states are constructed for the chosen 35 analogue days and transferred to the global prediction, resulting in a first prediction for each day. These interim results are independent for each variable and point on the reduced 100 km grid, so consistency in space and between variables is not ensured up to here. Second, for each predicted day, the pattern of the short-term variation of temperature and precipitation is compared to that of all observed days, and the most similar one is determined. For all output variables on the entire observational grid, the final high-resolution synthetic time series is constructed in adding the daily observed climatology of the day in year to be predicted and the short-term variability of the most similar observed day. This downscaling results in consistent multi-site and multi-variable datasets at the high resolution of the observational dataset (i.e. ~ 5 km). The downscaled subseasonal, seasonal and decadal predictions will be accessible via DWD's ESGF node (DWD-ESGF, 2022) in the coming months.

This downscaling procedure was originally generated to be applied to climate projections. It chooses the large-scale quantities with highest correlation to local quantities and offers high-resolution output data with clearly reduced systematic biases. In addition, all output variables are consistent in space which is essential for impact modelling. The downscaling does not select the large-scale quantities with largest prediction skill in comparison with observations. Hence, the skill of the global model is preserved at high resolution but not improved (Ostermöller et al., 2021). Bias correction and recalibration techniques addressing further (e.g. time-dependent) model errors are described in Section "Bias correction and recalibration".

Global observations

Observational data to evaluate global temperature predictions are taken from the ERA5 reanalyses (Hersbach et al., 2020). Based on the IFS Cy41r2, global hourly fields at a horizontal resolution of 31 km are provided from 1950 onwards. Improved model components and the hybrid incremental 4D-Var system (Bonavita et al., 2016) assimilating satellite data and in situ measurements from land stations, ships, buoys, radiosondes and aircraft reveal clear advances compared to former ECMWF reanalyses. The data is available from the CDS (C3S, 2022f).

For land-surface precipitation, global observations from the Full Data Monthly Product Version 2020 (Schneider et al., 2020a) of the Global Precipitation Climatology Centre (GPCC) at a 1° grid for 1891–2019 are used. This in situ reanalysis is the most accurate GPCC one and based on ~ 85,000 global stations. Recent months are taken from the near real-time GPCC Monitoring Product Version 2020 (Schneider et al., 2020b) interpolating stations of WMO's Global

Telecommunication System (GTS). For subseasonal predictions, daily precipitation of the GPCC Full Data Daily Version 2020 (Ziese et al., 2020) at a 1° global grid for 1982–2019 is applied, merging station records from different sources. Again, recent daily data are added from the GPCC First Guess Daily Product (Schamm et al., 2013) based on WMO GTS stations. Information on accessibility is given in the cited literature.

Precipitation observations over the global oceans are derived from the Global Precipitation Climatology Project (GPCP). Monthly fields at 2.5° resolution for 1979 until today are taken from the GPCP Climate Data Record (CDR) Version 2.3 (Adler et al., 2016), merging passive Microwave and infrared satellite estimates and in situ measurements. Daily fields from the GPCP Climate Data Record (CDR) Version 1.3 (Huffman et al., 2001, Adler et al., 2017) at 1° resolution for the period 1996 to today are applied to evaluate subseasonal predictions. The datasets can be accessed as described in the literature.

This combination of different precipitation products over land and ocean is done because the evaluation of decadal predictions needs to cover the long hindcast period 1961–2020. No global satellite product is available from 1961 on but station-based datasets are. Some tests using GPCC from 1961 to 1978 over land and GPCP from 1979 on globally revealed temporal inconsistencies due to changing datasets over land. Thus, GPCC is used from 1961 on over land and GPCP from 1979 on over the ocean (requiring a shorter evaluation period for the latter). The setting for decadal predictions was transferred to seasonal and subseasonal predictions to be comparable. However, one needs to be careful with GPCC data quality in regions of sparse observations, but this problem may be partly attenuated because global precipitation maps are shown at a coarse 5° grid aggregating more stations.

Observations for Germany

For Germany, precipitation predictions at high resolution are verified with HYRAS observations. The daily fields at 5 km grid for Germany and surrounding areas are calculated from nearly 6,200 station records. The combination of inverse distance weighting with a multiple linear regression considering orography can conserve the record values per grid box (Rauthe et al., 2013). Daily updates for Germany are available from 1951 onwards. Temperature observations from HYRAS provide daily fields for 1951–2015 at a 5 km grid. Operational updates are planned from 2023 on. 1,300 stations from Germany and neighboring regions are interpolated applying non-linear vertical profiles and inverse distance weighting and considering the effects of urban heat islands, distance to the sea and elevation (Razafimaharo et al., 2020). The HYRAS data are available on DWD's open data section on the Climate Data Center (CDC, 2022a).

We plan to use HYRAS temperature data as soon as they become operational in 2023. Until then, the operational monthly averaged daily 2 m air temperature grid over Germany available on DWD's CDC (2022b) is applied for seasonal and decadal predictions because it provides a longer time period from 1881 until today than HYRAS and has similar yearly means. The 1 km grid is calculated based on DWD station records (Kaspar et al., 2013), using more than 500 stations after 1951. The interpolation applies topographical height regression and inverse distance weighting (Müller-Westermeier, 1995) but local effects are not considered. Since subseasonal predictions need daily data, ERA5-Land reanalysis data (ECMWF, 2022e) are applied. They provide hourly data of surface variables from 1950 until few months before today. The ERA5 reanalysis is replayed over land at 9 km spatial resolution, using the Tiled ECMWF Scheme for Surface Exchanges over Land incorporating land surface hydrology (H-TESSEL) and IFS version CY45R1. Uncertainty of surface variables are provided from corresponding ERA5 fields at lower resolution (ECMWF, 2022f). ERA5-Land data is provided via the CDS (C3S, 2022f). Any possible inconsistency between ERA5-Land and HYRAS/CDC data (even if they are well correlated over time) will be corrected as soon as the operational HYRAS temperature data will be available in 2023.

Bias correction and recalibration

Since the empirical-statistical downscaling constructs synthetic time series based on high-resolution observations, the resulting time series reveal reduced climatological biases (Ostermöller et al., 2021). Furthermore, in computing anomalies of observations and models for different lead times separately over all start dates using the observed and the model's (lead-time dependent) climatology, respectively, the lead time dependent bias and thus, the model drift from its initial state to its climatology are adjusted (Goddard et al., 2013; Boer et al., 2016). This holds for subseasonal, seasonal and decadal predictions.

Additionally, the Decadal Forecast Recalibration Strategy (DeFoReSt, Pasternack et al., 2018) is applied to (yearly) decadal predictions of temperature and precipitation per grid box to address for lead and start time dependent conditional bias, drift and ensemble dispersion within a cross-validation setup which has proven to improve the skill. DeFoReSt is based on a parametric drift correction (Kruschke et al., 2015) with a third order polynomial along lead years (Gangstø et al., 2013) and a linear trend over start years (Kharin et al., 2012). A third and second order polynomial along lead years as well as a linear trend over start years are considered to adjust the conditional bias and the ensemble spread, respectively. In the development of this website, a more adaptive DeFoReSt version (Pasternack et al., 2021) is applied using an extra additive term for the ensemble spread adjustment to account for unconditional ensemble dispersion. Moreover, this adaptive version identifies the most relevant polynomial orders from the data directly, where the maximum order is derived by the original DeFoReSt version. To address large interannual variations, a third order polynomial over start years is used for ensemble mean correction of small-scale precipitation in Germany. The recalibrated output consists of yearly prediction data. The computation is based on the recalibration software (Pasternack et al, 2021) of the 'Free Evaluation System Framework for Earth System Modeling' (FREVA, Kadow et al., 2021). Its availability is described in these sources.

Both recalibration and skill assessment (see Section "Calculation of prediction skill") are computed on the full evaluation period from 1961 until 2020. Since long time periods are necessary to obtain robust results if recalibration and skill are variable in time and cross validation is applied following international guidelines, we did not split the evaluation period into two periods for recalibration and skill assessment. This is especially important when recalibration will be applied to subseasonal and seasonal predictions with even shorter evaluation periods in future (see outlook in Section "Conclusions and outlook").

Temporal and spatial aggregation

The DWD climate predictions website offers prediction products on different temporal and spatial scales. The temporal averaging and the spatial interpolation and aggregation are done equally for climate predictions and observations: subseasonal predictions of the next six weeks (starting on Monday) are averaged for different calendar weeks (Monday-Sunday): week 2 (day 8–14), week 3 (day 15–21), week 4 (day 22–28) and week 5 (day 29–35). The first week is not considered because it is almost over when the product is published after processing on Thursday, and the sixth week is omitted because of limited skill. Seasonal predictions are provided for running 3-month means of the coming six months: months 1–3, months 2–4, months 3–5 and months 4–6. Finally, decadal predictions of the next ten years are offered for the annual mean of year 1 and the five-year means of years 1–5, years 3–7 and years 6–10. Thus, four forecast periods are presented for each time scale.

Considering spatial scales, global prediction products cover the whole world at 5° resolution because the graphical representation of the prediction skill via the size of dots provides this resolution at global scale (see Section "Presentation of prediction and prediction skill"). Those for Europe are computed on a 1° grid for subseasonal and seasonal predictions and 2° grid for decadal products, corresponding to the original resolution of global decadal predictions. Please note that the publication of subseasonal predictions for Europe and the world was still in preparation at the time this article was written. Finally, the products of the statistical downscaling for Germany are displayed at ~20 km resolution, also for better graphical representation. Overall, regionally averaged prediction products consider the mean of all grid boxes within the selected region.

Within the 'e-shape' project (EuroGEO Showcases: Applications Powered by Europe; e-shape, 2022) as part of the EU Horizon 2020 programme, seasonal predictions for the German pilot city Aschaffenburg were developed, considering the mean of all EPISODES grid boxes at ~ 5 km resolution within the selected urban area. Since EPISODES output is based on original observations, this aggregation can be performed even if less than the common minimum of nine grid boxes is used. This approach was extended to cover the 16 capital cities of all German federal states and decadal predictions. However, this procedure was not yet implemented for subseasonal predictions because of high computing times within the limits of short operational time slots.

Calculation of ensemble mean and probabilistic climate predictions

Two prediction types are assessed for subseasonal, seasonal and decadal predictions: first, the ensemble mean prediction averages all ensemble members of the prediction model and computes the anomaly of this ensemble mean from the climatological average of the model hindcasts in a reference period. However, no information on the ensemble spread is given. In the development of this website, the WMO reference period 1991–2020 is applied for seasonal and decadal predictions, whereas the last 20 years are used for subseasonal predictions indicating the maximum hindcast length. To bridge this gap of different reference periods, we present all values of climatological means (and tercile thresholds) in basic climate predictions in addition to anomaly (and probabilistic) predictions which is very important to provide an appropriate product for different German users. We plan to evaluate with users if these different reference periods pose a challenge when comparing predictions across different timescales. If yes, we could use the observed offset between the climatologies of the last 20 years and 1991–2020 to also relate the anomalies of the subseasonal predictions to the WMO reference period 1991–2020 to allow one further step towards a seamless outlook.

Second, the probabilistic prediction is based on the distribution of the ensemble prediction. The climate characteristics of the hindcasts of the reference period (see above) are divided into the three categories of equal probabilities 'below normal', 'normal' and 'above normal', based on the 33rd and 66th percentiles (approximately terciles). For temperature, the categories are denoted as 'cold', 'normal' and 'warm' and for precipitation, they are indicated as 'dry', 'normal' and 'wet'. The tercile thresholds are applied to group the prediction ensemble members for the future in those three categories. The frequency of ensemble members in each category is used to estimate the predicted probability of occurrence (%) of each category. For small ensembles, the computation of probabilities based on frequencies is corrected to allow for small sample sizes and their uncertainties (Dirichlet-Multinomial Model; Agresti and Hitchcock, 2005). Thus, the corrected probabilities of a small sample N may deviate from the original frequencies 0/N, 1/N, …, N/N.

The computation of ensemble mean and probabilistic predictions is based on FREVA (Kadow et al., 2021) software routines. Information on accessibility is given in the cited article.

Calculation of prediction skill

To compute the skill of climate predictions the hindcasts started in the past are compared with observations in the evaluation period. Global observations (see Section "Global observations") are used for prediction products for Europe and the world, whereas high-resolution observations (see Section "Observations for Germany") are applied for those over Germany. The evaluation period is defined by the availability of hindcasts and observations: the last 20 years for subseasonal predictions (i.e. currently 2002–2021 for predictions started in 2022) and 1991–2020 for seasonal predictions (but 1992–2021 for forecast periods lasting into the next year). For decadal predictions, the time period 1961/ 1966–2020 is used for 1-/ 5-year means (to guarantee a common evaluation period for years 1–5, years 3–7 and years 6–10, when first start is end of 1960) and 1979/ 1984–2020 for precipitation over the ocean due to restricted availability of GPCP data.

The ensemble mean prediction skill is assessed by two different metrics: first, the Pearson correlation (see e.g. Ernste, 2011) describes the linear relationship of the ensemble mean prediction and the observational data over all start years in the past, applying anomalies compared to the long-term climatology of hindcasts and observations, respectively ('anomaly correlation'). A correlation coefficient of 1, 0 or −1 denotes a positive relationship, no correlation or a negative relationship between observations and predictions, respectively. It is characterized as a measure of association. Second, the Mean Squared Error Skill Score (MSESS, Murphy, 1988; Goddard et al., 2013; Kadow et al., 2016) relates the mean squared error $MSE_{P,O}$ of the climate prediction P_j compared to observations O_j along start years j to the mean squared error $MSE_{R,O}$ of a reference prediction R_j (see below) compared to observational data O_j:

$$MSESS_{P,R,O} = 1 - \frac{MSE_{P,O}}{MSE_{R,O}}, \text{with} MSE_{P,O} = \frac{1}{n}\sum\nolimits_{j=1}^{n}\left(P_j - O_j\right)^2 \tag{1}$$

The skill of the probabilistic prediction is evaluated via the Ranked Probability Skill Score (RPSS, Ferro et al., 2008; Wilks, 2011; Kruschke et al., 2014). Anomalies of climate predictions and observations compared to their respective long-term climatological value are divided into three categories ('above normal', 'normal' and 'below normal') separated by the 33rd and 66th percentile thresholds of their respective climate state within a reference period. The ranked probability score $RPS_{P,O}$ describes the squared error of the cumulative probability of the climate prediction $P_{j,k}$ compared to that of observations $O_{j,k}$ along K categories and n start years. The frequency of ensemble simulations in each category defines $P_{j,k}$. If the observed category is larger than k, $O_{j,k}$ is zero, otherwise one. The relationship between $RPS_{P,O}$ for the climate prediction and $RPS_{R,O}$ for a reference prediction defines the RPSS:

$$RPSS_{P,R,O} = 1 - \frac{RPS_{P,O}}{RPS_{R,O}}, \text{with} RPS_{P,O} = \frac{1}{n}\sum\nolimits_{j=1}^{n}\sum\nolimits_{k=1}^{K}\left(P_{j,k} - O_{j,k}\right)^2 \tag{2}$$

The MSESS and RPSS are larger than/ equal to/ smaller than zero if climate predictions show a higher/ similar/ lower agreement with the observed variability in the past than the reference prediction. A skill score of one defines perfect agreement because a perfect prediction reveals a MSE or RPS of zero. Skill scores are widely used to evaluate climate predictions (e.g. Goddard et al., 2013; Hermanson et al., 2022; WMO, 2021) but should be interpreted with caution because they may be impacted by observational uncertainty and biased in case of small samples (Wheatcroft, 2019). Please further note that the RPSS doesn't evaluate the skill per category but for all of them and may overestimate the skill of the 'normal' category because the outside categories usually have better skill.

The selection of reference predictions has been discussed with users at workshops and meetings to define those datasets commonly used as an alternative to climate predictions in Germany. Thus, a skill score helps users to decide if the 'new' climate prediction is better than, similar to or worse than what they used until now. For all climate predictions, we chose the long-term observed climate mean as reference prediction (denoting equal likelihoods for all categories for the RPSS). Additionally, uninitialized climate projections, i.e. an ensemble generated with the same model as the decadal climate predictions of this study but without initialization, are applied as reference prediction on the decadal timescale. Please note that a large part of the decadal temperature prediction skill against the reference prediction 'observed climatology' is due to the long-term climate trend which the constant climatology does not represent. Since the climate projections include this trend, the decadal prediction skill against climate projections describes rather the short-term impact of initialization. Both reference predictions have been used in several studies as baseline to evaluate decadal climate prediction skill (e.g. Goddard et al., 2013, Kadow et al., 2016, Kruschke et al., 2015, Paxian et al., 2019). We plan to evaluate with users in a survey if further reference predictions, e.g. extrapolated observed trends or persistence, would be appreciated. The concept of skill assessment using reference predictions is clearly communicated on the website, e.g. via a demonstrative video clip in German.

The significance of skill is tested for all metrics by means of jackknifing. Each year of the evaluation period is deleted once, and the corresponding skill is calculated for each sample. Skill is considered significant and not an artefact of random variations due to small samples if it is larger or smaller than zero with 95 % confidence, i.e. if less than 5% of the jackknife samples' skill is smaller or larger than zero. For decadal predictions, significance of skill is still tested via 500 non-parametric bootstraps, randomly selected with replacement. From the next publication phase in early 2023 on, the significance testing of decadal predictions will use jackknifing with five-year blocks considering autocorrelation. This is done because jackknifing shows less errors, e.g. for variables with a strong trend, and is more decisive, i.e. showing more green or red and less yellow traffic lights which is advantageous for user decisions, and quicker in an operational context than bootstrapping.

The metrics were computed based on the FREVA (Kadow et al., 2021) routines ProblEMS (PROBabiListic Ensemble verification for MiKlip using SpecsVerification; Richling et al., 2017, applying packages from Siegert, 2014) and MurCSS (Murphy-Epstein decomposition and Continuous Ranked Probability Skill Score; Illing et al., 2014). The cited articles describe how to access the original code.

Presentation of prediction and prediction skill

The DWD climate predictions website was developed based on user surveys, workshops and meetings to ensure that the developed products meet their needs: first, since user demands vary widely, it was not possible to design a perfect solution for all. Thus, a layered website was developed offering basic and expert climate predictions. The basic climate predictions are simple, regionally averaged and available for Germany, four German regions and 17 German cities. The expert climate predictions are complex, gridded and provided for Germany (at high spatial resolution), Europe and the world. The presentation of expert probabilistic maps is more complex than basic ones (including the probabilities of the most probable categories). and prediction skill maps are offered in addition. Second, many German users are interested in accessing the values behind the plots. Thus, in addition to maps for certain time intervals and time series for certain regions, value tables of predictions and corresponding climate means and tercile thresholds from observations are presented for the basic climate predictions of Germany, German regions and cities.

Finally, for more transparency, users appreciate to obtain the prediction together with its quality (or skill). A traffic light was developed showing a green, yellow or red light if the climate prediction is significantly better, not significantly different or significantly worse than the reference prediction, respectively. The MSESS evaluates the ensemble mean prediction, whereas the RPSS assesses the probabilistic prediction. For the basic climate predictions and the time series of the expert climate predictions, the traffic light accompanies all regionally averaged products. For the high-resolution maps of the expert climate predictions, one dot is displayed per model grid box: its color indicates the prediction, and its size denotes the skill, following the three categories of the traffic light defining large (green), medium-sized (yellow) and small dots (red). Note that this procedure does not display the 'absolute' measure of verification but the 'relative' skill score of the climate prediction compared to the alternatively used reference prediction to reveal its added value (see Section "Presentation of prediction and prediction skill"). The 'absolute' measure of association is indicated by the correlation coefficient which is presented additionally.

Process of user interaction

The DWD climate predictions website is based on the MiKlip decadal predictions website which was further developed following user needs. The process of user interaction began with a first survey gathering general user needs in terms of decadal climate predictions in 2016. The next survey was distributed in 2017 evaluating the understandability and usability (relevance) of the MiKlip decadal predictions website. Both surveys were already stated in the introduction section. The next survey was initiated shortly before the decadal predictions were published on the DWD climate predictions website beginning of 2020, again evaluating the understandability and usability of the predictions. The most recent survey was made available at the beginning of 2022 after the seasonal predictions were published on the DWD website. Since the subseasonal predictions were published in October 2022 the next survey is planned for the beginning of 2023. All surveys were made available online to users known from former workshops or interactions.

Furthermore, DWD hosts annual user workshops. From 2016 until 2020, the major focus was on decadal prediction. From 2021 on, the workshop addressed subseasonal, seasonal and decadal climate predictions as well as climate projections. Since the workshop includes several sessions for discussion or testing tools in small groups it was undertaken in person from 2016 until 2019, gathering 20–30 interested participants each year. Due to the Corona pandemic the workshop was conducted as online or hybrid events since 2020, reaching even more (100–120) participants. Finally, individual user meetings are conducted with selected users from different sectors asking for specific advice in terms of climate predictions. The meetings were undertaken in person or online depending on the state of the Corona pandemic.

The participants of surveys, workshops and meetings were mainly from public authorities but also from the private sector, international organizations or the research sector. DWD hosted many attendees working in the field of climatology, climate change adaptation or mitigation, hydrology or agriculture and some members of the forestry, insurance, energy, disaster risk reduction and health sectors. We mainly reached people with medium or high level of meteorological understanding but only some people with low background knowledge. Thus, we tried to address more intermediate users, like overarching associations for insurance or agriculture, which can translate the relevant climate information to 'their' end users.

The users reported on their daily working processes and their needs for climate predictions in terms of variables, time, space and uncertainties. The surveys included links to the website including necessary background information to understand the presented products. The workshops and individual meetings included introduction talks presenting the website to provide a basis for discussion. The results of this user interaction were adjusted for the background of the participants. The major results and their impacts on the further development of the website are documented in the DWD newsletters on decadal climate predictions (2016–2020) or climate predictions and projections (from 2020 on) published in German language twice a year (accessible via the DWD climate predictions website). In this manuscript, the results of this user interaction process are presented in Section "User feedback". Since the numbers of participants of surveys, workshops and meetings were strongly varying, we summarize the results comprehensively for the whole process instead of presenting them separately for each user consultation.

Results

In this section, the general structure of the DWD climate predictions website is briefly outlined. Then, the different prediction products of basic and expert climate predictions, i.e. ensemble mean and probabilistic predictions and prediction skill, are described and displayed with the help of example plots. Finally, user feedback on the understandability and usability of this website which helped to shape the products is presented.

General structure of the website

The DWD climate predictions website (DWD, 2022b) offers subseasonal, seasonal and decadal climate predictions for Germany, German regions and cities, Europe and the world. The publication of subseasonal predictions for Europe and the world was in preparation at the time this article was written. On the start page, one can choose between the simple basic climate predictions and the complex expert climate predictions. In both cases, the timescales can be selected on the second intermediate page. Additionally, the choice between predictions and skill is possible for expert climate predictions. Finally, the product page presents the climate prediction products as maps, time series or tables. The webpages offer links to current news, short frequently asked questions (FAQs) and detailed background information on climate predictions, models and skill, information on how to assess the different product graphics, data access and publications as well as a video clip explaining the concept of prediction skill and a feedback button.

Basic climate predictions

The basic climate predictions are focused on Germany, presenting predictions for whole Germany and four German regions (north, east, south, west). For seasonal and decadal timescales, predictions for 17 German cities (see Section "Temporal and spatial aggregation") are available in addition. The prediction skill is displayed as traffic light, showing a green, yellow or red light if the skill score of the climate prediction compared to the commonly alternatively used reference prediction 'observed climate mean' is significantly positive, not significant or significantly negative (see Section "Presentation of prediction and prediction skill"). For each product, a figure caption is given within the plot to improve its understandability, including a simplified description of the skill traffic lights for basic predictions ('relatively good, satisfactory or poor prediction quality', see Section "User feedback") and the dates of prediction start and plot generation (to control different plot versions). For decadal predictions, these updates will be added with the next release at the beginning of 2023.

Basic climate predictions: ensemble mean predictions

The ensemble mean predictions present the anomalies compared to the climatology in the reference period (see Section "Calculation of ensemble mean and probabilistic climate predictions") by means of maps, time series and tables.

First, four German maps are displayed for the four standard forecast periods of a certain timescale (see Section "Temporal and spatial aggregation"). Each map presents the color-coded ensemble mean prediction and the skill traffic light for four German regions (and 17 German cities for seasonal and decadal predictions if a city is selected). If a region or city is chosen, it is framed in the plot (and enlarged by a magnifier in case of a city) and the observed climate mean in the reference period is given. Calculating the anomaly of the model prediction with respect to the model climatology (as done here) and relating it to the observed climatology leads to an inherent bias correction. Fig. 1 shows an example of the seasonal prediction for temperature in Germany, initialized in December 2022, but focuses on the first and last standard forecast period leaving out the intermediate ones. A temperature anomaly of −0.5–1.0 °C is predicted for northern and eastern Germany in December-February 2022/23 compared to the reference period 1991–2020. Slightly lower anomalies of −0.2–0.5 °C are shown for the remaining regions. The skill score compared to the reference prediction 'observed climate mean' is positive in all German regions (green traffic light). For March-May 2023, the predicted anomaly is positive (0.5–1.0 °C) and the skill traffic light shows red indicating decreasing skill with increasing lead time.

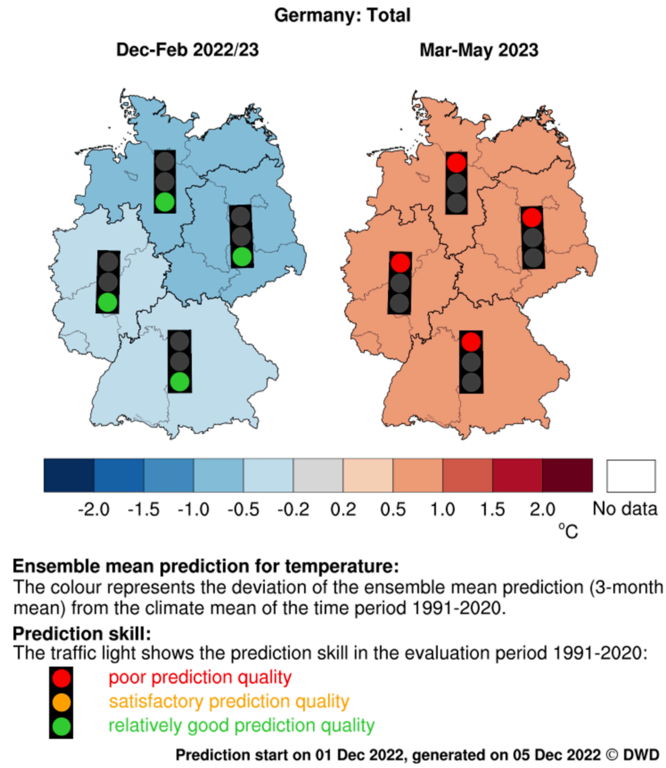

Fig. 1. Basic seasonal climate predictions: maps of ensemble mean predictions for temperature in Germany, started in December 2022. The intermediate forecast periods January-March and February-April 2023 are not shown here (published on www.dwd.de/climatepredictions).

Second, a time series displays the predictions for a selected German region or city as colored dots for the four standard forecast periods. The color of the dots follows the skill traffic light below the time series. Box and whisker plots present the minimum, the 25th, 50th and 75th percentiles and the maximum of the prediction ensemble, whereas the traffic light only evaluates the ensemble mean but not the spread. The ensemble spread is presented to explain to users that the ensemble mean prediction is accompanied by ensemble uncertainty, but that they should be cautious not to over-interpret the ensemble spread. Recalibration of subseasonal and seasonal predictions and verification measures of ensemble spread are still planned in future time (see outlook in Section "Conclusions and outlook"). The predictions can be compared to the minimum and maximum observations in the reference period illustrated by a grey band. The observed climate mean per forecast period is given on the y-axis. Fig. 2 shows the subseasonal prediction for temperature in western Germany, started on 21 November 2022. The ensemble mean prediction for the last week of November (week 2 after prediction start) is positive changing to a slightly positive anomaly in the next week and further approximating the zero-anomaly line in the last two weeks. However, the ensemble spread is large and includes both positive and negative anomalies, sometimes even exceeding the range between observed minima and maxima. The skill traffic light shows green for the first two weeks and yellow for the last ones.

Finally, the table gives the values of predictions and observed climate means and the skill traffic lights for the selected German region or city and the four standard forecast periods. The minimum and

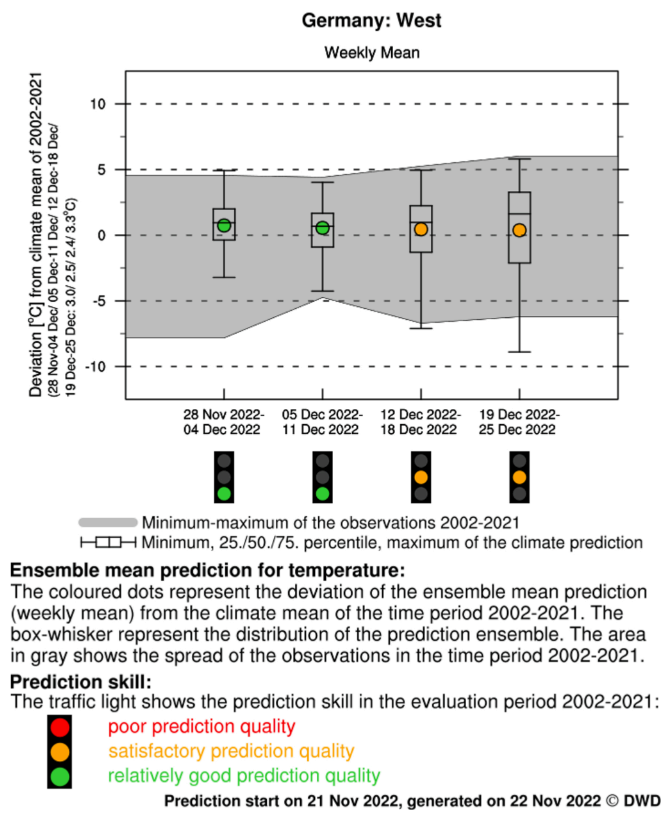

Fig. 2. Basic subseasonal climate predictions: time series of ensemble mean predictions for temperature in western Germany, started on 21 November 2022 (published on www.dwd.de/climatepredictions).

maximum values of the ensemble are added in brackets. Since the traffic lights are based on the MSESS they reflect the performance on amplitude of the ensemble mean anomalies but they don't evaluate the spread of the ensemble. Fig. 3 displays the decadal prediction for precipitation in

Germany: North Ensemble Mean Prediction in Comparison to the Climate Mean of the Time Period 1991-2020		
Time Period	Climate Mean	Climate Prediction
2022	731 l/m²	-81 l/m² (-264 l/m² – +90 l/m²)
2022-2026	738 l/m²	-95 l/m² (-181 l/m² – +17 l/m²)
2024-2028	738 l/m²	-89 l/m² (-190 l/m² – +12 l/m²)
2027-2031	738 l/m²	-60 l/m² (-150 l/m² – +36 l/m²)

Ensemble mean prediction for precipitation:
The table represents the deviation of the ensemble mean prediction (mean yearly sum) from the climate mean of the time period 1991-2020. Maximum and minimum of the ensemble are given in brackets.

Prediction skill:
The traffic light shows the prediction skill in the evaluation period 1966-2020:

significantly worse than the observed climate mean
comparable to the observed climate mean
significantly better than the observed climate mean

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Fig. 3. Basic decadal climate predictions: table of ensemble mean predictions for precipitation in northern Germany, started in November 2021 (published on www.dwd.de/climatepredictions).

northern Germany, initialized end of 2021. For all forecast periods, negative anomalies of the ensemble mean compared to the long-term climate mean are forecast, but the ensemble spread does also include small positive anomalies. The observed climate means of the reference period 1991–2020 are 731 l/m^2 for 1-year means and 738 l/m^2 for 5-year means. This small difference results from the fact that only those 1- or 5-year means lying completely within the reference period are considered. The skill traffic light is green for the second and third period and yellow for the others.

Basic climate predictions: probabilistic predictions

The probabilistic predictions display the probabilities of occurrence [%] of below normal, normal and above normal conditions based on the 33rd and 66th percentiles of the climate characteristics in the reference period (see Section "Calculation of ensemble mean and probabilistic climate predictions") applying maps, time series and tables.

The maps of probabilistic predictions are similarly structured to those of ensemble mean predictions, but the color-coded probabilistic prediction shows the most probable of the three categories and the 33rd and 66th percentiles of observations in the reference period are given defining the boundaries of the 'normal' category. If the 'below normal' and 'normal' categories or the 'above normal' and 'normal' ones or all three categories are all predicted with the highest probability, the category 'normal' is shown, leading to a 'less extreme' prediction. The result 'no data' is presented for missing values and if the 'below normal' and 'above normal' categories are both predicted with the highest probability, indicating an uncertain prediction voting equally for two opposed conditions. This approach to present probabilistic maps is clearly communicated in the 'Help to assess the graphics' section on the website, and the probabilities of all three categories are available in corresponding time series and tables. However, this approach will be part of the next survey to evaluate with users if an additional category 'equal chance' (e.g. if all categories are below 40%) or a label 'no data or no signal' (for missing values or predictions with highest probabilities of above and below normal conditions) would be clearer. The seasonal prediction for precipitation in the city of Hamburg, started in December 2022, is shown in Fig. 4. Again, only the first and last forecast periods are presented. The magnifier enlarges the predictions of 'dry conditions' in Hamburg and reveals green and red traffic lights for the first and last forecast period, respectively. The observed normal category is 168–229 l/m^2 for December-February and 139–170 l/m^2 for March-May in 1991–2020. Please note that predictions for cities may differ from their surrounding region because smaller areas are considered.

Additionally, a time series of bar charts displays the probabilistic predictions for a selected German region or city for the four standard forecast periods. Each bar chart shows the probabilities of occurrence [%] for all three categories 'below normal', 'normal' and 'above normal' for a certain period. The skill traffic lights are shown below the time series. The boundaries of the observed 'normal' categories are stated in the figure caption. Fig. 5 displays the subseasonal prediction for temperature in Germany, initialized on the 28 November 2022. For the first two weeks of December, cold conditions are predicted by most ensemble members. For the third week, all three categories are the most probable ones, resulting in a less extreme 'normal' prediction in the map (not shown). Most members vote for warm conditions in the fourth week. The traffic lights of the first three weeks show green and that of the last one reveals yellow.

Lastly, a table displays the numbers of the probabilities of occurrence [%] for all three categories, the observed boundaries of the 'normal' categories and the skill traffic lights for the chosen German region or city and the four standard forecast periods. The decadal prediction for temperature in the city of Magdeburg in eastern Germany, initialized end of 2021, is presented in Fig. 6. For 2022, ~78 % of the ensemble members vote for warm conditions, ~14 % for normal ones and ~8 % for a cold state. For 5-year means, the probability of high temperatures is even larger (~90–96 %). Note that the probabilities are corrected to

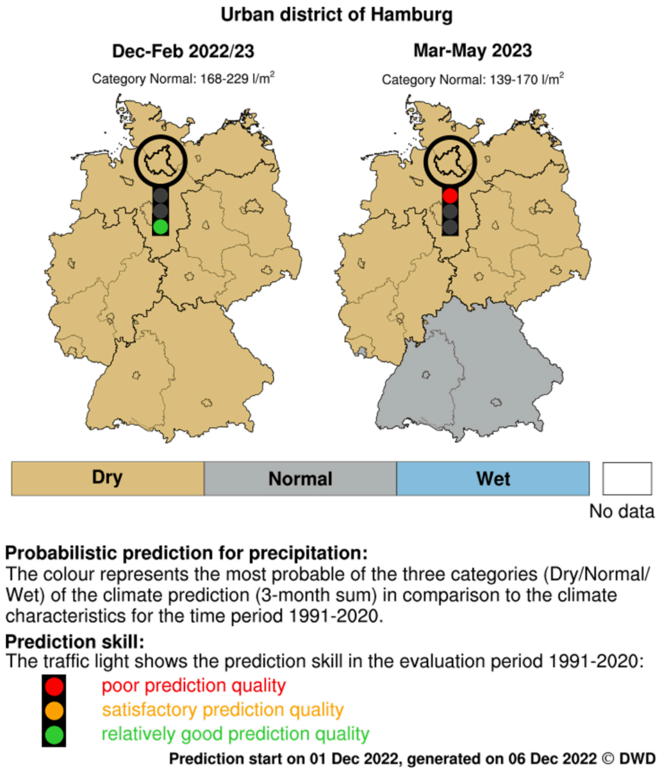


Fig. 4. Basic seasonal climate predictions: maps of probabilistic predictions for precipitation in the city of Hamburg, started in December 2022. The intermediate forecast periods January-March and February-April 2023 are not shown here (published on www.dwd.de/climatepredictions).

allow for small samples (here N = 16, see section "Calculation of ensemble mean and probabilistic climate predictions") and may deviate from the original frequencies 0/16, 1/16, …, 16/16. Green traffic lights are presented for all periods, evaluating the RPSS of the prediction. Further verification via reliability diagrams is planned in the near future (see outlook in section "Conclusions and outlook").

Expert climate predictions

The expert climate predictions present complex, gridded prediction products for Germany, Europe and the world at resolutions of ~20 km, 1–2° and 5°, respectively. The comparison of results for Germany and Europe enable to contrast predictions and prediction skill of the statistical downscaling with those of the global model on all time scales. Predictions are shown as maps and regionally averaged time series. Prediction skill is displayed as maps. The alternative reference prediction is the 'observed climate mean', but for longer-term decadal predictions the 'uninitialized climate projections' can also be selected. Again, a figure caption is added within each plot, including a detailed description of the skill traffic light ('significantly better than/ comparable to/ significantly worse than the chosen reference prediction') and the dates of prediction start and plot generation. For decadal predictions, these dates will be added beginning of 2023.

Expert climate predictions: ensemble mean and probabilistic predictions

The maps of the expert ensemble mean and probabilistic predictions are similar to the basic ones but per model grid box. The size of the dots per grid box indicates the skill (see Section "Presentation of prediction and prediction skill"). In addition to showing the color of the most probable category of the probabilistic predictions, the predicted probability of occurrence [%] of this category is displayed by the corresponding color scale to add more information to this expert level.

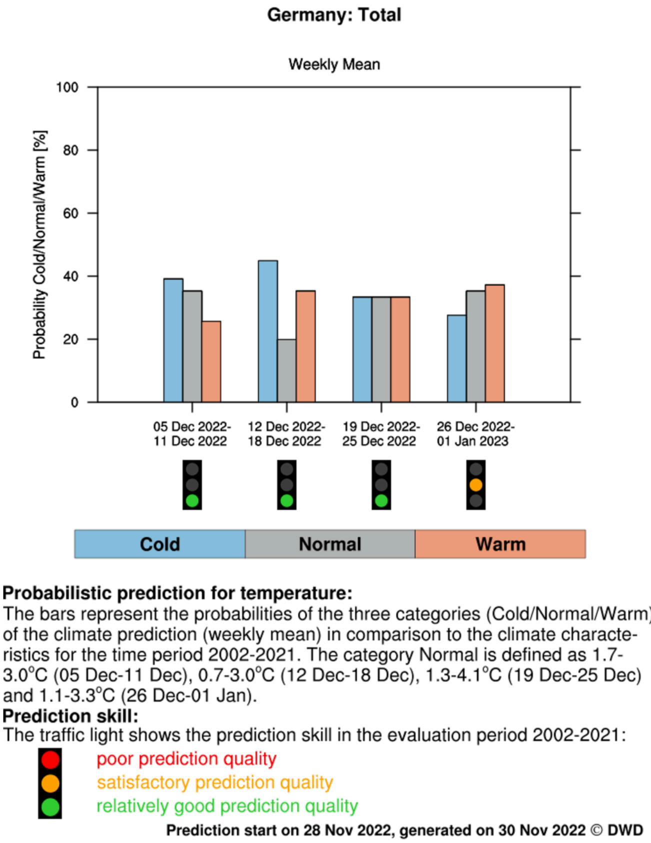
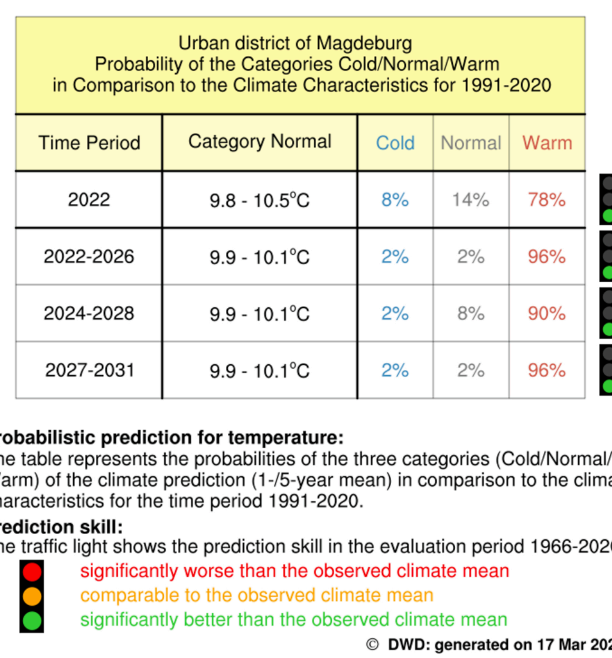


Fig. 5. Basic subseasonal climate predictions: time series of probabilistic predictions for temperature in Germany, started on 28 November 2022 (published on www.dwd.de/climatepredictions).



Urban district of Magdeburg
Probability of the Categories Cold/Normal/Warm
in Comparison to the Climate Characteristics for 1991-2020

Time Period	Category Normal	Cold	Normal	Warm
2022	9.8 - 10.5°C	8%	14%	78%
2022-2026	9.9 - 10.1°C	2%	2%	96%
2024-2028	9.9 - 10.1°C	2%	8%	90%
2027-2031	9.9 - 10.1°C	2%	2%	96%

Probabilistic prediction for temperature:
The table represents the probabilities of the three categories (Cold/Normal/Warm) of the climate prediction (1-/5-year mean) in comparison to the climate characteristics for the time period 1991-2020.
Prediction skill:
The traffic light shows the prediction skill in the evaluation period 1966-2020:
significantly worse than the observed climate mean
comparable to the observed climate mean
significantly better than the observed climate mean
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Fig. 6. Basic decadal climate predictions: table of probabilistic predictions for temperature in the city of Magdeburg in eastern Germany, started in November 2021 (published on www.dwd.de/climatepredictions).

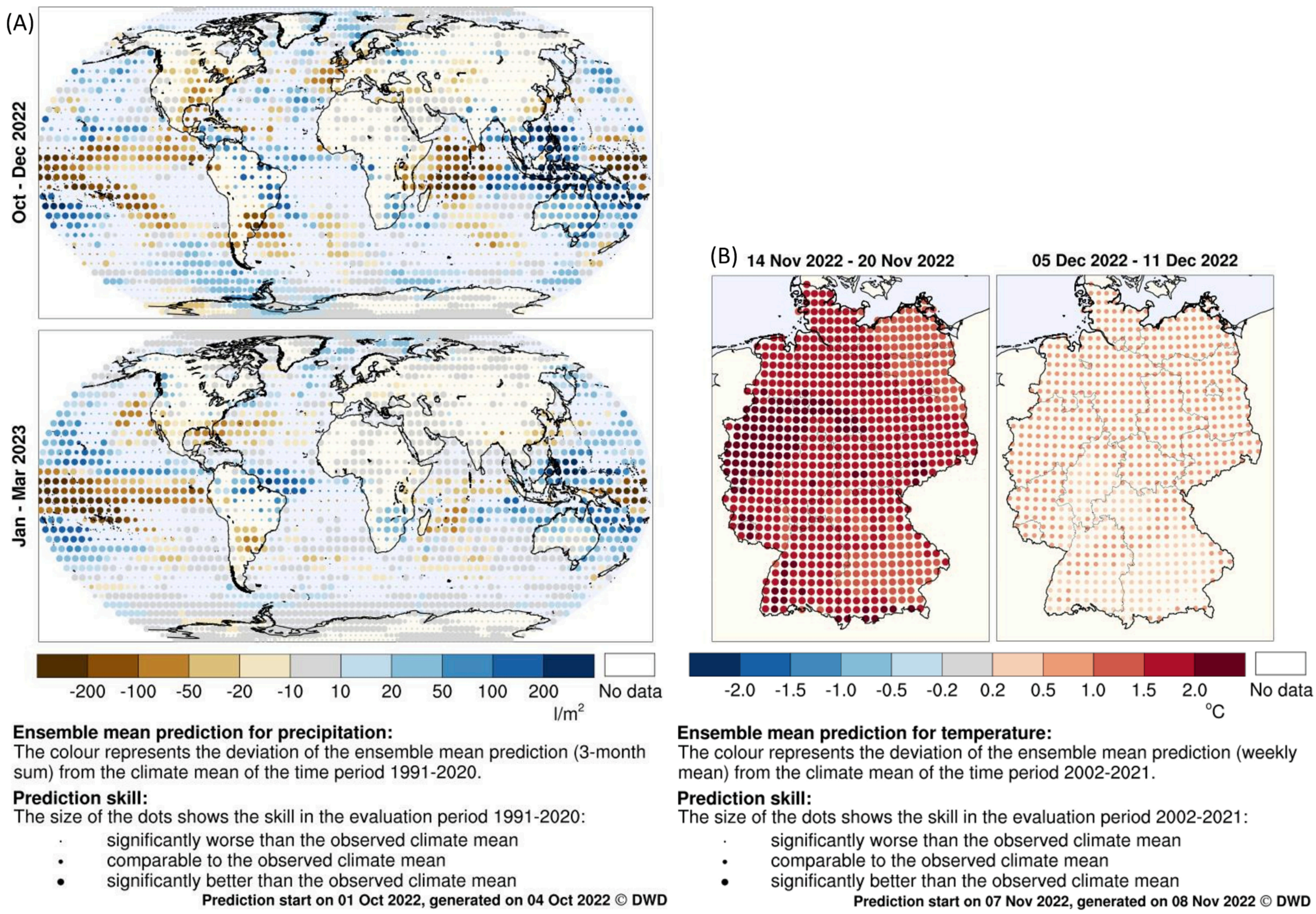

Fig. 7. Expert seasonal and subseasonal climate predictions: maps of ensemble mean predictions for global precipitation, started in October 2022 (A) and for temperature in Germany, started on 7 November 2022 (B). For all predictions, only the first and last forecast periods are shown here (published on www.dwd.de/climatepredictions).

Fig. 7(A) presents the first and last forecast periods of the seasonal ensemble mean prediction for global precipitation, initialized in October 2022, as an example. For October-December 2022, higher precipitation is forecast in Indonesia, Brazil and Australia, whereas lower precipitation is predicted in the central and eastern Pacific Ocean, the eastern United States, Argentina and the tropical Indian Ocean. In these regions the seasonal predictions reveal positive skill scores compared to the reference prediction ‘observed climate mean’ (denoted as large dots). Negative skill scores are found e.g. in parts of Asia (small dots). For January–March 2023, anomalies are stronger in the central Pacific and weaker in the eastern United States, the Indian Ocean, Indonesia and Australia. Fig. 7(B) shows the subseasonal ensemble mean prediction for temperature in Germany, started on 7 November 2022. For 14–20 November 2022, very high temperatures are predicted for western and south-western Germany exceeding the $+2.0$ °C anomaly and revealing positive skill scores compared to the reference prediction. The remainder of Germany presents less high but also positive anomalies. During 05–11 December 2022, skill scores are generally less positive and significant, showing negative skill scores compared to the reference prediction in some southern-eastern grid boxes.

The decadal probabilistic prediction for temperature in Europe, started end of 2021, is displayed in Fig. 8 for the first and last forecast periods. For 2022, the most probable category in most of Europe is the warm one. The probability of occurrence is highest (larger than 8 %) in Italy. In southern Scandinavia, the normal category is the most probable one. For 2027–2031, the probability of the warm category is larger than 85 % almost everywhere, indicating that small-scale variations of 1-year means are reduced and the climate trend is more obvious in 5-year means. Please note that probabilities of decadal predictions are recalibrated for reliability, but those of subseasonal and seasonal predictions are not yet recalibrated. This is planned to be done in near future (see outlook in Section “Conclusions and outlook”). The skill scores of the decadal predictions compared to the observed climate mean are positive in most of Europe (Fig. 8(A)), because the prediction model represents the observed climate trend which the constant climatological value does not. Comparing initialized decadal predictions with uninitialized climate projections (Fig. 8(B)) reveals the impact of initialization because both capture the climate trend. The added value of initialization is small in 2027–2031 (mainly prominent in parts of eastern Europe) but significant in the United Kingdom, southern Scandinavia and north-eastern Europe in 2022 (indicated by large dots), highlighting its prominent impact on shorter timescales. Recent studies show that long-term trends might have impacts even on subseasonal prediction skill, especially in the tropics (Wulff et al., 2022). Thus, considering uninitialized climate projections or an extrapolation of observed trends as reference predictions might also be relevant for subseasonal or seasonal predictions to investigate if prediction skill stems from long-term trends.

In addition to these maps, the expert climate predictions include regionally averaged time series of ensemble mean and probabilistic predictions for Germany, Europe and the world. Since these expert time series are displayed in exactly the same way as the basic time series no additional figures are shown here to illustrate them.

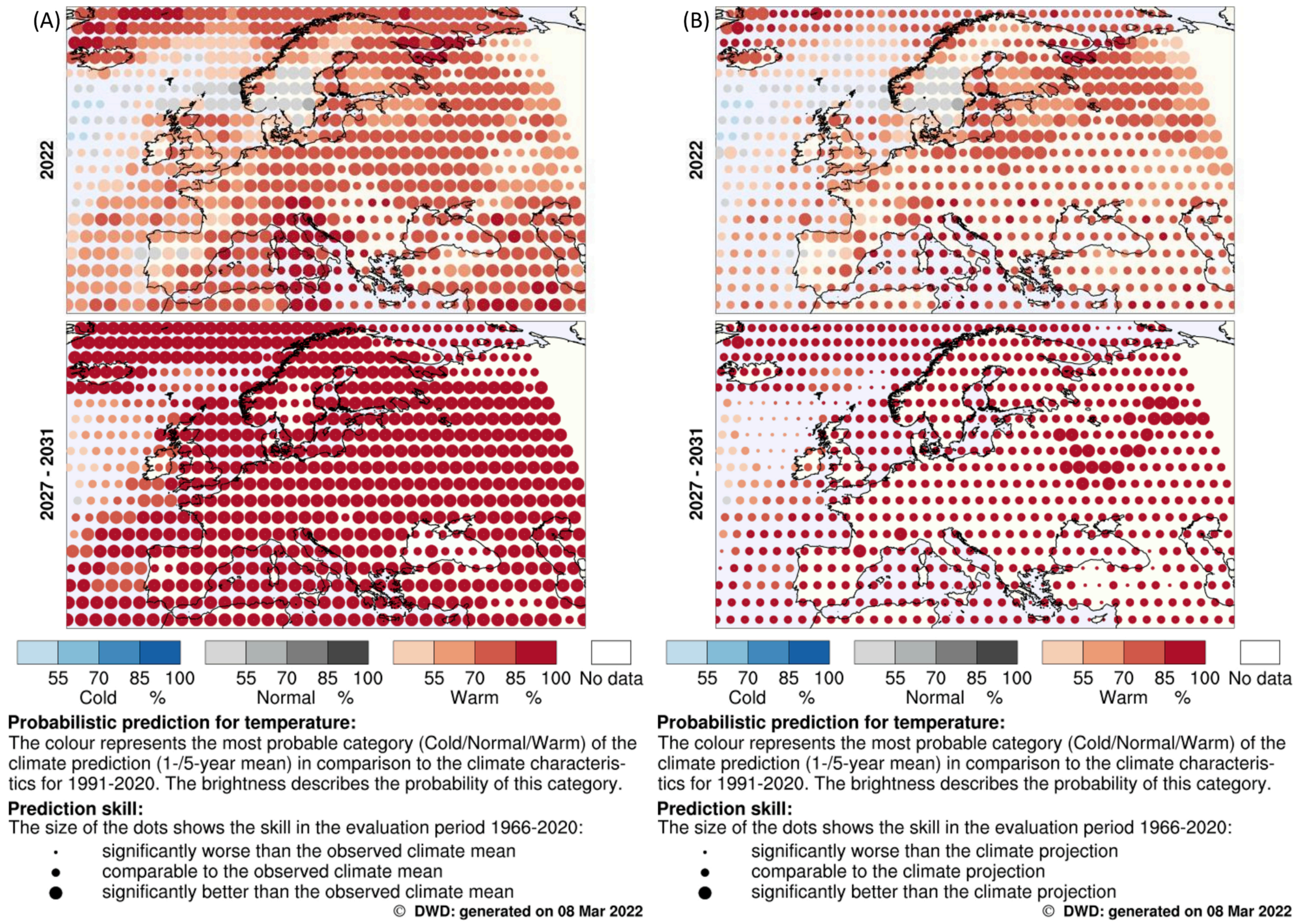

Fig. 8. Expert decadal climate predictions: maps of probabilistic predictions for temperature in Europe, started in November 2021, considering the reference predictions 'observed climate mean' (A) and 'climate projection' (B). For all predictions, only the first and last forecast periods are shown here (published on www.dwd.de/climatepredictions).

Expert climate predictions: ensemble mean and probabilistic prediction skill

Similar to the expert climate predictions, four skill maps are presented for the standard forecast periods of a timescale (see Section "Temporal and spatial aggregation"). The MSESS and RPSS present the skill scores per grid box defining the sizes of the dots in the expert ensemble mean and probabilistic predictions, respectively. The color scale identifies if climate predictions reveal positive (green) or negative (purple) skill scores compared to the reference prediction. To evaluate the 'absolute' measure of association of climate predictions the correlation coefficients between model and observations are displayed additionally, revealing positive (green) or negative correlations (purple). Statistically significant values are marked by black dots. Please note that the skill has been computed based on the verification of retrospective predictions with observations (see Section "Calculation of prediction skill") in the evaluation period (denoted in the figure caption within the plots) and used to assess the quality of the prediction of the future state of a certain time period (specified left of or above the plot).

Fig. 9 presents different skill scores and the correlation coefficients characterizing the predictions shown in Figs. 7 and 8 for the first forecast period. The MSESS of the seasonal ensemble mean prediction for global precipitation of Fig. 7(A) is displayed in Fig. 9(A). Significantly positive skill scores are found e.g. in the tropical Pacific and Indian Oceans, Indonesia and Australia, indicated by large dots in Fig. 7(A). On the contrary, significantly negative skill scores are prominent in the tropical Atlantic Ocean, Canada and central and northern Asia, denoting a lack of skill and relating to small dots in Fig. 7(A). Fig. 9(B) shows the correlation coefficients of the subseasonal prediction for temperature in Germany (Fig. 7(B)). Significantly positive correlations (higher than 0.6) are found for southern Germany, whereas lower correlations (0.4–0.6) are stated for northern Germany. The correlation coefficients are presented in addition to the MSESS but they are not applied to define the dot sizes of the predictions. Finally, the RPSS of the decadal probabilistic prediction for temperature in Europe considering the reference predictions 'observed climate mean' (Fig. 8(A)) and 'climate projections' (Fig. 8(B)) are displayed in Fig. 9(C) and (D). Compared to the observed climate mean significantly positive skill scores are found in large parts of Europe with maxima in south-western areas and Iceland. The RPSS is also significantly positive in western, northern and north-eastern regions when decadal predictions are contrasted with climate projections, but skill scores are lower and significance is not achieved in southern and eastern regions. Again, the RPSS is related to the dot sizes of the probabilistic predictions in Fig. 8.

User feedback

This section summarizes the user feedback on understandability and usability (relevance) of the DWD climate predictions website from all surveys, workshops and individual meetings and its impacts on the further development of the website. In general, users are very interested in climate predictions, and the website is in large parts understandable by most users. They realize the potential of climate predictions to be applied in operational decision making and longer-term planning.

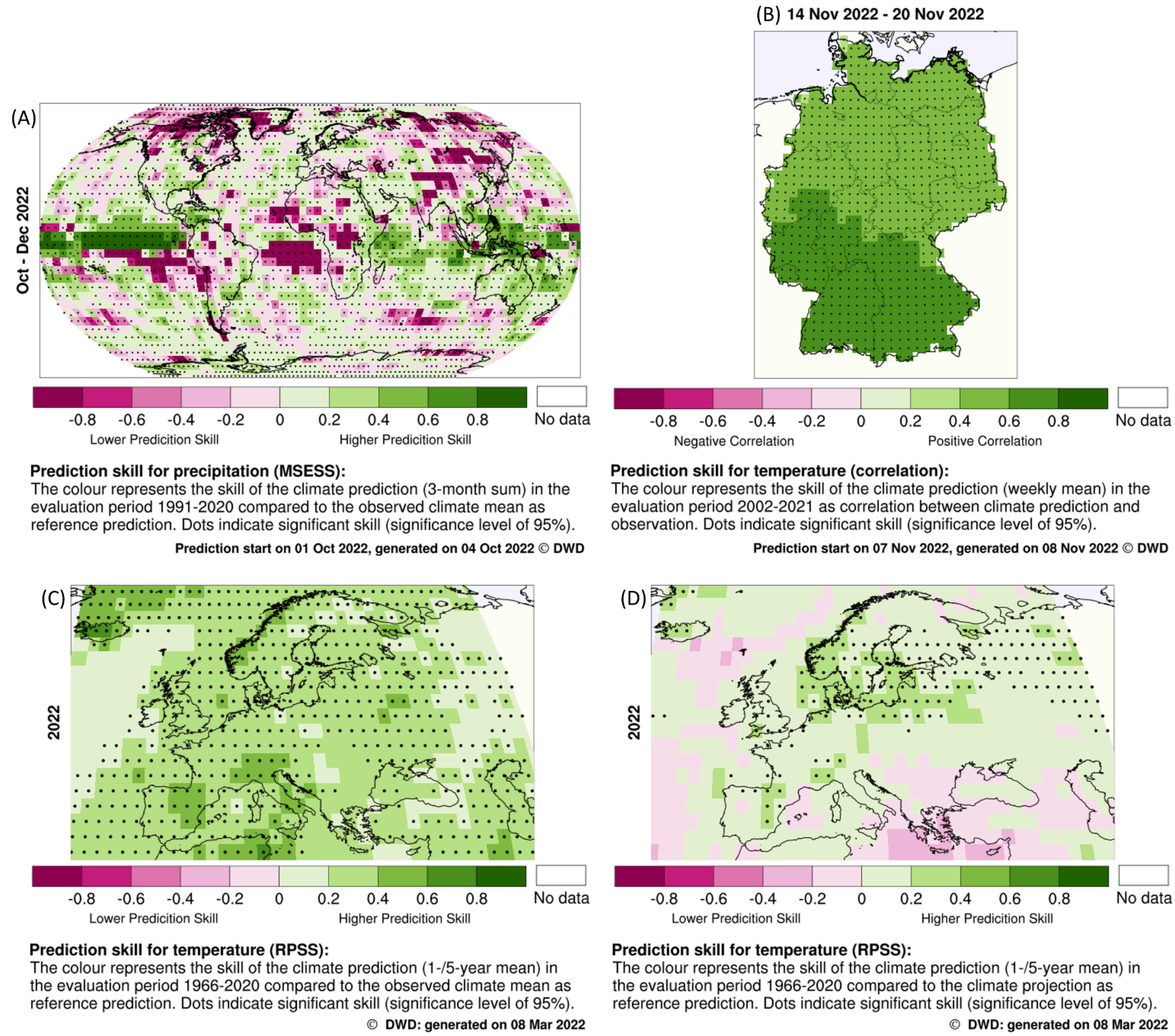

Fig. 9. Expert seasonal, subseasonal and decadal climate prediction skill: maps of MSESS for global precipitation, started in October 2022 (A), correlation coefficients for temperature in Germany, started on 7 November 2022 (B), and RPSS for temperature in Europe, started in November 2021, considering the reference predictions 'observed climate mean' (C) and 'climate projection' (D). For all skill scores and the correlation coefficients, only the first forecast period is shown here (published on www.dwd.de/climatepredictions).

Climate predictions can already be used in some working routines but there is still room for improvement.

We received positive feedback on the consistent presentation of products for subseasonal, seasonal and decadal climate predictions. The forestry sector suggested to include also multi-annual seasonal means, like 5-year summer or winter means. The focus on Germany as well as German regions and cities at high resolution was needed by many public authorities and impact modelers and could be realized, especially because EPISODES can preserve the prediction skill at high resolution. Temperature and precipitation are needed by most users, but additional user-oriented variables and indices are relevant, like wind (e.g. for the energy sector, Ostermöller et al., 2021) and extreme events such as droughts (e.g. for the water sector, Paxian et al., 2022), heat waves (e.g. for the agriculture sector, Solaraju-Murali et al., 2021) or storms (e.g. for the insurance sector, C3S, 2022a).

Most users appreciate both prediction types: ensemble mean and probabilistic predictions. However, some less experienced users have difficulties in understanding the expert probabilistic prediction map. Applying probabilistic predictions in their working routines might be challenging. We noticed that individual advice on workshops and meetings was very helpful for understanding and concluded that complex issues should be presented by demonstrative video clips and short FAQs in addition to existing detailed background information texts (see below). In this context less experienced users appreciate that the basic climate predictions are simpler and more understandable than the expert climate predictions.

Furthermore, information on uncertainty such as ensemble spread and prediction skill are very important. Most users understand the concept of skill scores of climate predictions compared to reference predictions including the fact that even a climate prediction with high average skill might be worse than the reference prediction sometimes. They appreciate the detailed background information on the website. Again, some less experienced users struggle with this concept or don't know how to cope with predictions of slightly positive or not significant skill in their working routines. Thus, the description of the skill traffic lights was simplified for the basic subseasonal and seasonal climate predictions, now reading 'relatively good, satisfactory or poor prediction quality'. The update for basic decadal predictions will be beginning of 2023. We added short FAQs and a video clip explaining the concept of prediction skill which is very much appreciated. Further user feedback on the skill concept is controversial and still under discussion: some users suggest not to show basic climate predictions with red skill traffic lights and to show the values of the reference predictions in addition. 'Absolute' measures of verification such as the correlation could be more highlighted, but the definition of thresholds between green, yellow and red traffic lights might be subjective since users would suggest different thresholds for their applications. Others agree with the concept of 'relative' skill scores to describe the best of all available products and to have a simple and clear definition of the skill traffic lights because they used the observed climatology and climate projections before climate predictions were published and the correlation is offered as additional information on the website. Another suggestion was to add new reference predictions, e.g. the extrapolation of observed trends.

Concerning the display of the prediction products, users suggested maps, time series and tables with background information text. DWD realized all those different formats, and tables of predicted values achieved highest scores in understandability and usability. Plots can be used for a qualitative assessment but numerical data offered via a data platform are needed for impact modelling as well.

Discussion

This section summarizes the design and development of the DWD climate predictions website described in this manuscript, draws key conclusions from the user feedback on understandability and usability of climate prediction products and presents an outlook for upcoming activities.

Summary

In this article, we presented the development of the DWD climate predictions website (DWD, 2022b) designed to cover the needs of government policy, economy and society in Germany for robust information on climate variability of the next weeks, months and years: a user-oriented climate prediction service offering consistent operational products at subseasonal, seasonal and decadal timescales. Since the website uses different models, observations and separate products across time scales, it is not fully seamless but provides a 'one-stop-shopping' outlook on a single platform. Global predictions from ECMWF and DWD are applied and statistically downscaled for Germany. The predictions are illustrated on two information layers to address different user groups: the simple basic climate predictions and the complex expert climate predictions. Two prediction types are presented: ensemble mean predictions describe anomalies compared to the climatology in a reference period. Probabilistic predictions depict the probability of occurrence [%] of three categories ('below normal', 'normal', 'above normal'), separated by the 33rd and 66th percentiles of the climate characteristics in the reference period. For each timescale, climate predictions are assessed for four forecast periods: week 2, 3, 4 and 5 for subseasonal predictions, months 1–3, 2–4, 3–5 and 4–6 for seasonal predictions and years 1, 1–5, 3–7 and 6–10 for decadal predictions.

The basic climate predictions display area-aggregated predictions for Germany, German regions and cities as maps, time series and value tables. Traffic lights show the prediction skill: green, yellow or red lights indicate that the climate predictions are significantly better, equal or worse in reproducing the observed variability than the alternatively applied reference prediction 'observed climate mean'. In addition to ensemble mean and probabilistic predictions the observed climate means and the observed tercile thresholds of the 'normal' category in the reference period are displayed.

The expert climate predictions display gridded predictions for Germany (at high spatial resolution), Europe and the world as maps and time series. The publication of subseasonal predictions for Europe and the world was in preparation at the time this manuscript was written. The color of each dot denotes the prediction and the size defines the skill: large, medium and small dots indicate green, yellow and red traffic lights. In addition to the reference prediction 'observed climate mean', the uninitialized 'climate projection' can be chosen for decadal predictions. The expert prediction skill maps present the MSESS and RPSS indicating the dot sizes of the ensemble mean and probabilistic predictions, respectively. The 'absolute' measure of association is evaluated additionally by correlations between model and observations. Significance of skill is assessed at a 95 % level.

The website was developed in close cooperation with users. Several feedback loops of surveys, workshops and individual meetings were conducted and evaluated. Most users understand the products of the website and realize the potential of future applications based on operational climate predictions. Thus, additional variables and numerical data for impact modelling are needed. However, some users state that understanding the prediction skill and applying probabilistic predictions in their working routines is challenging, revealing the need for more advice, e.g. via demonstrative video clips.

Conclusions and outlook

Based on the user feedback several conclusions can be drawn which motivate further activities to enhance the quality, understandability and usability of climate prediction products across different time scales:

First, the DWD climate predictions website presents predictions together with their skill to show the model's quality to predict the future climate development. Skill is found on all timescales, even for high resolution in Germany. However, the skill depends on the variable, region, time period and timescale and thus, on the user-specific application. To enhance the usefulness of climate predictions, the skill needs to be further improved, e.g. by applying larger multi-model ensembles increasing decadal prediction skill compared to single model output (Scaife and Smith, 2018). Analyses of multi-model ensembles are planned for seasonal and decadal predictions soon (if all input data for statistical downscaling are available). Multi-model subseasonal predictions are considered lastly because they are not yet completely harmonized. Besides, teleconnections between large-scale input and small-scale target variables can improve skill, e.g. for North Atlantic hurricanes (C3S, 2022a), but relationships need to be defined for each region and time period separately. The statistical downscaling could be enhanced preferring large-scale input variables with positive skill. In EPISODES this was not yet considered because the method was originally developed for climate projections (Kreienkamp et al., 2018), for which skill is not relevant. Furthermore, based on observed teleconnections, a prediction of the North Atlantic Oscillation (NAO) can be set up for the next months. Considering only those seasonal ensemble members close to the predicted NAO (called 'subsampling approach') can improve winter temperature skill in Germany (Dalelane et al., 2020). An improvement for all variables, spatial scales and timescales might be achieved in applying recalibration (Pasternack et al. 2021). For subseasonal and seasonal predictions, however, the statistical parameters of the recalibration need to be adjusted for each case.

Second, the website was developed in close cooperation with users considering several feedback loops which is essential to guarantee its understandability and usability (relevance). The feedbacks show that the website is in large parts understandable by most users. Some users have difficulties in understanding the probabilistic predictions and the 'relative' prediction skill scores compared to a reference prediction. We will try to overcome this and clarify complex issues by providing further demonstrative video clips like recently done for the prediction skill. Furthermore, 'absolute' measures of verification could be used to define the skill traffic light instead of or in addition to the 'relative' skill scores, but the definition of thresholds between green, yellow and red might be subjective since users would suggest different thresholds. Since similar thresholds might be relevant for users of the same sector, we could use sector-specific absolute thresholds defined in cooperation with users. Basic climate predictions with red skill traffic lights could be greyed out, and reference predictions could be shown in addition to climate predictions. Further skill measures, e.g. verification metrics for the ensemble spread, reliability diagrams or Receiver Operating Characteristics (ROC) scores evaluating probabilistic categories separately, or reference predictions, e.g. the extrapolation of observed trends or persistence, could be added. Concerning the presentation of probabilistic maps, we plan to evaluate with users if an additional category 'equal chance' (e.g. if all categories are below 40%) or a label 'no data or no signal' (for missing values or predictions with highest probabilities of above and below normal conditions) would be appreciated. If evaluated by users to be beneficial, we could use the difference between the observed climatologies of the WMO reference period 1991–2020 and the last 20 years to relate the anomalies of subseasonal predictions as well to the 1991–2020 period (similar to seasonal and decadal predictions) to enable a more seamless outlook. The understandability of prediction products could also be enhanced including more interactive presentations, e.g. permitting the selection of regions or time steps via mouse clicks on maps or time series.

Finally, user feedbacks reveal that climate predictions can already be used in some working routines but there is still room to improve their usability: many users struggle with predictions of slightly positive or not significant skill. Thus, guidelines should be offered on how to cope with such uncertain information. Furthermore, additional user-oriented variables, indices or timescales are planned, like wind, extreme events such as droughts, heat waves or storms and multi-annual seasonal means. Predictions of the El Nino Southern Oscillation, the NAO, sea surface temperatures or sea level pressures might be relevant for scientific users to analyze model dynamics and teleconnections. Besides prediction plots on an operational website, the numerical prediction data for impact modeling will be offered on an ESGF platform. Lastly, a time series across all climate time scales combining observations, subseasonal, seasonal and decadal predictions and climate projections is planned to allow the next step towards a seamless management of adaptation measures to cope with climate variability of the next weeks, months, years and decades.

CRediT authorship contribution statement

A. Paxian: Conceptualization, Project administration, Writing – original draft, Methodology, Visualization. **B. Mannig:** Methodology, Software, Writing – review & editing. **M. Tivig:** Visualization, Software, Writing – review & editing. **K. Reinhardt:** Methodology, Software, Writing – review & editing. **K. Isensee:** Visualization, Software, Writing – review & editing. **A. Pasternack:** Methodology, Software, Writing – review & editing. **A. Hoff:** Methodology, Software, Writing – review & editing. **K. Pankatz:** Methodology, Software, Writing – review & editing. **S. Buchholz:** Visualization, Software, Writing – review & editing. **S. Wehring:** Methodology, Software, Writing – review & editing. **P. Lorenz:** Methodology, Software, Writing – review & editing. **K. Fröhlich:** Funding acquisition, Writing – review & editing. **F. Kreienkamp:** Funding acquisition, Writing – review & editing. **B. Früh:** Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The sources of all data from global subseasonal, seasonal and decadal climate predictions, statistical downscaling and observations as well as the FREVA software routines for post-processing prediction data are given in the manuscript. Many datasets are publicly available. Some datasets will be published in the coming months but may be provided upon request. The publicly available software routines have been further developed in some cases. Most of these modified scripts may also be shared upon request. However, some modifications of these software routines are confidential because they have been funded internally at DWD and thus, cannot be provided. – Andreas Paxian

Data availability

Data will be made available on request.

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