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# World Meteorological Organization (WMO)-Accredited Infrastructure to Support Operational Climate Prediction

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**ABSTRACT:** The World Meteorological Organization (WMO) is a specialized agency of the United Nations (UN) system, with an intergovernmental mandate for coordinating the generation and exchange of weather, climate, and water information across its members. WMO has played a vital role in coordinating production and dissemination of weather forecasts from short to medium range whereby global weather forecasts from large operational centers are made available to all WMO members to serve needs of stakeholders at the local level. In recent decades, there has also been an increasing demand for similar forecasts on longer lead times that include prediction on subseasonal, seasonal, and annual to decadal leads. To address the increasing requirements for forecast services by members, WMO has been actively accrediting and coordinating the essential forecast infrastructure that includes provision of forecasts from WMO designated Global Producing Centers and collection of forecasts by Lead Centers to facilitate the dissemination of information and products to WMO members and relevant nongovernmental organizations. Although the basic ingredients of the infrastructure are now in place, the uptake of the forecast information has been suboptimal. To engage the community in developing solutions to enhance the utilization of available information, this paper summarizes the WMO infrastructure for long-range forecasts, particularly for seasonal time scale, and follows with a discussion of current issues that are hindering their uptake. Finally, a set of proposals to advance the utilization of the available information from the WMO long-lead forecast infrastructure are discussed.

**SIGNIFICANCE STATEMENT:** Because of ongoing changes in climate, the frequency of weather and climate hazards has been increasing and so is the demand to anticipate climate variations with longer lead times. To meet the demand for relevant climate information to manage climate risks for its members, the World Meteorological Organization (WMO) has been proactive in developing and coordinating the required infrastructure based on the latest scientific advances, with cascading of forecast information from global to regional to national scales. The uptake of the forecast information, however, has lagged mainly due to lack of awareness and technical capacities. In this paper, with the intent of engaging the community, the current impediments and solutions to improve the utilization of long-range forecasts are discussed.

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## 1. Introduction

Climate variability on subseasonal to decadal time scales influences various extreme phenomena including prolonged droughts; cold spells, flooding, and tropical storm activity; and intense fire seasons. These phenomena have consequences for various aspects of societal well-being. Understanding and anticipating climate variability on subseasonal to decadal time scales (hereafter referred to as S2D) can help mitigate adverse effects of climate variability or take advantage of favorable conditions. Toward this goal, in recent decades, advances in observing systems, climate models, and computing have resulted in the implementation of operational predictions to anticipate S2D climate variability (Graham et al. 2011; Kirtman et al. 2014; Vitart et al. 2017; Kushnir et al. 2019; Pegion et al. 2019; Merryfield et al. 2020; Hermanson et al. 2022).

One of the primary tools for anticipating S2D climate variability is dynamical climate prediction models initialized from the current state of various components of the Earth system. An ensemble of forecasts is generated to estimate the associated uncertainties that are inherent in climate predictions. Individual forecast members in the ensemble are initialized with minor differences in the initial conditions and/or small perturbations to the model parameters. As the forecast lead time increases, these differences evolve to sample future states of the Earth system and thereby provide a probabilistic estimate for plausible future climate.

Although complex and requiring substantial infrastructural and computing resources, dynamical prediction methods have advantages that include an ability to represent the entire climate system and interlinkages between its components; an ability to handle unprecedented forecast situations; incorporating nonlinearities in responses to external forcings; realizing prediction skill from a combination of initial and boundary conditions; and quantification of uncertainty, among others. Given the advantages of dynamical predictions, such methods are now the preferred approach for S2D prediction (see references above).

Prediction of climate variability based on dynamical methods, particularly on the global scale, requires a large outlay of resources and thus is only within the wherewithal of advanced operational centers. As forecasts themselves are global, information available from these large operational centers can be used at regional and national levels by National Meteorological and Hydrological Services (NMHSs). A point to note is that by supporting an infrastructure of observations that are critical for initializing dynamical prediction systems, all NMHSs make valuable contribution to the WMO forecasting infrastructure.

A robust global weather and climate enterprise, however, requires efficient coordination mechanisms for the exchange and flow of data and information among NMHSs and other relevant stakeholders and is underpinned by mutually agreed standards and protocols.


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Such coordination in support of making weather and climate prediction information as a public good is one of the primary goals of the WMO.

In this paper, the current operational infrastructure of S2D predictions using dynamical models within the purview of WMO is discussed. For the readers not familiar with the working structure of the WMO, an overview is first provided (section 2). In section 3, the current infrastructure for S2D predictions, and how the global forecast information, following a cascading forecast paradigm, is utilized at the regional and national level is discussed. Section 4 reviews the current shortcomings and impediments in the use of global S2D forecasts at the local level and provides a segue to section 5 where the WMO Operational Climate Prediction (OCP) workshop series is highlighted. The paper concludes with a summary and the outcomes of the most recent (third) OCP workshop held in September 2022. The appendix contains a list of acronyms used in this paper.

## 2. The World Meteorological Organization

The WMO is a specialized agency of the United Nations (UN) system, with an intergovernmental mandate for coordinating the generation and exchange of weather, climate, and water information across its members and partners. It is the UN's authoritative voice on weather, climate, and water. The WMO is currently comprised of 193 member states and territories.

The latest WMO Strategic Plan 2024–27 (WMO 2023b) adopted by the 19th World Meteorological Congress, in May–June 2023, defined the directions and priorities to advance the WMO activities and enable all members to improve their products and services. Recently, the Early Warnings for All (EW4All) Executive Action Plan (WMO 2022a), developed by the UN Secretary General, assigned the key role to WMO and its partners[1] and was unveiled at COP27.

To meet its goal of delivering weather and climate services to all, WMO fosters collaborative mechanisms to enhance the exchange of necessary information among members. To achieve this, WMO relies on three infrastructural components, WMO Integrated Global Observing System (WIGOS),[2] WMO Information System (WIS),[3] and WMO Integrated Processing and Prediction System (WIPPS).[4] For the exchange of observational information, the WIGOS coordinates development of technical standards for observation networks for Earth system measurements. The WIGOS also develops data formats to ensure collected data are quality retained, comparable, interoperable, and interchangeable. The WIPPS enables all members to make use of and benefit from the advances in operational prediction systems extending from nowcasting to annual-to-decadal climate predictions. The observational data and forecast products are made available to all members and relevant operational organizations through WIS (Fig. 1).

The forecast and analysis component of the WMO infrastructure, under the WIPPS, is a three-category system comprised of the World Meteorological Centers (WMCs), Regional Specialized Meteorological Centers (RSMCs), and National Meteorological Centers (NMCs), referred to a WIPPS designated centers. The three-level system ensures that global scale prediction products are available to regional and national scale prediction, and as the information cascades to regional and national level, value is added at each level. All WIPPS activities are defined in the manual on the WMO Integrated Processing and Prediction System (WMO 2023a), hereafter referred to as the manual on the WIPPS. For each activity, the designation criteria and the minimum set of mandatory products are explicitly defined in the manual on the WIPPS, which an operational center is required to fulfil when the center wishes to seek WMO designation and become part of the WIPPS infrastructure.

[1] https://www.un.org/en/climatechange/early-warnings-for-all.
[2] https://community.wmo.int/en/activity-areas/WIGOS.
[3] https://community.wmo.int/en/activity-areas/wis.
[4] https://community.wmo.int/en/activity-areas/wmo-integrated-processing-and-prediction-system-wipps.


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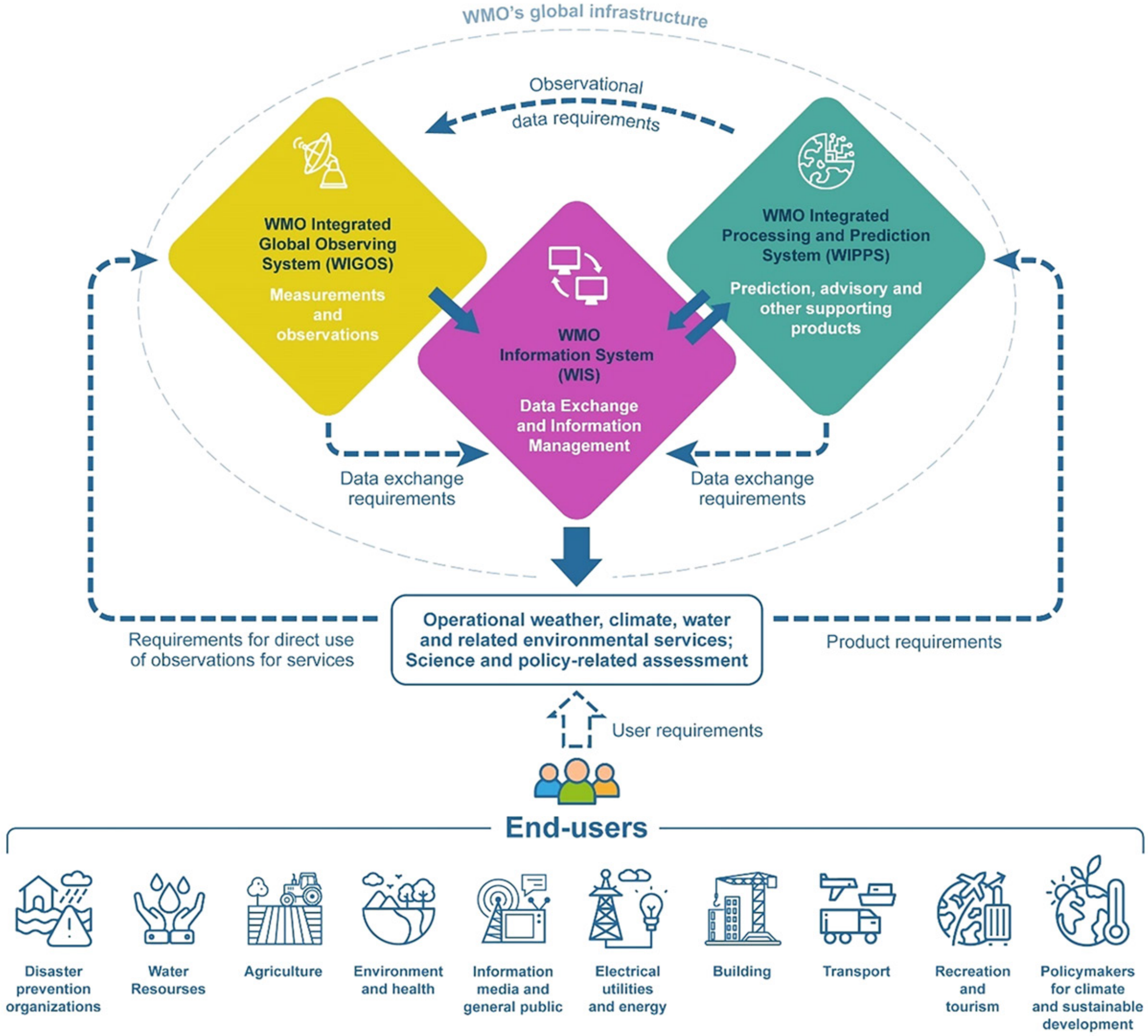


**Fig. 1. Three major components of WMO operational infrastrucuture that include collection and dissemination of observations (WIGOS), operational analysis and predictions (WIPPS), and a framework for sharing data (WIS). WMO members set mutually agreed standards and protocols that underpin the exchange of information.**

## 3. WMO infrastructure for climate predictions

***a. WMO structure for S2D predictions.*** The current operational infrastructure within WMO related to S2D predictions addresses three distinct time scales: subseasonal (2–5 weeks), seasonal (month to a year), and annual-to-decadal (year to a decade). For each forecast time scale, included in the manual on the WIPPS, are the mandatory functions that the WIPPS designated centers (referred to as Global Producing Centers) shall perform in accordance with the specified criteria. Historically, the development of the WIPPS operational climate prediction infrastructure proceeded from seasonal, then to annual-to-decadal, and most recently, to include subseasonal predictions. The chronological order of maturing of operational systems followed the scientific advances in the understanding of climate variability and predictability on the respective time scales. The WMO functional structure for all three time scales is similar, and for the sake of brevity, only the infrastructure for seasonal predictions, with the longest history of operational implementation, is described below to illustrate the approach. To complement, the unique aspects of issues associated with the infrastructure on different time scales are also noted.

The seasonal prediction infrastructure is comprised of several Global Producing Centers (GPCs) and a Lead Center (LC). GPCs provide global seasonal forecasts while the LC is


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responsible for collecting seasonal forecasts from all GPCs and developing products based on the multimodel approach, along with harmonizing the GPC products in terms of data specification and formats. At present, there are 15 designated WIPPS GPCs for seasonal prediction,[5] formally referred to as WMO Global Producing Centers for Seasonal Prediction (GPCs-SP). All GPCs-SP are required to produce seasonal forecasts at least once a month for the coming season.

In the utilization of these seasonal forecasts, it is immediately apparent that individual NMHSs face an uphill task in accessing the seasonal forecast data from multiple operational centers and, subsequently, perform necessary postprocessing to develop products for their stakeholders. A more efficient data sharing structure would be for a single center to gather seasonal forecasts from all GPCs-SP and develop products based on postprocessing of the multimodel ensemble used by NMHSs, Regional Climate Centers (RCCs), and Regional Climate Outlook Forums (RCOFs). Indeed, this is the rationale for a separate WIPPS activity for an LC for coordination of Seasonal Prediction Multi-Model Ensemble (LC-SPMME[6]). Following this strategy, the overall structure of GPCs-SP and LC-SPMMF, representing a hub and spoke paradigm, is a more efficient approach for the delivery of seasonal forecast information than a point-to-point paradigm for dissemination and uptake of the forecasts from each GPC-SP (Fig. 2).

[5] For WIPPS designated centers for seasonal prediction see WMO (2023a).

[6] https://wmolc.org/.

***b. WMO Mechanisms for supporting climate services.*** For delivering information to support climate services effectively, it is imperative that appropriate operational mechanisms are in place to generate, exchange, and disseminate information globally, regionally, and nationally. Within the Global Framework for Climate Services (GFCS),

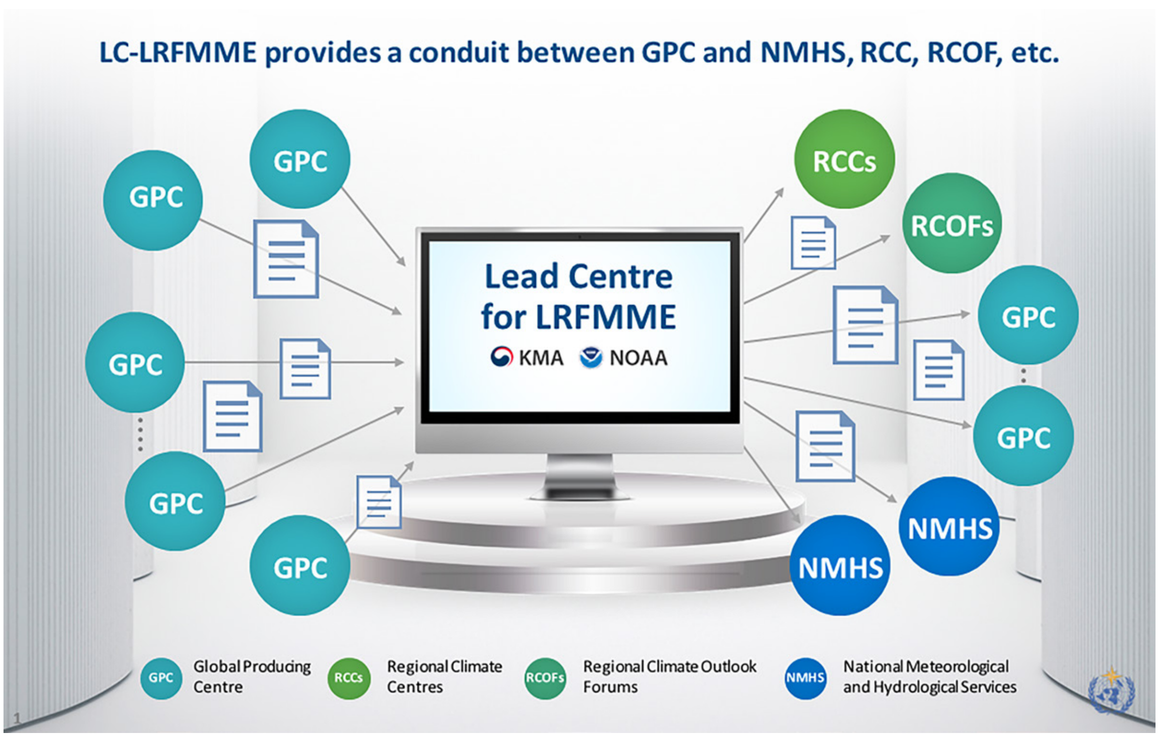


**Fig. 2. A schematic of the current operational infrastructure for seasonal forecasts of WMO. Seasonal forecasts are generated by multiple GPCs that provide data to the LC for seasonal forecast. The responsibility of the LC is to postprocess seasonal forecasts and develop products based on multimodel approach. Multimodel forecasts are provided to all WMO members and various WMO-accredited operational entities such as RCCs and RCOFs. We note that although all designated GPC's are forecast providers, they can also be users of products from the LC and, thereby, can benefit from the multimodel ensemble approach.**


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the Climate Service Information System (CSIS) is the principal mechanism defined to routinely collate, store, and process information about past, present, and future climate (WMO 2011; Allis et al. 2019; Hewitt et al. 2020).

The implementation strategy of the CSIS is by the design closely tied to the WIPPS infrastructure and is based on a three-tiered structure of collaborating institutions (global, regional, and national) to ensure that climate information and products are generated, exchanged, and disseminated in an authentic and efficient manner. One of the primary functions of CSIS entails climate prediction undertaken through a global–regional–national system of interlinked producers and providers (Fig. 3).

As mentioned in section 3a, WMO has also established WIPPS activities for subseasonal and annual-to-decadal predictions, along with their respective LCs, constituting the backbone for operational climate prediction infrastructure for those time ranges on the global scale. For each S2D time scale, the main direction of global prediction information flow is from the GPCs to the Lead Centre, to the regional entities such as the RCCs and RCOFs, and onward to NMHSs, which serve the national end users. Value addition, for example, through application of forecast calibration/downscaling/verification and regional/local knowledge, occurs at each stage (Graham et al. 2011).

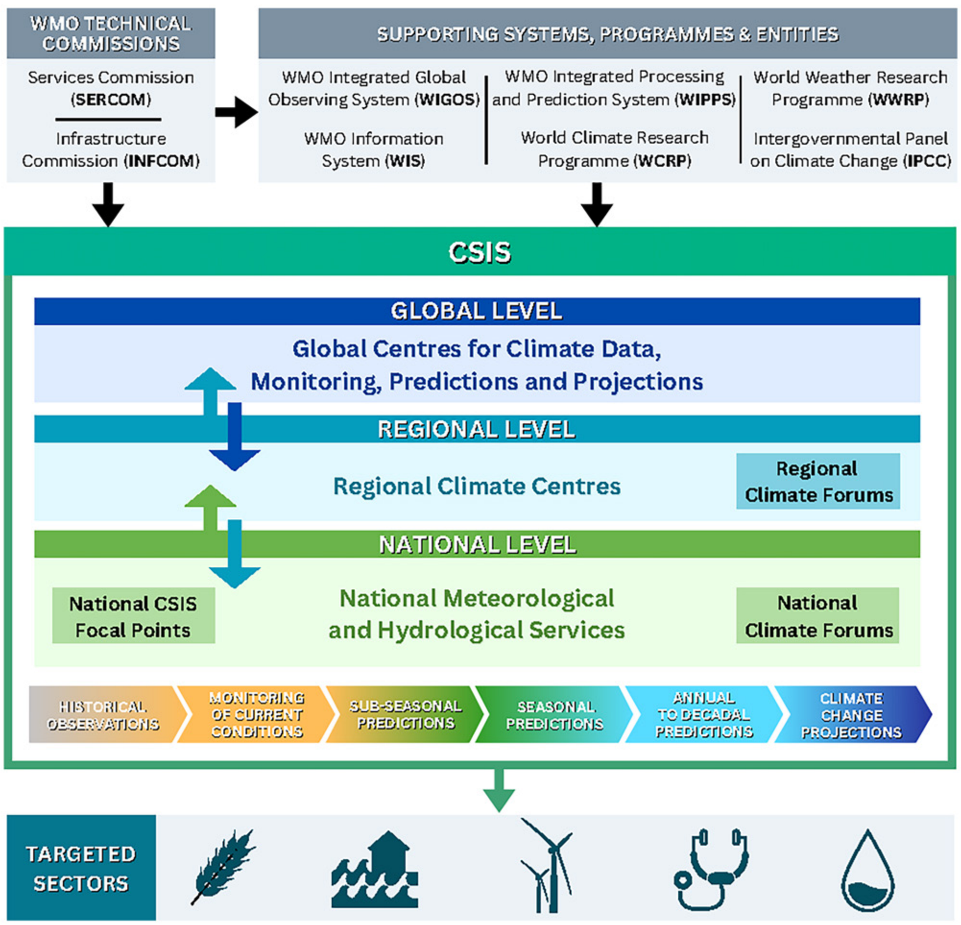


**Fig. 3.** A schematic of the three-tiered approach to implementing the CSIS, illustrating the cascading forecast process. Forecast information at the global scale is utilized by regional entities such as RCCs and RCOFs, which communicate regional scale information to the NMHSs. Value addition occurs at each stage of the cascading forecast process through methods like forecast calibration, downscaling, and regional/national expert assessments. The horizontal axis represents the continuum of data extending from historical observations to current conditions to predictions and projections for different time scales. Ideally, forecast information for different time scales should blend seamlessly; however, this remains a challenging goal.


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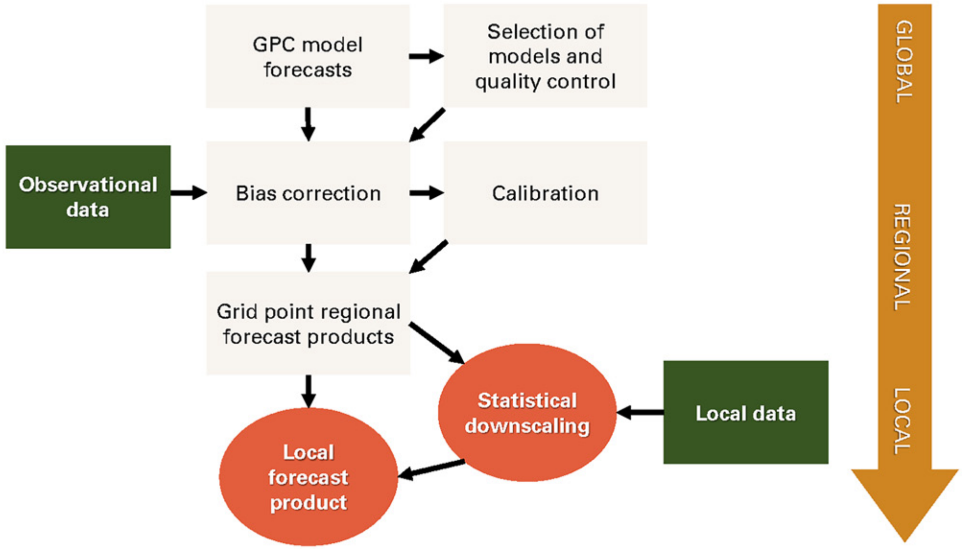


**Fig. 4.** A schematic of the recommended objective procedure for generating seasonal forecasts at the regional and national levels starting from the forecasts from GPCs. The first step in the approach is to choose GPCs for which skillful forecasts will be available in a consistent manner and further, if warranted, select a subset of models for multimodel ensemble (see discussion in section 4b on challenges related to selection of models). Next, model forecasts need to be bias corrected, calibrated, and combined using the multimodel approach, leading to seasonal forecasts at the regional level. The forecasts at the regional level can be downscaled to the local level using statistical techniques. The forecast development process highlights the basic concept of the cascading forecast process from the global to the regional to the national level (WMO 2020).

There has been a surge over the last decade in the use of GPC products on regional as well as national scales, particularly in the case of seasonal prediction. However, the vast inventory of global climate prediction data is still considered underutilized, primarily due to lack of awareness and the required technical competencies at the regional and national levels. Recognizing this, WMO is developing a series of guidance documents that describe the technical aspects of the cascading forecast process. WMO recently published a detailed guidance on operational practices for objective seasonal forecasting (WMO 2020), which outlined a recommended procedure for developing seasonal forecasts at the regional and national levels (Fig. 4).

Although within the purview of WMO, the overall strategy for developing regional and national climate predictions is in place; as discussed next, gaps in the global forecast infrastructure and in the cascading forecast process remain and need to be addressed.

## 4. Current shortcomings in the WMO infrastructure for climate predictions

***a. Inconsistencies in the forecast system configurations.*** One of the foremost shortcomings of the current seasonal forecast infrastructure is the disparity in the ways operational forecast systems are configured. Differences include the scheduling for forecast generation, length, and period of the hindcasts (retrospective predictions used for verification, calibration, and value addition), consistency between hindcast and real-time forecasts, and ensemble size. This disparity in forecast configurations is in contrast with the homogeneity in the operational systems for numerical weather prediction (NWP); for example, scheduling NWP systems at different operational centers tends to follow the same timing.

For operational seasonal predictions, the scheduling of forecasts varies widely, from "burst" mode where the full ensemble is generated from a single start date, to "lagged" mode, where ensemble members are produced each day or at some other higher frequency prior to the target forecast period. Burst mode forecasts are more skillful just after they are produced, but lagged


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ensembles are more flexible in that they can provide more frequent forecast updates and they could be more skillful for longer lead times when forecasts pooled from various start dates can provide a larger ensemble. An important benefit of frequent initialization from different dates is that processes, which can affect long lead times but can quickly evolve, such as sudden stratospheric warmings (Scaife et al. 2022) and the Madden–Julian Oscillation (Vitart 2017) can be better captured. Currently, the two approaches to initialization are roughly equally represented across current subseasonal and seasonal operational prediction systems.

Hindcast periods are similarly diverse and range from around 20 years to several decades. In deciding on the length of the hindcasts, there is a dependence on the processes being predicted: attempting to capture longer time-scale variations requires longer hindcasts to assess the prediction skill of underlying variability. However, lengthening of the hindcast period is limited by practical consideration of the availability of computing resources and from degradation in forecast processing due to inconsistencies arising from historical changes to the observing system, in particular, the advent of the satellite record since the late 1970s.

Another important consideration in the length of the hindcast period is its primary focus. If the main goal is for mean bias correction, often by subtracting the mean of hindcasts as a function of lead time and start date, then meeting this goal requires shorter hindcast periods and smaller ensemble sizes. On the other hand, if hindcasts are to provide accurate estimates of expected forecast skill, then longer hindcast periods are called for to increase the size of the historical sample. However, longer hindcast poses an added complexity if the climate is nonstationary. In such instances, proper estimates of forecast skill and removing nonstationary trends could be problematic. Last, if the hindcast period differs across seasonal prediction systems, then the unification of forecasts using multimodel ensemble approaches proves difficult.

There is also a range of current approaches for generating hindcasts, for example, generating hindcasts in real time, slightly ahead of the forecast, or in a single exercise prior to when a forecast system is updated. Having a mix of two approaches adds complexities to combining forecasts from multiple systems.

Ensemble sizes vary between prediction systems, which makes quantitative comparison difficult as there are clear increases in skill with ensemble size for both deterministic and probabilistic skill measures (Kumar and Hoerling 2000; Kumar et al. 2001; DelSole et al. 2014). Furthermore, some regions of the globe require fewer ensemble members before skill saturates than others. While an ensemble size of around 15–20 is adequate to capture much of seasonal prediction skill in the tropics (Kumar et al. 2013), much larger ensemble sizes are required for a similar purpose in the extratropics (Scaife et al. 2014). This also means that differences in ensemble size between hindcasts and forecasts hinder straightforward assessment of prediction skill (Ferro et al. 2008) and prevent optimal recalibration and combination of multimodel forecasts.

Model resolution also varies across operational forecast systems. Until recently, most operational forecast systems employed typically around 1° ocean resolution and ~100-km atmosphere resolution, but this has now increased in some cases to fractions of a degree in the ocean and a few tens of kilometer in the atmosphere. Again, although there is no absolute consensus on the requirements on the resolution for longer range forecasts, some centers report reduction in bias and gains in skill from the use of higher resolution (e.g., MacLachlan et al. 2015). Nonetheless, it is not clear whether additional, and affordable, increases in atmospheric resolution are likely to lead to further skill, and some centers are now focusing on larger ensemble sizes (Doi et al. 2019; Scaife et al. 2019) given the clear benefits to forecast skill from increasing ensemble size for equivalent costs. It is important to note that while users often demand high spatial resolution, this does not imply that the


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best strategy is to run forecasts at high resolution. Indeed, forecasts of seasonal anomalies are often on broad scales in space and time and so skillful forecasts can often result from 100-km atmospheric resolution models representing insightful large-scale predictors that correlate well with local conditions (e.g., Liu et al. 2018; Svensson et al. 2015).

Finally, we note two additional impediments with the use of long-range forecasts. The first is related to model output data availability. While some single and multimodel data portals allow access to data (e.g., Buontempo et al. 2022), this serves those well trained in the complex process of bias correction and ensemble combination, while most users may simply prefer processed output or regular diagnostic feeds to inform decision-making. The second impediment is how to connect these time scales with shorter range weather forecasts and longer-term climate projections. Again, this requires expertise and there is unlikely to be a single best approach. However, provision of at least some comparable forecast diagnostics to inform decisions transitioning across time scales appears to offer benefits worth pursuing.

To summarize, in setting up the operational infrastructure for long-range forecasts within the available computational resources, many choices need to be made regarding hindcast period and their length, ensemble size, burst versus lagged ensemble, on-the-fly versus static hindcasts, consistency between hindcasts, real-time forecasts, etc. In the absence of a consensus, different operational centers have adopted different forecast configurations, hampering the cascading forecast process and contributing to inadequate utilization of the available forecast infrastructure.

***b. Need for guidance for implementing various procedures in the cascading forecast process.*** In addition to the diversity in the operational forecast configuration for long-range prediction systems, there is a need for awareness of, and guidance on, aspects of the cascading forecast process from global dynamical model outputs to regional and local forecasts serving stakeholders.

Approaches for model selection and multimodel ensembles are one such aspect in the cascading process. Although combining multiple model outputs often provides better skill than individual models and improves reliability (Weigel et al. 2009; Kirtman et al. 2014), large skill differences between models may exist regionally, in which case careful model selection can be preferable to combining all available models (e.g., Endris et al. 2021). Although research is underway to determine whether it is advantageous to apply weightings to multimodel combinations (Hemri et al. 2020; Wei et al. 2022), based on the current state of understanding, a set of recommendations, together with corresponding tools that could be used at the regional and local levels, remains a gap.

Raw model outputs have systematic errors that must be corrected through postprocessing. Most fundamentally, the mean systematic error, or bias, is removed by subtracting corresponding mean values from the hindcasts over the chosen climatological base period. However, this basic procedure does not correct for errors in higher-order moments such as the variance, for which an additional correction is sometimes applied, for example, in producing El Niño–Southern Oscillation (ENSO) forecasts (e.g., Merryfield and Lee 2023). In addition, model systematic errors can vary over time, particularly when long hindcast periods are employed such as for annual-to-decadal forecasts (Kharin et al. 2012). Reducing nonstationary systematic errors is another area where ongoing research efforts and practical guidance (Kumar et al. 2012; Meehl et al. 2022) are required.

Forecast uncertainty and associated probabilities are determined from the spread of the bias-corrected forecast ensemble. Improvements in probabilistic skill and reliability can be achieved by fitting those values to an appropriate distribution and then adjusting the parameters of that distribution through a calibration procedure. This processing chain is illustrated


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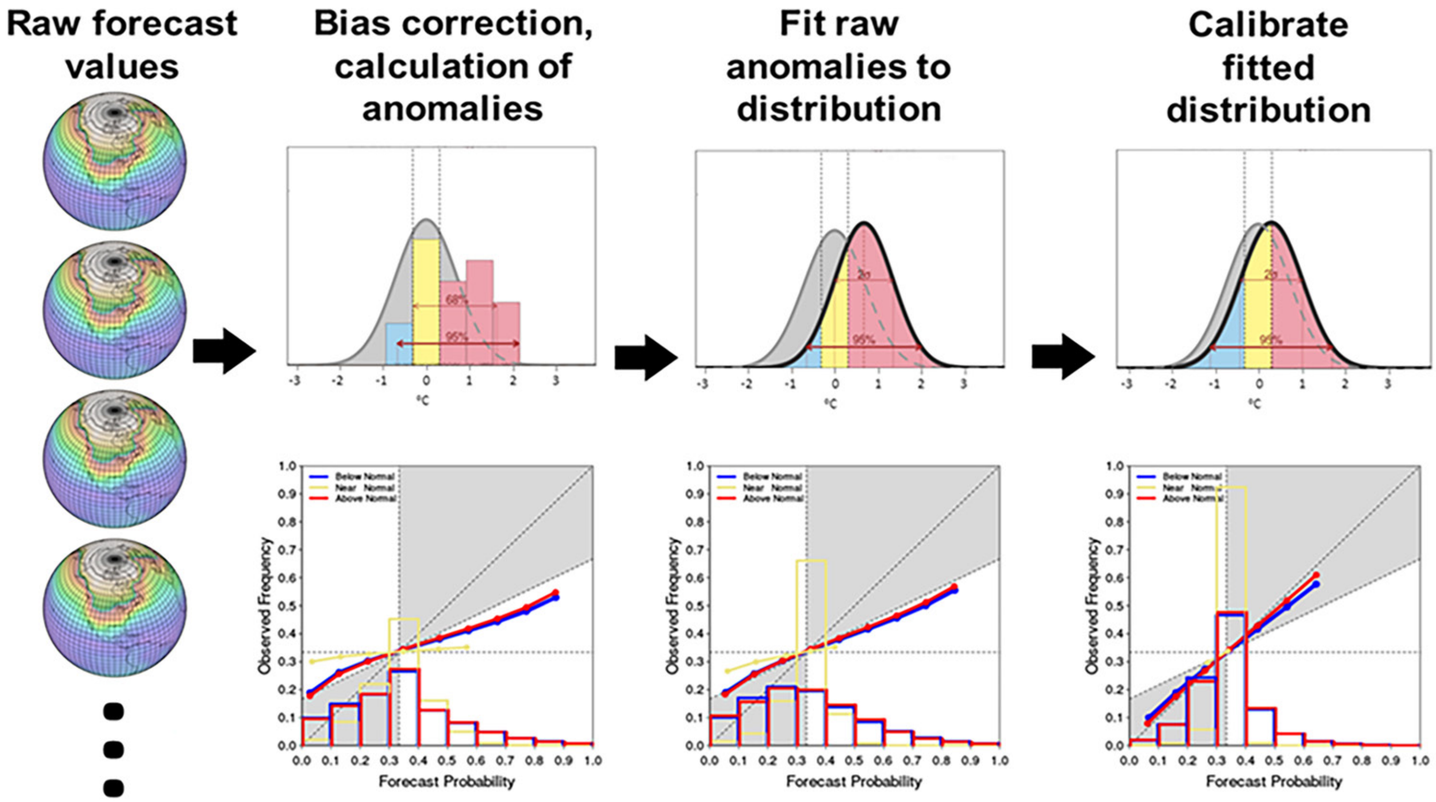


**Fig. 5. Schematic depiction of a chain of postprocessing steps leading from raw model output to a calibrated probabilistic forecast. Model output from an ensemble forecast (first column) at a particular location is bias corrected to provide a sample of raw forecast anomalies (second column), where blue, yellow, and red denote anomalies in the below-, near-, and above-normal terciles of the climatological distribution indicated by the gray curve. This sample is fit to a parametric distribution (third column), the parameters of which are adjusted systematically through a calibration procedure to maximize probabilistic performance and improve reliability (fourth column) (from WMO 2020).**

in Fig. 5. Various calibration methods have been devised, though as yet little practical guidance is available regarding their relative advantages and shortcomings.

Downscaling from the coarse spatial resolution of global models to finer regional and local scales that are subject to topographic and other influences is an important need. It is not yet clear how much additional prediction skill comes from regional dynamical downscaling (e.g., Robertson et al. 2012; Freire et al. 2022). Because of this and the substantial computational effort and data sharing that dynamical downscaling requires, downscaling has primarily employed statistical methods, for example, via the widely used Climate Predictability Tool (CPT) (Mason 2011; Mason and Tippett 2017). Nonetheless, needs for dynamical downscaling capabilities have been expressed by RCCs, and community efforts to explore the benefits of developing such capabilities could be considered if sufficient resources and supporting infrastructure are available.

Although not specifically problematic for the uptake of long-range forecasts, one further issue faced by regional forecasters is consistency across national and regional borders, as illustrated by the example in Fig. 6. This coordination and communication issue could be overcome straight away by cooperation among global and regional forecast producers.

***c. Issues in product development and communication.*** Climate predictions are often communicated as probabilistic forecasts that quantify chances of different outcomes being realized. A standard format is to display probabilities for mean conditions during the forecast period in three categories separated by terciles of the climatological distribution, often


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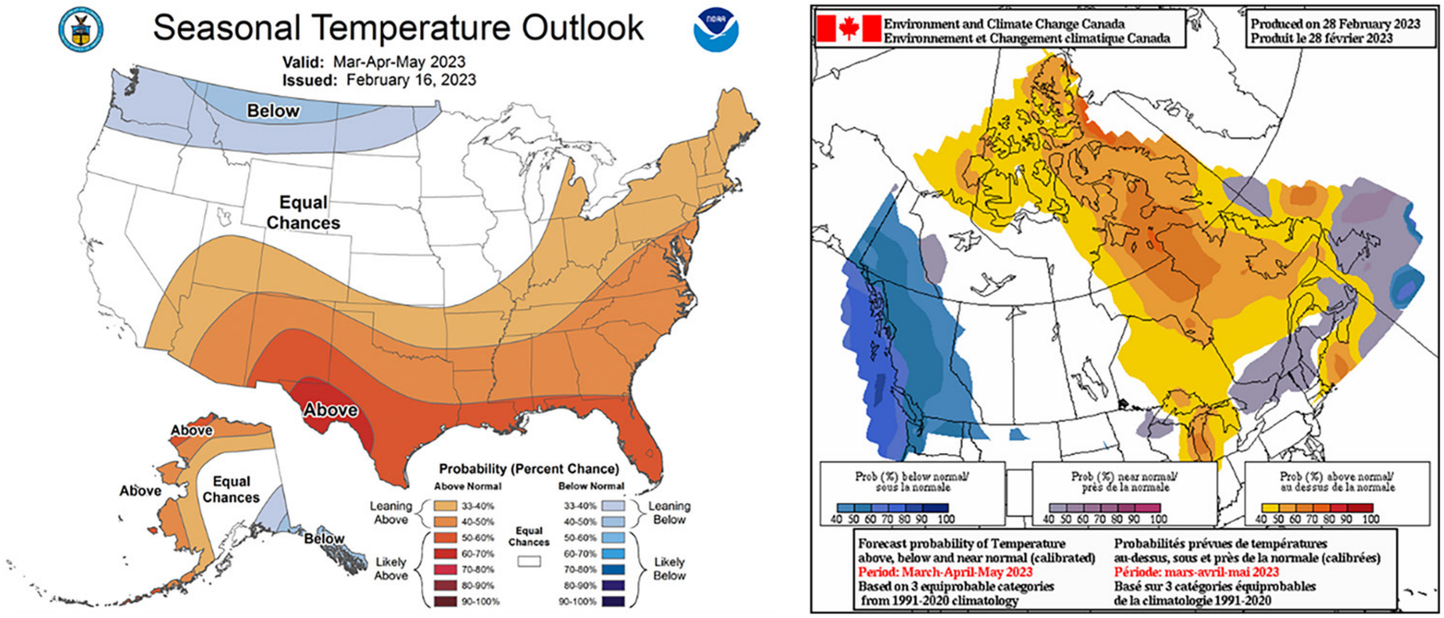


**Fig. 6. Official seasonal temperature outlooks for March–April–May 2023 (left) for the United States from NOAA and (right) for Canada from ECCC, illustrating inconsistencies in lead time, display format, and forecast probabilities across national borders.**

labeled as below-, near-, and above-normal. While this framework is easily interpretable and, further, has been a useful standard, it is not especially well suited for decision-making because the tercile thresholds are often not directly relevant for users. A complementary approach is to provide a mean and uncertainty range or to provide exceedance probabilities for percentile or absolute thresholds that users can select to address specific applications and needs, including vulnerabilities to extremes. This capability exists, although it has not yet been implemented within the WMO infrastructure.

Similar considerations apply to the communication of predictive information as graphics or text. Probabilistic information needs to be conveyed in an understandable but not oversimplified manner. Addressing forecast communication issues needs to connect with, and leverage, research initiatives exploring presentation of forecast information in various formats (Christel et al. 2018; Manrique-Suñén et al. 2023).

It is essential to also convey how much trust should be placed in the forecast, based both on past performance (deduced from comparison of hindcasts with observations) and inferred conditional skill specific to a particular forecast being made (e.g., Dunstone et al. 2023). Ideally, every forecast should be accompanied by information on the associated uncertainty reflecting its conditional skill rather than just skill measures based on the complete set of hindcasts which convey only average performance for conditions during the hindcast period (Kumar 2007). Formulating such information represents another challenge for the research and operational communities.

A further constraint on product development and communication is that currently model output data are often exchanged only as monthly means (particularly for seasonal forecasts). This limits the types of products that can be formulated, whereas availability of higher-frequency daily or subdaily fields would enable predictions for sector-relevant climate indices that depend on daily values, such as growing degree days, the number of days exceeding specified rainfall thresholds, and rainy season onset and cessation dates. Of course, such predictions are useful only if they are skillful and reliable (Coelho et al. 2017; MacLeod 2018; Gbangou et al. 2019; Dirkson et al. 2021). Work needs to be done to establish if temporal downscaling from monthly means can yield skill for higher frequency


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variability. Greater availability of high-frequency data will doubtless accelerate research and development supporting such applications.

## 5. The WMO operational climate prediction workshop series

Given various issues faced in the uptake and better utilization of long-range forecast infrastructure within WMO discussed in the previous section, a WMO OCP workshop series was established.

Leading to the OCP workshop series, in 2013, WMO organized the Workshop on "Operational Long-Range Forecasting: GPCs and RCCs, in support of NMHSs and RCOFs." This workshop was hosted by the Brazilian Meteorological Service (INMET) in Brasília, Brazil, on 25–27 November 2013, and brought together the operational seasonal prediction community to review practices, share experiences, and strengthen collaboration among global, regional, and national producers of seasonal climate prediction. The workshop identified the need to integrate the research community into future workshops. In 2015, the WMO initiated a workshop series on operational climate prediction, generalizing its scope to include S2D time scales and revising the layout to bring together both the operational and research communities.

The overarching aim of the WMO OCP workshops is to bring together representatives of operational, research, and services communities to advance communication and coordination and to have a better understanding of the gaps, needs, and approaches enabling improved coordination and collaboration among them. The OCP workshop is therefore a platform to i) review progress in the understanding of climate prediction and its implementation in operations, ii) communicate research needs from the operational community, for example, the ones discussed in the previous section, and iii) communicate user needs from the climate services to the climate prediction community to stimulate the development of new operational forecast products.

As such, the OCP workshops provide an opportunity to assess the efficacy of the existing WMO infrastructure for delivering climate predictions at global, regional, and national levels and to identify gaps for future improvements. Additionally, the OCP series is considered to be a mechanism to raise awareness and facilitate operational use, by all WMO members, of the WMO infrastructure for climate prediction for climate risk management. Most recently, the OCP-3 workshop was organized in 2022 along thematic sessions addressing these aims.[7] The scope of the workshop was intentional in that it focused on forecasts on all three—subseasonal, seasonal, and annual-to-decadal—time scales.

[7] https://community.wmo.int/en/meetings/third-wmo-workshop-operational-climate-prediction-ocp-3-20-22-september-2022.

A targeted outcome of the OCP-3 workshop was to develop recommendations that could be addressed collaboratively by the operational, research, and service communities. The following recommendations, which further corroborate various issues raised in section 4, were synthesized:

- Perform an assessment of the efficacy of the cascading forecast process from global to regional and national level products.
- Focus on advancing understanding of mechanisms and drivers of climate predictability.
- Establish commonly agreed regional domains to subset GPC products across all time scales.
- Make sure that RCCs and NMHSs have easy access to WMO Lead Center's real time as well as hindcast data archives.
- Identify reliable methods of a priori identification of windows of forecast opportunity.


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- Implement WMO Unified Data Policy (WMO 2022b) in support of free access to operational climate prediction.
- Address the need to go beyond the provision of time averages of standard meteorological variables to get closer to users' needs, typically more specific information than is usually provided.
- Address the need for forecast calibration considering the existence of conditional skill (specific to certain conditions) and unconditional skill (overall forecast system performance estimated using all available hindcasts).

## 6. Summary and future steps

Spurred on by advances in observing systems, modeling and computing, improvements in scientific understanding for climate variability, and a desire to anticipate climate variations beyond weather time scales, a robust infrastructure for S2D predictions is now in place as part of the WMO. These global forecast systems, which are maintained by large operational centers, have the requisite information necessary to benefit all. It has also been recognized that the uptake of the forecast information has been slow, and discussions in various forums have led to the identification of gaps that need to be addressed. A summary of these gaps together with steps forward to address them are discussed next.

***a. Addressing infrastructure gaps.*** An outstanding issue facing the WMO climate prediction infrastructure is the inhomogeneity in the configuration of forecast systems at different operational centers. In contrast to weather predictions, climate predictions have an added challenge that real-time forecasts must be accompanied by a set of hindcasts. The combination of real-time forecasts and the need for hindcasts creates a large trade space of competing demands between model resolution, ensemble size, hindcast period, burst versus lagged ensemble, and static versus on-the-fly hindcasts, decisions which must be made at each operational center to fit the selected forecast configuration within the constraints of available computing resources. We note that within the WMO long-range forecast infrastructure, issues themselves are time scale dependent. For example, start dates for seasonal predictions have wider array of choices across operational centers compared to that for subseasonal or decadal predictions.

It is also known that certain decisions have implications for prediction skill; for example, increase in ensemble size relates to an increase in skill (Kumar and Hoerling 2000; Kumar et al. 2001; DelSole et al. 2014). Similarly, decisions on the length of hindcast period have implications for the estimation of skill, bias correction, and calibration of real-time forecasts (Kumar 2009). Without appropriate guidance on the relative influence of various decisions on the forecast skill, each operational center is left to make its own decisions on forecast configurations for different time scales, leading to the current state of diversity in forecast configurations for climate predictions that continues to befuddle advances in the use of S2D predictions.

It is also well established that the efficacy of multimodel ensemble techniques, for example, which underpin the concept of LCs, is undermined by the diversity in forecast configurations. To overcome this impediment, in collaboration with the research community, developing recommendations on forecast system configuration design would go a long way in enhancing the uptake and utility of climate predictions.

***b. Addressing gaps in practical guidelines for steps in the cascading forecast process.*** The efficacy of the cascading forecast process is crucial in the utilization of global forecasts at the regional and national level. Although appropriate guidance for seasonal forecasts


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has been developed by the WMO on good practices that should be followed in the cascading forecasting process (WMO 2020), and further, for the delivery of information to stakeholders, the high-level guidance itself is not sufficient. This is because there are a baffling number of approaches available for practical implementation of steps in the cascading forecast process, for example, model selection, bias correction and calibration, multimodel ensemble, downscaling, verification, and forecast format and communication. To advance the operational climate prediction efforts within WMO, it is necessary that high-level guidance for cascading forecast process be complemented with recommended tools for implementing various steps. These recommendations for different time scales should also be provided with a library of necessary software that could be used for easier implementation, such as through the "Climate Services Toolkit" being developed as an enabling mechanism of the CSIS implementation.

In implementing this recommendation, coordination with the research community will be necessary. Based on current scientific understanding, the research community could provide a set of recommendations on the tools that could be used in the cascading forecasting process. Having such recommendations, and associated software, will facilitate the utilization of global forecasts to meet global, regional, national, and local needs. It is noted that as research advances evolve, the recommendations could be updated, as necessary.

***c. Addressing data availability gaps.*** As was discussed earlier, at present, sharing of data by global centers, and further, collection of data from GPCs by the LCs, focuses on the time-averaged quantities, particularly for seasonal forecasts. Many user-oriented applications of climate predictions, however, can benefit from the availability of higher frequency data. Although such data from forecast systems are available, because of their volume, their sharing with WMO members in real time is a challenging task. Given the technological advances, however, sharing of data is not insurmountable and for subseasonal forecasts is already in place. Once again, appropriate dialogues between forecast providers and user requirements resulting in workable solutions are needed to show the benefit of using high temporal resolution data in place of temporal mean data. Beyond provision for sharing high temporal resolution data, providing adequate guidance on how forecast data should be used is also necessary to avoid misinterpretation and misuse, and further, to be cognizant of the limitations in the use of long-range forecasts.

***d. Research gaps.*** Substantial efforts are devoted at operational centers toward improvements in data assimilation techniques and models to improve global prediction systems on all time scales, and such advances also translate into improving the quality of S2D predictions. There are additional research gaps, however, that are specific to advancing climate prediction efforts. Examples include the following:

- Advancing our understanding of sources of predictability: Understanding of the sources of predictability, including teleconnection pathways that link climate variability across various parts of the globe, underpins the scientific basis of S2D predictions. This understanding also helps communicate the physical basis behind the climate forecasts and thereby helps improve the credibility of forecast providers. Such knowledge also facilitates identification of instances of forecasts of opportunity when added confidence in climate predictions can be placed. Although tremendous advances in understanding climate predictability have been made, continued efforts to advance this understanding are still required to understand low-frequency variability and the associated coupling


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processes. Understanding of causes of model biases for simulating teleconnection patterns is also a key area for continued research, model improvement, and recalibration of forecasts.

- Relative importance of various choices in deciding S2D forecast system configuration on realizing predictability: In deciding on the forecast configuration, decisions must be made to fit the forecast system within available computing resources. These decisions have implications for converting predictability into realizable skill. Answers to such questions are important in providing practical guidance to operational centers on forecast configuration and to improve homogenization across forecasts issued by different centers.
- Forecast communication: An important aspect of climate prediction is the communication of forecast skills to users. The expected skill of the forecast system can be estimated based on the hindcasts, but this skill estimate is unconditional to individual forecasts. Because of sampling issues, estimating conditional skill is a challenging problem but is essential not only for communicating forecasts to the users but also to assign confidence to the forecasts. For a reliable forecast system, the assigned forecast probabilities also reflect the chance of its success. Consequently, forecast communication also connects with methods to calibrate real-time forecasts. Continued effort is needed to advance current issues related to linking conditional and unconditional skill, forecast reliability and calibration, hindcast length, etc.
  - For seasonal forecasts, another aspect is the potential to communicate a broader range of information beyond anomalies of 3-month means. The scope of information could cover the probability of occurrence of climate indices relevant to different sectors like the number of stormy days, heating days, blocking days, season onsets, or the probability of extreme events. Again, skill and multimodel approach plays an essential part along with the development of appropriate post processing tools. Further, different regions undergo different seasonal cycles which need to be acknowledged in the dissemination of outlook bulletins.

In this paper, we highlighted the current WMO infrastructure for S2D predictions. Along with the advances in developing the operational S2D prediction systems, we also highlighted various issues that continue to hinder its uptake. To resolve some of the issues, communication and collaboration between forecast providers, research community, and users would be important. Toward that, the operational climate prediction workshop series would play an important role in bringing three communities together.

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**Data availability statement.** No datasets were generated or analyzed during the current study.


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## APPENDIX

### List of Acronyms

| | |
|---|---|
| CSIS | Climate Services Information System |
| ENSO | El Niño–Southern Oscillation |
| EW4All | Early Warnings for All |
| GFCS | Global Framework for Climate Services |
| GPC | Global Producing Center |
| GPC-SP | Global Producing Center for Seasonal Prediction |
| LC | Lead Center |
| NMHS | National Meteorological and Hydrological Service |
| NMC | National Meteorological Center |
| NWP | Numerical weather prediction |
| OCP | Operational Climate Prediction |
| RCC | Regional Climate Center |
| RCOF | Regional Climate Outlook Forum |
| RSMC | Regional Specialized Meteorological Center |
| S2D | Subseasonal to decadal |
| WIGOS | WMO Integrated Global Observing System |
| WIS | WMO Information System |
| WIPPS | WMO Integrated Processing and Predictions System |
| WMC | World Meteorological Center |
| WMO | World Meteorological Organization |
| UN | United Nations |


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