The Critical Need for Hindcast Infrastructure in Climate Science and Sectoral Applications

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Abstract:
Forecasting the impacts of climate extremes is challenging, but critical to a range of sectors, including agriculture, water management, public health and safety, infrastructure, energy, national defense, and ecology. Foundational to these forecasts are hindcast archives, which are routinely used for applications produced for the private sector and agencies, including NASA, NOAA, USAID, the US Department of Defense, and the US Army Corps of Engineers. Forecast and hindcast archives, furthermore, underpin scientific inquiry funded by all of the above agencies as well as the US NSF. In this article, we catalog the sector-specific decision support systems that depend upon hindcast model archives and survey the current state of hindcast archive infrastructure. We find that despite the tremendous amount of investment and decision support that depends on hindcast archives, the United States has a relatively fragile, underfunded hindcast archive, especially when compared with the Copernicus system in Europe. We conclude with recommendations for improving hindcast archive infrastructure to support routine sector-specific applications and improve resilience to climate extremes.

Section 1.1: Introduction

Hindcasts, also known as re-forecasts, are model forecast runs produced retrospectively using only information that was available at the time of initialization. Hindcasts are often used to evaluate model forecast characteristics and to correct systematic biases in forecasts. The primary multi-model collections of seasonal climate forecasts and their associated hindcasts are the North American Multi-Model Ensemble (NMME; Becker et al., 2022; Kirtman et al., 2014) and the Copernicus Climate Change Services (C3S; Balmeseda et al. 2024; Buontempo et al., 2022). Similar repositories of multi-model subseasonal climate forecasts and their associated hindcasts have been produced by the Subseasonal Consortium (SubC; previously SubX; Pegion et al. 2019), the Subseasonal to Seasonal Prediction Project (S2S; Vitart et al. 2017), and the International Grand Global Ensemble (TIGGE; Swinbank et al., 2016).

Multi-model hindcast archives of dynamical forecast models are important for advancing both our scientific understanding of climate extremes and our ability to predict them in real-time. Such hindcast archives are understood to underpin well-known public-facing climate forecasts, but they also provide the foundation for a wide variety of critical sector-specific systems that are less widely known. Forecasting the impacts of climate extremes presents challenges to a range of sectors, including agriculture, water management, public health and safety, infrastructure, energy, national defense, and ecology. These events are often complex and rare, such that building skillful, robust forecast systems using the observational record alone is not possible.

Section 1.2: The routine uses of forecast and hindcast archives

Multi-model forecast and hindcast archives updated in real-time are valuable for their ability to improve climate forecast skill. Long hindcast records are used for determining forecast biases and other errors, allowing for the real-time calibration of forecasts (Hamill et al. 2005) of important climate parameters such as 2m temperature and sea surface temperature (SST; Becker et al., 2022; Kirtman et al., 2014). As such, multi-model forecast and hindcast archives have demonstrated value within the climate community. Outside of the climate community, they have enabled a wide variety of private and public applications that underpin decision support systems across agencies and disciplines.

For example, official National Oceanic and Atmospheric Administration (NOAA) forecasts of ENSO depend upon the NMME. Predictions of ENSO are often displayed as indices of the Niño regions of SST or sea level pressure anomalies, especially those from the Niño-3.4 region (Barnston et al., 1997). In addition to their in-house seasonal forecast systems, other national meteorological and hydrological services that produce ENSO updates also rely on other multi-model systems, such as the World Meteorological Organization (WMO) Long-Range Forecast Multi-model ensemble (Bojovic et al., 2022).

Ocean hindcasts from NMME have also been used to support living marine resource management (Jacox et al. 2020; Tommasi et al., 2017a; Tommasi et al., 2017b; Hervieux et al., 2019). For example, NOAA uses NMME SST output to generate experimental forecasts of warm ocean temperature extremes known as marine heatwaves (Jacox et al. 2022). The same model output has been used to generate forecasts of marine ecological indicators in the California Current System, such as the Habitat Compression Index, which indicates the likelihood of negative human-wildlife interactions like whale entanglements and ship strikes (Brodie et al 2023). In both examples, the multi-model mean forecast skill noticeably exceeded the skill from any individual model, further highlighting the benefit of multi-model forecast and hindcast archives in supporting marine resource management strategies.

Hindcasts of inundation (e.g., storm surge or total water level) and waves are commonly used in applications along the coast. Coastal regions are extremely vulnerable to the damaging impacts of coastal flooding and sea level rise due to increased population and development, complex environments, and the confluence of multiple hydrologic and hydrodynamic forcings across timescales (Sweet et al., 2022; May et al., 2023). The insurance industry and emergency management group often rely on hindcasts of surge and waves from past events for risk and damage assessment to public infrastructure and private property (TDI, 2016; FEMA, 2019; Moghimi et al, 2020). Wave hindcast climatologies are particularly useful for design and construction purposes against extreme events due to the lack of observational data, such as from Wave Watch III hindcast archive (2012) and the USACE Coastal and Hydraulics Laboratory Wave Information Study (Halls et al., 2024). Sea surface height predictions are regularly output by many operational models, both on subseasonal timescales, including by CFSv2 (Saha et al, 2014) and the European Centre for Medium-Range Weather Forecasts (ECMWF)'s Integrated Forecasting System (IFS), and on seasonal time scales, by multi-model ensembles from both the NMME (Becker et al., 2022) and C3S (Balmeseda et al. 2024). Many of these hindcasts have been recently evaluated for U.S. coastal skill (Shin and Newman 2021; Long et al., 2025; Albers et al., 2025) and may also be further downscaled to finer coastal scales (Long et al. 2023). Hindcasts are critical to assessing and improving the CFS and IFS systems for these applications.

Hindcast data also underpins many operational hydrological forecasting systems. The NOAA National Weather Service Hydrologic Ensemble Forecasting System (HEFS; Demargne et al. 2014) is operational across the US (Fresch M. 2024), providing ensemble streamflow prediction for the water resources community. Critical to this operational implementation was the calibration and validation of HEFS using the Global Ensemble Forecast System version 12 (GEFSv12) meteorological hindcasts (Guan et al. 2022). HEFS hindcasts are also relied upon for evidence-based decision-making. For example, the New York City Department of Environmental Protection (NYCDEP) uses HEFS hindcasts to optimize and validate its Operational Support Tool, which is vital to its reservoir management and infrastructure planning (Porter et al. 2015). Shifting the streamflow forecasting paradigm to include using seasonal forecasts and hindcasts has been identified as a key pathway towards improving streamflow prediction (Wood et al. 2020; Slater et al., 2019; Slater and Villarini, 2018), which is critical for the NWS River Forecast Centers whose mission is to deliver river and flood forecasts and warnings to protect life and property. Outside of the US, both the Global Flood Awareness System (GLoFAS; Alfieri et al., 2013; Emerton et al., 2018) and the European Multi-model ensemble of hydrological forecasts (Copernicus, 2021) rely on seasonal forecasts calibrated using hindcast archives to produce operational, near-real-time forecasts of streamflow for use by decision-makers and in early warning systems.

In the agriculture sector, hindcasts are an integral part of developing seasonal forecasts for food security early warning systems. These forecasts include forecasts of rainy season onset provided to national meteorological departments (White et al., 2022; Robertson et al., 2019), hydrological forecasts of soil moisture (Arsenault et al., 2020; Hazra et al., 2023; Esit et al., 2021; Silvestri et al., 2024; Zhou et al., 2021; Bergaoui et al., 2022), total water storage (Cook et al., 2021), crop-relevant water stress metrics (Funk et al., 2021), and crop yield forecasts made using either process-based crop models (Boas et al., 2023) or statistical models (Pons et al., 2021; Zachow et al., 2023; Bento et al., 2022; Anderson et al., 2024). Each of these applications is developed and calibrated using hindcast data, with many of the operational products leveraging a multi-model hindcast ensemble to improve forecast skill (Hazra et al., 2023). As food security early warning systems are becoming increasingly sophisticated, forecast and hindcast archives are playing a larger role in such systems. For example, nearly all of the forecasts routinely provided to the United States Agency for International Development (USAID's) Famine Early Warning Systems Network (FEWS NET) depend on multi-model hindcast archives, including the ENSO and subseasonal-to-seasonal forecasts produced by NOAA and WMO, tailored regional climate forecasts (Funk et al., 2023), hydrological forecasts of soil moisture and streamflow (Arsenault et al., 2020; Hazra et al., 2023), crop-relevant water stress forecasts (Funk et al., 2021), and crop yield forecasts (Anderson et al., 2024).

Forecast and hindcast archives play an important role in national defense as well. The United States Air Force produces routine, near-real-time subseasonal to seasonal hydrological forecasts using the Global Hydro-Intelligence system (Arsenault et al., 2024). The system uses multi-model precipitation forecasts from NMME together with the National Aeronautic Space

Administration (NASA) Land Information System (Kumar et al., 2006) to produce daily hydrological outputs that include soil moisture and streamflow. These forecasts provide information on the likely development of droughts and floods to support the United States military.

Finally, hindcasts support emerging transdisciplinary efforts, including better understanding and predicting fire danger (Di Giuseppe et al. 2020; Di Giuseppe et al. 2024) and risks of vector-borne disease (Rocque et al. 2021; Landman et al. 2020; Muñoz et al., 2017; Muñoz et al., 2020). One well-known vector-borne forecast focuses on malaria outbreaks on subseasonal-to-seasonal timescales. Malaria hindcasts based on temperature and precipitation output from climate models have shown particular skill at forecasting outbreaks at 1-2 week lead times (Kim et al. 2019) and on seasonal timescales (MacLeod et al. 2015). Operational malaria forecasts from the private sector have also recently been developed.

Table 1 Routinely produced use cases that depend on hindcast model archives.

Product	Producer	Use case	Citation
Streamflow forecasts	NOAA	Flood risk, water supply, environmental flows.	Demargne et al. (2014); Porter et al. (2015)
Streamflow forecasts	Copernicus Emergency Management Service	Global flood risk forecasts	Alfieri et al. (2013); Emerton et al. (2018)
Streamflow forecasts	Copernicus Emergency Management Service	European flood risk forecasts	Smith et al. (2016); Copernicus (2021)
ENSO forecasts	NOAA	Multi-sectorial applications	McPhaden et al. (2006)
Marine heatwaves	NOAA	Marine resource management	Jacox et al. (2022)
Sea surface height	NOAA NCEP CFSv2	Subseasonal to annual coastal inundation/flood risk	Saha et al. (2014)
Sea surface height	ECMWF IFS and/or SEAS5	Subseasonal to annual coastal inundation/flood risk	Albers et al. (2025); Balmeseda et al. (2024)
Subseasonal agroecological drought forecast	JHU	Soil moisture drought monitor for the	Zhou et al. (2021)

		International Centre for Integrated Mountain Development (ICIMOD)	
Seasonal agroecological drought forecast	IWMI	Drought monitoring, food security early warning	Bergaoui et al. (2022)
Seasonal soil moisture and streamflow forecasts	NASA	Drought monitoring, food security early warning for USAID's FEWS NET	Arsenault et al. (2020); Hazra et al. (2023)
Subseasonal to seasonal soil moisture and streamflow forecasts	US Air Force / NASA	Hydrological forecasting for US DoD	Arsenault et al. (2024)
Seasonal crop yield forecasts	UMD	Food security early warning for USAID's FEWS NET	Anderson et al. (2024)
Fire danger forecasts	Copernicus Emergency Management Service	Global forest fire information monitoring and forecasting	Di Giuseppe et al. (2020), Di Giuseppe et al. (2024)
S2S forecasts for renewable energy	Salient Predictions	Peak load forecasting	Salient, 2024a
S2S forecasts for private-sector agriculture	Salient Predictions	Subseasonal drought forecasts	Salient, 2024b
Seasonal malaria forecasts	Clinton Health Access Initiative	Health sector	https://dashboards.endmalaria.org/forecastingCommodities/short-term-forecast
Seasonal forecasts of environmental suitability for vector-borne diseases	IRI, Columbia University; University of Pretoria	Health sector	(Muñoz et al. 2017; Muñoz et al. 2020; Landman et al. 2020)

Forecast and hindcast archives are critical not just for sectoral applications but also for developing and applying novel methods, such as machine learning (ML), which can help improve both forecast skill and our understanding of the climate system (e.g., Vitart et al. 2022; Richter et al., 2024). Large hindcast datasets can be used to overcome limited sample sizes in training datahungry ML models for climate prediction (e.g., Shin et al. 2020, Ahn et al. 2022), although longer hindcasts could further improve ML-based climate prediction (e.g., He et al. 2022). Hindcasts of dynamical models allow for learning model biases that can improve downstream predictions for stakeholders (e.g., Kim et al. 2019, Kim et al. 2021, Golian et al. 2022, Slater et al. 2023, Zhang et al. 2024). ML can learn and correct such biases, as recently shown for temperature and precipitation, where subseasonal forecast improvements exceeded 60% and 40%, respectively, over common baselines (Mouatadid et al. 2023). The flexibility of ML also has opened new opportunities in the fusion of physical science data and information most relevant to decision-makers and stakeholders, leading to ML-based efforts focused on accelerating risk and intervention assessments (Porciello et al. 2020; Zennaro et al. 2021; Vosper et al. 2023). Large hindcasts are needed to both train ML-based models and serve as benchmarks to ensure that data-driven predictions are trustworthy (e.g., Qian et al. 2020, Gibson et al. 2021, McGovern et al. 2022, Molina et al. 2023) and associated uncertainties are well-calibrated (e.g., Chapman et al. 2022, Haynes et al. 2023).

Section 1.2 Scientific use-cases

Hindcast databases are also a critical tool to bridge the gap between the climate science research and prediction communities. ENSO provides a prime example. The peer-reviewed literature is rich with analyses discovering that certain climate patterns, often referred to as "ENSO precursors," can extend the lead time for predicting ENSO. Analysis of hindcast databases, however, serves as a critical test as to whether these precursor claims hold up for actual initialized predictions. For example, NMME hindcasts have been analyzed to test whether extratropical climate modes are reliable predictors of ENSO (Larson and Kirtman 2014; You and Furtado 2019), and both NMME and ECMWF hindcasts have been used to argue that oceanic heat content in the equatorial Pacific increases the predictability of ENSO (Larson and Pegion 2020; Sharmila et al. 2023). NMME hindcasts have also been used to assess the sensitivity of North American seasonal climate prediction skill to ENSO diversity (Infanti and Kirtman 2016), a hypothesis motivated by observational and model analysis (e.g., Kug et al. 2009).

Multi-model forecast and hindcast archives have likewise been used to improve our understanding of tropical Pacific SST biases and systematic errors in climate models (Newman and Sardeshmukh 2017; Beverley et al., 2023, 2024; L'Heureux et al., 2022; Balmaseda et al., 2024), which present a major barrier to understanding how climate change will affect many regions in the decades to come. The NMME archive, for example, has been used as a key piece of evidence to resolve the "East Africa Paradox," which refers to the discrepancy between projected wetting and observed drying of the East African long rains over the last 40 years (Schwarzwald and Seager, 2024).

Large ensembles of hindcasts have furthermore been used to understand and characterize tail risks to food production systems. The Unprecedented Simulated Extreme Ensemble (UNSEEN) method has been used to estimate the return period of heat extremes in the maize triangle of South Africa (Bradshaw et al., 2022) and the joint occurrence of climate extremes during the wheat growing season in China and the US Midwest (Coughlan de Perez et al., 2023). Using hindcasts to characterize the probability of tail risk events to food production systems, such as multiple breadbasket failures, is often essential given that the short historical record precludes such an analysis.

Section 2: Current hindcast archive landscape

Section 2.1 How are the needs of the hindcast archive unique?

Developing and maintaining effective forecast and hindcast archives presents a number of unique challenges due to the near real-time nature of the data and the decentralization of the data production. Forecast and hindcast archives must contend with frequent updates in modeling and data assimilation systems, limitations in human and computational resources, and the need for education and training, particularly for new users.

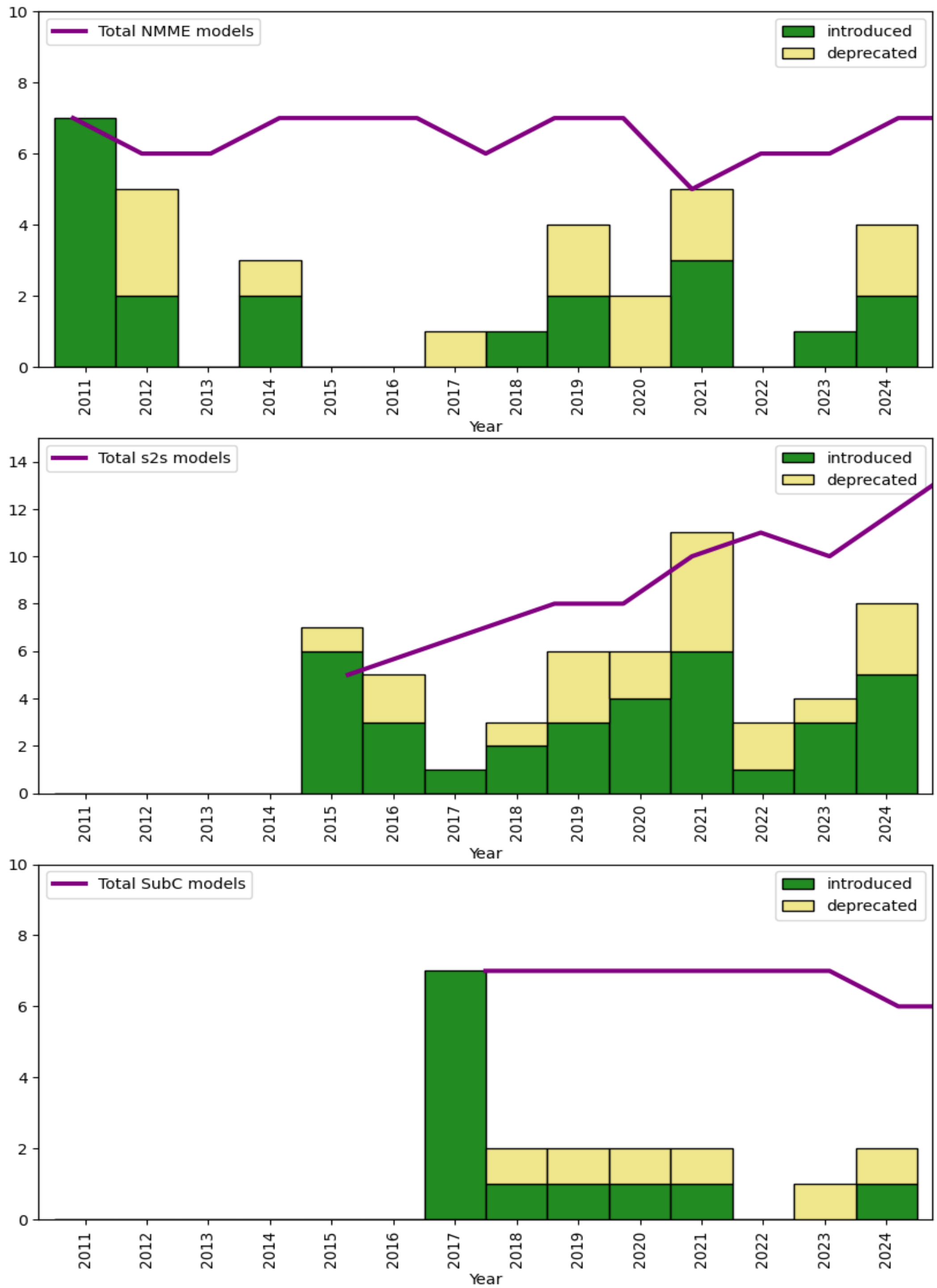

Figure 1: Total number of models, as well as the number of models either introduced or deprecated each year in the S2S, SubC, and NMME databases.

Nevertheless, a long-term hindcast archive is essential to improve model forecasts. Hindcasts, for example, are needed to identify and minimize the effect of model-dependent biases and drifts in the forecasting system. Aligning the model's initial conditions with observations introduces model drifts that vary with forecast initialization time, lead time, and location (Kumar et al., 2014), as recently highlighted in ENSO forecasting (Tippett et al., 2020). These forecast drifts are model-specific as they are attributable to model errors and discrepancies between the model's preferred climatology and observed climatology, among other things.

Limited computational resources often constrain the production of hindcast runs such that achieving a consistent hindcast protocol across modeling centers is a challenge. The optimal length of hindcast data required remains uncertain and is influenced by factors including the type of application, continuity in observational streams, and available computational and data-archiving resources. Different archives have made different decisions about how best to allocate limited computational resources when developing a hindcast archive protocol. A recent sub-seasonal forecast experiment, initialized weekly, archived hindcast data spanning 22 years from 1999 to 2020 (Richter et al., 2022; 2024). Seasonal to multiyear forecasting systems, initialized four times a year, have archived hindcast data for 50 years from 1970 to 2019 (Yeager et al., 2022). The ECMWF seasonal forecasting system, initialized biannually (May 1 and Nov. 1), provides longer hindcast data ranging from 1901 to 2010 (Johnson et al., 2019). CFSv2 monthly and seasonal hindcast data cover the period from 1982 to 2010. Developing research-based guidelines on the optimal length, frequency, and variables of hindcast data could be one avenue toward maximizing the benefit of such archives while minimizing the computational costs associated with producing hindcast data.

Section 2.2 How are hindcasts currently archived?

Hindcasts are currently archived in multiple locations. As a case in point, the NMME is a collection of different models run at NOAA, NASA, the University of Miami, and Environment and Climate Change Canada (ECCC). Each agency or institution has its own established portals to disseminate its own model data. However, the NMME project collected real-time monthly averaged data into a single archive at the International Research Institute for Climate and Society (IRI), Climate Data Library (IRIDL). This additional effort to provide a single repository for multiple models' hindcast and real-time forecast data is supported by an interagency memorandum of understanding (MOU) currently led by the NOAA Weather Program Office (WPO). Past temporary funding efforts have also led to a collection of retrospective NMME forecasts from older model versions hosted in two separate archives at the National Centers for Environmental Information and the National Center for Atmospheric Research.

A similar repository of multi-model hindcasts and forecasts for the subseasonal timescale called the Subseasonal Consortium (SubC; previously SubX), is also maintained and distributed at the IRIDL. SubX was a NOAA-funded project to support subseasonal prediction efforts. SubX consisted of hindcasts and real-time forecasts from seven models run by NOAA, NASA, ECCC, Navy, and U. Miami (Pegion et al. 2019). Each modeling group performed its own hindcasts and forecasts following an agreed-upon protocol and provided the data to the SubX database at the IRIDL (Pegion et al. 2019). Although NOAA funding for SubX ended, the project continues with limited and patchwork funding as the Subseasonal Consortium (SubC) and continues to provide hindcasts and forecasts at the IRIDL because the project members believe in the value of the archive and that continuity is in the interest of the research and user communities. Another successful repository of multiple model hindcasts and real-time forecasts is the Copernicus Climate Change Service (C3S) provided by the Copernicus Earth Observation Program of the European Union. C3S is operated by ECMWF on behalf of the EU and holds eight to nine of the WMO Global Producing Centers' long-range forecast models. Individual institutions contribute through individual service contracts with the EU, while others are provided in-kind, based on bilateral agreements with ECMWF or the EU.

An archive on the subseasonal timescale was created as part of the WWRP/WCRP Subseasonal to Seasonal Prediction (S2S) Project. Although the S2S project concluded in 2023, the S2S database continues to be maintained by ECMWF and the 13 model providers (https://confluence.ecmwf.int/display/S2S/Models), which are mostly Global Producing Centers. The S2S database contains an archive of both the forecasts issued since 2015 and the hindcasts that were made to accompany the forecasts. As the forecasting systems evolved since 2015, new hindcast sets were archived, providing a record from which model improvements could be quantified (WMO, 2024). It is a database of opportunity in which the hindcast protocol was left up to the contributing centers. The S2S database archiving protocol specified uniform post-processing of up to 90 model variables at daily resolution on a uniform 1.5-degree latitude-longitude grid. A much smaller number of ocean variables on a 1-degree grid are also included (Vitart et al. 2017). The S2S database currently contains over 250TB of data at ECMWF and CMA. With NOAA support, the S2S database has also been archived in the IRI Data Library on a continuing basis. The latter provides users with the big advantage of a uniform interface across the SubX, S2S, NMME, and C3S (limited subset) databases. The S2S database was used to benchmark AI/ML postprocessing methods through a forecasting competition run in 2021 (Vitart et al. 2022).

Without formal coordination stemming from these interagency MOUs and contracts, there would be no effort to collate the models in one location. In the absence of them, model developers continue to follow their own agency's protocols for disseminating their data, whether through FTP or more advanced climate data stores and graphical user interfaces. These approaches mean that users are required to learn a number of different methods and strategies for obtaining model data through various distributors. Systems that are built on a patchwork of data from different locations furthermore require constant revision to account for changing locations and formats of data at each modeling center. Continuously cobbling together data from these various repositories is a time-intensive process that is a chokepoint for those who want to process and analyze model data in a timely manner.

As an example, the WWRP/WCRP S2S Database and SubX/SubC were developed separately and without direct coordination. The different protocols between the two make it challenging for users to use data from both databases. As a result, most researchers and users choose one or the other, but rarely do they use both together. Although there was some overlap in personnel working on the projects, ultimately, the funding mechanisms strongly influenced the different design protocols of the two databases. Better coordination and funding for these large community hindcast and forecast efforts are needed to avoid such problems.

Additionally, when there are no MOUs and sustained support is lacking, there is no confidence in the longevity of the data and archive, and potential users are hesitant to invest time in developing a workflow to use them. This is evidenced by SubC, which did not have formal MOUs in place and was year-to-year funded with no commitment to longer-term funding. A SubX user's workshop highlighted the need for, and interest in, SubX data but also the hesitation by users to invest in developing workflows without funding stability (Bassett et al. 2022).

Section 3: Improving hindcast archive infrastructure

The ideal model hindcast data archive would be hosted in one location, with agreed-upon consistent protocols, data quality and metadata standards set in place, and the aggregation of real-time data operating on a predetermined schedule. The more successful examples of this, like the Climate Data Store and Copernicus, typically provide example codes to ingest the data. Their archives also have additional functionality that makes extracting subsets of the data (e.g., one forecast lead time or one geographic domain) fairly straightforward. Such standards enable end users to develop stable workflows for downstream applications, effectively removing the bottleneck between the proposed potential application of multi-model forecasts and realized operational value. We identify the following recommended practices for forecast and hindcast archives:

1. Establish a protocol that standardizes the spatial and temporal resolution, initialization frequency, and minimum length of record required for inclusion in the archive.
2. Provide access to all hindcasts in a single, centralized, open-access repository with comprehensive documentation that includes dataset descriptions, model configurations, data processing methods, and guidance on known issues and limitations.
3. Update the hindcast archive in near real-time with a consistent release date to enable operational and near-real-time applications.
4. Maintain hindcast runs with detailed documentation based on previous versions of models to enable scientific research.
5. Implement a catalog with search and filter options, and allow users to subset hindcasts by model, initialization date, lead time, location, and variable prior to downloading data.
6. Provide equitable access to hindcast data by minimizing, to the extent possible, the computational burden required to download and post-process hindcast data. This includes providing pre-calculated lead-dependent climatologies so that anomalies can easily be calculated without the need to download the entire hindcast archive for a given variable.

To achieve these standards will require international coordination and sustained multi-agency support for forecast and hindcast archives. Hindcast archives are critical aspects of sector-specific routine applications produced for the private sector and agencies, including NASA, NOAA, USAID, the US Department of Defense, and the US Army Corps of Engineers. Forecast and hindcast archives, furthermore, underpin scientific inquiry funded by all of the above agencies as well as the US National Science Foundation (NSF). And yet, in the US, forecast and hindcast archives are not funded or maintained to the standards set by the Copernicus system in Europe. If the multi-model forecast and hindcast infrastructure in the US is not supported, it is likely that users will either stop using multi-model ensembles altogether or that they will increasingly turn to multi-model systems that do not include US-based models, such as Copernicus. The former would degrade the skill of sector-specific applications in the US, while the latter would reduce the use of US-based forecast models and, thus, US-global leadership in climate prediction and sectoral applications. The US currently has an underfunded, fragile, hindcast archive infrastructure upon which a tremendous amount of investment and decision support depends. It is critical that our hindcast archive infrastructure be brought into the 21st century if we are to continue to support and advance our decision-support capabilities and actionable Earth system science.

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