

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

Weston Anderson^{1a}, Marybeth C. Arcodia,^b Dillon Amaya,^c Emily Becker,^d John A. Callahan,^{e,f} Jason C. Furtado,^g Benjamin Kirtman,^d Sanjiv Kumar,^h Michelle L. L'Heureux,ⁱ Sarah M. Larson,^j Dan Li,^k Maria J. Molina,^a Matthew Newman,^c Kathleen Pegion,^g Andrew Robertson,^l Erin Towler,^c and Baoqiang Xiang^{m,n}

KEYWORDS:

Forecasting;
Hindcasts;
Decision making;
Decision support;
Policy

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 model archives, which are routinely used for applications produced for the private sector and agencies, including the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), the U.S. Department of State, and the U.S. Department of Defense. Forecast and hindcast archives underpin scientific inquiry funded by these agencies, particularly in relation to forecasting weather and climate extremes, as well as by the U.S. National Science Foundation (NSF). In this article, we catalog the sector-specific decision support systems that depend upon hindcast archives and survey the current state of hindcast archive infrastructure. We find that despite the tremendous amount of investment and the dependent decision support systems, the U.S. hindcast archive is relatively fragile and underfunded, 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.

SIGNIFICANCE STATEMENT: Forecasting the impacts of climate extremes is critical to a range of sectors, including agriculture, water management, public health and safety, infrastructure, energy, national defense, and ecology. Archives of model forecast runs are critical to these efforts. We outline how archives of model forecasts are critical for routine applications produced for the private sector and for a range of government agencies. Indeed, having a robust model forecast archive allows scientists to understand potential model biases in different weather types and also assess the potential of these models to accurately forecast extreme weather events. We find that despite the number of sectors that depend on accurate forecasts, the United States has a relatively fragile and underfunded archive infrastructure when compared with the equivalent system in Europe.

DOI: 10.1175/BAMS-D-24-0311.1

Corresponding author: Weston Anderson, weston@umd.edu

Manuscript received 19 November 2024, in final form 17 September 2025, accepted 24 October 2025

© 2026 American Meteorological Society. This published article is licensed under the terms of the default AMS reuse license. For information regarding reuse of this content and general copyright information, consult the AMS Copyright Policy (www.ametsoc.org/PUBSReuseLicenses).

AFFILIATIONS: ^a University of Maryland, College Park, College Park, Maryland; ^b Colorado State University, Fort Collins, Colorado; ^c NOAA/Physical Sciences Laboratory, Boulder, Colorado; ^d University of Miami, Miami, Florida; ^e Ocean Associates, Inc., Arlington, Virginia; ^f NOAA/Center for Operational Oceanographic Products and Services, Silver Spring, Maryland; ^g University of Oklahoma, Norman, Oklahoma; ^h Auburn University, Auburn, Alabama; ⁱ NOAA/Climate Prediction Center, College Park, Maryland; ^j North Carolina State University, Raleigh, North Carolina; ^k Boston University, Boston, Massachusetts; ^l Columbia University, New York, New York; ^m NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey; ⁿ Cooperative Programs for the Advancement of Earth System Science, University Corporation for Atmospheric Research, Boulder, Colorado

1. Introduction

Hindcasts, also known as reforecasts, are model forecast runs produced retrospectively using modern models and analysis systems but without observation or analysis inputs beyond the initialization time. Hindcasts are often used to evaluate model forecast characteristics and to correct systematic biases in forecasts. The primary multimodel collections of seasonal climate forecasts and their associated hindcasts are the North American Multimodel Ensemble (NMME; Becker et al. 2022; Kirtman et al. 2014), the Asia–Pacific Economic Cooperation (APEC) Climate Center Multimodel Ensemble (Yhang et al. 2025; Min et al. 2014), and the Copernicus Climate Change Services (C3S; Balmaseda et al. 2024; Buontempo et al. 2022). Similar repositories of multimodel 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 (S2S) Prediction project (Vitart et al. 2017), and the THORPEX Interactive Grand Global Ensemble (TIGGE; Swinbank et al. 2016).

Multimodel 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 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.

2. Current hindcast archive landscape

a. The routine uses of forecast and hindcast archives. Multimodel 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. 2006) of important climate parameters such as 2-m temperature and sea surface temperature (SST; Becker et al. 2022; Kirtman et al. 2014). As such, multimodel hindcast archives are critical for quantifying the forecast skill of our forecast models. Such quantification allows users and practitioners to understand the capability of the models for forecasting extremes and ultimately establish a level of trust in those forecasts. Outside of the climate community, they have enabled a wide variety

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 Climate Change Service, Climate Data Store (2021)
ENSO forecasts	NOAA	Multisectorial applications	McPhaden et al. (2006)
Marine heat waves	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), Balmaseda et al. (2024)
Subseasonal agroecological drought forecast	JHU	Soil moisture drought monitor for the International Centre for Integrated Mountain Development (ICIMOD)	Zhou et al. (2021)
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 FEWS NET	Arsenault et al. (2020), Hazra et al. (2023)
Subseasonal to seasonal soil moisture and streamflow forecasts	U.S. Air Force/NASA	Hydrological forecasting for U.S. DoD	Arsenault et al. (2024)
Seasonal crop yield forecasts	UMD	Food security early warning for 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, 2024)
S2S forecasts for renewable energy	Salient Predictions	Peak load forecasting	https://www.salientpredictions.com/blog/revolutionizing-agricultural-planning-the-impact-of-reliable-seasonal-forecasts-for-ab-inbev
S2S forecasts for private-sector agriculture	Salient Predictions	Subseasonal drought forecasts	https://www.salientpredictions.com/blog/warmest-winter-on-record-delivers-billions-in-profits-to-citadel
Seasonal malaria forecasts	Clinton Health Access Initiative	Health sector	https://dashboards.endmalaria.org/en/short-term-forecast
Seasonal forecasts of environmental suitability for vector-borne diseases	IRI, Columbia University; University of Pretoria	Health sector	Muñoz et al. (2017, 2020), Landman et al. (2020)

of private and public applications that underpin decision support systems across agencies and disciplines (see Table 1).

For example, official National Oceanic and Atmospheric Administration (NOAA) forecasts of ENSO depend upon the NMME hindcasts (L'Heureux et al. 2020; CPC 2021). Predictions of ENSO are often displayed as indices of the Niño regions of SST or as differences in sea level pressure anomalies, especially those from the Niño-3.4 region (Barnston et al. 1997). ENSO forecasts require hindcasts to calibrate model forecasts and evaluate multimodel forecast skill (L'Heureux et al. 2019). In addition to their in-house seasonal forecast systems, other national meteorological and hydrological services that produce ENSO updates also rely on other multimodel hindcast archives, such as the World Meteorological Organization (WMO) Long-Range Forecast Multimodel 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,b; Hervieux et al. 2019). For example,

NOAA uses NMME SST output to generate experimental forecasts of warm ocean temperature extremes known as marine heat waves (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 each of these products, hindcasts are required to calibrate the model and estimate the skill of the model. In both examples, the multimodel mean forecast skill noticeably exceeded the skill from any individual model, further highlighting the benefit of multimodel forecast and hindcast archives in supporting marine resource management strategies.

Hindcasts are also used in applications along U.S. coasts. 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 time scales (Sweet et al. 2022; May et al. 2023). Sea surface height predictions are regularly output by many operational models, both on subseasonal time scales, 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 multimodel ensembles from both the NMME (Becker et al. 2022) and C3S (Balmaseda 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 Global Ensemble Forecast System (GEFS) and IFS systems for these applications.

Hindcast data also underpin many operational hydrological forecasting systems. The NOAA National Weather Service Hydrologic Ensemble Forecast Service (HEFS; Demargne et al. 2014) is operational across the United States (Fresch 2024), providing ensemble streamflow prediction for the water resources community. Critical to this operational implementation was the calibration and validation of HEFS using the GEFS, 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 toward 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 United States, both the Global Flood Awareness System (GLOFAS; Alfieri et al. 2013; Emerton et al. 2018) and the European multimodel ensemble of hydrological forecasts (Copernicus Climate Change Service, Climate Data Store 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. 2025; 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 multimodel 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 Famine Early Warning Systems Network (FEWS NET) depend on multimodel hindcast-calibrated forecasts, including ENSO and subseasonal-to-seasonal forecasts produced by NOAA and other national meteorological agencies coordinated by the 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 U.S. 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 multimodel hindcast-calibrated precipitation forecasts from NMME together with the National Aeronautics and 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 U.S. military.

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

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 data-hungry 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 that associated uncertainties are well calibrated (e.g., Chapman et al. 2022; Haynes et al. 2023). ML-based approaches trained on hindcast datasets are presently being used in operational contexts, including as an aid to forecasters at the Weather Prediction Center for excessive rain outlooks (Hill et al. 2023; Schumacher et al. 2021).

b. 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 demonstrate that knowledge of oceanic heat content in the equatorial Pacific increases the prediction skill 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 analyses (e.g., Kug et al. 2009).

Multimodel 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 identify Pacific SST trends as the cause of the “East Africa Paradox,” which refers to the discrepancy between projected wetting and observed drying of the East African March–May “long” rains season 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 U.S. 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.

c. How are the needs of the hindcast archive unique? Developing and maintaining effective forecast and hindcast archives present 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 (Fig. 1), limitations in human and computational resources, and the need for education and training, particularly for new users.

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, 2012), 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. Indeed, the computational costs of producing hindcast archives and the lack of institutional support for doing so have been identified previously and have led to the discontinuation of past hindcast archives such as the GEFS/R archive (Hamill et al. 2013). 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 subseasonal forecast experiment, initialized weekly, archived hindcast data spanning 22 years from 1999 to 2020 (Richter et al. 2022, 2024). Seasonal-to-multiyear forecasting systems, such as the NCAR Seasonal-to-Multiyear Large Ensemble (SMYLE) system, initialized four times a year,

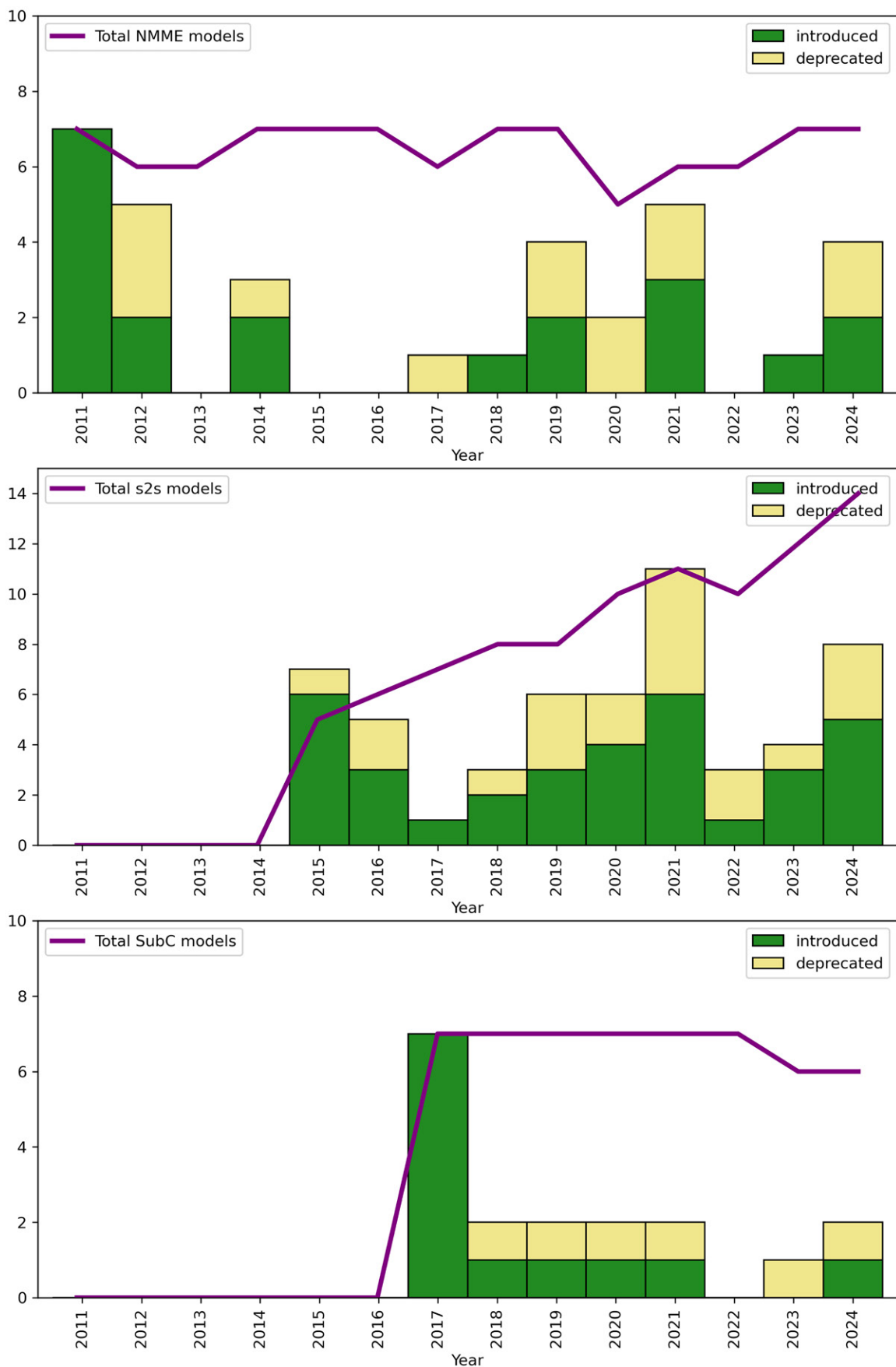


FIG. 1. Total number of models, as well as the number of models either introduced or deprecated each year in the S2S, SubC, and NMME databases.

have archived hindcast data for 50 years from 1970 to 2019 (Yeager et al. 2022). The ECMWF seasonal forecasting system, initialized biannually (1 May and 1 November), 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.

d. 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 has 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 U.S. National Science Foundation (NSF) National Center for Atmospheric Research.

A similar repository of multimodel hindcasts and forecasts for the subseasonal time scale called the 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 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 C3S provided by the Copernicus Earth Observation Program of the European Union. C3S is operated by ECMWF on behalf of the European Union and holds eight to nine of the WMO Global Producing Centers' long-range forecast models. Individual institutions contribute through individual service contracts with the European Union, while others are provided in kind, based on bilateral agreements with ECMWF or the European Union.

An archive on the subseasonal time scale was created as part of the World Weather Research Programme (WWRP)/WCRP S2S Prediction 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 have evolved since 2015, new hindcast sets were archived, providing a record from which model improvements could be quantified. 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 postprocessing of up to 90 model variables at daily resolution on a uniform 1.5° latitude–longitude grid. A much smaller number of ocean variables on a 1° grid are also included (Vitart et al. 2017). The S2S database currently contains over 250 TB of data at ECMWF and China Meteorological Administration (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 artificial intelligence (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, it would be far more difficult to collate model runs into coherent multimodel hindcast archives. 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 choke point 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).

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 multimodel forecasts and realized operational value. We identify the following recommended practices for forecast and hindcast archives:

- 1) Establish a protocol that standardizes the minimum spatial and temporal resolution, initialization frequency, minimum set of standard variables, and minimum length of record required for inclusion in the archive. While a less stringent protocol may lower the barrier to entry for new models, creating multimodel ensembles requires standardization either at the time of running or in postprocessing.
- 2) Provide access to all hindcasts in a 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 research on skill improvement and applications requiring ensembles of hindcasts.
- 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 postprocess hindcast data. This includes providing precalculated 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, the U.S. Agency for International Development (USAID), the U.S. Department of Defense, and the U.S. Army Corps of Engineers. Forecast and hindcast archives, furthermore, underpin scientific inquiry funded by all of the above agencies as well as the U.S. National Science Foundation (NSF). Yet, in the United States, forecast and hindcast archives are not funded or maintained to the standards set by the Copernicus system in Europe.

By supporting North American multimodel hindcast archives, the United States has the opportunity to build systems that meet the operational prediction needs of North American users and partners. If the multimodel forecast and hindcast infrastructure in the United States is not supported, it is likely that users will either stop using multimodel ensembles altogether or that they will increasingly turn to multimodel systems that exclude many U.S.-based models, such as Copernicus. The former would degrade the skill of sector-specific applications in the United States, while the latter would reduce the use of U.S.-based forecast models and, thus, U.S.-global leadership in climate prediction and sectoral applications. Furthermore, relying on the Copernicus system will cede all decisions about archive standards, model requirements, product schedule, and reliability to European partners. The decisions of whether to include nonoperational models, which variables to archive, and how to develop the archive protocol would all be driven by European partners and funders without regard to the needs of U.S. partners. The many U.S.-based applications that depend on hindcast infrastructure would similarly depend on European funders.

The United States 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 twenty-first century if we are to continue to support and advance our decision-support capabilities and actionable Earth system science.

Acknowledgments. The authors thank the U.S. CLIVAR Predictability, Prediction, and Applications Panel for its efforts to engage on the topic, as well as to the experts who contributed their time presenting at panel meetings, including Dr. William Merryfield, Dr. Jadwiga (Yaga) Richter, and Dr. Anca Brookshaw. M. C. A was funded, in part, by NOAA Grant NA24OARX431C0065-T1-01 and by the Regional and Global Model Analysis program area of the U.S. Department of Energy's (DOE) Office of Biological and Environmental Research (BER) as part of the Program for Climate Model Diagnosis and Intercomparison Project. The scientific results and conclusions, as well as any view or opinions expressed herein, are those of the authors and do not necessarily reflect the views of NWS, NOAA, or the Department of Commerce.

Data availability statement. Data analyzed in this study are openly available at the locations cited in the text and in the reference section.

References

- Ahn, S., T. D. Tran, and J. Kim, 2022: Systematization of short-term forecasts of regional wave heights using a machine learning technique and long-term wave hindcast. *Ocean Eng.*, **264**, 112593, <https://doi.org/10.1016/j.oceaneng.2022.112593>.
- Albers, J. R., M. Newman, M. A. Balmaseda, W. Sweet, Y. Wang, and T. Xu, 2025: Assessing subseasonal forecast skill for use in predicting US coastal inundation risk. *Ocean Sci.*, **21**, 1761–1785, <https://doi.org/10.5194/os-21-1761-2025>.
- Alfieri, L., P. Burek, E. Dutra, B. Krzeminski, D. Muraro, J. Thielen, and F. Pappenberger, 2013: GloFAS—Global ensemble streamflow forecasting and flood early warning. *Hydrol. Earth Syst. Sci.*, **17**, 1161–1175, <https://doi.org/10.5194/hess-17-1161-2013>.
- Anderson, W., and Coauthors, 2024: Preseason maize and wheat yield forecasts for early warning of crop failure. *Nat. Commun.*, **15**, 7262, <https://doi.org/10.1038/s41467-024-51555-8>.
- Arsenault, K. R., and Coauthors, 2020: The NASA hydrological forecast system for food and water security applications. *Bull. Amer. Meteor. Soc.*, **101**, E1007–E1025, <https://doi.org/10.1175/BAMS-D-18-0264.1>.
- Arsenault, K. R., and Coauthors, 2024: Global Hydro-Intelligence (GHI): Initializing and Predicting Global S2S Hydrometeorological Extremes. Subseasonal and Seasonal Applications Workshop, NASA Goddard Space Flight Center, 20 pp., https://ntrs.nasa.gov/api/citations/20240011222/downloads/Arsenault_et_al_NOAAUFSWorkshop_Sept2024_final.pdf.
- Balmaseda, M. A., R. McAdam, S. Masina, M. Mayer, R. Senan, E. de Boissésón, and S. Gualdi, 2024: Skill assessment of seasonal forecasts of ocean variables. *Front. Mar. Sci.*, **11**, 1380545, <https://doi.org/10.3389/fmars.2024.1380545>.
- Barnston, A. G., M. Chelliah, and S. B. Goldenberg, 1997: Documentation of a highly ENSO-related SST region in the equatorial Pacific. *Atmos.–Ocean*, **35**, 367–383, <https://doi.org/10.1080/07055900.1997.9649597>.
- Bassett, C., and Coauthors, 2022: SubX current and potential users forum report. NOAA, 25 pp., <https://doi.org/10.25923/a7kd-c322>.
- Becker, E. J., B. P. Kirtman, M. L'Heureux, Á. G. Muñoz, and K. Pegion, 2022: A decade of the North American Multimodel Ensemble (NMME): Research, application, and future directions. *Bull. Amer. Meteor. Soc.*, **103**, E973–E995, <https://doi.org/10.1175/BAMS-D-20-0327.1>.
- Bento, V. A., A. Russo, E. Dutra, A. F. Ribeiro, C. M. Gouveia, and R. M. Trigo, 2022: Persistence versus dynamical seasonal forecasts of cereal crop yields. *Sci. Rep.*, **12**, 7422, <https://doi.org/10.1038/s41598-022-11228-2>.
- Bergaoui, K., and Coauthors, 2022: MENAdrought synthesis of drought monitoring, early warning, and seasonal forecasting tools and capability development. USAID, 74 pp., <https://doi.org/10.5337/2023.202>.
- Beverley, J. D., M. Newman, and A. Hoell, 2023: Rapid development of systematic ENSO-related seasonal forecast errors. *Geophys. Res. Lett.*, **50**, e2022GL102249, <https://doi.org/10.1029/2022GL102249>.
- , —, and —, 2024: Climate model trend errors are evident in seasonal forecasts at short leads. *npj Climate Atmos. Sci.*, **7**, 285, <https://doi.org/10.1038/s41612-024-00832-w>.
- Boas, T., H. R. Bogen, D. Ryu, H. Vereecken, A. Western, and H. J. Hendricks Franssen, 2023: Seasonal soil moisture and crop yield prediction with fifth-generation seasonal forecasting system (SEAS5) long-range meteorological forecasts in a land surface modelling approach. *Hydrol. Earth Syst. Sci.*, **27**, 3143–3167, <https://doi.org/10.5194/hess-27-3143-2023>.
- Bojovic, D., A. Nicodemou, A. L. St. Clair, I. Christel, and F. J. Doblas-Reyes, 2022: Exploring the landscape of seasonal forecast provision by Global Producing Centres. *Climatic Change*, **172**, 8, <https://doi.org/10.1007/s10584-022-03350-x>.
- Bradshaw, C. D., and Coauthors, 2022: Unprecedented climate extremes in South Africa and implications for maize production. *Environ. Res. Lett.*, **17**, 084028, <https://doi.org/10.1088/1748-9326/ac816d>.
- Brodie, S., and Coauthors, 2023: Ecological forecasts for marine resource management during climate extremes. *Nat. Commun.*, **14**, 7701, <https://doi.org/10.1038/s41467-023-43188-0>.
- Buontempo, C., and Coauthors, 2022: The Copernicus Climate Change Service: Climate science in action. *Bull. Amer. Meteor. Soc.*, **103**, E2669–E2687, <https://doi.org/10.1175/BAMS-D-21-0315.1>.
- Chapman, W. E., L. Delle Monache, S. Alessandrini, A. C. Subramanian, F. M. Ralph, S. P. Xie, S. Lerch, and N. Hayatbini, 2022: Probabilistic predictions from deterministic atmospheric river forecasts with deep learning. *Mon. Wea. Rev.*, **150**, 215–234, <https://doi.org/10.1175/MWR-D-21-0106.1>.
- Cook, B. I., K. Slinski, C. Peters-Lidard, A. McNally, K. Arsenault, and A. Hazra, 2021: The efficacy of seasonal terrestrial water storage forecasts for predicting vegetation activity over Africa. *J. Hydrometeor.*, **22**, 3121–3137, <https://doi.org/10.1175/JHM-D-21-0046.1>.
- Copernicus Climate Change Service, Climate Data Store, 2021: Multi-model seasonal forecasts of river discharge for Europe from January 2021 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), <https://doi.org/10.24381/cds.52f45864>.
- Coughlan de Perez, E., H. Ganapathi, G. I. Masukwedza, T. Griffin, and T. Kelder, 2023: Potential for surprising heat and drought events in wheat-producing regions of USA and China. *npj Climate Atmos. Sci.*, **6**, 56, <https://doi.org/10.1038/s41612-023-00361-y>.
- CPC, 2021: Long-lead forecast tool discussion and analysis. https://www.cpc.ncep.noaa.gov/products/predictions/long_range/tools.html.
- Demargne, J., and Coauthors, 2014: The science of NOAA's operational Hydrologic Ensemble Forecast Service. *Bull. Amer. Meteor. Soc.*, **95**, 79–98, <https://doi.org/10.1175/BAMS-D-12-00081.1>.
- Di Giuseppe, F., C. Vitolo, B. Krzeminski, C. Barnard, P. Maciel, and J. San-Miguel, 2020: Fire Weather Index: The skill provided by the European Centre for Medium-Range Weather Forecasts ensemble prediction system. *Nat. Hazards Earth Syst. Sci.*, **20**, 2365–2378, <https://doi.org/10.5194/nhess-20-2365-2020>.
- , —, C. Barnard, G. Libertá, P. Maciel, J. San-Miguel-Ayán, S. Villaume, and F. Wetterhall, 2024: Global seasonal prediction of fire danger. *Sci. Data.*, **11**, 128, <https://doi.org/10.1038/s41597-024-02948-3>.
- Emerton, R., and Coauthors, 2018: Developing a global operational seasonal hydro-meteorological forecasting system: GloFAS-Seasonal v1. 0. *Geosci. Model Dev.*, **11**, 3327–3346, <https://doi.org/10.5194/gmd-11-3327-2018>.
- Esit, M., S. Kumar, A. Pandey, D. M. Lawrence, I. Rangwala, and S. Yeager, 2021: Seasonal to multi-year soil moisture drought forecasting. *npj Climate Atmos. Sci.*, **4**, 16, <https://doi.org/10.1038/s41612-021-00172-z>.
- Fresch, M., 2024: The Hydrologic Ensemble Forecast Service - Overview and future development. *38th Conf. on Hydrology*, Baltimore, MD, Amer. Meteor. Soc., 2B.2, <http://ams.confex.com/ams/104ANNUAL/webprogram/Paper431510.html>.
- Funk, C., and Coauthors, 2021: An agro-pastoral phenological water balance framework for monitoring and predicting growing season water deficits and drought stress. *Front. Climate*, **3**, 716568, <https://doi.org/10.3389/fclim.2021.716568>.
- , and Coauthors, 2023: Tailored forecasts can predict extreme climate informing proactive interventions in East Africa. *Earth's Future*, **11**, e2023EF003524, <https://doi.org/10.1029/2023EF003524>.
- Gibson, P. B., W. E. Chapman, A. Altinok, L. Delle Monache, M. J. DeFlorio, and D. E. Waliser, 2021: Training machine learning models on climate model output yields skillful interpretable seasonal precipitation forecasts. *Commun. Earth Environ.*, **2**, 159, <https://doi.org/10.1038/s43247-021-00225-4>.
- Golian, S., C. Murphy, R. L. Wilby, T. Matthews, S. Donegan, D. F. Quinn, and S. Harrigan, 2022: Dynamical–statistical seasonal forecasts of winter and summer precipitation for the Island of Ireland. *Int. J. Climatol.*, **42**, 5714–5731, <https://doi.org/10.1002/joc.7557>.
- Guan, H., and Coauthors, 2022: GEFsV12 reforecast dataset for supporting subseasonal and hydrometeorological applications. *Mon. Wea. Rev.*, **150**, 647–665, <https://doi.org/10.1175/MWR-D-21-0245.1>.
- Hamill, T. M., J. S. Whitaker, and S. L. Mullen, 2006: Reforecasts: An important dataset for improving weather predictions. *Bull. Amer. Meteor. Soc.*, **87**, 33–46, <https://doi.org/10.1175/BAMS-87-1-33>.

- , G. T. Bates, J. S. Whitaker, D. R. Murray, M. Fiorino, T. J. Galarneau Jr, Y. Zhu, and W. Lapenta, 2013: NOAA's second-generation global medium-range ensemble reforecast dataset. *Bull. Amer. Meteor. Soc.*, **94**, 1553–1565, <https://doi.org/10.1175/BAMS-D-12-00014.1>.
- Haynes, K., R. Lagerquist, M. McGraw, K. Musgrave, and I. Ebert-Uphoff, 2023: Creating and evaluating uncertainty estimates with neural networks for environmental-science applications. *Artif. Intell. Earth Syst.*, **2**, 220061, <https://doi.org/10.1175/AIES-D-22-0061.1>.
- Hazra, A., and Coauthors, 2023: NASA's NMME-based S2S hydrologic forecast system for food insecurity early warning in southern Africa. *J. Hydrol.*, **617**, 129005, <https://doi.org/10.1016/j.jhydrol.2022.129005>.
- He, S., X. Li, L. Trenary, B. A. Cash, T. DelSole, and A. Banerjee, 2022: Learning and dynamical models for sub-seasonal climate forecasting: Comparison and collaboration. *Proc. AAAI Conf. Artif. Intell.*, **36**, 4495–4503, <https://doi.org/10.1609/aaai.v36i4.20372>.
- Hervieux, G., M. A. Alexander, C. A. Stock, M. G. Jacox, K. Pegion, E. Becker, F. Castruccio, and D. Tommasi, 2019: More reliable coastal SST forecasts from the North American multimodel ensemble. *Climate Dyn.*, **53**, 7153–7168, <https://doi.org/10.1007/s00382-017-3652-7>.
- Hill, A. J., R. S. Schumacher, and I. L. Jirak, 2023: A new paradigm for medium-range severe weather forecasts: Probabilistic random forest-based predictions. *Wea. Forecasting*, **38**, 251–272, <https://doi.org/10.1175/waf-d-22-0143.1>.
- Infanti, J. M., and B. P. Kirtman, 2016: North American rainfall and temperature prediction response to the diversity of ENSO. *Climate Dyn.*, **46**, 3007–3023, <https://doi.org/10.1007/s00382-015-2749-0>.
- Jacox, M. G., and Coauthors, 2020: Seasonal-to-interannual prediction of North American coastal marine ecosystems: Forecast methods, mechanisms of predictability, and priority developments. *Prog. Oceanogr.*, **183**, 102307, <https://doi.org/10.1016/j.pocean.2020.102307>.
- , and Coauthors, 2022: Global seasonal forecasts of marine heatwaves. *Nature*, **604**, 486–490, <https://doi.org/10.1038/s41586-022-04573-9>.
- Johnson, S. J., and Coauthors, 2019: SEAS5: The new ECMWF seasonal forecast system. *Geosci. Model Dev.*, **12**, 1087–1117, <https://doi.org/10.5194/gmd-12-1087-2019>.
- Kim, H., Y. G. Ham, Y. S. Joo, and S. W. Son, 2021: Deep learning for bias correction of MJO prediction. *Nat. Commun.*, **12**, 3087, <https://doi.org/10.1038/s41467-021-23406-3>.
- Kim, Y., and Coauthors, 2019: Malaria predictions based on seasonal climate forecasts in South Africa: A time series distributed lag nonlinear model. *Sci. Rep.*, **9**, 17882, <https://doi.org/10.1038/s41598-019-53838-3>.
- Kirtman, B. P., and Coauthors, 2014: The North American Multimodel Ensemble: Phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction. *Bull. Amer. Meteor. Soc.*, **95**, 585–601, <https://doi.org/10.1175/BAMS-D-12-00050.1>.
- Kug, J.-S., F.-F. Jin, and S.-I. An, 2009: Two types of El Niño events: Cold tongue El Niño and warm pool El Niño. *J. Climate*, **22**, 1499–1515, <https://doi.org/10.1175/2008JCLI2624.1>.
- Kumar, A., M. Chen, L. Zhang, W. Wang, Y. Xue, C. Wen, L. Marx, and B. Huang, 2012: An analysis of the nonstationarity in the bias of sea surface temperature forecasts for the NCEP Climate Forecast System (CFS) version 2. *Mon. Wea. Rev.*, **140**, 3003–3016, <https://doi.org/10.1175/MWR-D-11-00335.1>.
- Kumar, S., P. A. Dirmeyer, and J. L. Kinter III, 2014: Usefulness of ensemble forecasts from NCEP Climate Forecast System in sub-seasonal to intra-annual forecasting. *Geophys. Res. Lett.*, **41**, 3586–3593, <https://doi.org/10.1002/2014gl059586>.
- Kumar, S. V., and Coauthors, 2006: Land information system: An interoperable framework for high resolution land surface modeling. *Environ. Modell. Software*, **21**, 1402–1415, <https://doi.org/10.1016/j.envsoft.2005.07.004>.
- Landman, W. A., N. Sweijid, N. Masedi, and N. Minakawa, 2020: The development and prudent application of climate-based forecasts of seasonal malaria in the Limpopo province in South Africa. *Environ. Dev.*, **35**, 100522, <https://doi.org/10.1016/j.envdev.2020.100522>.
- Larson, S. M., and B. P. Kirtman, 2014: The Pacific meridional mode as an ENSO precursor and predictor in the North American Multimodel Ensemble. *J. Climate*, **27**, 7018–7032, <https://doi.org/10.1175/JCLI-D-14-00055.1>.
- , and K. Pegion, 2020: Do asymmetries in ENSO predictability arise from different recharged states? *Climate Dyn.*, **54**, 1507–1522, <https://doi.org/10.1007/s00382-019-05069-5>.
- L'Heureux, M. L., and Coauthors, 2019: Strength outlooks for the El Niño–Southern Oscillation. *Wea. Forecasting*, **34**, 165–175, <https://doi.org/10.1175/WAF-D-18-0126.1>.
- , A. F. Z. Levine, M. Newman, C. Ganter, J.-J. Luo, M. K. Tippett, and T. N. Stockdale, 2020: ENSO prediction. *El Niño Southern Oscillation in a Changing Climate, Geophys. Monogr.*, Vol. 253, Amer. Geophys. Union, 227–246, <https://doi.org/10.1002/9781119548164.ch10>.
- , M. K. Tippett, and W. Wang, 2022: Prediction challenges from errors in tropical Pacific sea surface temperature trends. *Front. Climate*, **4**, 837483, <https://doi.org/10.3389/fclim.2022.837483>.
- Long, X., S.-I. Shin, and M. Newman, 2023: Statistical downscaling of seasonal forecasts of sea level anomalies for U.S. coasts. *Geophys. Res. Lett.*, **50**, e2022GL100271, <https://doi.org/10.1029/2022gl100271>.
- , and Coauthors, 2025: Evaluating current statistical and dynamical forecasting techniques for seasonal coastal sea level prediction. *J. Climate*, **38**, 1477–1503, <https://doi.org/10.1175/JCLI-D-24-0214.1>.
- MacLeod, D. A., A. Jones, F. Di Giuseppe, C. Caminade, and A. P. Morse, 2015: Demonstration of successful malaria forecasts for Botswana using an operational seasonal climate model. *Environ. Res. Lett.*, **10**, 044005, <https://doi.org/10.1088/1748-9326/10/4/044005>.
- May, C. L., and Coauthors, 2023: Coastal effects. *Fifth National Climate Assessment*, A. R. Crimmins et al., Eds., U.S. Global Change Research Program, 1–43, <https://doi.org/10.7930/NCA5.2023.CH9>.
- McGovern, A., I. Ebert-Uphoff, D. J. Gagne, and A. Bostrom, 2022: Why we need to focus on developing ethical, responsible, and trustworthy artificial intelligence approaches for environmental science. *Environ. Data Sci.*, **1**, e6, <https://doi.org/10.1017/eds.2022.5>.
- McPhaden, M. J., S. E. Zebiak, and M. H. Glantz, 2006: ENSO as an integrating concept in earth science. *Science*, **314**, 1740–1745, <https://doi.org/10.1126/science.1132588>.
- Min, Y.-M., V. N. Kryjov, and S. M. Oh, 2014: Assessment of APCC multimodel ensemble prediction in seasonal climate forecasting: Retrospective (1983–2003) and real-time forecasts (2008–2013). *J. Geophys. Res. Atmos.*, **119**, 12 132–12 150, <https://doi.org/10.1002/2014jd022230>.
- Molina, M. J., J. H. Richter, A. A. Glanville, K. Dagon, J. Berner, A. Hu, and G. A. Meehl, 2023: Subseasonal representation and predictability of North American weather regimes using cluster analysis. *Artif. Intell. Earth Syst.*, **2**, e220051, <https://doi.org/10.1175/AIES-D-22-0051.1>.
- Mouatadid, S., P. Orenstein, G. Flaspohler, J. Cohen, M. Oprescu, E. Fraenkel, and L. Mackey, 2023: Adaptive bias correction for improved subseasonal forecasting. *Nat. Commun.*, **14**, 3482, <https://doi.org/10.1038/s41467-023-38874-y>.
- Muñoz, Á. G., M. C. Thomson, A. M. Stewart-Ibarra, G. A. Vecchi, X. Chourio, P. Nájera, Z. Moran, and X. Yang, 2017: Could the recent Zika epidemic have been predicted? *Front. Microbiol.*, **8**, 1291, <https://doi.org/10.3389/fmicb.2017.01291>.
- , X. Chourio, A. Rivière-Cinamon, M. A. Diuk-Wasser, P. A. Kache, E. A. Mordecai, L. Harrington, and M. C. Thomson, 2020: AeDES: A next-generation monitoring and forecasting system for environmental suitability of Aedes-borne disease transmission. *Sci. Rep.*, **10**, 12640, <https://doi.org/10.1038/s41598-020-69625-4>.
- Newman, M., and P. D. Sardeshmukh, 2017: Are we near the predictability limit of tropical Indo-Pacific sea surface temperatures?. *Geophys. Res. Lett.*, **44**, 8520–8529, <https://doi.org/10.1002/2017GL074088>.
- Pegion, K., and Coauthors, 2019: The Subseasonal Experiment (SubX): A multimodel subseasonal prediction experiment. *Bull. Amer. Meteor. Soc.*, **100**, 2043–2060, <https://doi.org/10.1175/BAMS-D-18-0270.1>.

- Pons, D., Á. G. Muñoz, L. M. Meléndez, M. Chocooj, R. Gómez, X. Chourio, and C. G. Romero, 2021: A coffee yield next-generation forecast system for rain-fed plantations: The case of the Samalá Watershed in Guatemala. *Wea. Forecasting*, **36**, 2021–2038, <https://doi.org/10.1175/WAF-D-20-0133.1>.
- Porciello, J., M. Ivanina, M. Islam, S. Einarson, and H. Hirsh, 2020: Accelerating evidence-informed decision-making for the Sustainable Development Goals using machine learning. *Nat. Mach. Intell.*, **2**, 559–565, <https://doi.org/10.1038/s42256-020-00235-5>.
- Porter, J. H., A. H. Matonse, and A. Frei, 2015: The New York City Operations Support Tool (OST): Managing water for millions of people in an era of changing climate and extreme hydrological events. *J. Extreme Events*, **2**, 1550008, <https://doi.org/10.1142/S2345737615500086>.
- Qian, Q. F., X. J. Jia, and H. Lin, 2020: Machine learning models for the seasonal forecast of winter surface air temperature in North America. *Earth Space Sci.*, **7**, e2020EA001140, <https://doi.org/10.1029/2020EA001140>.
- Richter, J. H., and Coauthors, 2022: Subseasonal Earth system prediction with CESM2. *Wea. Forecasting*, **37**, 797–815, <https://doi.org/10.1175/waf-d-21-0163.1>.
- , and Coauthors, 2024: Quantifying sources of subseasonal prediction skill in CESM2. *npj Climate Atmos. Sci.*, **7**, 59, <https://doi.org/10.1038/s41612-024-00595-4>.
- Robertson, A. W., and Coauthors, 2019: Subseasonal forecasts of the 2018 Indian summer monsoon over Bihar. *J. Geophys. Res. Atmos.*, **124**, 13861–13875, <https://doi.org/10.1029/2019JD031374>.
- Rocque, R. J., and Coauthors, 2021: Health effects of climate change: An overview of systematic reviews. *BMJ Open*, **11**, e046333, <https://doi.org/10.1136/bmjopen-2020-046333>.
- Saha, S., and Coauthors, 2014: The NCEP Climate Forecast System version 2. *J. Climate*, **27**, 2185–2208, <https://doi.org/10.1175/JCLI-D-12-00823.1>.
- Schumacher, R. S., A. J. Hill, M. Klein, J. A. Nelson, M. J. Erickson, S. M. Trojniak, and G. R. Herman, 2021: From random forests to flood forecasts: A research to operations success story. *Bull. Amer. Meteor. Soc.*, **102**, E1742–E1755, <https://doi.org/10.1175/BAMS-D-20-0186.1>.
- Schwarzwal, K., and R. Seager, 2024: Revisiting the “East African paradox”: CMIP6 models also struggle to reproduce strong observed long rain drying trends. *J. Climate*, **37**, 6641–6658, <https://doi.org/10.1175/JCLI-D-24-0225.1>.
- Sharmila, S., H. Hendon, O. Alves, A. Weisheimer, and M. Balmaseda, 2023: Contrasting El Niño–La Niña predictability and prediction skill in 2-year reforecasts of the twentieth century. *J. Climate*, **36**, 1269–1285, <https://doi.org/10.1175/JCLI-D-22-0028.1>.
- Shin, J.-Y., K. R. Kim, and J.-C. Ha, 2020: Seasonal forecasting of daily mean air temperatures using a coupled global climate model and machine learning algorithm for field-scale agricultural management. *Agric. For. Meteorol.*, **281**, 107858, <https://doi.org/10.1016/j.agrformet.2019.107858>.
- Shin, S.-I., and M. Newman, 2021: Seasonal predictability of global and North American coastal sea surface temperature and height anomalies. *Geophys. Res. Lett.*, **48**, e2020GL091886, <https://doi.org/10.1029/2020GL091886>.
- Silvestri, L., M. Saraceni, B. Brunone, S. Meniconi, G. Passadore, and P. B. Cerlini, 2025: Assessment of seasonal soil moisture forecasts over Central Mediterranean. *Hydrol. Earth Syst. Sci.*, **29**, 925–946, <https://doi.org/10.5194/hess-29-925-2025>.
- Slater, L. J., and G. Villarini, 2018: Enhancing the predictability of seasonal streamflow with a statistical-dynamical approach. *Geophys. Res. Lett.*, **45**, 6504–6513, <https://doi.org/10.1029/2018GL077945>.
- , —, A. A. Bradley, and G. A. Vecchi, 2019: A dynamical statistical framework for seasonal streamflow forecasting in an agricultural watershed. *Climate Dyn.*, **53**, 7429–7445, <https://doi.org/10.1007/s00382-017-3794-7>.
- , and Coauthors, 2023: Hybrid forecasting: Blending climate predictions with AI models. *Hydrol. Earth Syst. Sci.*, **27**, 1865–1889, <https://doi.org/10.5194/hess-27-1865-2023>.
- Smith, P. J., and Coauthors, 2016: On the operational implementation of the European Flood Awareness System (EFAS). *Flood Forecasting: A Global Perspective*, Academic Press, 313–348.
- Sweet, W. V., and Coauthors, 2022: Global and regional sea level rise scenarios for the United States: Updated mean projections and extreme water level probabilities along U.S. coastlines. NOAA, NOS Tech. Rep. NOS 01, 111 pp., https://earth.gov/sealevel/us/internal_resources/756/noaa-nos-techrpt01-global-regional-SLR-scenarios-US.pdf.
- Swinbank, R., and Coauthors, 2016: The TIGGE project and its achievements. *Bull. Amer. Meteor. Soc.*, **97**, 49–67, <https://doi.org/10.1175/BAMS-D-13-00191.1>.
- Tippett, M. K., M. L. L’Heureux, E. J. Becker, and A. Kumar, 2020: Excessive momentum and false alarms in late-spring ENSO forecasts. *Geophys. Res. Lett.*, **47**, e2020GL087008, <https://doi.org/10.1029/2020GL087008>.
- Tommasi, D., and Coauthors, 2017a: Managing living marine resources in a dynamic environment: The role of seasonal to decadal climate forecasts. *Prog. Oceanogr.*, **152**, 15–49, <https://doi.org/10.1016/j.pocean.2016.12.011>.
- , C. A. Stock, K. Pegion, G. A. Vecchi, R. D. Methot, M. A. Alexander, and D. M. Checkley Jr., 2017b: Improved management of small pelagic fisheries through seasonal climate prediction. *Ecol. Appl.*, **27**, 378–388, <https://doi.org/10.1002/eap.1458>.
- Vitart, F., and Coauthors, 2017: The Subseasonal to Seasonal (S2S) Prediction Project database. *Bull. Amer. Meteor. Soc.*, **98**, 163–173, <https://doi.org/10.1175/BAMS-D-16-0017.1>.
- , and Coauthors, 2022: Outcomes of the WMO prize challenge to improve subseasonal to seasonal predictions using artificial intelligence. *Bull. Amer. Meteor. Soc.*, **103**, E2878–E2886, <https://doi.org/10.1175/BAMS-D-22-0046.1>.
- Vosper, E., P. Watson, L. Harris, A. McRae, R. Santos-Rodriguez, L. Aitchison, and D. Mitchell, 2023: Deep learning for downscaling tropical cyclone rainfall to hazard-relevant spatial scales. *J. Geophys. Res. Atmos.*, **128**, e2022JD038163, <https://doi.org/10.1029/2022JD038163>.
- White, C. J., and Coauthors, 2022: Advances in the application and utility of subseasonal-to-seasonal predictions. *Bull. Amer. Meteor. Soc.*, **103**, E1448–E1472, <https://doi.org/10.1175/BAMS-D-20-0224.1>.
- Wood, A., L. Woelders, and J. Lukas, 2020: Streamflow forecasting. *Colorado River Basin Climate and Hydrology: State of the Science*, J. Lukas and E. Payton, Eds., Western Water Assessment, University of Colorado Boulder, 287–333.
- Yeager, S. G., and Coauthors, 2022: The Seasonal-to-Multiyear Large Ensemble (SMYLE) prediction system using the Community Earth System Model version 2. *Geosci. Model Dev.*, **15**, 6451–6493, <https://doi.org/10.5194/gmd-15-6451-2022>.
- Yhang, Y.-B., C.-M. Lim, and D. Jeong, 2025: APEC climate center multi-model ensemble dataset for seasonal climate prediction. *Sci. Data.*, **12**, 303, <https://doi.org/10.1038/s41597-025-04643-3>.
- You, Y., and J. C. Furtado, 2019: The relationship between South Pacific atmospheric internal variability and ENSO in the North American Multimodel Ensemble Phase-II models. *Geophys. Res. Lett.*, **46**, 12398–12407, <https://doi.org/10.1029/2019GL084637>.
- Zachow, M., R. D. S. N. Júnior, and S. Asseng, 2023: Seasonal climate models for national wheat yield forecasts in Brazil. *Agric. For. Meteorol.*, **342**, 109753, <https://doi.org/10.1016/j.agrformet.2023.109753>.
- Zennaro, F., E. Furlan, C. Simeoni, S. Torresan, S. Aslan, A. Critto, and A. Marcomini, 2021: Exploring machine learning potential for climate change risk assessment. *Earth. Sci. Rev.*, **220**, 103752, <https://doi.org/10.1016/j.earscirev.2021.103752>.
- Zhang, L., S. Gao, and T. Yang, 2024: Adapting subseasonal-to-seasonal (S2S) precipitation forecast at watersheds for hydrologic ensemble streamflow forecasting with a machine learning-based post-processing approach. *J. Hydrol.*, **631**, 130643, <https://doi.org/10.1016/j.jhydrol.2024.130643>.
- Zhou, Y., B. F. Zaitchik, S. V. Kumar, K. R. Arsenault, M. A. Matin, F. M. Qamer, R. A. Zamora, and K. Shakya, 2021: Developing a hydrological monitoring and sub-seasonal to seasonal forecasting system for South and Southeast Asian river basins. *Hydrol. Earth Syst. Sci.*, **25**, 41–61, <https://doi.org/10.5194/hess-25-41-2021>.