WINTER 2021-2022

GFDL BULLETIN

Research Highlights from the Geophysical Fluid Dynamics Laboratory Community

Advancing the Modeling, Understanding, and Prediction of Weather and Climate

ARE MULTI-SEASONAL FORECASTS OF ATMOSPHERIC RIVERS POSSIBLE?

Geophysical Research Letters *K-C. Tseng[1,2], N. Johnson[1], S. Kapnick[1], T. Delworth[1], F. Lu[1,2], W. Cooke[1], A. Wittenberg[1], A. Rosati[1,3], L. Zhang[1,3], C. McHugh[1,4], X. Yang[1], M. Harrison[1], F. Zeng[1], G. Zhang[1,2,5], H. Murakami[1,3,6], M. Bushuk[1,3], L. Jia[1,3]*

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In Western North America, 30% of the annual precipitation is determined by atmospheric rivers (ARs) that occur during less than 15% of the winter season. ARs are beneficial to water supply but can also produce extreme precipitation hazards when making landfall. Consequently, ARs exert significant socioeconomic impacts on this region.

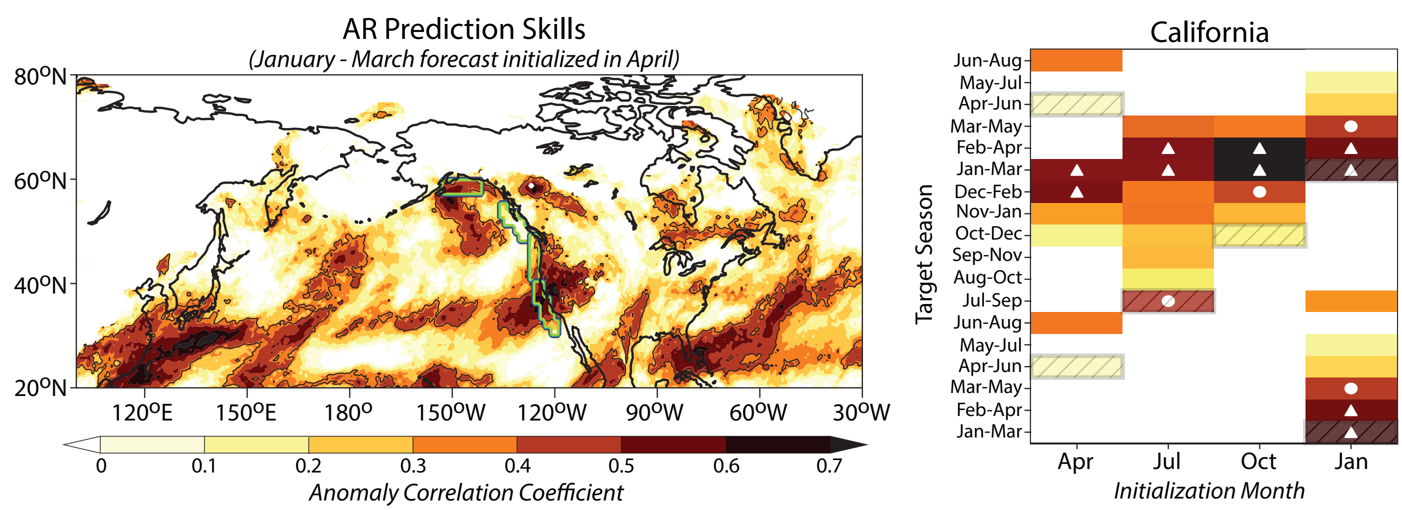
This research uses GFDL's new SPEAR seasonal-to-decadal forecast system to produce multi-seasonal AR frequency forecasts with predictive skill at least 9 months in advance. Most research has focused on the sub-seasonal prediction (5 weeks or less) of ARs and only limited efforts have been made for AR forecasts on multi-seasonal timescales, which are crucial for water resource management and disaster preparedness.

Additional analysis explores the dominant predictability sources and challenges for multi-seasonal AR prediction. Regional dependence of atmospheric river prediction can be explained by its connection to the leading pattern of large-scale atmospheric variability over the North Pacific.

A prototype seasonal atmospheric river probabilistic forecast product derived from SPEAR output shows the potential of enhancing NOAA's existing seasonal hydroclimate outlooks. The successful prediction of hydrological extremes brought on by atmospheric rivers provides timely benefits to sectors including agriculture, energy production and water resource management.

OAR Goals: Make Forecasts Better

Prediction of Hydrological Extremes Using SPEAR



The left panel shows that forecasts initialized in April have strong prediction skill for January-March atmospheric river (AR) activity on the West Coast of the US, and the right panel shows how skill varies with lead time for California. Both white dots and white triangles indicate SPEAR outperforms the persistence forecast.

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S2S PREDICTION IN GFDL SPEAR: MJO DIVERSITY AND TELECONNECTIONS

Bulletin of the American Meteorological Society *B. Xiang[1,2], L. Harris[1], T. Delworth[1], B. Wang[3], G. Chen[4], J-H. Chen[1,2], S. Clark[1,5], W. Cooke[1,2], K. Gao[1,2], J. Huff[1,2], L. Jia[1,2], N. Johnson[1], S. Kapnick[1], F. Lu[1,6], C. McHugh[1,7], Y. Sun[1,6], M. Tong[1], X. Yang[1], F. Zeng[1], M. Zhao[1], L. Zhou[1,6], X. Zhou[2,8]*

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Prediction on weather and seasonal timescales has become routine, but the "subseasonal" timescale of a few weeks has proven difficult. The Madden-Julian oscillation (MJO), a large complex of tropical thunderstorms, is the dominant subseasonal phenomenon over the tropics, and its prediction is critical for subseasonal prediction of tropical cyclones, atmospheric rivers, and other extreme events.

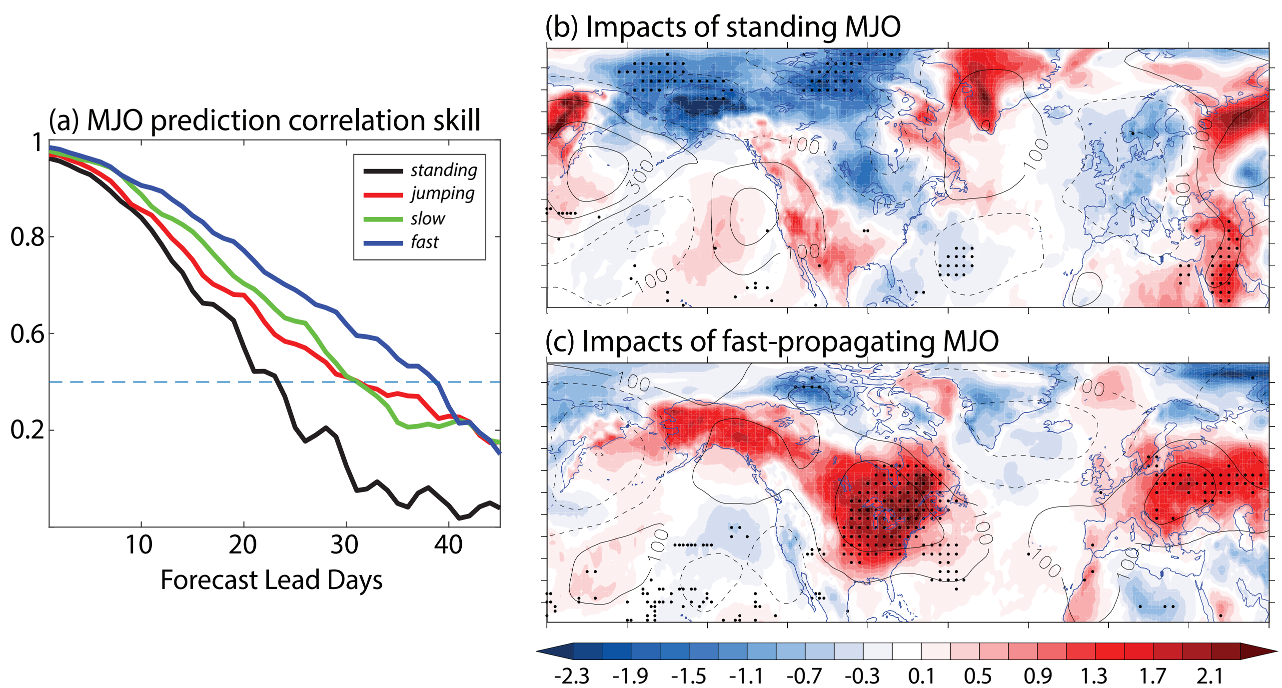
GFDL has developed a new subseasonal prediction system using the GFDL Seamless System for Prediction and Earth-system Research (SPEAR), a global atmosphere-ocean-land-sea ice coupled climate model. In 20 years of wintertime forecasts, this study found that the average prediction skill of the MJO was 30 days, placing it among the very best MJO prediction models in the world.

MJO events vary from event to event in their strength, life cycle, and propagation. The study showed that 4 distinct patterns of the MJO each have their own predictability. For the "fast-propagating" form, SPEAR is able to predict the MJO to 38 days. In contrast, the "standing" pattern is much more challenging, with predictability dropping to 23 days. SPEAR also accurately predicts the formation of new MJOs and the worldwide influence of each particular pattern on surface temperatures, crucial in using the MJO to predict extreme events. Forecasters can gain a better understanding of the MJO's impacts by considering the MJO pattern, and potentially take advantage of certain patterns to issue extended range forecasts, in addition to the traditional indices.

The SPEAR seasonal prediction system is participating in the North American Multi-Model Ensemble. SPEAR, developed within the Flexible Modeling System, shares two key model components with the Unified Forecast System (UFS) model: the FV3 dynamical core and MOM6 ocean model. Knowledge derived from SPEAR and its predictions can be used to assist in the development and application of the UFS subseasonal forecast system.

OAR Goals: Make Forecasts Better

SPEAR's Skill with Subseasonal Prediction of MJO



a) The correlation skill for four types of MJO as a function of forecast lead days. Dashed line (at 0.5) denotes useful forecast skill. b) Observational 2-meter temperature (shading; °C) and 500 hPa geopotential height (contours; m²/s²) anomalies associated with the standing MJO averaged over the time period of 11-20 days after the peak convective phase over the equatorial Indian Ocean. The black stippling denotes the regions with significant 2-meter temperature anomalies. c) Same as b) above, but for the fast-propagating MJO.

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GFDL BULLETIN

SIMULATED GLOBAL COASTAL ECOSYSTEM RESPONSES TO A HALF-CENTURY INCREASE IN RIVER NITROGEN LOADS

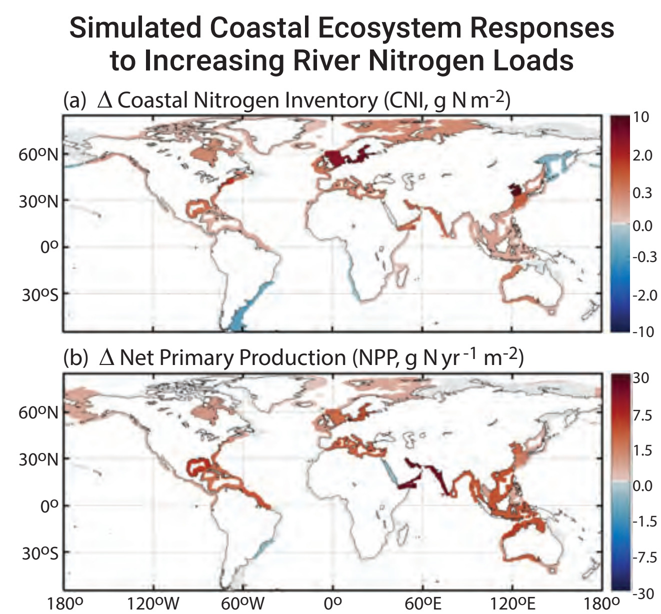
Geophysical Research Letters

X. Liu[1,2], C. Stock[2], J. Dunne[2], M. Lee[1,2], E. Shevliakova[2], S. Malyshev[2], and P.C.D. Milly[3]

DOI 10.1029/2021GL094367

Coastal oceans host diverse ecosystems and serve as important habitats for marine fish species. Over the past century, anthropogenic activities have resulted in substantial climatic and land use changes that stress coastal environments, often leading to eutrophication, harmful algal blooms, and deoxygenation. Rivers are a primary source of eutrophication, supplying an increasing amount of anthropogenic nitrogen to the coastal ocean over the past century.

This study investigated simulated coastal ecosystem responses to increasing river nitrogen loads for the period between 1959 and 2010. Simulations revealed a ubiquitous global response, yet the sensitivity of each coastal ecosystem to increasing river nitrogen loads varied considerably. Elevated river nitrogen loads resulted in a 5.5% increase in the global coastal nitrogen inventory and commensurate increases in productivity and organic material supplied to the benthos. The response in coastal ecosystems with long residence times and high levels of nitrogen limitation, however, could be 2-5 times the global mean response. The findings of this study have important policy implications for the development of eutrophication mitigation strategies.



Area-normalized changes in a) coastal nitrogen inventory and b) coastal net primary production in the globally distributed Large Marine Ecosystems averaged between 1961 and 2010. These changes reflected coastal ecosystem responses to long-term changes in riverine nitrogen inputs, calculated by contrasting two retrospective MOM6-COBALTv2 simulations with dynamically changing and climatological river nitrogen inputs, respectively.

The scale of coastal environments and the complex underlying processes challenge observation-based analyses in even the most well-monitored systems. Global syntheses are hindered by coarse resolutions of current-generation global models necessitated by computational limitations. The ocean physical model for this study was configured from an enhanced-resolution version of GFDL's Modular Ocean Model (MOM6) and its accompanying Sea Ice Simulator (SIS2), integrated with GFDL's Carbon, Ocean Biogeochemistry and Lower Trophics (COBALT) marine biogeochemical model. COBALT simulates global-scale dynamics of carbon, nitrogen, phosphorus, iron, and oxygen, along with some phytoplankton zooplankton groups. The dynamically changing river freshwater and nitrogen fluxes are simulated by GFDL's land-watershed model LM3-TAN, which incorporates global river routing and lakes into a terrestrial ecosystem to simulate nitrogen storage and cycling processes.

OAR Goals: Drive Innovative Science

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SCIENTISTS IN THE SPOTLIGHT

V. "Ram" Ramaswamy, GFDL Director

V. "Ram" Ramaswamy was elected a **2021 Fellow of the American Physical Society** for his "pioneering research on radiative transfer in the climate system, especially regarding the impacts of anthropogenic changes in carbon dioxide and ozone on stratospheric dynamics, and the effects of aerosols on tropospheric temperatures & the hydrological cycle."

BRIDGING OBSERVATIONS, THEORY AND NUMERICAL SIMULATION OF THE OCEAN USING MACHINE LEARNING

M. Sonnewald[1,2,3], R. Lguensat[4,5], D.C. Jones[6], P. D. Dueben[7], J. Brajard[5,8], V. Balaji[1,2,4]

Environmental Research Letters

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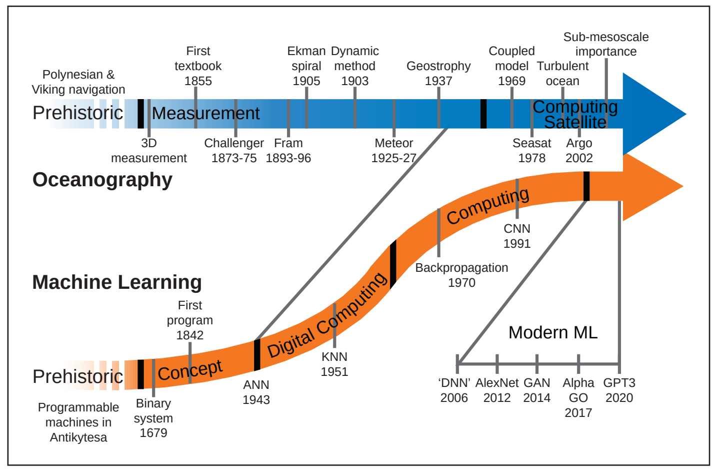
Machine learning (ML) is a computational advance that allows us to extract the underlying physical structures embedded in data, and connect them with theory to make predictions about the world. This review covers the current scientific insight offered by applying ML to ocean science and points to where there is imminent potential.

Beyond vast amounts of complex data ubiquitous in many modern scientific fields, the ocean poses a combination of unique challenges that ML can help address. Available observational data is largely spatially sparse, limited to the surface, and with few time series spanning more than a handful of decades. Important timescales span seconds to millennia, with strong scale interactions and numerical modeling efforts complicated by details such as coastlines.

The authors focus on the use of ML for *in situ* sampling and satellite observations and the extent to which ML applications can advance theoretical oceanographic exploration, as well as aid numerical simulations. ML has potential for building numerical models from theory, and for accelerating numerical models through the emulation of physics. In addition, ML can play a role in improving the predictions made by numerical models, by understanding and correcting systematic errors in model predictions. Additional applications covered in this review include model error and bias correction, and current and potential use within data assimilation.

Progress in physical oceanography has been concurrent with the increasing sophistication of tools available for its study. These advances show that ML in the modern era will influence ocean sciences, as many other fields, by bringing empirical science and theoretical science closer together.

Oceanography and Machine Learning Moving Towards Each Other



Timeline sketch of oceanography (blue) and ML (orange). The timelines of oceanography and ML are moving towards each other, and interactions between the fields where ML tools are incorporated into oceanography has the potential to accelerate discovery in the future. Distinct "events" marked in grey. Each field has gone through stages (black), with progress that can be attributed to the available tools. With the advent of computing, the fields were moving closer together in the sense that ML methods generally are more directly applicable. Modern ML is seeing a very fast increase in innovation, with much potential for adoption by oceanographers.

OAR Goals: Drive Innovative Science

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RECENTLY HONORED SCIENTISTS AT GFDL

Thomas Delworth, Senior Scientist

Honoring his lifelong work, the American Geophysical Union presented Tom Delworth with the prestigious **2021 Bert Bolin Award and Lecture**. His research is known for advancing the scientific frontiers involving the role of oceans in the global climate system, with emphasis on climate variability, change, and predictability, from seasonal to centennial time scales.

Alistair Adcroft, Research Oceanographer

Alistair Adcroft earned the **2021 American Geophysical Union Ocean Sciences Award** for his research developing numerical models of ocean circulation at GFDL and Princeton University. Presented biennially, the award recognizes outstanding leadership or service to the ocean sciences by a senior scientist.