FALL 2020

GFDL BULLETIN

Research Highlights from the Geophysical Fluid Dynamics Laboratory Community

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

GFDL SHiELD: A UNIFIED SYSTEM FOR WEATHER-TO-SEASONAL PREDICTION

Journal of Advances in Modeling Earth Systems

L. Harris[1], L. Zhou[1,2], S-J. Lin[1], J-H. Chen[1,3], X. Chen[1,2], K. Gao[1,2], M. Morin[1,3], S. Rees[1,3], Y. Sun[1,2], M. Tong[1,4], B. Xiang[1,3], M. Bender[1,2], R. Benson[1], K-Y. Cheng[1,2], S. Clark[1,5], O. Elbert[1,5], A. Hazelton[1,2], J.J. Huff[1,3], A. Kaltenbaugh[1,3], Z. Liang[1], T. Marchok[1], H.H. Shin[1,3], W. Stern[1]*

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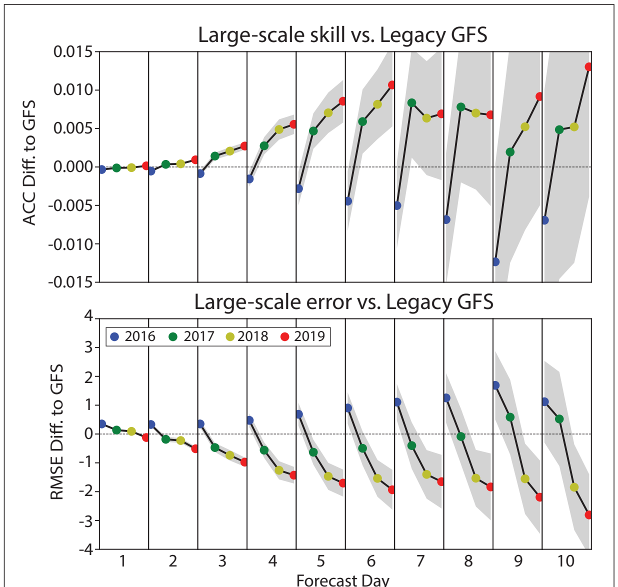
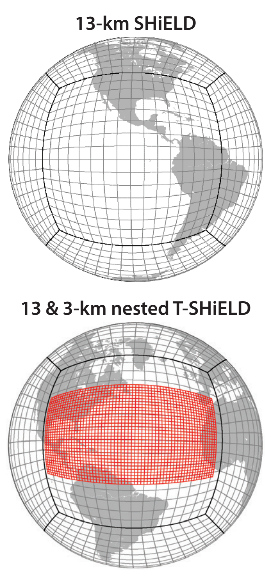
GFDL has developed a unified "one code, one executable, one workflow" global prediction modeling system. NOAA uses separate models for short-range, long-range, seasonal, and hurricane forecasting. Having separate models multiplies the effort needed to maintain and upgrade each model, and makes it difficult to move improvements from one model to another. GFDL scientists have developed a new unified weather modeling system, the System for High-Resolution Prediction on Earth-to-Local Domains (SHiELD), which can be configured for a variety of applications. SHiELD's multiple configurations show prediction skill and simulation fidelity matching or exceeding those of existing U.S. weather forecast models. SHiELD links together high-resolution short-range (0–60 hour), global medium-range (2–10 days), hurricane, and subseasonal (10–40 days) forecast models in the same system. This enables transfer of innovations and advances between forecast models, facilitating a truly seamless atmospheric modeling system.



Global prediction skill

Year-over-year improvement in SHiELD's large-scale global prediction skill, for each day of the forecast length. The top panel is a measure of accuracy (higher is better); the bottom panel is a measure of error (lower is better); both compared to the then-operational legacy GFS run by the National Weather Service. The gray shading indicates the run-to-run variability in the skill or errors.



Global grids

Two global grids used in SHiELD's unified system. The top globe is the GFS-like SHiELD configuration for 10-day forecasts. The bottom globe shows, in red, the nested or 'zoomed' grid over the Atlantic, useful for forecasting hurricanes.

The FV3 Dynamical Core provides a powerful foundation for unified prediction modeling, allowing a global model to efficiently zoom-in over regions of interest, so that forecasts of extreme weather that are currently limited to 1–2 days of lead time can be extended into the medium range and beyond. SHiELD began as a GFS-like model built to test an FV3-based model in a realistic forecasting environment, and through collaborations with community partners at NCEP, AOML, the University of Oklahoma, and elsewhere, grew into a powerful system with many applications. The authors gradually improved the representation of different atmospheric features, then expanded into new uses for the system, including short-range severe thunderstorm prediction, hurricane forecasting, and weather forecasts as long as six weeks in the future. Many of the components of SHiELD are used by models being developed by the National Weather Service for use by weather forecasters, so the advances described in this paper can be rapidly introduced into those models, eventually improving official forecasts.

This work demonstrates a concrete implementation of the Unified Forecast System (UFS) using the same components being used to build UFS. Further, it demonstrates the value of exchanging advances between SHiELD and other UFS configurations, and with other modeling systems based on the GFDL FV3 Dynamical Core. Real-time forecasts from SHiELD are available at shield.gfdl.noaa.gov/new.

OAR Goals: Make Forecasts Better

[1]NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, NJ
[2]Cooperative Institute for Modeling the Earth System, Program in Oceanic and Atmospheric Sciences, Princeton Univ., Princeton, NJ
[3]University Corporation for Atmospheric Research, Boulder, Colorado; [4]SAIC, Princeton, NJ; [5]Vulcan, Inc., Seattle, Washington
*Current affiliation: NOAA/Atlantic Oceanographic and Meteorological Laboratory, Miami, Florida

A MECHANISM FOR THE ARCTIC SEA ICE SPRING PREDICTABILITY BARRIER

Geophysical Research Letters

M. Bushuk[1,2], M. Winton[1], D. Bonan[3], E. Blanchard-Wrigglesworth[4], T. Delworth[1]

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Observations over the past 40 years have documented a significant decline in Arctic sea-ice extent and thickness. These rapid changes and their implications for Northern communities, shipping industries, wildlife, fisheries, and natural resource industries have created an emerging operational need for regional summer sea-ice predictions. Recent work has shown evidence for an Arctic sea ice spring predictability barrier, which may fundamentally limit the accuracy of predictions made before May. However, the physical mechanism for this barrier has remained elusive. This research reveals a mechanism for the Arctic sea ice spring predictability barrier, examines the evolution of the predictability barrier under climate change, and describes implications for future Arctic seasonal prediction systems.

The authors find that summer sea-ice predictability is limited in winter months by synoptically-driven sea-ice mass export and negative feedbacks from sea-ice growth. The spring predictability barrier results from a sharp increase in predictability at melt onset, when ice-albedo feedbacks act to enhance and persist the preexisting export-generated mass anomaly. The predictability barrier is expected to shift earlier under Arctic warming due to shifts in melt onset timing. These results imply that ice thickness observations collected after melt onset are particularly critical for summer Arctic sea-ice predictions.

This study answers the key question of how far in advance we can expect to make skillful predictions of summer Arctic sea ice. The authors also identify satellite sea ice thickness measurements, collected after melt onset, as a key observational need for future seasonal prediction systems.

OAR Goals: Drive Innovative Science

GFDL SCIENTISTS IN THE SPOTLIGHT

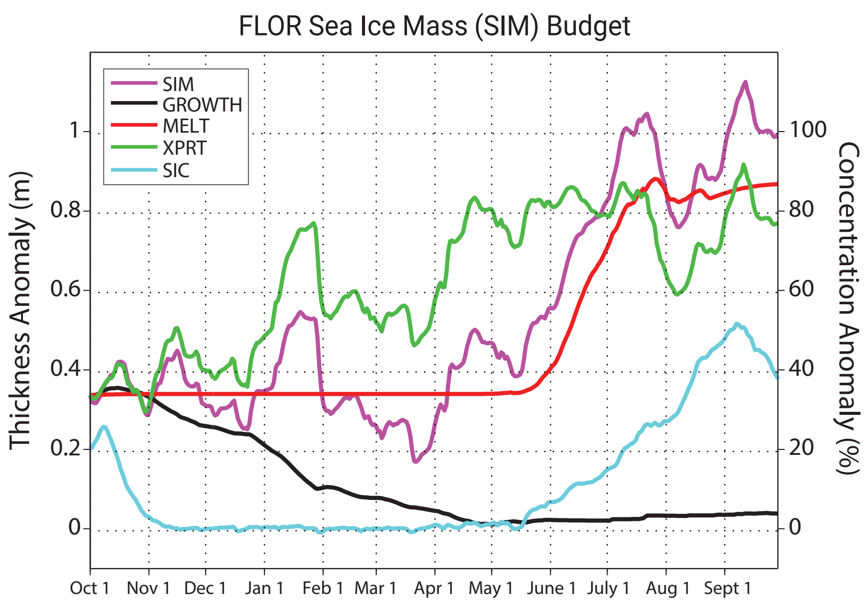
V. “Ram” Ramaswamy

GFDL’s Director delivered the 2020 **Jule Gregory Charney Lecture** at the Fall meeting of the American Geophysical Union.

Ram was selected in recognition of the leadership role he has played in a range of problems central to climate modeling and the study of climate change, especially in the areas of radiative transfer and radiative forcing.

Key aspects of the proposed mechanism for the spring predictability barrier

This figure shows the evolution of sea ice mass (SIM) anomalies (magenta curves) from October 1 through to the following summer in the GFDL Forecast-oriented Low Ocean Resolution (FLOR) model. Ice export (green curves) is the dominant driver of regional SIM variability in fall, winter, and spring seasons. These export-generated variations are partially opposed by the negative ice growth-thickness feedback (black curves). Export-driven mass anomalies represent the accumulated effect of synoptic events which are inherently unpredictable beyond a few weeks. Consequently, summer sea ice concentration (SIC) predictability increases over the winter months, but at a relatively modest rate. The predictability barrier timing is characterized by a rapid increase in predictability due to melt-generated SIM anomalies (red curves), beginning at the time of melt onset. These melt-driven anomalies act to “lock in” the pre-existing export-driven mass anomaly via positive ice-albedo feedbacks, which enhance the mass anomaly. This anomaly persists through the melt season, creating a corresponding late-summer SIC anomaly (cyan curves).



[1]NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, NJ; [2]University Corporation for Atmospheric Research, Boulder, Colorado
[3]Environmental Science and Engineering, California Institute of Technology, Pasadena, CA; [4]Department of Atmospheric Sciences, University of Washington, Seattle, WA

INCREASED RISK OF THE 2019 ALASKAN JULY FIRES DUE TO ANTHROPOGENIC ACTIVITY

Bulletin of the American Meteorological Society

Y. Yu[1,2], J.P. Dunne[1], E. Shevliakova[1], P. Ginoux[1], S. Malyshev[1], J.G. John[1], J.P. Krasting[1]

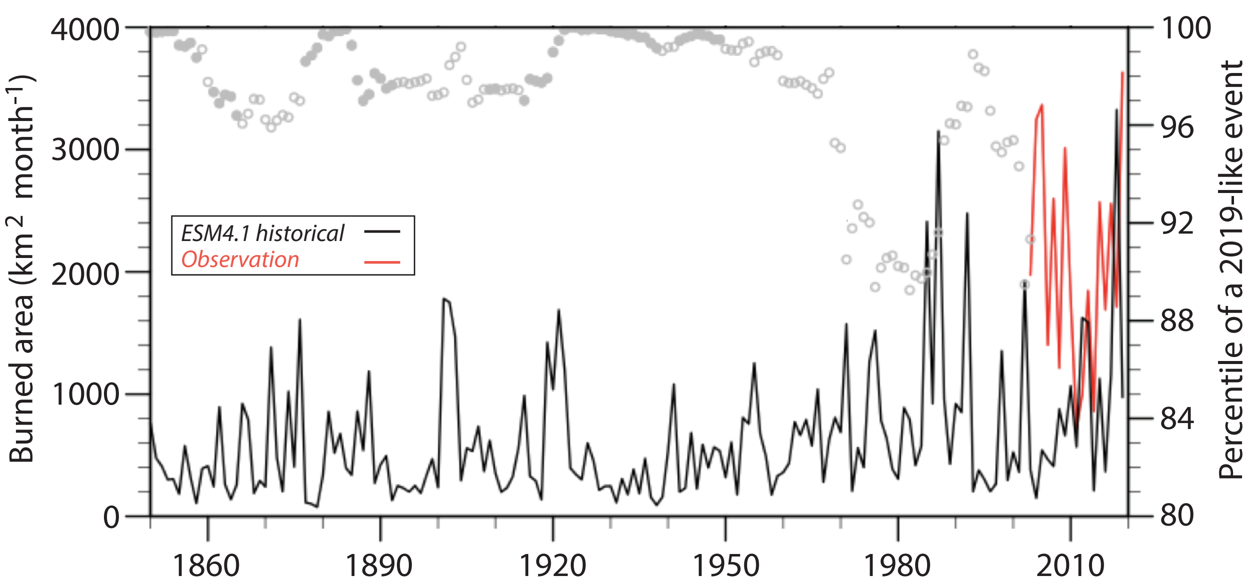
DOI: 10.1175/BAMS-D-20-0154.1 (In press.)

Extreme wildfires have increased in Alaska, affecting the economy and public health of the entire region. Alaska fires emit about 50% more carbon than California fires annually. In extreme years, Alaska's fire carbon emissions may be 8 times more than California's. GFDL scientists assessed the influence of human activities on extreme fires in Alaska, taking advantage of the modeling capability of GFDL's Earth System Model (ESM4.1) to simulate the complex interactions between fire, climate, land ecosystem, and human activity. Their findings indicate that a three-fold increased risk of Alaska's extreme fires during recent decades can be attributed to primarily anthropogenic ignition and, secondarily, climate-induced biofuel abundance. Anthropogenic ignition includes intentional or unintentional activities, such as land and ecosystem management, smoking, railroad sparks, and powerlines.

July 2019 saw record-breaking wildfires that burned over 3,600 km^2 and emitted an estimated 3.5 Tg of carbon in Alaska, equivalent to 37% of the total carbon emission from human activity in Alaska in 2016. This study showed that the probability of exceeding the burned area equivalent to the 2019 extreme fire season in Alaska increased from 2% before the 1950s to 7% after the 1950s.

The dynamical fire model in ESM4.1 enables representation of long-duration and quickly-spreading wildfires and accounts for effects of both changes in land surface meteorological and forest conditions, facilitating comprehensive projections of joint states of climate, ecosystems, and fire. The authors combined ESM4.1 simulations with satellite data to evaluate how several factors contribute to the occurrence of extreme fire seasons in Alaska: natural and anthropogenic ignition activities; anthropogenic climate variability and change; and human influence on the land ecosystem. By sorting out controlling factors of wildfires in Alaska, this modeling study improves our understanding of the impact of climate change on wildfires in Alaska, enabling better predictions.

OAR Goals: Make Forecasts Better



Observational and GFDL ESM4.1 historical distribution of Alaska's July fire activity

The time series of Alaska's July burned area (km^2 $month^{-1}$) from GFDL's ESM4.1 historical simulation and observation (left Y-axis) suggest an increase in Alaska's July fire activity during recent decades. The grey circles (right Y-axis) represent the likelihood that the 2019 extreme event falls outside of the historical statistical distribution during each 17-year window, e.g. the last circle for 2003-2019. Filled circles indicate periods with significant difference in the distribution of burned area compared with 2003-2019, suggesting a regime shift in the statistical distribution of Alaska's July fire activity in the 1950s. According to ESM4.1, the average of the simulated burned area in the past four decades exceeds the average over the previous century. The recent exceedance of fire activity was further supported by the observational record.

[1]NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, NJ; [2]Program in Oceanic and Atmospheric Sciences, Princeton University, Princeton, NJ

ESTUARINE FORECASTS AT DAILY WEATHER TO SUBSEASONAL TIME SCALES

Earth and Space Science

A.C. Ross[1,2], C.A. Stock[2], K.W. Dixon[2], M.A.M. Friedrichs[3], R.R. Hood[4], M. Li[4], K. Pegion[5], V. Saba[6], G.A. Vecchi[7,8]

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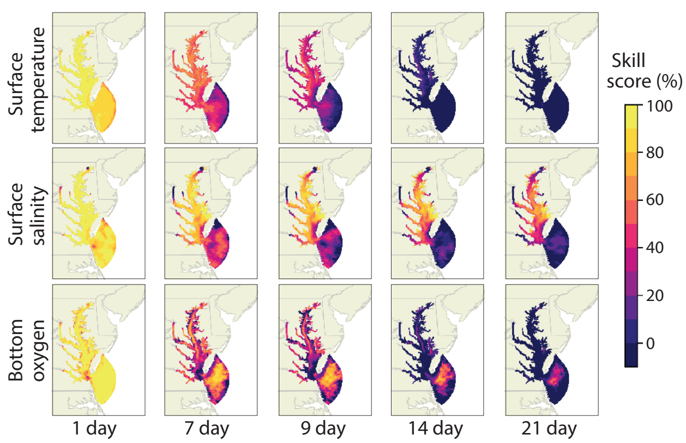
GFDL scientists have demonstrated that temperature and salinity can be skillfully forecast at both the bottom and surface levels of an estuary up to two weeks in advance. NOAA currently maintains a number of operational forecast systems for estuaries, including in Chesapeake Bay, Delaware Bay, and San Francisco Bay, most of which forecast conditions for the next 48 hours. These short-term estuary and coastal ocean forecasts have been shown to protect lives and property from storm surge, assist search and rescue operations, and protect public health. Obtaining additional benefits from these forecast systems, such as improved management of ecologically and economically important fisheries, would require forecasts with longer lead times.

Estuaries are shallow coastal bodies of water, so they respond strongly to atmospheric forcing, and since skillful atmospheric weather forecasts are currently possible out to around 10 days, longer lead forecasts of estuaries should be possible. Estuaries are also driven by predictable tidal cycles of velocity and elevation, which should enhance predictive skill. To test whether extended lead forecasts for estuaries are possible, the authors developed a model system for producing 35-day forecasts of temperature, salinity, and dissolved oxygen in Chesapeake Bay. An ocean model routinely used in the Chesapeake Bay research and forecasting community was forced using 35-day atmospheric forecasts from NOAA's Global Ensemble Forecast System. A total of 425 retrospective forecast simulations were produced, covering the warm seasons of 1999 to 2015. These forecasts were compared to observations, and to the results from a numerical model hindcast simulation designed to reproduce historical conditions. The findings demonstrate that temperature and salinity can be skillfully forecast at both the bottom and surface levels of the estuary up to two weeks in advance. Forecast skill is higher for salinity and for bottom variables. The skill of the forecasts can be significantly improved by producing multiple ocean model forecasts, each driven by a different atmospheric forecast ensemble member, and averaging the results. Bottom dissolved oxygen remains challenging to forecast. The authors also closely evaluated the skill of the forecasts during two extreme events (Hurricane Irene in August 2011 and a heat wave in June 2008), and the system forecasted both events well. These results demonstrate the substantial potential for extended-range estuarine forecasts and the possibility of using these forecasts to prepare for the impacts of extreme events.

OAR Goals: Make Forecasts Better



Chesapeake forecast skill evaluated against hindcast

Figure (left): *Skill of the sea surface temperature, sea surface salinity, and bottom oxygen forecasts for Chesapeake Bay, at 1 day after the initial forecast day, at 7 days (the start of the second week of forecasts), at 9 days (the lead time when atmospheric temperature forecasts become unskillful), and at 14 and 21 days (the start of the third and fourth week of forecasts, respectively). Color shading indicates the mean square error skill score, with skill scores of 100% indicating a perfect set of forecasts and skill scores of 0% indicating that the forecasts have a mean square error equivalent to the error of a naive forecast of the seasonally varying long-term mean (i.e. the climatology). Skill scores below zero are considered unskillful.*

[1] Program in Atmospheric and Oceanic Sciences, Princeton University, Princeton, NJ
[2] NOAA/GFDL, Princeton, NJ
[3] Virginia Institute of Marine Science, William & Mary, Gloucester Point, VA
[4] Horn Point Lab, University of Maryland Center for Environmental Science, Cambridge, MD
[5] Atmospheric, Oceanic & Earth Sciences Department, George Mason University, Fairfax, VA
[6] NOAA Northeast Fisheries Science Center, GFDL, Princeton, NJ
[7] Department of Geosciences, Princeton University, Princeton, NJ
[8] Princeton Environmental Institute, Princeton University, Princeton, NJ

GFDL SCIENTISTS IN THE SPOTLIGHT

Tom Knutson, head of GFDL's Weather and Climate Dynamics Division was recently elected a **Fellow of the American Geophysical Union**, "for exceptional contributions to the understanding of the relation between climate and hurricanes and the detection-and-attribution of climate change."

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Thomas Delworth, John Dunne, Stephen Griffies, Larry Horowitz, Vaishali Naik, and Andrew Wittenburg

were recognized on the Web of Science Group's 2020 List of Highly Cited Researchers

This index identifies the most influential scientists, who are authors of the papers that were most frequently cited by their peers over the last decade.

See GFDL's full bibliography at:
https://www.gfdl.noaa.gov/bibliography

Geophysical Fluid Dynamics Laboratory
https://www.gfdl.noaa.gov
201 Forrestal Road
Princeton, NJ 08540-6649

Contact: *Maria Setzer • maria.setzer@noaa.gov*