Global physical and biogeochemical modeling & predictions: capabilities & challenges

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Increasing risk associated with climate warming

(a) Global surface temperature change
Increase relative to the period 1850–1900

Projections for different scenarios
- SSP1-1.9
- SSP1-2.6 (shade representing very likely range)
- SSP2-4.5
- SSP3-7.0 (shade representing very likely range)
- SSP5-8.5

(b) Reasons for Concern (RFC)
Impact and risk assessments assuming low to no adaptation

Risk/impact:
- Very high
- High
- Moderate
- Undetectable

Transition range
Confidence level assigned to transition range
- Low
- Very high

Historical average temperature increase in 2011–2020 was 1.09°C (dashed line) range 0.95–1.20°C
Earth System Models: holistic representations of climate-biosphere interactions

Bonan & Doney, Science (2019)
Intrinsic variability affects near-term outcomes

Intrinsic variability contributes to future climate outcomes

Trends 2006–2055

200 m O$_2$

mmol m$^{-3}$ (50 yr)$^{-1}$

Long, unpublished
Finding forced trends in ocean oxygen

CESM Large Ensemble: Linear trends in 200 m dissolved oxygen (2006–2055)

\[ \psi_i(t, x) = \tilde{\psi}_i(t, x) + \psi^s(t, x) \]

\[ \tilde{\psi}_i(t, x) \]

\[ \psi^s(t, x) = \frac{1}{m} \sum_{i=1}^{m} \psi_i(t, x) \]

Inspired by Deser et al.
The climate system is highly dynamic

Intrinsic variability affects near-term outcomes

200 m O$_2$
Trends due to natural variability 2006–2055

Long, unpublished
Initialized prediction

Forced boundary condition problem

Decadal predictions

Initial value problem

Weather predictions
Seasonal to interannual predictions
Long term climate change projections

day  week  month  season  year  decade  century

Memory in the climate system
Robust skill of decadal climate predictions

Decadal Climate Prediction Project (DCPP)

- Large multi-model ensembles enable reduction in noise necessary to achieve skillful prediction.

- Initialized DCPP ensembles exhibit robust near-term (5-10 yr) skill improvements over uninitialized projection ensembles.

Anomaly correlation coefficient: [-1, 1]

\[
\text{ACC} = \frac{\sum_{i=1}^{N}(f_i - \bar{f})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^{N}(f_i - \bar{f})^2} \sqrt{\sum_{i=1}^{N}(o_i - \bar{o})^2}}
\]

Phase of variability in forecast (\(f_i\)) relative to observations (\(o_i\)).

CMIP5 DCPP
8 systems
\(N_{\text{init}}=71\)
\(N_{\text{uninit}}=56\)

Ocean biogeochemistry & ecology predictions using Earth system models

Decadal predictions of the North Atlantic CO₂ uptake
Hongmei Li¹, Tatiana Ilyina¹, Wolfgang A. Müller¹ & Frank Sienz¹

Environmental Research Letters
Oceanic Rossby waves drive inter-annual predictability of net primary production in the central tropical Pacific
Sebastian Brune¹, Maria Esther Caballero Espejo¹, David Marcolino Nielsen¹, Hongmei Li¹, Tatiana Ilyina¹ and Johanna Baehr¹

Marine Management
Seasonal to multiannual marine ecosystem prediction with a global Earth system model
Jong-Hee Park¹,²,³, Charles A. Stock⁴, John P. Dunne⁵, Xiaosong Yang⁶, Anthony Rosati²

Skilful decadal-scale prediction of fish habitat and distribution shifts
Mark R. Payne, Anna K. Miesner, Noel Keenleyside, Shutong Yang, Stephen G. Yeager, Gokhan Danabasoglu, Daniela Matei
doi: https://doi.org/10.1101/2021.07.07.451446

Multiyear predictability of tropical marine productivity
Roland Séférian¹,², Laurent Bopp³, Marion Gehlen³, Didier Swingedouw⁴, Juliette Mignot⁴, Eric Guilyardi⁴, and Jérôme Servonnat⁴

Decadal climate predictions with the Canadian Earth System Model version 5 (CanESM5)
Reinel Sospedra-Alfonso, William J. Merryfield, George J. Boer, Viatcheslav V. Kharin, Woo-Sung Lee, Christian Seiler, and James R. Christian
# Community Earth System Model Prediction Experiments

<table>
<thead>
<tr>
<th></th>
<th>CCSM4-DP (no BGC)</th>
<th>DPLE</th>
<th>SMYLE</th>
<th>HRDP (no BGC)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model</strong></td>
<td>CCSM4</td>
<td>CSM1.1</td>
<td>CSM1.1</td>
<td>CSM1.3</td>
</tr>
<tr>
<td>- ocn</td>
<td>POP2 (1°, 60L)</td>
<td>POP2 (1°, 60L)</td>
<td>POP2 (0.1°, 62L)</td>
<td></td>
</tr>
<tr>
<td>- atm</td>
<td>CAM4-FV (1°, 26L)</td>
<td>CAM5-FV (1°, 30L)</td>
<td>CAM5-SE (0.25°, 30L)</td>
<td></td>
</tr>
<tr>
<td>- Ind</td>
<td>CLM4 (1°)</td>
<td>CLM4 (1°)</td>
<td>CLM4 (1°)</td>
<td>CLM4 (0.25°)</td>
</tr>
<tr>
<td>- ice</td>
<td>CICE4 (1°)</td>
<td>CICE4 (1°)</td>
<td>CICE5 (1°)</td>
<td>CICE4 (0.1°)</td>
</tr>
<tr>
<td><strong>Forcing</strong></td>
<td>CMIP5 RCP4.5 (from 2006)</td>
<td>CMIP5 RCP8.5 (from 2006)</td>
<td>CMIP6 SSP3-7.0 (from 2015)</td>
<td>CMIP5 RCP8.5 (from 2006)</td>
</tr>
<tr>
<td><strong>Initialization</strong></td>
<td>Full Field CORE-FOSI (1°)</td>
<td>Full Field JRA-FOSI (1°)</td>
<td>Full Field JRA-FOSI (1°)</td>
<td>Full Field JRA-FOSI (0.1°)</td>
</tr>
<tr>
<td>- ocn/ice</td>
<td>CCSM4 Ensemble</td>
<td>CESM1-LE</td>
<td>JRA55 Reanalysis</td>
<td>JRA-FOSI (0.1°)</td>
</tr>
<tr>
<td>- atm</td>
<td>CCSM4 Ensemble</td>
<td>CESM1-LE</td>
<td>CRU-JRAv2</td>
<td>JRA55 Reanalysis</td>
</tr>
<tr>
<td>- Ind</td>
<td></td>
<td></td>
<td></td>
<td>HighResMIP Tier 1 (AMIP)</td>
</tr>
<tr>
<td><strong>Hindcasts</strong></td>
<td>Nov 1&lt;sup&gt;st&lt;/sup&gt; 1955-2014 (N=60) 120 months</td>
<td>Nov 1&lt;sup&gt;st&lt;/sup&gt; 1954-2017 (N=64) 122 months</td>
<td>Feb 1, May 1, Aug 1, Nov 1 1970-2019 (N=200) 24 months</td>
<td>Nov 1&lt;sup&gt;st&lt;/sup&gt; 1982,1984,…, 2016 (N=18) 62 months</td>
</tr>
<tr>
<td><strong>Ensemble Size</strong></td>
<td>10</td>
<td>40</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td><strong>Simulation Years</strong></td>
<td>6,000</td>
<td>26,000</td>
<td>8,000</td>
<td>930</td>
</tr>
</tbody>
</table>

DPLE = Decadal Prediction Large Ensemble; SMYLE = Seasonal-to-Multiyear Large Ensemble; FOSI = Forced Ocean Sea-Ice Simulation
Heat content anomaly, N. Atlantic Subpolar gyre ($z > -275$ m)

De-drifting requires removal of lead-time dependent climatology
Spurious El Niño events from initialization shock

Yeager, Danabasoglu, et al. BAMS (2018)

Predictability for observed ($O$) & model ($M$) climate variable:

Combination of predictable signal ($S$) & chaotic noise ($N$)

\[ O = S_o + N_o \]
\[ M = S_m + N_m \]

Ensemble averaging to reduce noise:

\[ M = S_m + \frac{N_m}{\sqrt{n}} \]
Skillful multiyear predictions of pH in the California Current System

Potential predictability of surface pH anomalies

Thermocline oxygen concentrations are highly predictable

Anomaly correlation coefficient $[O_2]$ on $\sigma_\theta = 26.5$

$[O_2]$ on $\sigma_\theta = 26.5$ corr w/ PV

$PV \approx \left( \frac{L}{\rho} \right) \frac{\partial \rho}{\partial z}\$

PV low
$O_2$ high

Negative PV-$O_2$ correlation

Courtesy S. Yeager
Predicting aerobic habitat

\[ \Phi = \frac{O_2 \text{ supply}}{\text{Metabolic demand}} = A_o \exp \left( \frac{-E_o}{k_B T} - \frac{1}{T_{ref}} \right) \]

\( P_{O_2} \) at constant \( \Phi \)

Metabolic Index (\( \Phi \)) at 200 m ACC

Metabolic Index (\( \Phi \)) at 200 mΔACC (over persistence)

after Deutsch et al., *Nature* (2020)
NPP predictability in coastal North American LMEs
Chlorophyll Prediction in GFDL model

Prediction skill arises primarily from successfully simulating the chlorophyll response to the El Niño–Southern Oscillation and capturing the winter reemergence of subsurface nutrient anomalies in the extratropics...
Seasonal-to-Multiyear Large Ensemble (SMYLE)

May initialization
Diatom fraction
a) diat frac ACC, May init, JJA

Diatom fraction
b) diat frac ACC, May init, SON

Diatom fraction
c) diat frac ACC, May init, DJF

e-ratio
a) eratio ACC, May init, JJA

e-ratio
b) eratio ACC, May init, SON

e-ratio
c) eratio ACC, May init, DJF

Particulate export (100m)
a) POC FLUX 100m ACC, May init, JJA

Particulate export (100m)
b) POC FLUX 100m ACC, May init, SON

Particulate export (100m)
c) POC FLUX 100m ACC, May init, DJF

Courtesy of Kristen Krumhardt
The Flying Leap* 2.0: Building toward fully prognostic fish

FEISTY Total Fish Biomass Simulations

CESM Forced Ocean Sea-Ice Integration (w/ fish offline)

Annual mean of total fish biomass

Coefficient of variation ($\sigma/\mu$) of total fish biomass

Petrik et al., Prog. Oceanog. (2019)

*Inez Fung
Chlorophyll Conc. (mg/m³) from CESM Model: 01–MAY–1987

LR: ~100 km grid

HR: ~10 km grid

Units: mg/m³
HRDP: SST Anomaly Correlation

HRDP:

Start dates: Nov. 1 1982, 84, 86, ..., 2016

Ensemble: 10 x 5 years

White contours: 0.6 and 0.8 correlation

Courtesy of Ping Chang & Dan Fu
HRDP: Tropical Cyclone Frequency

AR TD correlation (Lead Year 1; dot: p-value<0.05)

R=0.71 (120-180E, 0-30N)

Observation MJJASON
CESM-HR DPLE LY1 MJJASON

Courtesy of Ping Chang & Dan Fu
A signal-to-noise paradox in climate science

Predictability for observed (O) & model (M) climate variable:

Combination of predictable signal (S) & chaotic noise (N)

\[ O = S_o + N_o \]
\[ M = S_m + N_m \]

Ensemble averaging to reduce noise:

\[ M = S_m + N_m / \sqrt{n} \]
High resolution (HR) vs. Low resolution (LR) variance ratio

Chang, Zhang, et al., JAMES (2020)
Mesoscale variability drives air-sea turbulent heat flux

Monthly anomaly correlations

R > 0: Ocean drives atmosphere
R < 0: Atmosphere drives ocean

A signal-to-noise paradox in climate science

Ratio of predictable components: $[0, \infty)$

$$\text{RPC} = \frac{\sigma_{\text{sig}}^0/\sigma_{\text{tot}}^0}{\sigma_{\text{sig}}^f/\sigma_{\text{tot}}^f} = \frac{\text{ACC}}{\sigma_{\text{sig}}^f/\sigma_{\text{tot}}^f}$$

The discrepancy between signal-to-total variance fraction in forecasts and observations.

RPC = 1: proportion of predictable variance is the same for observations and model

RPC > 1: signal-to-noise paradox; model signal-to-noise is too weak, the proportion of predictable variance is higher in observations

(Scaife et al. 2014; Eade et al. 2014; Siegert et al. 2016; Scaife & Smith 2018; Strommen & Palmer 2018; Yeager et al. 2018; Zhang & Kirtman 2019a,b; Zhang et al. 2021; ...)

SLP skill is quite sensitive to ensemble size. DPLE skill scores are comparable to HRDP only with 40-members.
High ACC in HRDP achieved with RPC~1 (in contrast to DPLE).

Note: RPC in DPLE would be even higher if ACC from HRDP were used.

\[ \text{RPC} = \frac{\sigma_{\text{sig}}^o / \sigma_{\text{tot}}^o}{\sigma_{\text{sig}}^f / \sigma_{\text{tot}}^f} \geq \frac{\text{ACC}}{\sigma_{\text{sig}}^f / \sigma_{\text{tot}}^f} \]

Courtesy of Steve Yeager
$1\degree$ CESM-LE: Data from a *single* variable
(1920–2100)

3D Ocean Field
Monthly time resolution
(single precision)

~60 GB

35 Ensemble Members
(different initializations)

Full Ensemble (1 variable)

~2 TB
Discussion

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