Integrating plankton observations and models: implications for ecological forecasting

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Ecological forecasting needs an integration of biological observations with ecosystem models

- Large-scale forecasting successes
- Plankton imaging systems for 3-D biological data
- Challenges and opportunities for models:
  - Representing soft bodied plankton
  - Reconciling scales of variability
Dynamical models simulate processes from the bottom-up

COBALT Ocean Biogeochemical Model
Stock et al. 2014
Chlorophyll prediction skill from an Earth System Model

- Lead Time (mon)
- Initialization Month
- Park et al. 2019 Science

- Skill exceeds persistence
- Skill does not exceed persistence
Annual fish catch prediction

1. Bottom-up forcing dominated
2. Predictable bottom-up forcing
3. Predictable fish catch by predicted bottom-up forcing

✓ Predictor: predicted SST or CHL
✓ Lead time: 1 year

Park et al. 2019 Science
**California Current Fish Catch**

- **R = 0.77**
- **R = 0.63**

**Forecast lead time:** 0-1 years

**Forecast lead time:** 1-2 years

**Correlation coefficients with individual fisheries**

* Significant at 90% confidence interval

- North Pacific hake
- Pacific sardine
- Pacific mackerel
- Yellowfin tuna
- Albacore
- California anchovy
- California market squid
- Ocean shrimp

Park et al. 2019

**Images:**
- Sardine
- Pacific hake
- Yellowfin tuna
- California market squid

*Shuttershock: Shane Gross*
Path forward for ecological forecasting: integrating 3-dimensional biological observations
Plankton nets: labor intensive and systematically biased

Remsen et al. 2004
Plankton imaging systems

Phytoplankton —— LOPC —— VPR —— UVP5 —— ISIIS

Zooplankton
Opportunity for models:
- include soft-bodied plankton
- reconcile scales of variability
How to incorporate soft-bodied zooplankton?

1. Explicit gelatinous zooplankton (GZ) functional groups

2. Trait-based zooplankton
   Metabolic relationships based on C:Vol ratio?
1. Explicit GZ:
Hard vs. soft bodied zooplankton simulation

DJF
Mesozooplankton, top 200m, DJF

JJA
Mesozooplankton, top 200m, JJA

Hard-bodied

Tunicates, top 200m, DJF

Tunicates, top 200m, JJA

Soft-bodied

GZ-COBALT in GFDL-ESM4
2. Trait-based zooplankton: Normalized biomass size spectra

Plankton size-spectra slope, 0-10 m

MARBL-SPECTRA model in CESM2

\[
\ln(NB) = -0.88 \ln(\text{mass}) + 3.1
\]

Shallower slopes:
- Larger sized plankton
- Longer food chains
- Higher trophic transfer efficiency
- Increased zooplankton detritus
- Larger, faster sinking detritus
- Export > Recycling

Steeper slopes:
- Smaller sized plankton
- Shorter food chains
- Lower trophic transfer efficiency
- Increased phyto-detritus
- Smaller, slower sinking detritus
- Recycling > Export
Plankton size spectra slopes from observations
Plankton size spectra slopes from observations

Size spectra slopes on a 0.5° grid
Submesoscale process studies at intermediate scales

Process Study Ocean Model

- 100 km x 100 km domain
- 1 km resolution
- Mahadevan (2016)

High resolution submesoscale model

- 10 km x 10 km domain
- 25 m resolution
- Ideal scales for comparing with biological observations

Large Eddy Simulation

- 2 km x 2 km domain
- 1 m resolution
- Whitt, Lévy, Taylor (2017)
Prime opportunity for integrating biological observations and models

• Next generation observational tools: imaging systems

How to integrate?
1. Various methods to include soft bodied plankton
2. Reconcile scales of variability between observations and models

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Advancing Marine Biogeochemical and Ecosystem Reanalyses and Forecasts as Tools for Monitoring and Managing Ecosystem Health

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Underwater Vision Profiler 5 (UVP5)

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