Seasonal-interannual prediction of sea surface height using an ocean-atmosphere dynamical model “SINTEX-F”

Takeshi Doi, Masami Nonaka, Swadhin K. Behera
(APL/VAiG/JAMSTEC)

PICES2019
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- loss of amenities
- loss of property, cultural resources and values,
- loss of tourism, recreation and transportation functionality
- increased risk of loss of life
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Skillful seasonal-interannual forecast is necessary to reduce the risks!
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The skill is derived from the ability to predict ENSO accurately, and is in the oceanic Kelvin, Rossby, coastally-trapped waveguides extending from the Pacific equatorial region (McIntosh et al. 2015).
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Use grids of "cell" for the Earth

Calculate partial differential eq.

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The SINTEX-F1 numerical/dynamical seasonal prediction system (Luo et al. 2005) (developed at JAMSTEC under the EU-Japan collaboration)
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Skill assessment is

- Based on anomaly correlation coefficient (ACC) between obs. and re-forecast output.
- Re-forecast period: issued of the first date of every month in years 1993-2010
- Reference data: AVISO+ data in 1993-2010
- Monthly climatology in 1993-2009
- Anomaly (deviation from monthly climatology) is linearly detrended
Diff'rence in ACC between SSH and SST predictions

(a) Mar. 1st ini.  
(b) Jun. 1st ini.  
(c) Sep. 1st ini.  
(d) Dec. 1st ini.

Lead month (1.5-2.5 month)

Maskout for low skill of SSH (ACC<0.5)
Q1. Is it possible beyond 7-month lead time?
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A1. We found that the skillful prediction regions in the North Pacific (30°-40°N, 180°W-160°W), off the west coast of Australia and California, and western tropical Atlantic, up to 18-month lead time.
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A1. We found that the skillful prediction regions in the North Pacific (30–40N, 180W-160W), off the west coast of Australia and California, and western tropical Atlantic, up to 18-month lead time.

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A2. Yes. SSH prediction skill is high relative to SST prediction skill over the Pacific warm pool region in DJF about 5 month-lead, some regions in the North Pacific (30–40N, 180W–160W) beyond 12 month-lead, off the west coast of the South American Continent around 7-9 month lead time. Higher prediction skill of SSH than that of SST may suggest that ocean dynamical process is more importance relative to thermodynamical process in those regions.
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Some preliminary analysis
ACC for DJF of next year from June 1st (19.5 month lead)

(a) SSH

(b) SST
ACC for DJF of next year from June 1st (19.5 month lead)

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(b) SST

Time series of DJF_SSHA averaged in the box (cm)

Individual ensemble member (19.5-month lead prediction)

Obs. Ensemble mean
ACC for DJF of next year from June 1st (19.5 month lead)

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Time series of DJF_SSHA averaged in the box (cm)
Individual ensemble member (19.5-month lead prediction)
Obs.
Ensemble mean

Time series of DJF_SSTA averaged in the box (°C)

Ensemble mean
Obs.
Successful prediction of positive SSH anomaly in 2000/01 DJF issued on June 1, 1999, may be the key.
Regional anomaly (in 30-40N, 180W-160W) plumes from JJA1999 to MAM2001 (prediction issued on June 1, 1999)

The positive anomaly persisted to SON2000, and recovered to DJF2000/01

The positive anomaly disappeared in SON2000
Ekman upwelling anom. (1×10^{-6} m/s)

Reanalysis

Prediction issued on June 1, 1999

Net heat flux anom (W m^{-2})

Reanalysis

Prediction issued on June 1, 1999

Decaying

Downwelling
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Further research are required to understand the processes...
Another research direction:
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Introduce new prediction system (SINTEX-F2)
Schematic of numerical seasonal prediction: “baton pass”

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2. Initialization (assimilation)

3. Numerical integration by a model

\[ x(t_0) + \Delta t \times M = X(t_0 + \Delta t) \]

Prediction of future
Two strategies are possible for improving the prediction skill: 
#1 model development and #2 ocean initialization

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Figure 3.1. Progress in the seasonal forecast skill of the ECMWF operational system since it became operational around 1996. The yellow bar shows the relative reduction in mean absolute error of forecast of SST in the eastern Pacific (NINO3) integrated over the 1-6 months lead time. Contribution from model development (blue bar) and ocean initialization (red bar) are equally important. Developments in ocean and atmosphere models also contribute to the ocean initialization.

Seasonal forecasts use lower resolution models than those in NWP, mainly because the length of the integration, the number of ensemble members and the need for calibration adds to the computational cost. The atmospheric model has a typical resolution of 0.5-1 degree in the horizontal, with 60 to 90 vertical levels. The ocean resolution is typically 1 degree (with equatorial refinement), although in the latest MetOffice seasonal forecasting system the ocean resolution is of 0.25 (at expense of reducing the reforecast data set). The forecast lead time is typically 6-7 months, sometimes extended up to 12 months. The real time forecasts require about 40-50 ensemble members. The calibration reforecasts span a period of approximately 30 years, with hindcasts initialized every month using a reduced ensemble (~11-15 members). In total, about 200 years-worth of coupled model integration years are needed for a seasonal forecast at 7 months lead time initialized from a single calendar month. Or in other words, 2400 years-worth of coupled integrations are needed for seasonal forecasts initialized each month.

Seasonal forecasts use both the NRT data stream for initialization of real time, and the BRT data stream in the reanalyses needed for the calibration data set. BRT data is also used for verification.

3.1 Ocean Initialization

The simplest way of providing initial conditions is to run an ocean model forced with observed winds and fresh-water fluxes from atmospheric reanalyses and with a strong constraint to

[Balmaseda et al. 2015]
Two strategies are possible for improving the prediction skill:

1. **Model Development**
2. **Ocean Initialization**

**Schematic of numerical seasonal prediction: “baton pass”**

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2. **Initialization** (assimilation)
3. **Numerical integration** by a model

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**Which step is more critical?**

Some previous works (e.g. ECMWF system) suggest that #1 model development and #2 ocean initialization are equally important for improving seasonal prediction skill.

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How to improve the seasonal prediction system
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Strategy 1: Model development (Doi et al. 2016, JAMES)
From SINTEX-F1 to SINTEX-F2 (high-res. & sea ice)
How to improve the seasonal prediction system

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  From SINTEX-F1 to SINTEX-F2 (high-res. & sea ice)

Strategy 2: Ocean Initialization (Doi et al. 2017, JC)
  From SST-nudging to three dimensional variational scheme (3DVAR)
  using 3D profile data of Temperature and Salinity
Strategy 1: Model development (Doi et al. 2016, JAMES)

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Initialization: SST-nudging scheme
- 12 ensemble members
- 2 sst data (1º weekly, 0.25º daily) × 3 nudging strengths × 2 physical schemes for SVS ocean mixing (Sasaki et al. 2012)

“A high-resolution with a dynamical sea-ice model” may improve the coastal climate phenomena and the mid, high-latitude climate.
Strategy 2: Ocean Initialization (Doi et al. 2017, JC)

The initialization skill of subsurface ocean

ACC for D20A in May in 1983-2015
(a) SST-nudging v.s. EN4

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Strategy 2: Ocean Initialization (Doi et al. 2017, JC)

The initialization skill of subsurface ocean

Initial state of subsurface ocean in the tropical Indian Ocean and the tropical Atlantic, and the mid-latitude is closer to the observation by the new initialization scheme.

Initialization of SST + Subsurface T & S
ACC of SSH prediction from June 1st
ACC of SSH prediction from June 1st
Prediction of SSH anom. in DJF2000/01 issued on June 1, 2000 (1 × 10^{-1} cm)
Prediction of SSH anom. in DJF2004/05 issued on June 1, 2004 (1 × 10^{-1} cm)

(a) AVISO

(b) F1

(c) F2

(d) F2–3DVAR
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✓ In 2000/01DJF, SSH prediction in some region of the North Pacific is improved mainly due to the model development (high-resolution?)
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Further research are required to understand the processes...
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Toward ocean service for stakeholders...

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- We hope that those information is helpful for prediction beyond ocean physical variables (e.g. chl-α)
End