Status of climate prediction and future challenges

a perspective from Norway ...

F. COUNILLON, N. KEENLYSIDE, Y. WANG, I. BETHKE, M. KIMMRITZ, G. DUANE, ...
Seasonal-to-decadal prediction: an initial value and boundary value problem

IPCC, AR5, 2013
Where does the skill comes from

(Mariotti et al., 2018)
Norwegian Climate Prediction Model (NorCPM)

Norwegian Earth System model

Data assimilation (EnKF)

Ensemble

Observations

Objectives

• Long climate reanalysis
• Skillful and reliable climate prediction
  CMIP6 Decadal Prediction Project
  Climate Services (hydropower, insurance, fisheries ..)

(Counillon et al. 2016)
In Norway HPC and storage are national infrastructure Currently:
  - Lenovo Nextscale Mx360 (~1.1 Pflops)

In 2020:
  - Bull sequana XH2000 Atos (~6 Pflops)
Using retrospective hindcast to assess the prediction skill

Seasonal prediction

1985 Feb May Aug Nov Year+1 Reanalysis 1980-2010 ~900 MY

26*4 hindcast runs 
~1000 MY

12 months 9 members

CMIP6 Decadal Prediction Project (DCPP)

1950 1960 1961 1962 yr+1 Reanalysis 30 members present ~2000 MY

~6000 MY

10 years 10 members

384 cpuhours/MY
4 MY/day
Seasonal prediction tested by restrospective hindcast from 1980-2010

NorCPM is competitive with NNME just using SST observations

(Wang et al, 2019)
Seasonal-to-decadal prediction skill with SST and hydrographic profiles

- Observation-based temperature

- Historical
- Reanalysis
- Hindcast

- Climate prediction 6-8 yrs after initialization

- Observation-based temperature

- Warm Atlantic Water
- Cold Arctic Water

- Subpolar Gyre

- Winter sea surface temperature (°C)

- SST [°C] r = 0.70

- SAT [°C] r = 0.46

- Precip. [mm] r = 0.46

- Sea Ice [10^3 km^2] r = -0.55

- Årthun et al. 2017

- Årthun et al. 2018

Also of cod!

Courtesy H. Langehaug
Impact of resolution on the Predictability mechanisms of northern climate

Advection of ocean anomaly from the sub polar gyre yields predictability in northern climate

Propagation of anomaly more coherent with obs in NorESM-H

Working on a prediction system based on the high resolution version with an alternatively cheaper DA

Maximum correlation at each station

(Langehaug et al. 2018)
How to make best use of sea ice concentration
A twin experiment

Strongly coupled DA (SCDA) of ocean and sea ice yields improvements over weakly CDA with flow dependent DA

Updating the whole multcategory sea ice model state outperforms assimilation of aggregated thickness and concentration

(Kimmritz et al. 2018)
Enhancing seasonal prediction in the Arctic
**Detrended correlation skill of sea ice extent in real framework**

Kimmritz et al. sub

Complementing our system with sea ice concentration data greatly improved our prediction of sea ice extent

1985:2010
- means not significant
Strongly coupled data assimilation

Is it possible to assimilate observation across compartments?

- Improve dynamical consistency of the system
- More optimal use of observations across compartments (some are poorly observed)

Courtesy of Steve Penny
Strongly coupled data assimilation

*Penny et al. 2019*

Use a simple coupled ocean atmosphere model (MOOAM, Cruz et al. 2016) and assimilate at each time step.

- SCDA outperforms forced DA systems and WCDA systems.
- Converges with atmospheric obs in the ocean with flow dependent DA methods.
- Converges with ocean obs only in the atmosphere with flow dependent DA method and very frequent assim window.

Frequent assimilation is likely to be too expensive for us!
Can we find a cheap alternative to strongly coupled data assimilation

- Nudging our atmospheric component towards atmospheric reanalysis
- Assimilating atmospheric observations into the ocean observation using the lead average cross-covariance method (Lu et al. 2015a,b) may allow us to excerpt skill from the extensive atmospheric observation network
Available observations for constraining the climate system

There are very many more observations in the atmosphere than in the ocean

Laloyaux et al. 2018
Persistent model biases – dramatic improvement unlikely soon

- Bias is often larger than the signal we analyze or predict
- Progress in reducing these bias is very slow
Parameter estimation
As example for sea ice

Ensemble data assimilation can estimate model parameter and their uncertainty by using a so called state augmentation (Anderson 2001)

Twin experiment:

With real data

Massonnet et al. 2014
• Several parameters can be tuned simultaneously
• Optimisation procedure is done automatically by assimilation
• Get the likelihood of each parameter
• Allow for spatially varying or time evolving parameters
• Advanced scheme (smoother and iterative scheme) allows improved performance

With real data

Optimal parameter are only optimal for a specific system (& resolution)

Massonnet et al. 2014
- Several parameters can be tuned simultaneously
- Optimisation procedure is done automatically by assimilation
- Get the likelihood of each parameters
- Allow for spatially varying or time evolving parameters
- Advanced scheme (smoother and iterative scheme) allows improved performance

With real data:
- Very many parameters and little obs
- Bias are coupled and involved multi-scale interaction
- Parameters values may get unphysical
- Different schemes works better in different condition/regions (not a the parameter value)

Optimal parameter are only optimal for a specific system (& resolution)

*Massonnet et al. 2014*
Super modelling
An example with L63

\[ \dot{x} = \sigma (y - x) \]
\[ \dot{y} = x(\rho - z) - y \]
\[ \dot{z} = xy - \beta z \]

A super model adds connections to the other imperfect models

Example:

\[ \dot{x}_1 = \sigma_1 (y_1 - x_1) + C_{12}^x (x_2 - x_1) + C_{13}^x (x_3 - x_1) \]

Nudging to other supermodel

In **training phase** you use observations to estimate the nudging coefficients (and constrain the state during)

In **verification phase** the coefficient are frozen and the system can be used as a new dynamical system

<table>
<thead>
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<th></th>
<th>(\sigma)</th>
<th>(\rho)</th>
<th>(\beta)</th>
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<tr>
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Super ensemble
Mean of unconnected models

Supermodel
Verification
Super modelling
A first attempt with GCM

Climatological Precipitation in Tropical Pacific

(Shen et al. 2016, 2017)
Super modelling for an earth system model

In the following we only use SST with equal weight:

- Does the system synchronise variability?
- Is bias improved?
- Is variability damped?

No synchronisation of atm for now

- Generate synthetic observations
- Assimilate synth obs back into each models ensure dynamical consistency and multivariate updates
- The three models are then propagated
- Possible to assimilate real data in addition for forecasting

\[ SM_{\text{mix}} = a \cdot M1 + b \cdot M2 + c \cdot M3 \]

Find a, b and c so that \( a+b+c=1 \)
Is bias improved?

The bias of each model is reduced
Is variability synchronised?

**Unconnected**

Pacific, NINO3.4 (5S-5N/170W-120W)

Atlantic, ATL3 (3S-3N/20W-0)

Indian Ocean, IOD (10S-10N/50E-70E) - (10S-0/90E-110E)

**Supermodel**

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Is variability Damped?

Deseasoned SST variability

Mean of unconnected model

Supermodel

observations

Variability is overly damped!
Influence of synchronization strength

If synchronisation is too weak, variability gets even more damp than with unconnected model.
Conclusions

• In some regions, seasonal-to-decadal prediction reaching sufficient skill to be used by stakeholders
• Increasing the resolution improves the mechanism of predictability mechanism in the Nordic region
• Most of the skill resides in the ocean but further constraining the sea ice, land and atmospheric should allow enhancing the prediction skill
• Strongly coupled data assimilation can be a game changer for seamless climate prediction but computational resource required are yet too high
  ➔ can we find cheaper alternative?
• Model bias is a major challenge for hindcast performance and data assimilation:
  • Parameter estimation and flux correction can help reducing them and improve the forecast accuracy
  • Super modelling provide an alternative
    • Works well with toy model and an ESM version is being built and tested