Environment and Climate Change Canada
Environnement et Changement climatique Canada

Canada

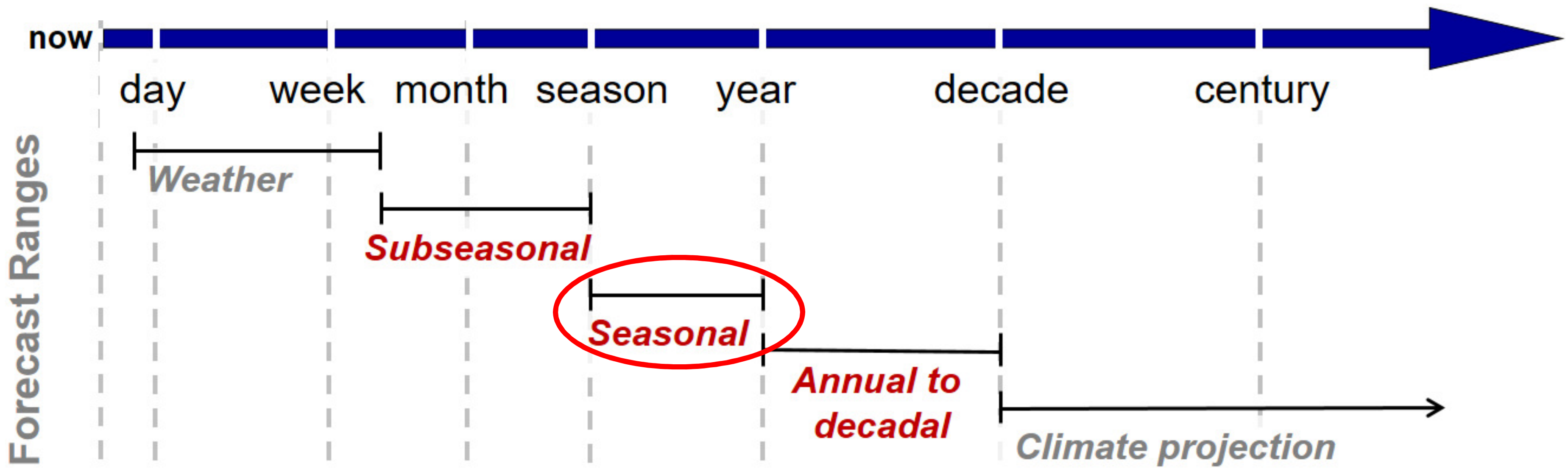
Seasonal prediction of the cryosphere

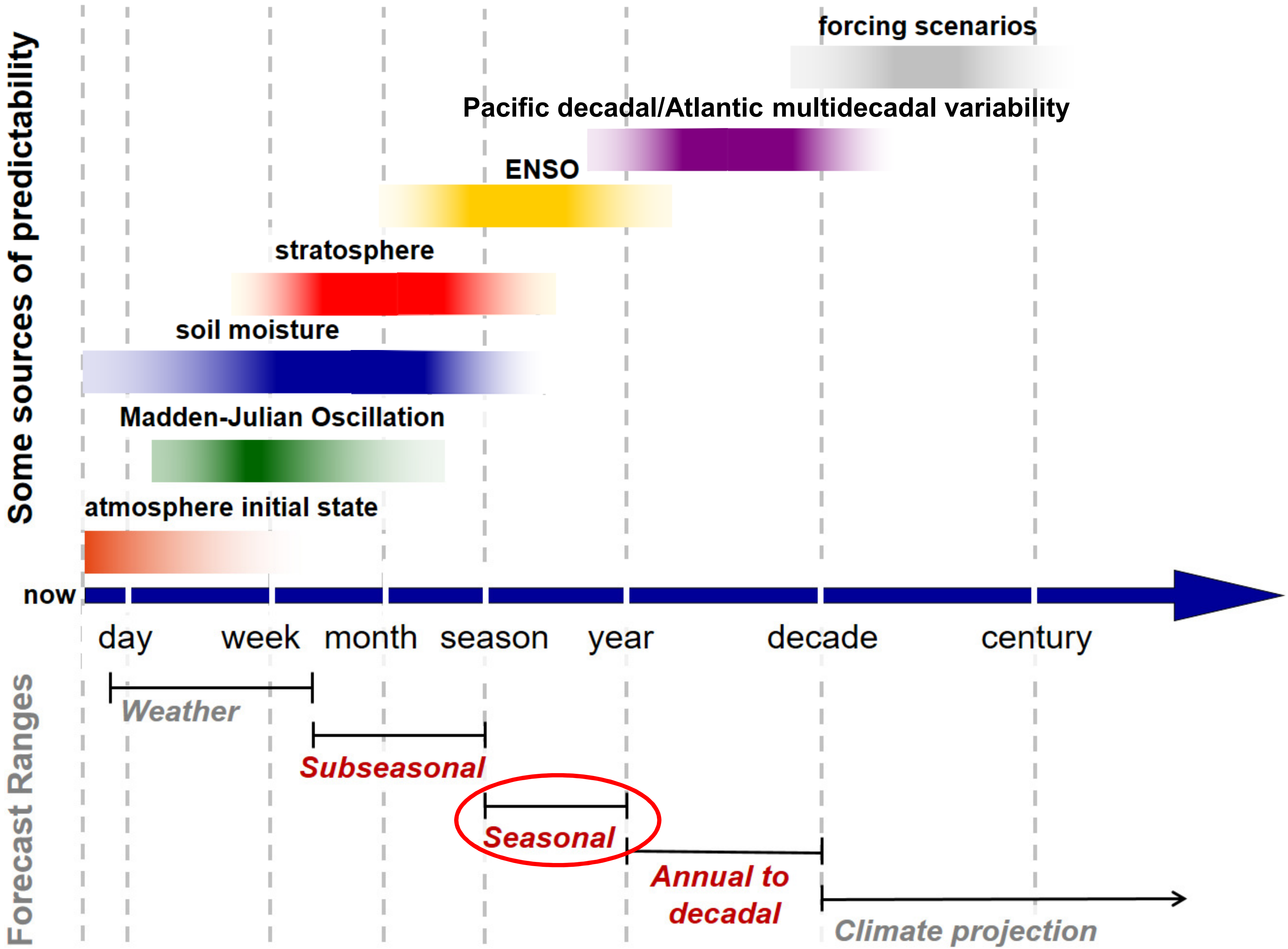
Bill Merryfield

Canadian Centre for Climate Modelling and Analysis (CCCma)

CITES-2019, 3 June 2019

Time scales for seasonal prediction





Some sources of predictability
forcing scenarios
Pacific decadal/Atlantic multidecadal variability
ENSO
stratosphere
soil moisture
Madden-Julian Oscillation
atmosphere initial state
now
day
week
month
season
year
decade
century
Forecast Ranges
Weather
Subseasonal
Seasonal
Annual to decadal
Climate projection

How seasonal forecasts are produced

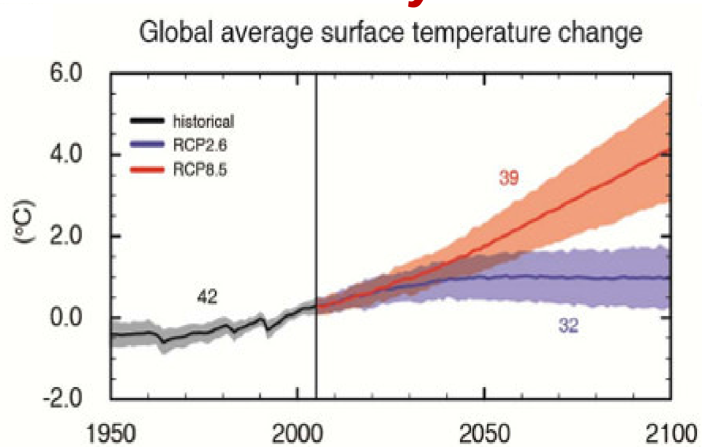
Weather forecast

1-10 days

- Weather prediction model
- Current global observations used to initialize model

Climate projection

10-100 years



- Climate model (atmosphere /ocean/land/sea ice)
- Initial conditions not critical

How seasonal forecasts are produced

Weather forecast

1-10 days

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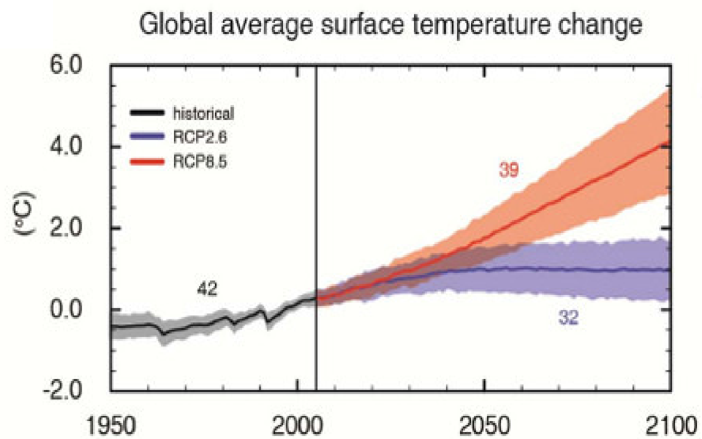
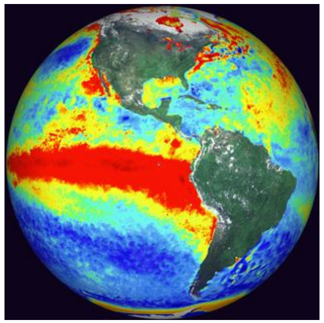
Climate projection

10-100 years

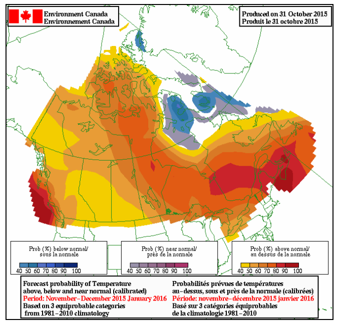


- Climate model (atmosphere /ocean/land/sea ice)
- Initial conditions not critical

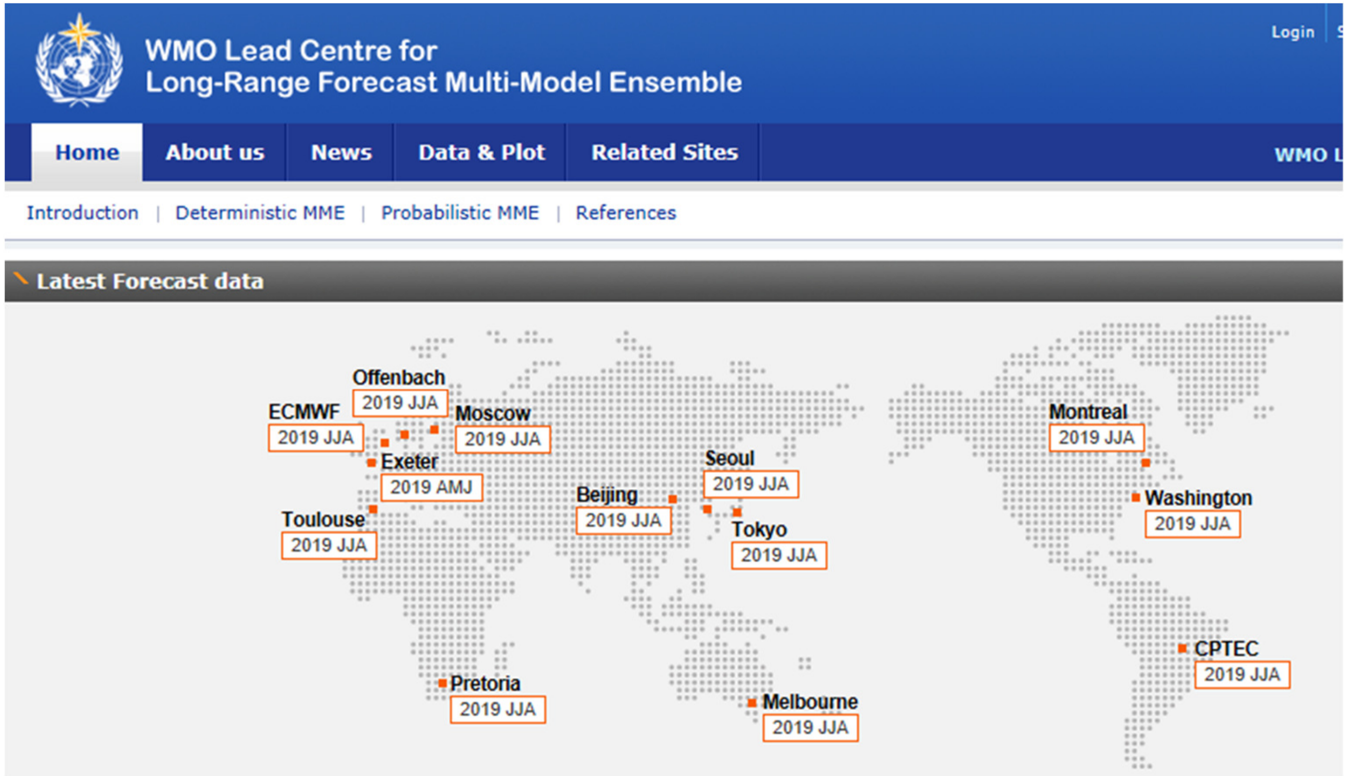


Seasonal forecast

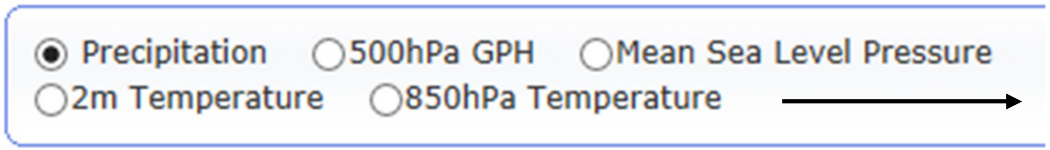
1-12 months

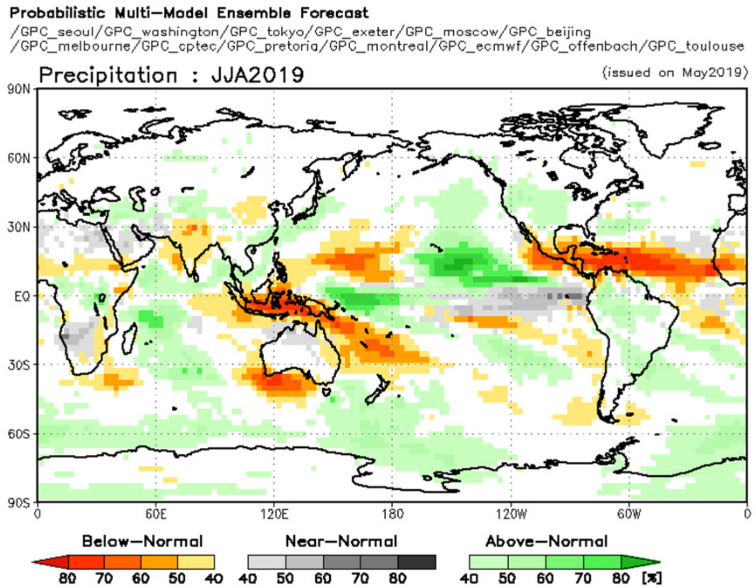


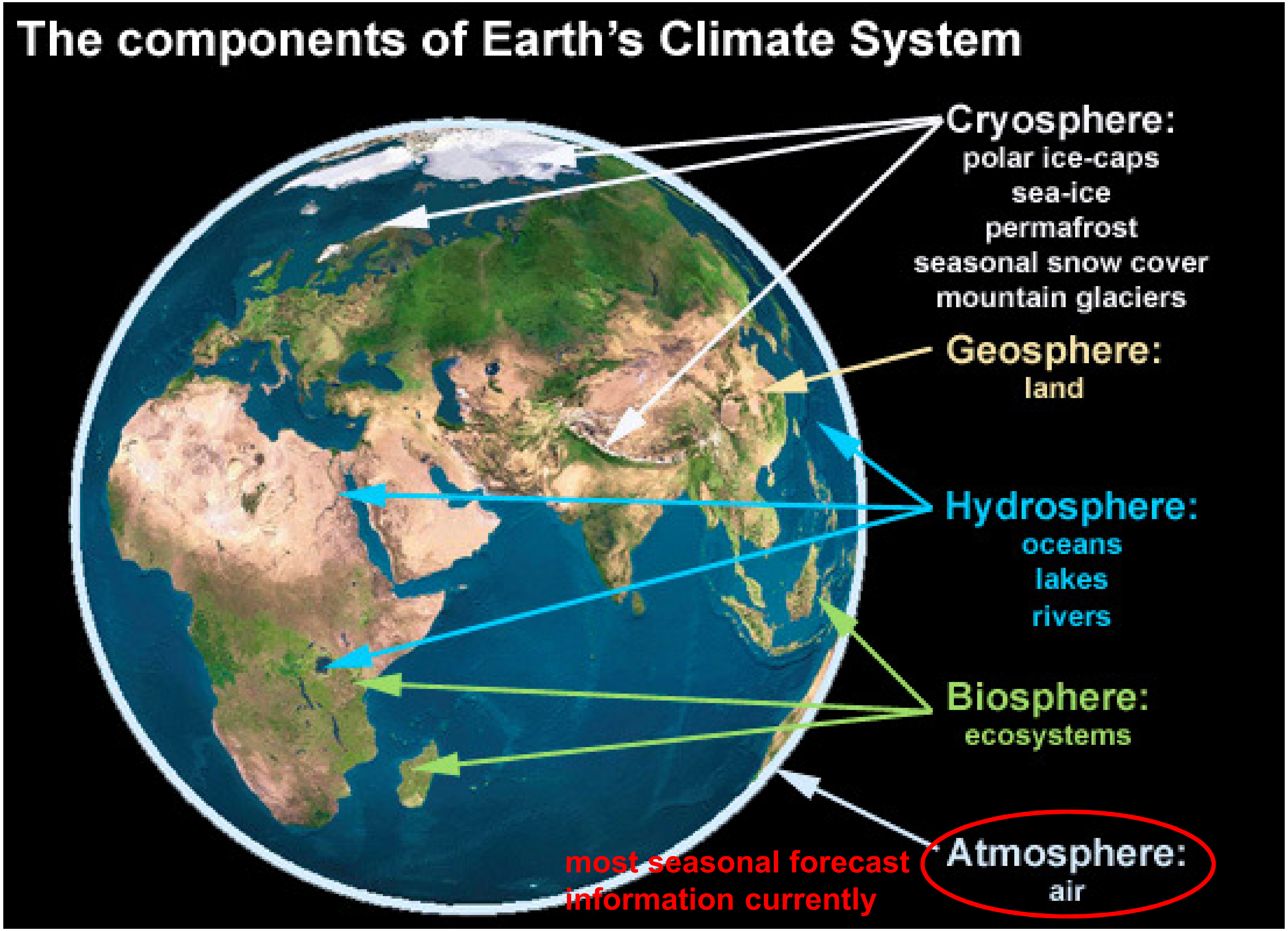
WMO seasonal Forecast Global Producing Centres



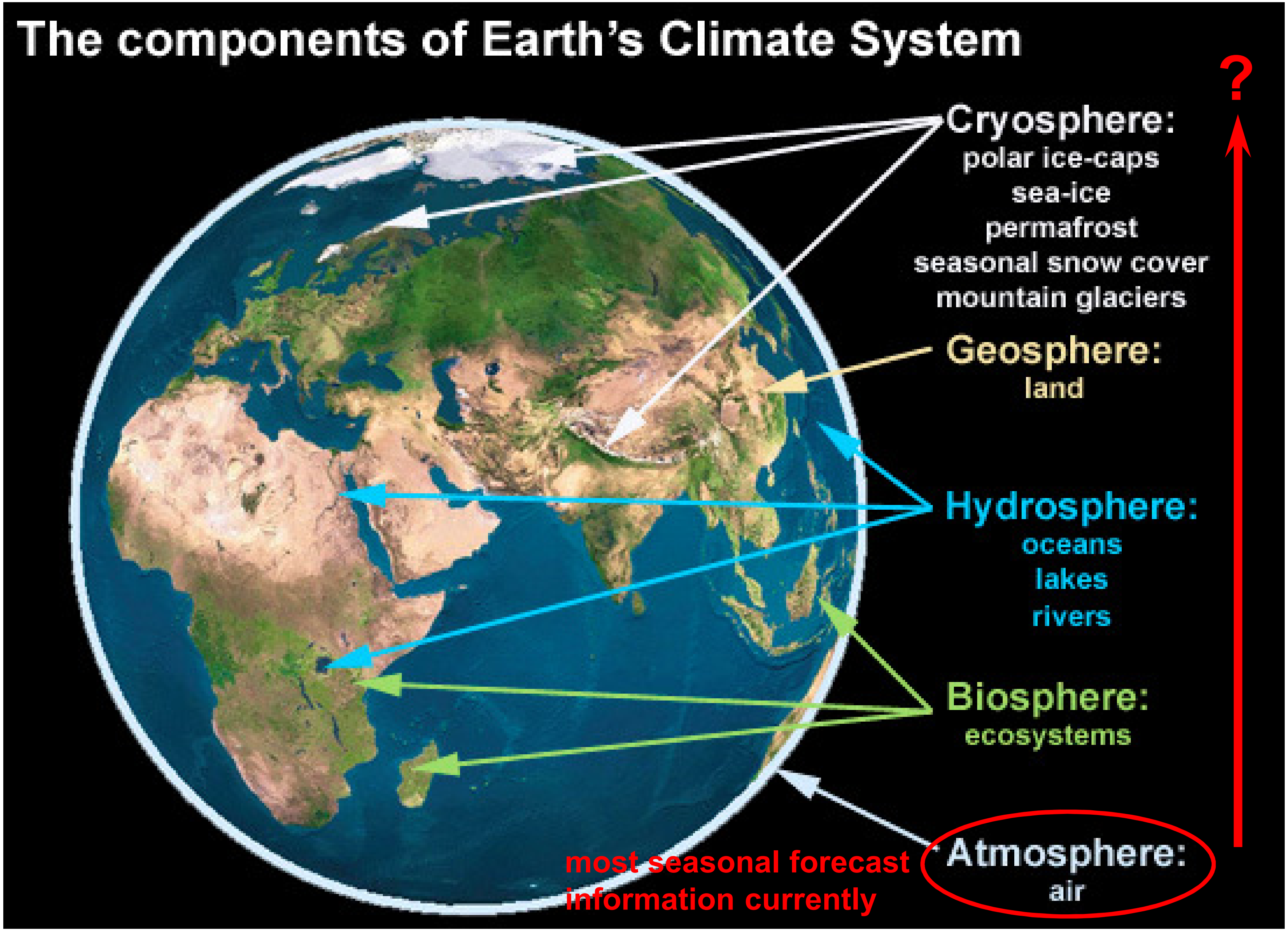
Available seasonal forecast variables:







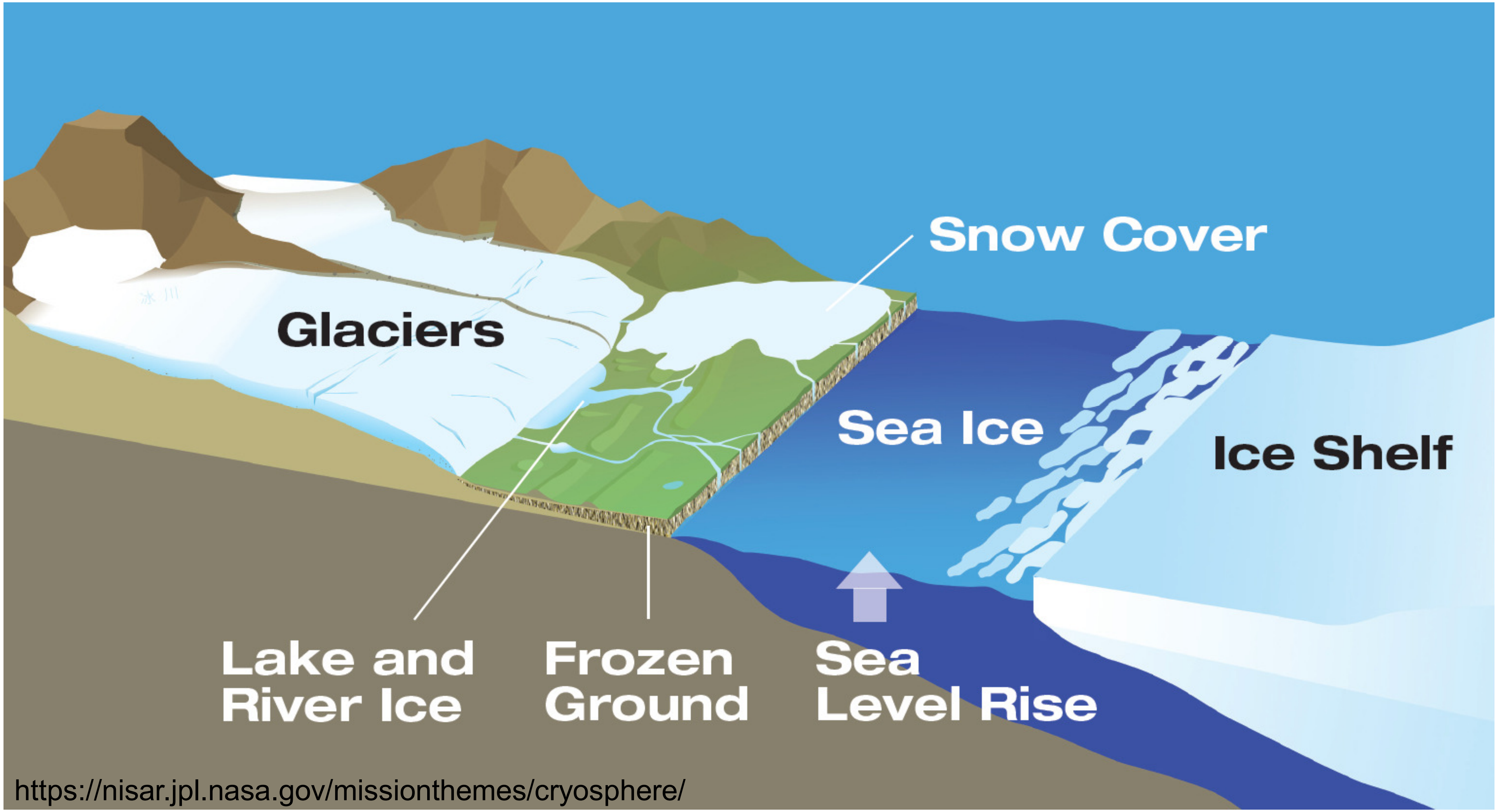
http://www.climate-change-knowledge.org/earth_system.html



http://www.climate-change-knowledge.org/earth_system.html

Components of the Earth's cryosphere

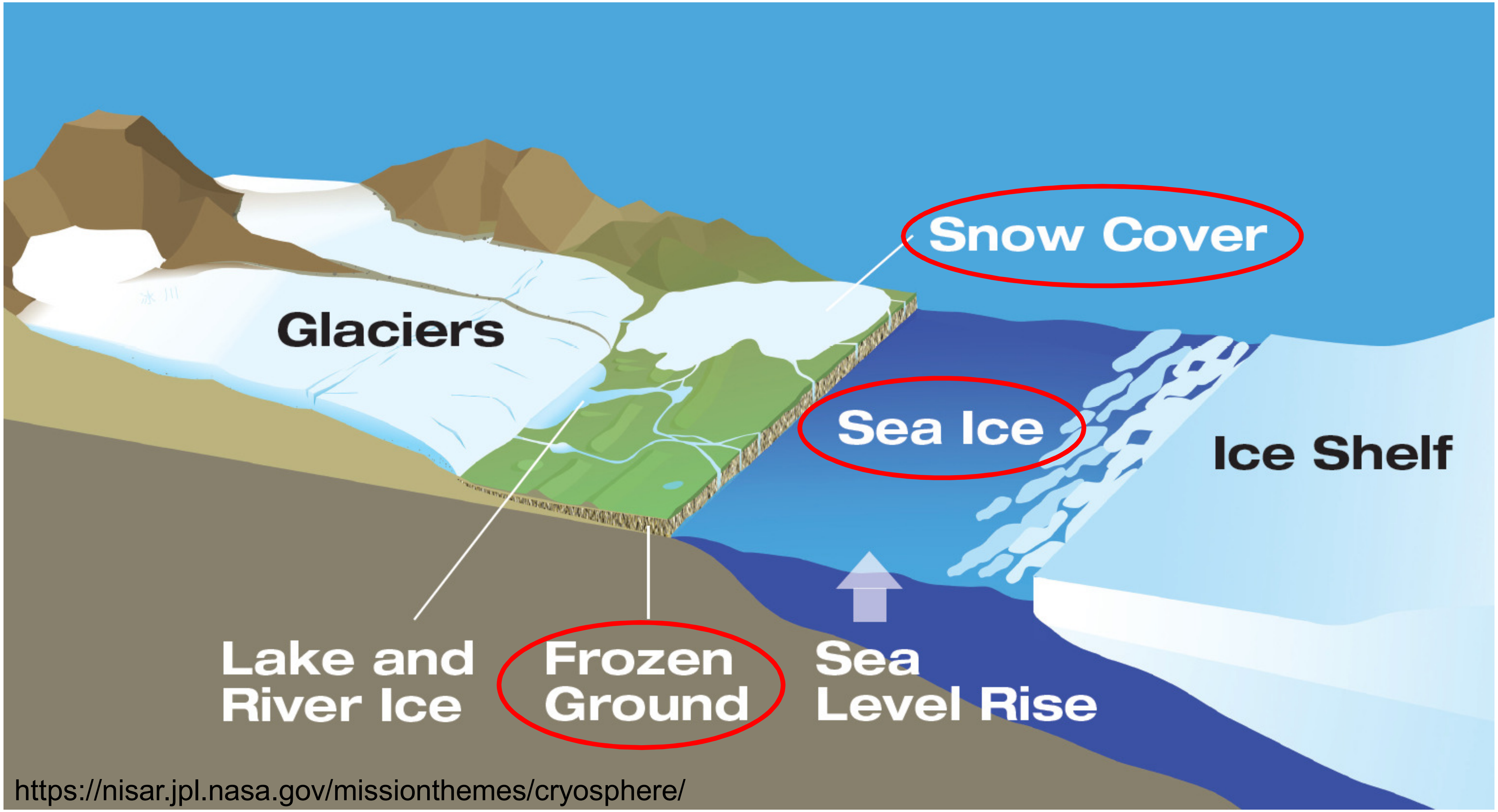
The cryosphere is the *frozen water part of the Earth system**



*https://oceanservice.noaa.gov/facts/cryosphere.html

Components of the Earth's cryosphere

The cryosphere is the *frozen water part of the Earth system**



Considered this talk

*https://oceanservice.noaa.gov/facts/cryosphere.html

Necessary conditions for useful dynamical seasonal forecasts

1) Variations of *X* must be *predictable*

2) Forecast system must represent *sources of predictability*, such as
   - initial conditions
   - climate influences that drive variability of *X*

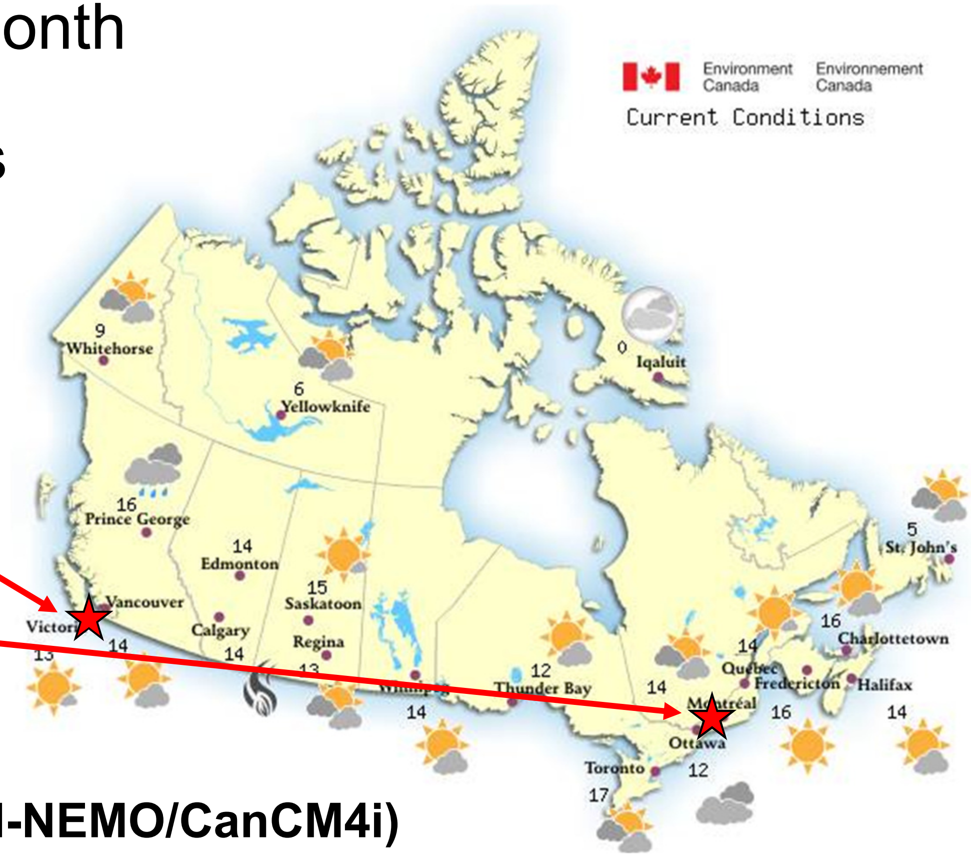
3) Observations of *X* must be sufficiently good that *skill* of forecasts can be assessed

→ *If these conditions are met then there is potential for useful predictions*

Canadian Seasonal to Interannual Prediction System (CanSIPS)

CanSIPS

- Operational at GPC Montreal since Dec 2011
- 2 models CanCM3/4, 10 ensemble members each
- Hindcast verification period = 1981-2010
- Initialized at start of every month
- Forecast range = 12 months

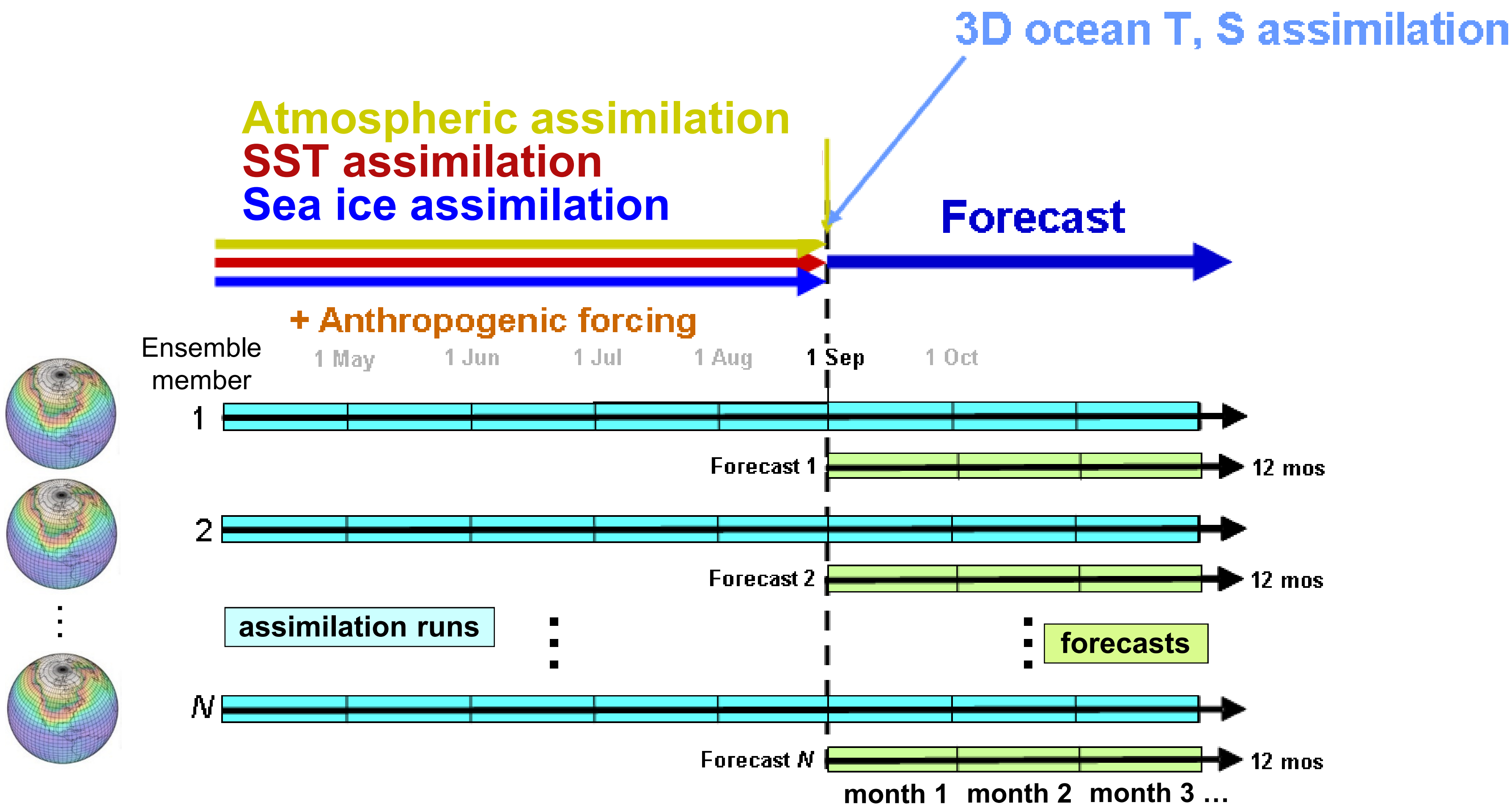


Climate Modelling Research (Victoria)

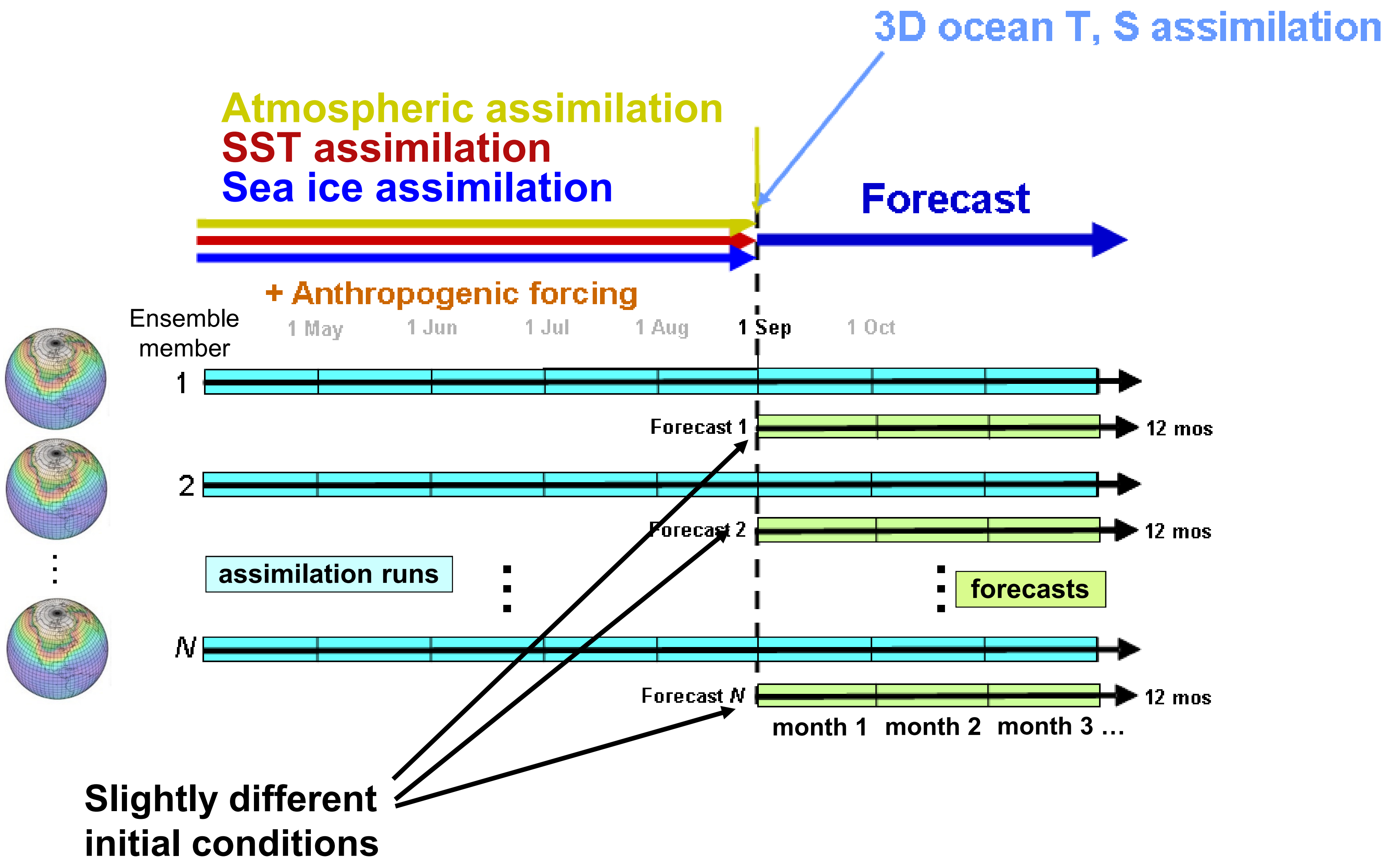
Operations (Dorval, near Montreal)

Coming August 2019: CanSIPSv2 (GEM-NEMO/CanCM4i)

CanSIPS initialization



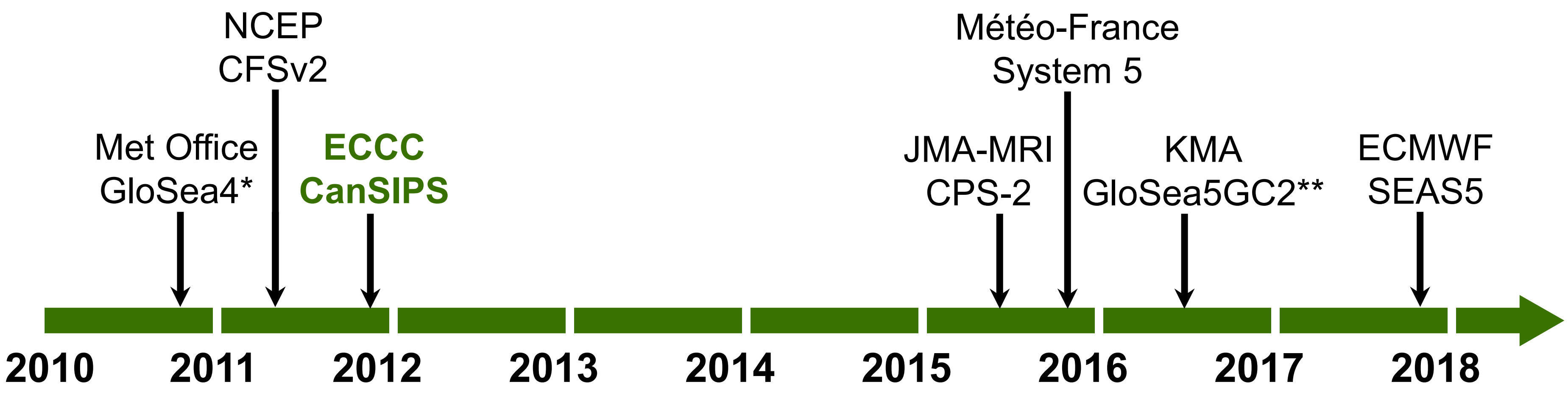
CanSIPS initialization



Seasonal prediction of sea ice

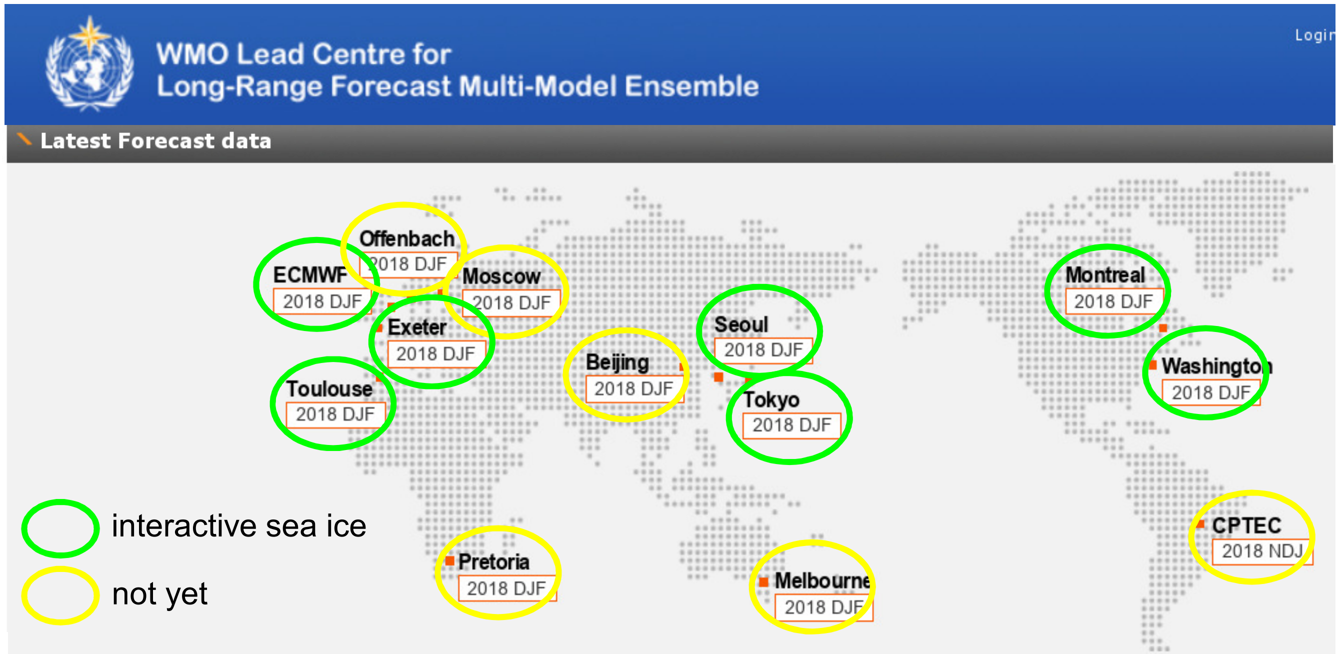
Timeline for seasonal sea ice forecasting

WMO operational models



*1st operational seasonal prediction system with interactive sea ice

**mirrors current Met Office system

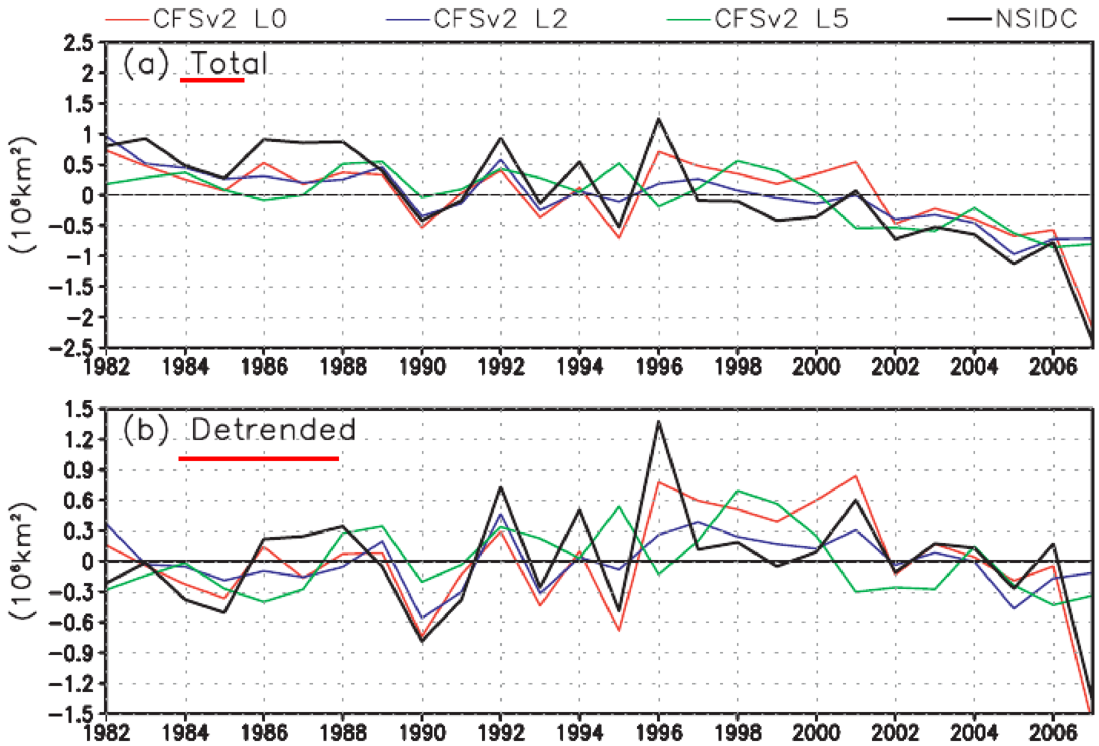


Forecasts of pan-Arctic sea ice extent

Example: CFSv2 (GPC Washington)

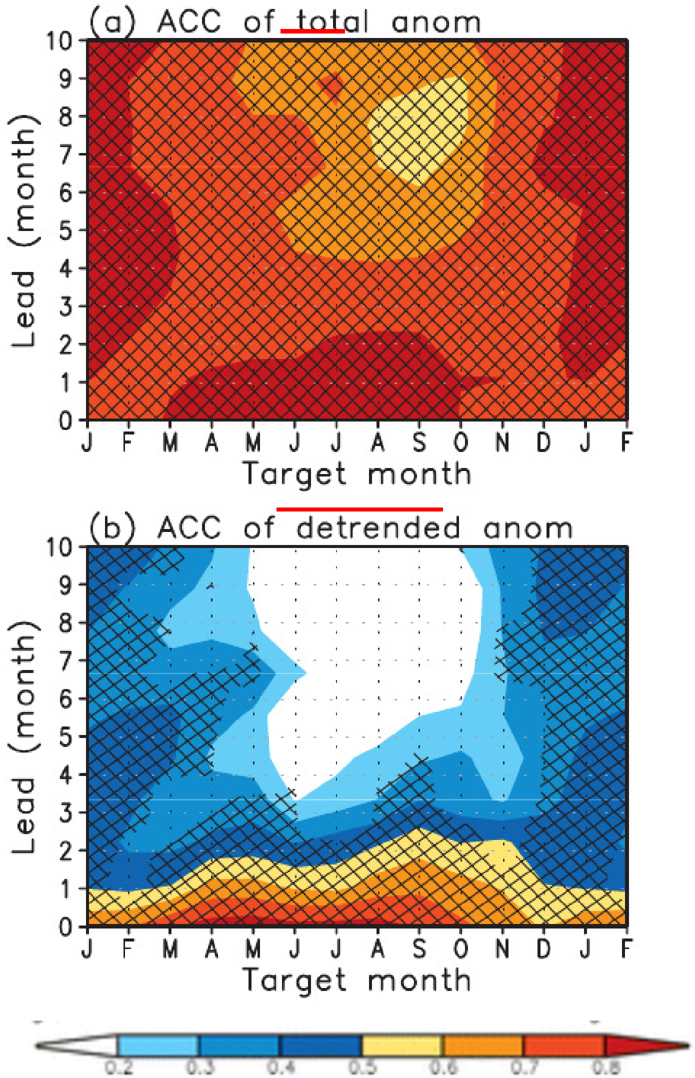
Hindcasts for September extent

Lead times of 0, 2, 5 months **Obs**



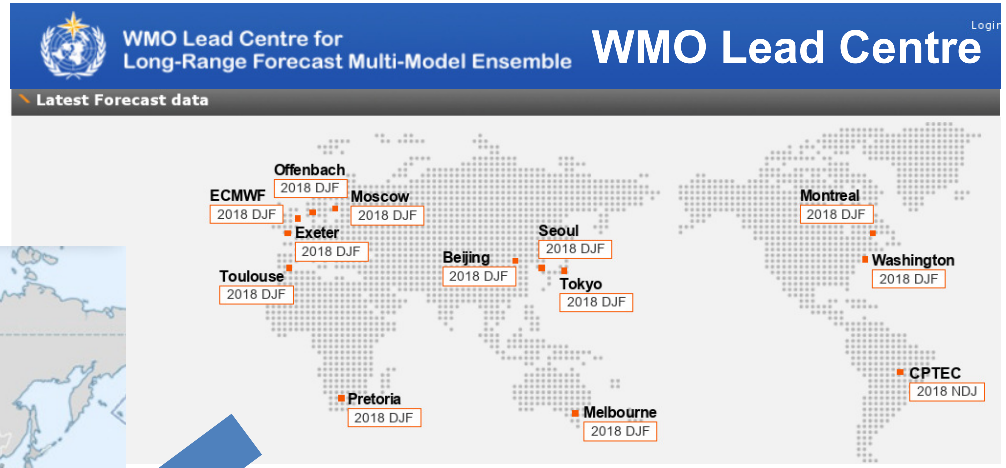
Wang et al., *MWR* (2013)

Anomaly correlation skill

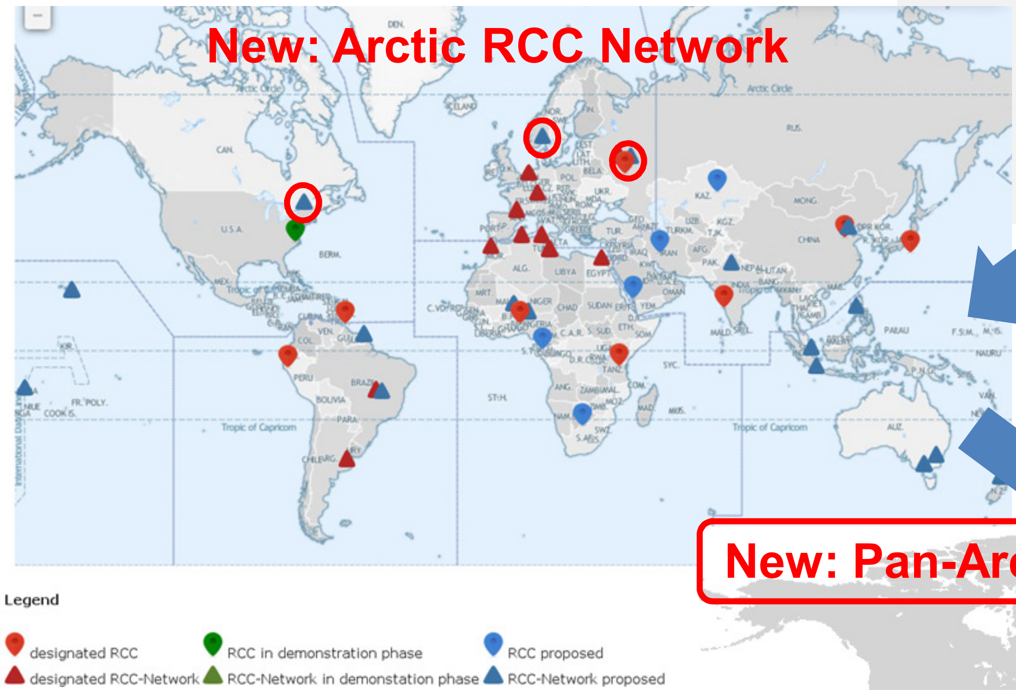


→ ***Interesting to scientists, not so much to users***

WMO Regional Climate Services

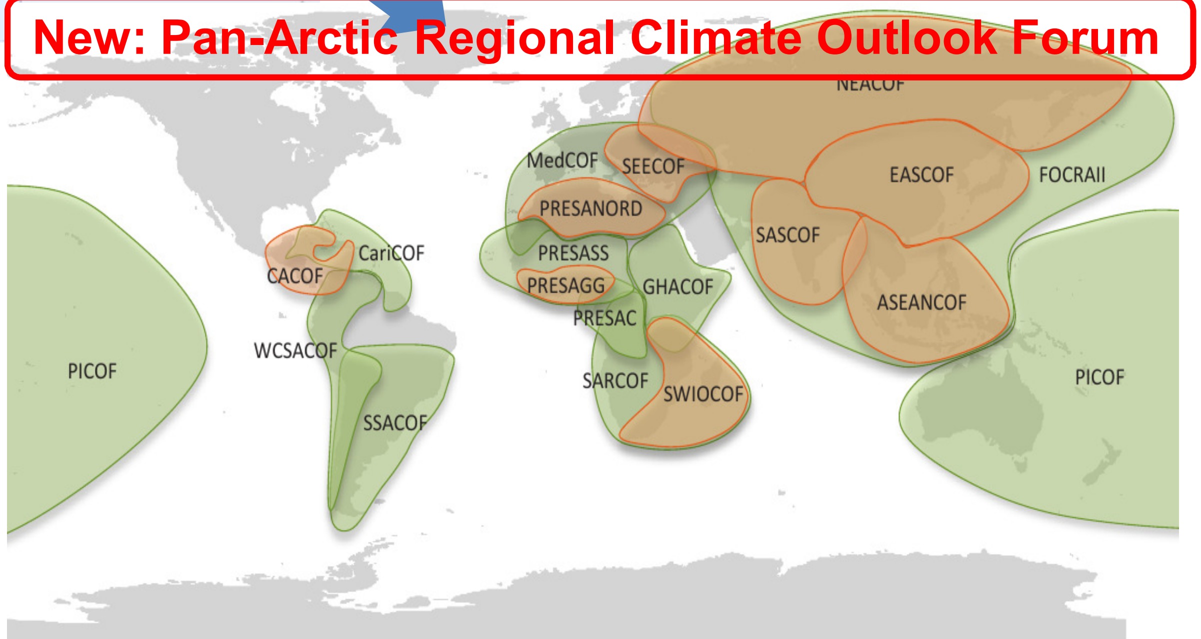


Regional Climate Centres (RCCs)



(PARCOF)

New: Pan-Arctic Regional Climate Outlook Forum



Regional Climate Outlook Forums (RCOFs)

Arctic Regional Climate Centre Network

CLIMATE MONITORING | LONG-RANGE FORECASTING | DATA ACCESS | REGIONAL SERVICES | ABOUT US

Welcome to the Arctic RCC Network

RCCs are Centres of Excellence that assist WMO Members in a given region to deliver better climate services and products including regional long-range forecasts, and to strengthen their capacity to meet national climate information needs.

ArcRCC-Network is based on the WMO RCC concept with active contributions from all the Arctic Council member countries through a mutually agreed structure consisting of three sub-regional geographical nodes, namely, (i) North America Node, (ii) Northern Europe and Greenland Node and (iii) Eurasia Node.

Norway: data services

Canada: forecast production

Russia: climate monitoring

Sea ice = Highly Recommended Product

Sea ice forecast product development

Forecasting Regional Arctic Sea Ice from a Month to Seasons

FRAMS objective: develop user-relevant, multi-model sea ice forecasts, informed by WMO GPCs, for ArcRCC & PARCOF

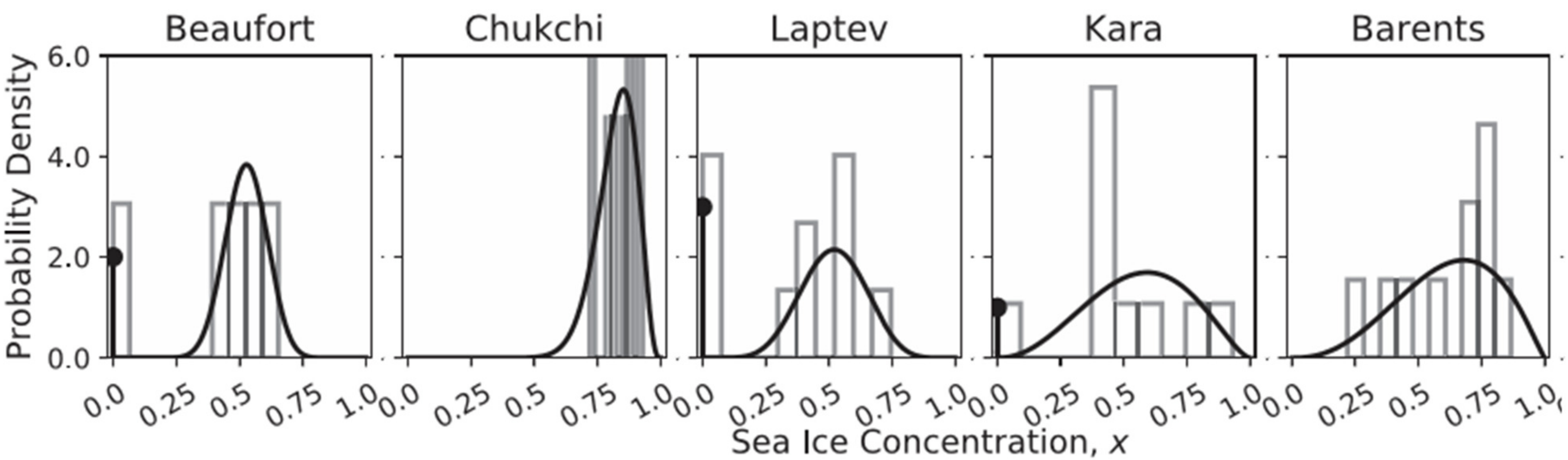
MEOPAR

YOPP YEAR OF POLAR PREDICTION

FRAMS

Calibrated multi-model forecasts of Sea Ice Probability P(SIC>X%)

Step 1: fit ensemble forecast sea ice concentrations to inflated beta distribution f



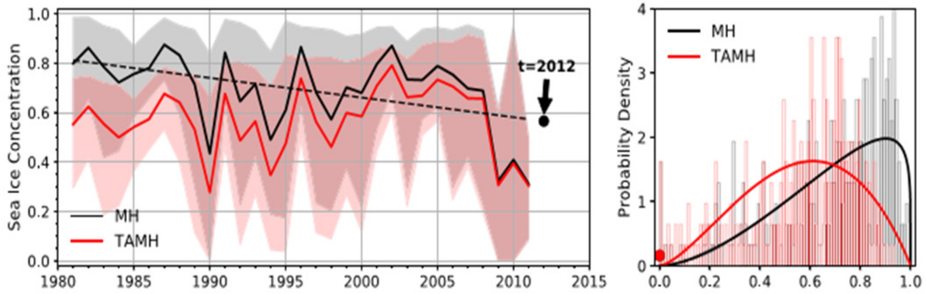
$$f(x;\alpha,\beta,p,q) = p(1-q)\delta(x) + (1-p)f_{\mathrm{beta}}(x;\alpha,\beta) + pq\delta(x-1),$$

$$f_{\mathrm{beta}}(x;\alpha,\beta) = \frac{1}{B(\alpha,\beta)}x^{\alpha-1}(1-x)^{\beta-1}, \quad 0 \le x \le 1$$

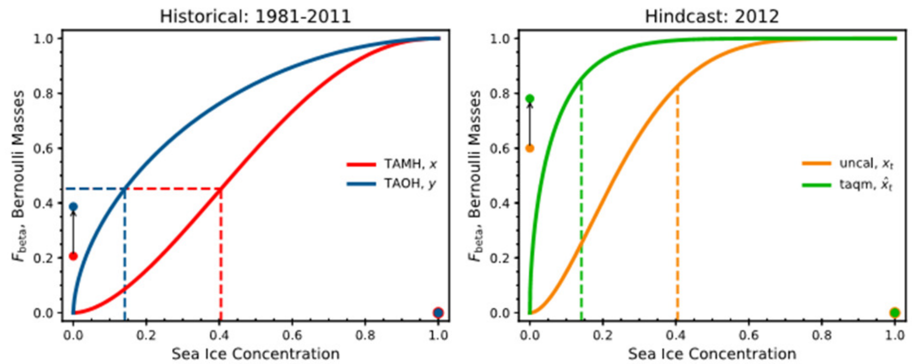
Calibrated multi-model forecasts of Sea Ice Probability P(SIC>X%)

Step 2: trend-adjusted quantile mapping

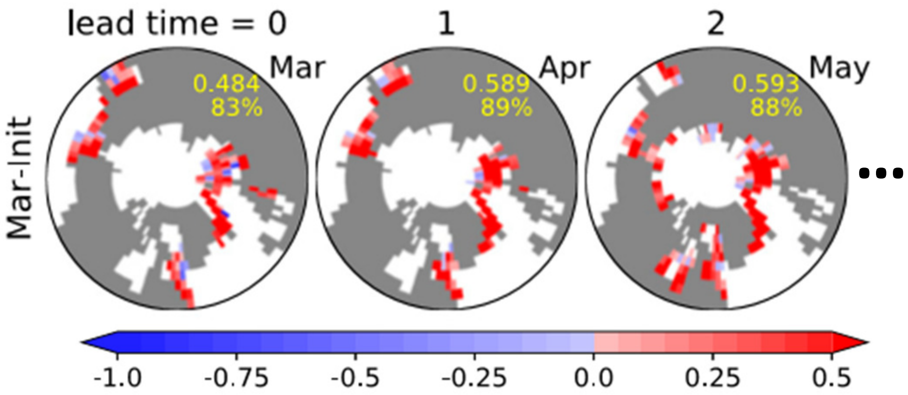
- remove linear trends to obtain Trend Adjusted Model Historical (TAMH) and Trend Adjusted Observed Historical (TAOH) distributions



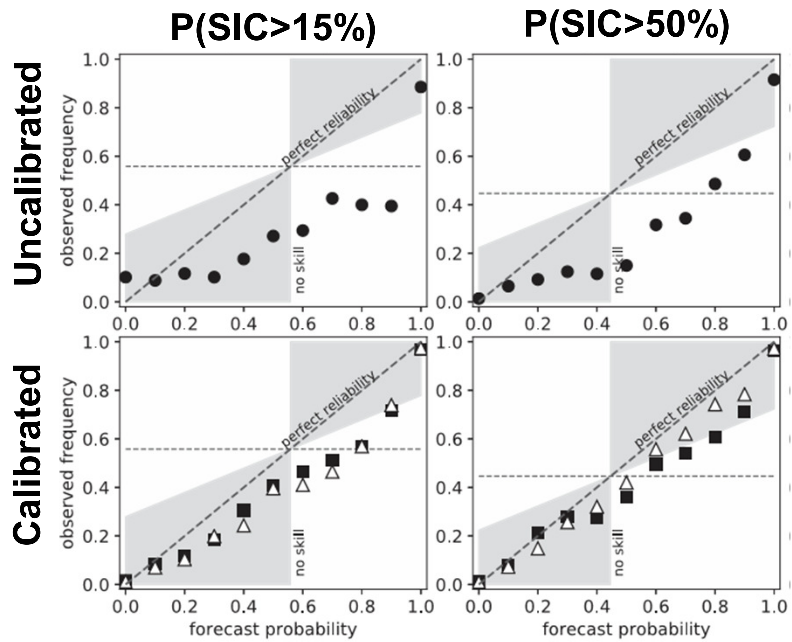
- obtain TAMH→TAOH quantile mapping, apply to each forecast:



- P(SIC>X%) from adjusted distribution has improved reliability and skill:



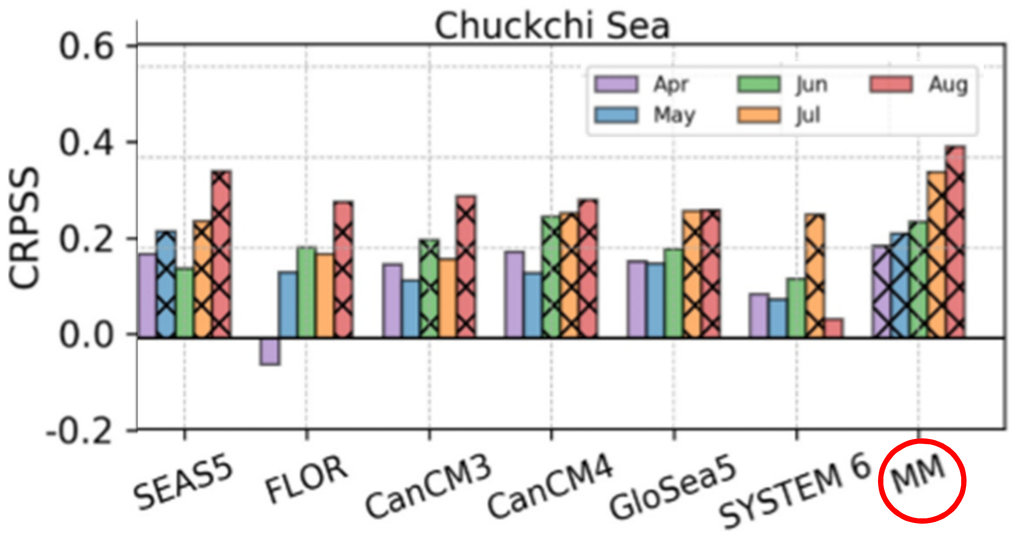
Continuous Ranked Probability Skill Score (CRPSS)



Calibrated multi-model forecasts of Sea Ice Probability P(SIC>X%)

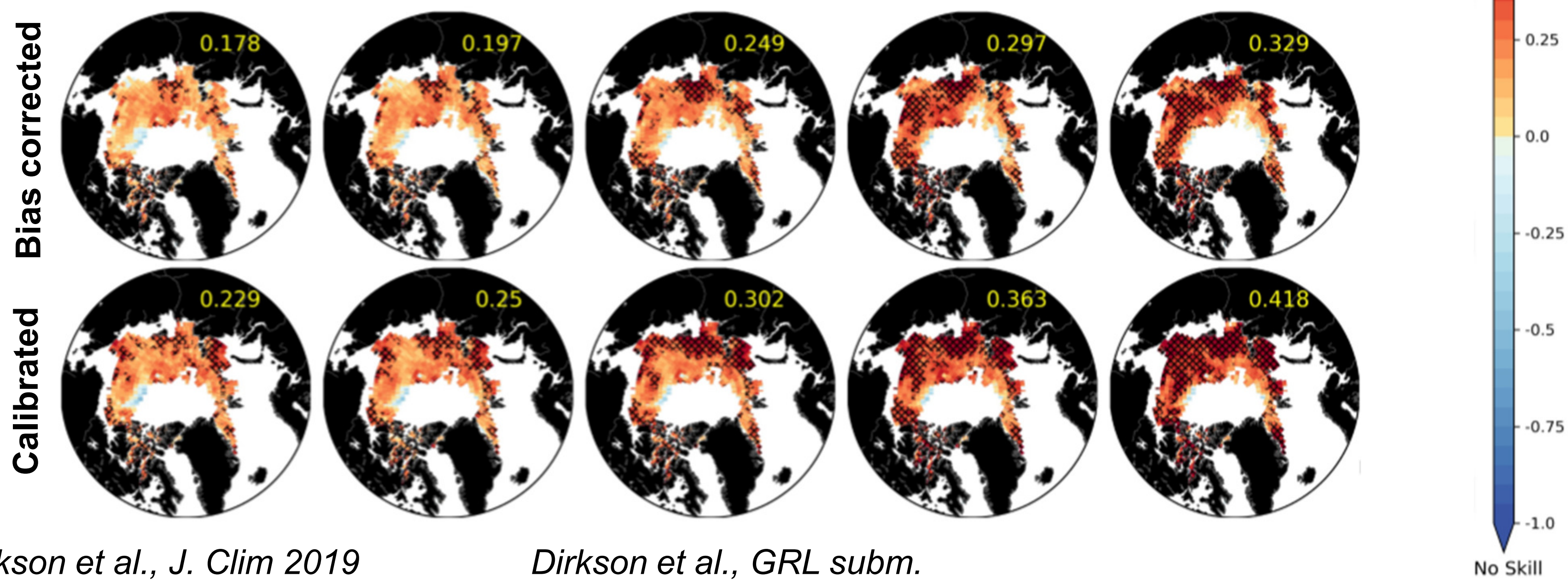
Step 3: Multi-model (MM) forecast

- MM forecast based on 6 models outperforms all individual models:



- MM skill > than for standard bias correction without calibration:

CRPSS vs trend-adjusted observed climatology

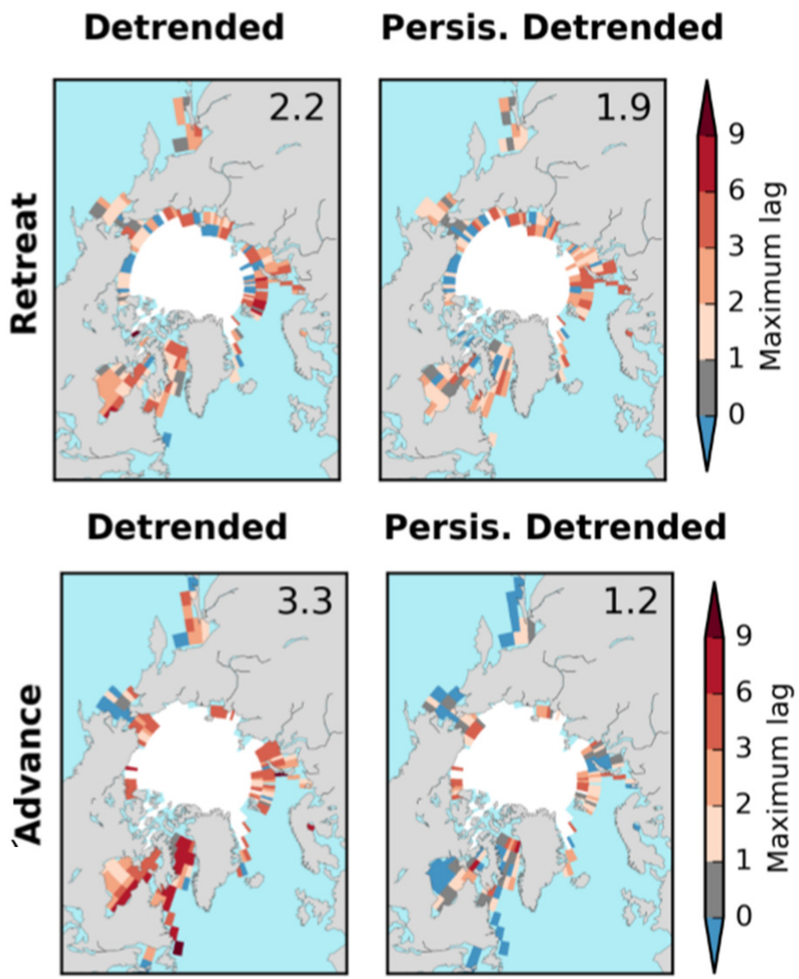


Dirkson et al., J. Clim 2019   *Dirkson et al., GRL subm.*

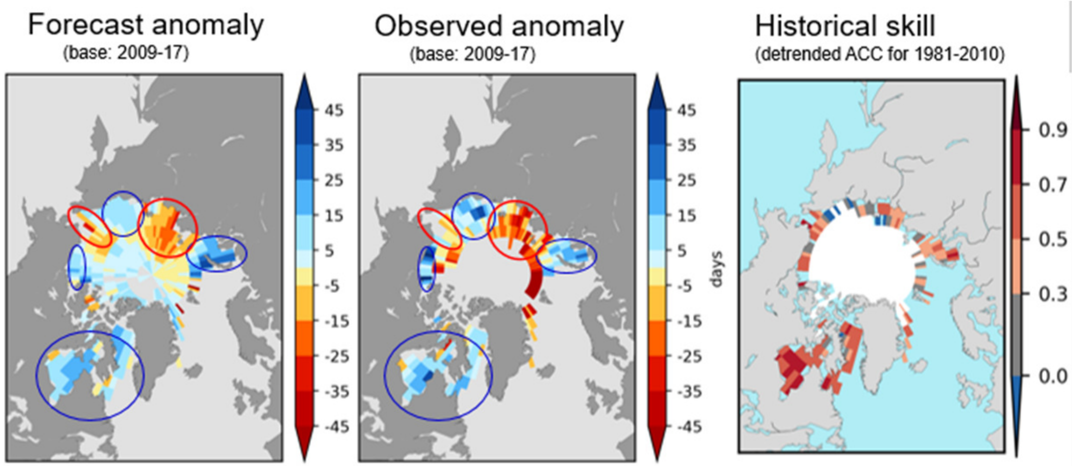
Ice-free dates & freeze-up dates

- Define (requires daily SIC data):
  - Ice-free date (IFD) = first calendar day with SIC < 50%
  - Freeze-up date (FUD) = first calendar day with SIC > 50%

Maximum lead time with skill (months)



2018 IFD forecast



- Next:
  - Probabilistic IFD/FUD forecasts
  - Multi-model IFD/FUD forecasts

Sigmond et al., GRL 2016
Dirkson et al., to be subm.

PARCOF
Pan-Arctic Regional Climate Outlook Forum

Environment and Climate Change Canada

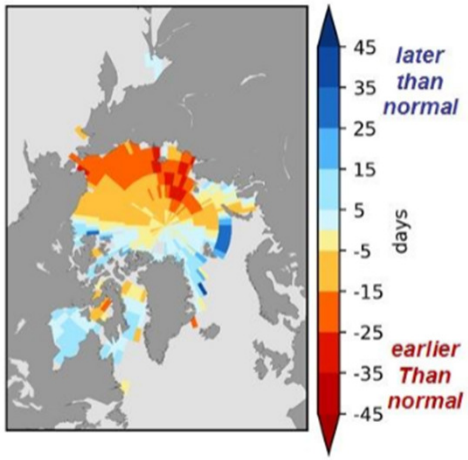
WORLD METEOROLOGICAL ORGANIZATION

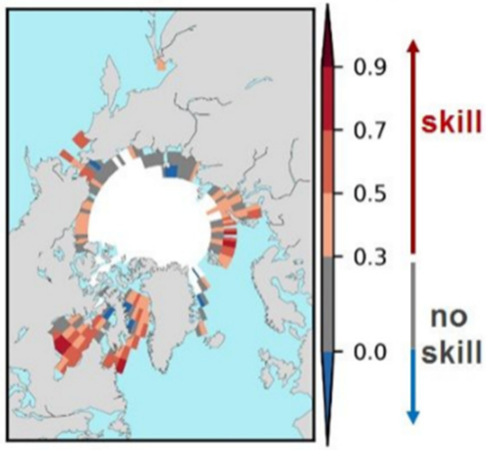
Russian Federal Service for Hydrometeorology and Environmental Monitoring

Norwegian Meteorological Institute

Third Session of the Pan-Arctic Regional Climate Outlook Forum (PARCOF-3), Rovaniemi, Finland, May 2019

Consensus Statement for the Arctic Summer 2019 Season Outlook





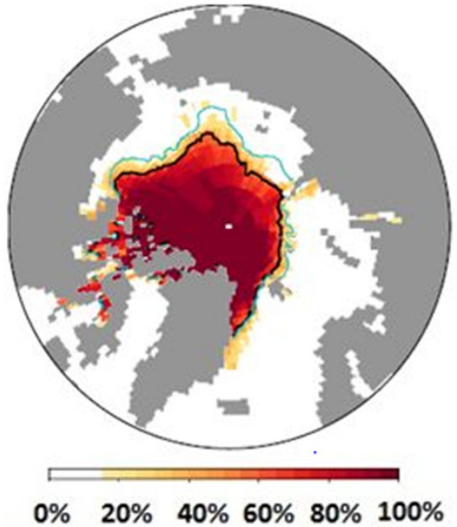


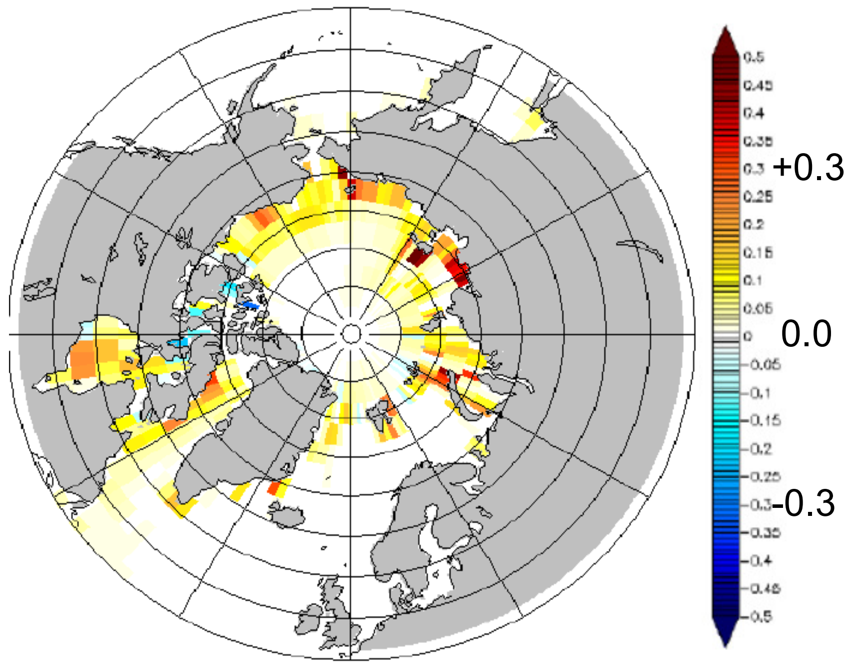
Figure 9. September 2019 probability of sea ice at concentrations greater than 15% from CanSIPS (ECCC). Ensemble mean ice extent from CanSIPS (black) and observed mean ice extent 2009-2017 (green).

PARCOF sea ice forecasts from CanSIPS until real-time multi-model products available

Comments on sea ice observations

- Initializing and verifying seasonal forecasts of sea ice is a great challenge
- Sea ice thickness (SIT) is sparsely observed, satellite SIT observations from CryoSat, etc. exist only for recent years
- Even SIC, "well observed" by satellite since ~1979, can have big differences between datasets
- CanSIPS forecasts shown here are from experimental version having improved SIC and SIT initialization

CMC – NSIDC SIC, July 2014



Seasonal prediction of snow cover

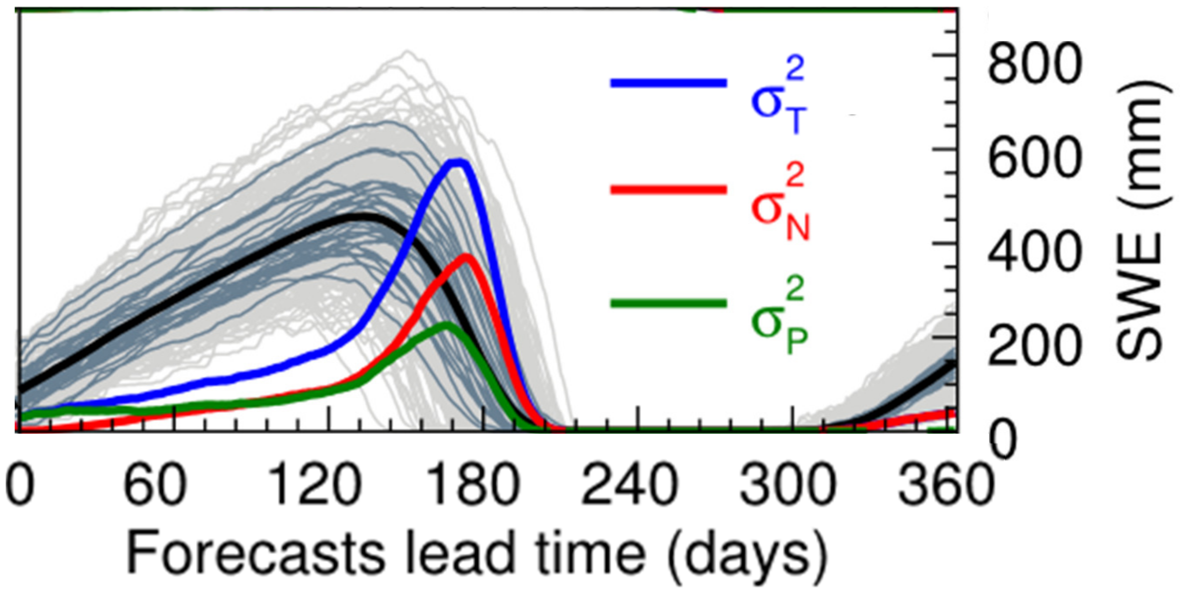
CanSIPS predictions of snow cover

- Consider snow water equivalent (SWE), “snowpack”
- Units kg/m^2, or mm
- Important for water resources, etc.
- Strong interannual variations
- Is it predictable on (multi-)seasonal time scales?

Model estimates of SWE predictability

- Consider all ensemble members ensemble means climatological mean for a model grid cell in British Columbia, Canada

hindcasts initialized 1 Dec 1981-2010



total variance σ_T^2 for all ensemble members
noise variance σ_N^2 = total variance – variance of ensemble means
potentially predictable variance $\sigma_P^2 = \sigma_T^2 - \sigma_N^2$

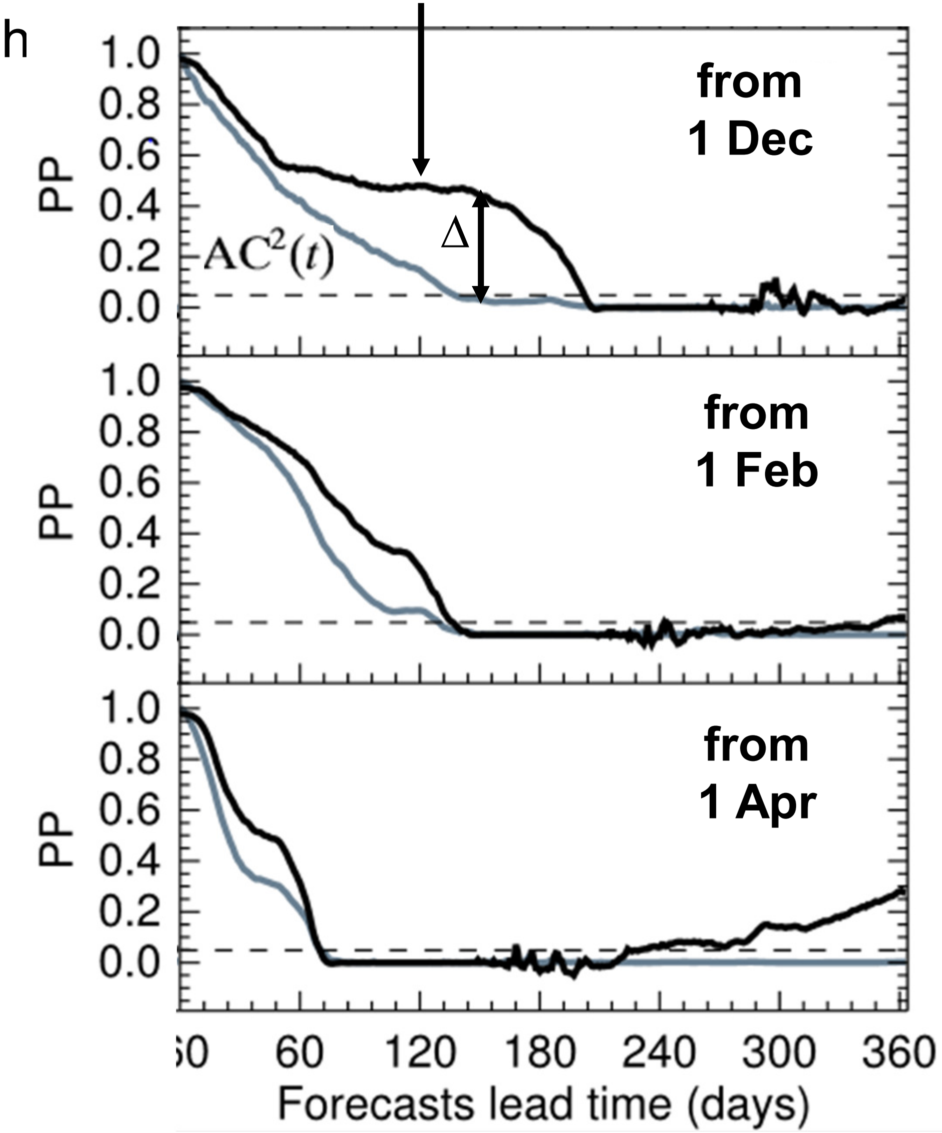
Potential predictability variance fraction: $\mathrm{PP}(t) = \sigma_P^2(t)/\sigma_T^2(t)$

Sospedra-Alfonso et al.,J. Hydromet. 2016a, b

Model estimates of SWE predictability

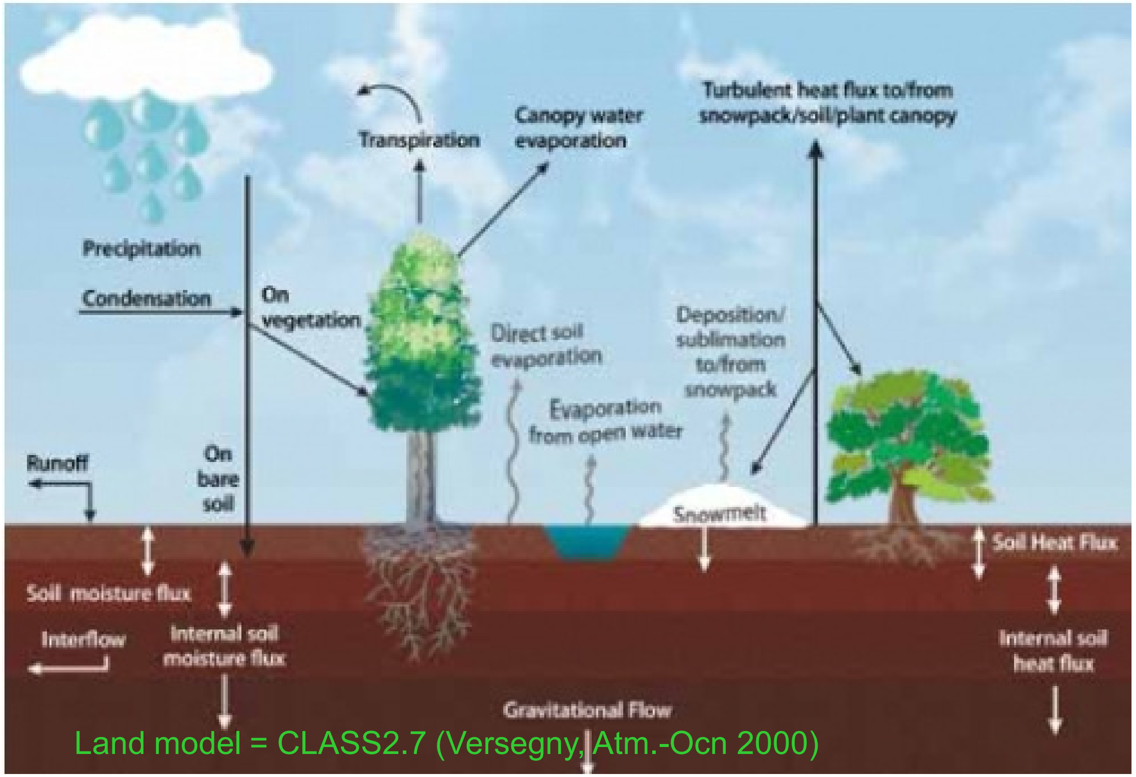
- Potential predictability variance fraction for same grid cell in British Columbia, Canada
- Lagged autocorrelation $AC^2(t)$ with initial value = PP attributable to persistence of initial values
- Δ = PP(t) – AC2(t) = PP attributable to prediction of future conditions
- PP re-emerges after summer melt (no persistence)
- Does PP translate into skill?

$$PP(t) = \sigma_P^2(t)/\sigma_T^2(t)$$



Sospedra-Alfonso et al.,J. Hydromet. 2016a, b

CanSIPS Land initialization



www.eoearth.org/view/article/152990

Direct atmospheric initialization through assimilation of gridded 6-hourly T, q, u, v using incremental analysis update

Indirect land initialization through response to model atmosphere

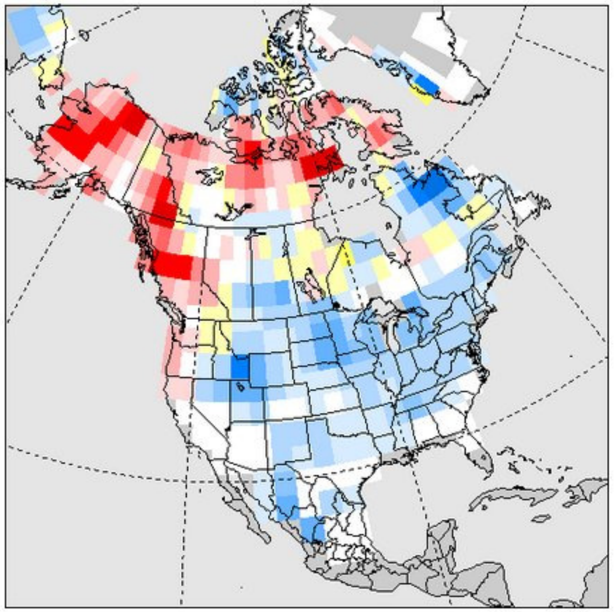
Differences between model initial SWE values and in situ observations similar to gridded SWE datasets → *SWE initialization reasonably good*

CanSIPS snow water equivalent (SWE) forecasts & skill

JFM 2012 (lead 0)

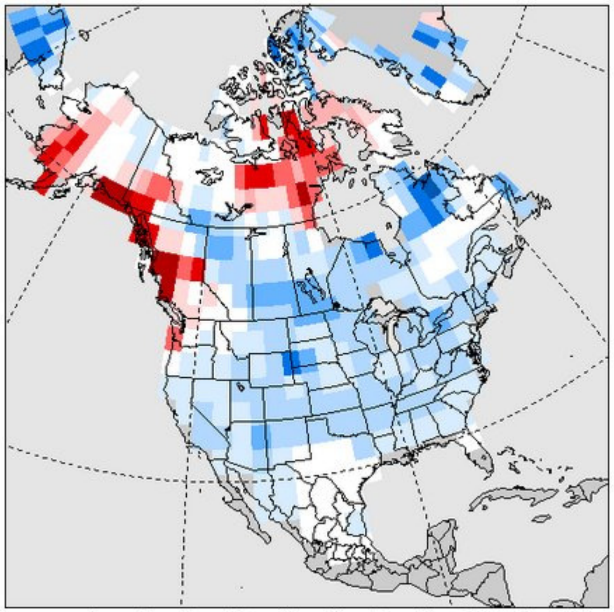
- **3-category probabilistic forecast (left)**
- **MERRA verification (right)**

Snow Mass(gamma), 3-category Probabilistic Forecast
year=2012, JFM, 0-month lead



12-season calibrated probability forecast.
40 50 60 70 80 90 100 40 50 60 70 80 90 100 40 50 60 70 80 90 100
below normal (%) near normal (%) above normal (%)
Areas where forecast probability exceeds 40% are shaded in colours.
White color indicates areas where forecast probabilities of all 3 categories are

Snow Mass(gamma), Observed Percentile
year=2012, JFM (merra)

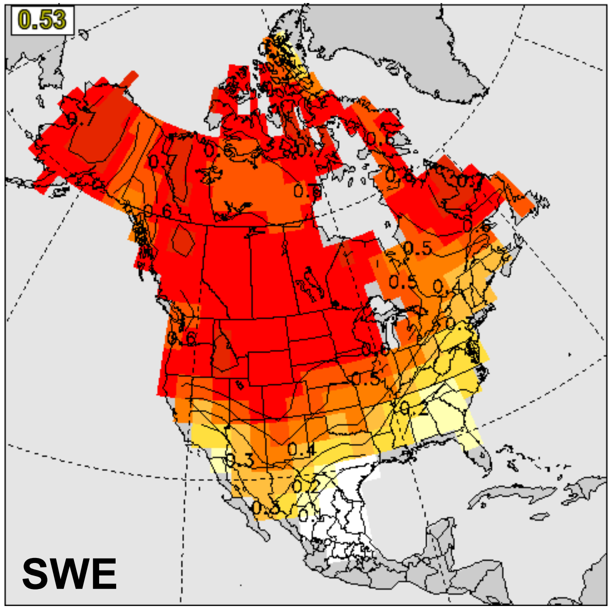


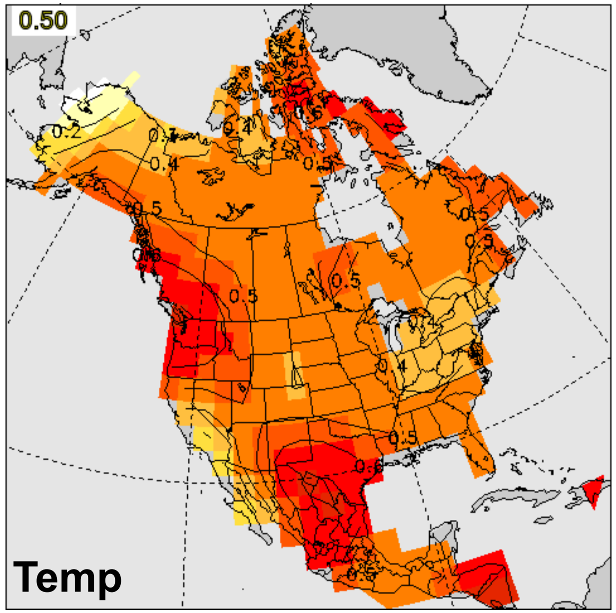
1 5 10 20 33 67 80 90 95 99
below normal near normal above normal
Below normal observed percentiles (<33%) are in blue shades.
Near normal observed percentiles (33% - 67%) are in white.
Above normal observed percentiles (>67%) are in red shades.

Anomaly correlation

JFM (lead 0)

- **SWE (left)**
- **Temperature (right)**
- **SWE skill attributable to**
  - Accurate SWE initialization
  - Tendency for initial snowpack anomalies to persist
  - Ability to predict future climate





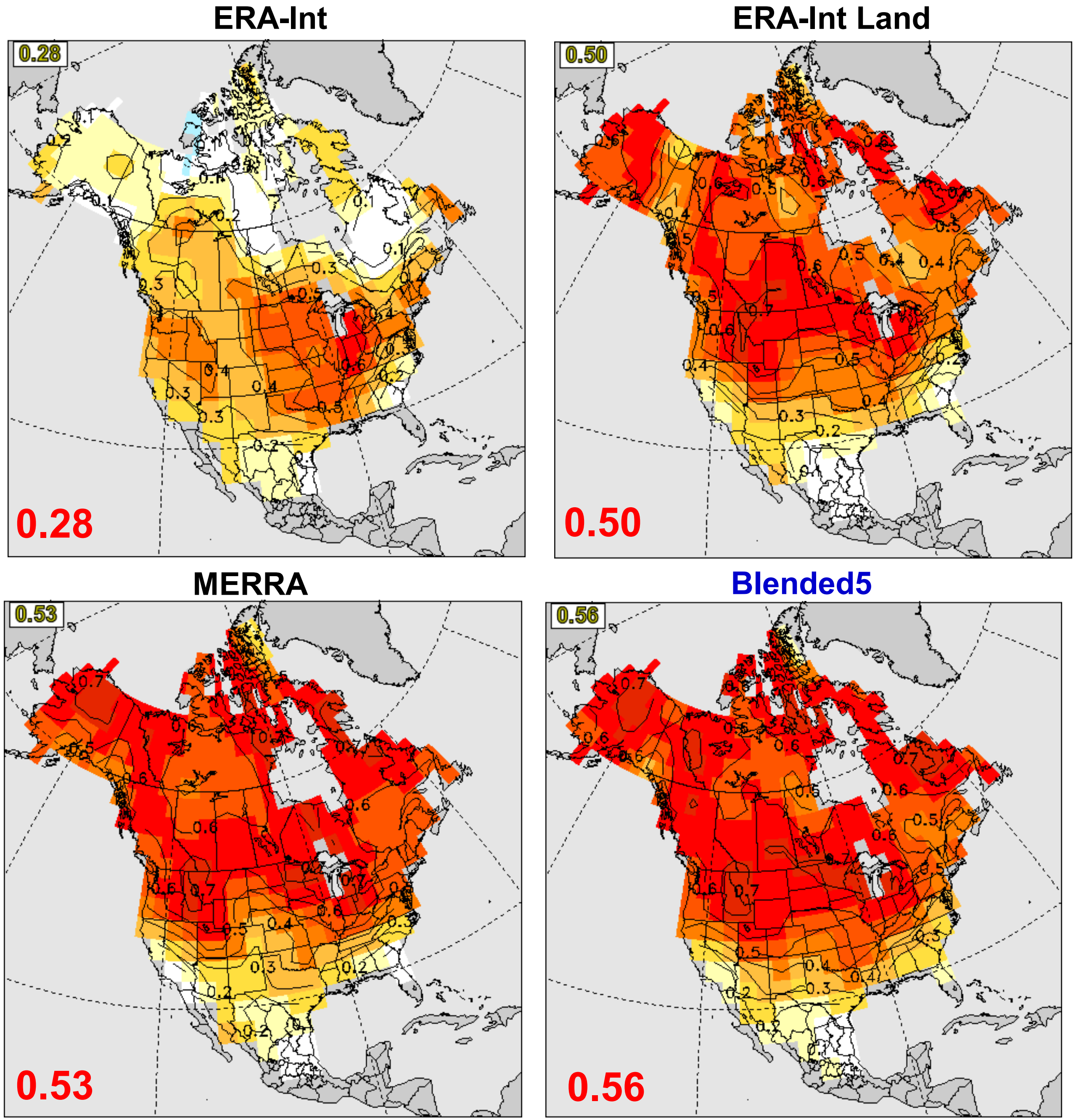
Dependence of SWE skill on verification dataset

FMA lead 0 anomaly correlation

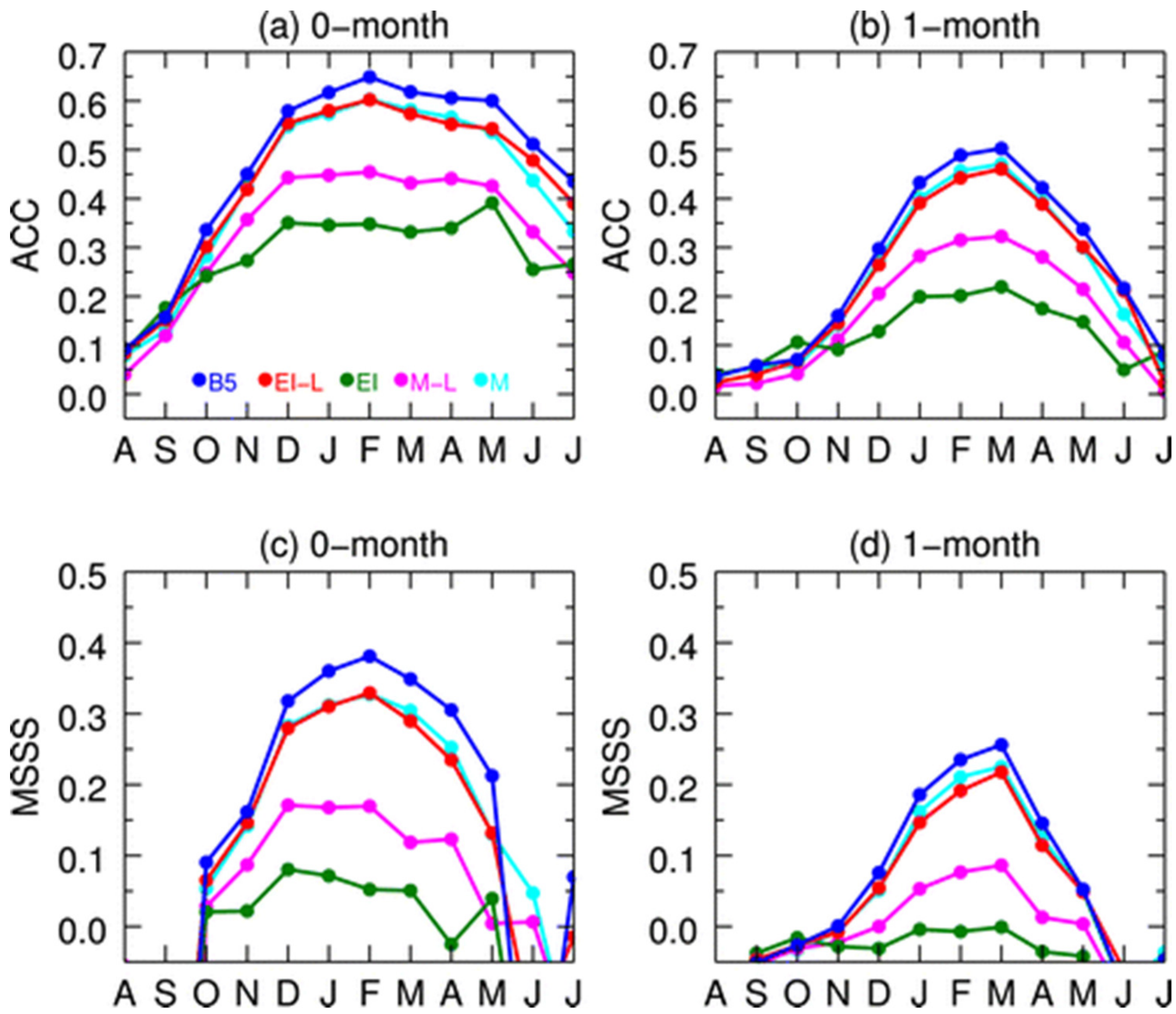
Single-product verifications

Multi-product verification using blended mean of
- **Crocus**
- **ERA-I/Land**
- **MERRA**
- **GlobSnow**
- **GLDAS-2**

Mudryk et al.,J. Clim. 2016



Dependence of SWE skill on verification dataset

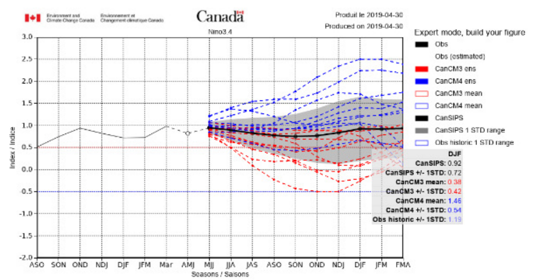


CanSIPS operational SWE predictions

Above normal favored

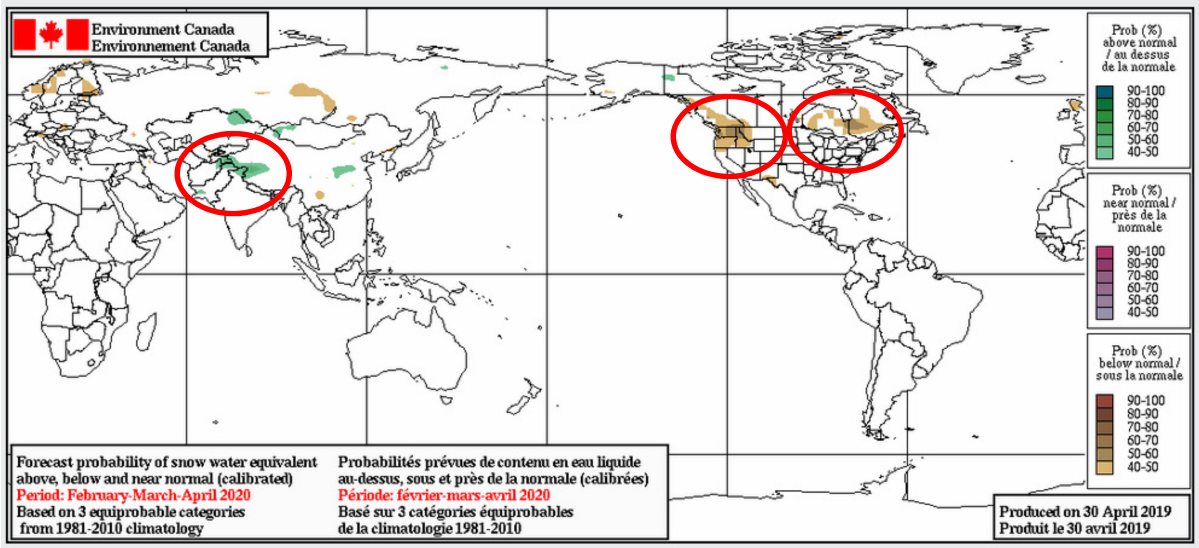
Below normal favored

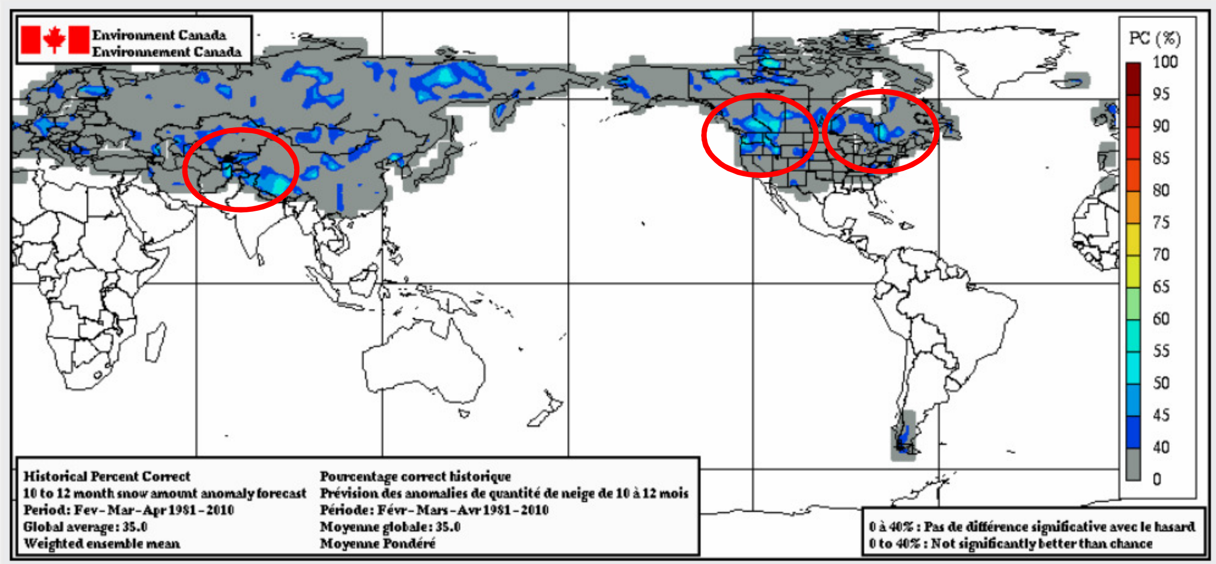
Signal apparently due to weak-moderate forecast El Nino



Percent correct skill

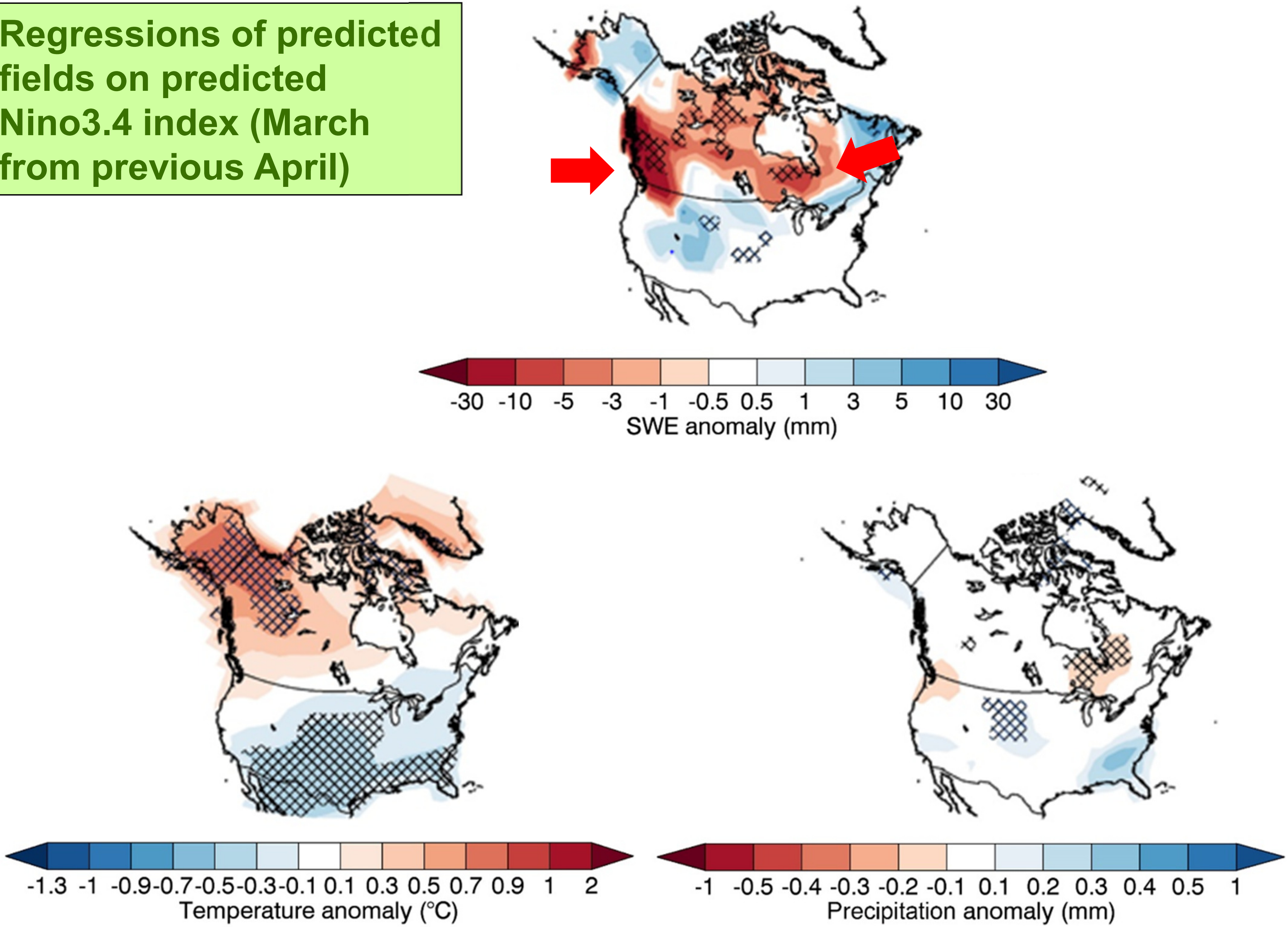
SWE tercile probabilities for FMA 2020 from May 2019





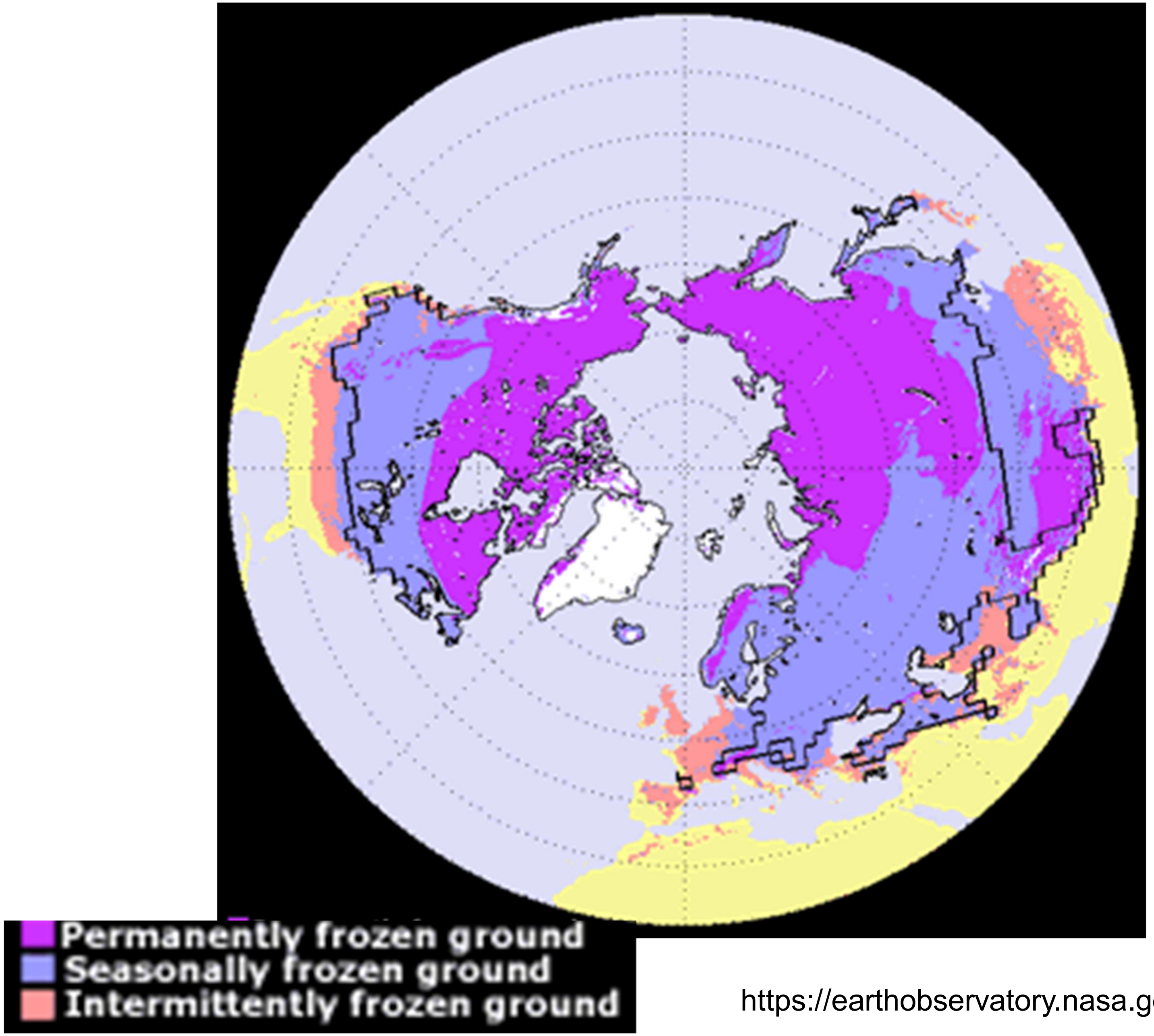
http://climate-scenarios.canada.ca

Regressions of predicted fields on predicted Nino3.4 index (March from previous April)



Seasonal prediction of seasonally frozen ground

Extent of seasonally frozen ground



https://earthobservatory.nasa.gov/features/FrozenSoils

Depth of seasonally frozen ground

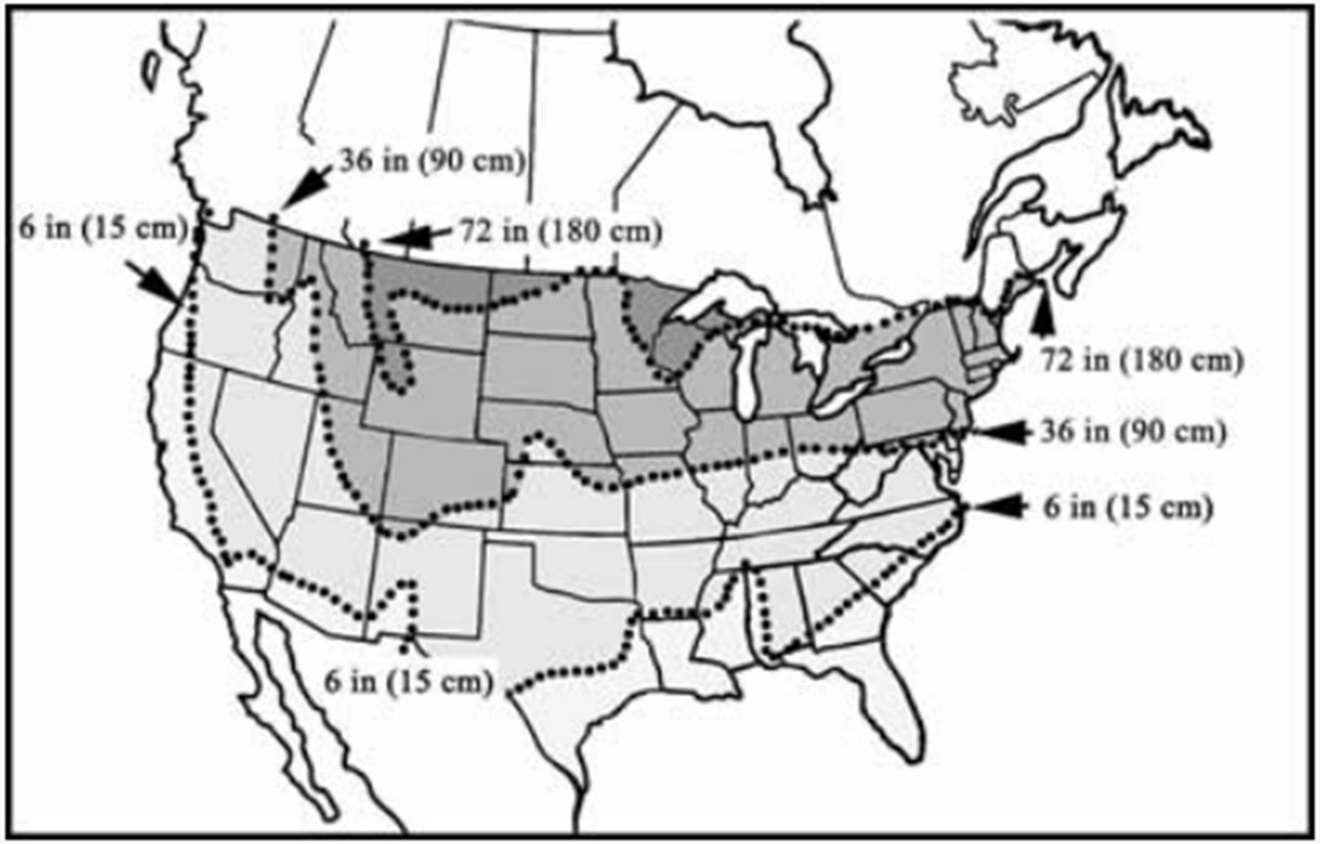
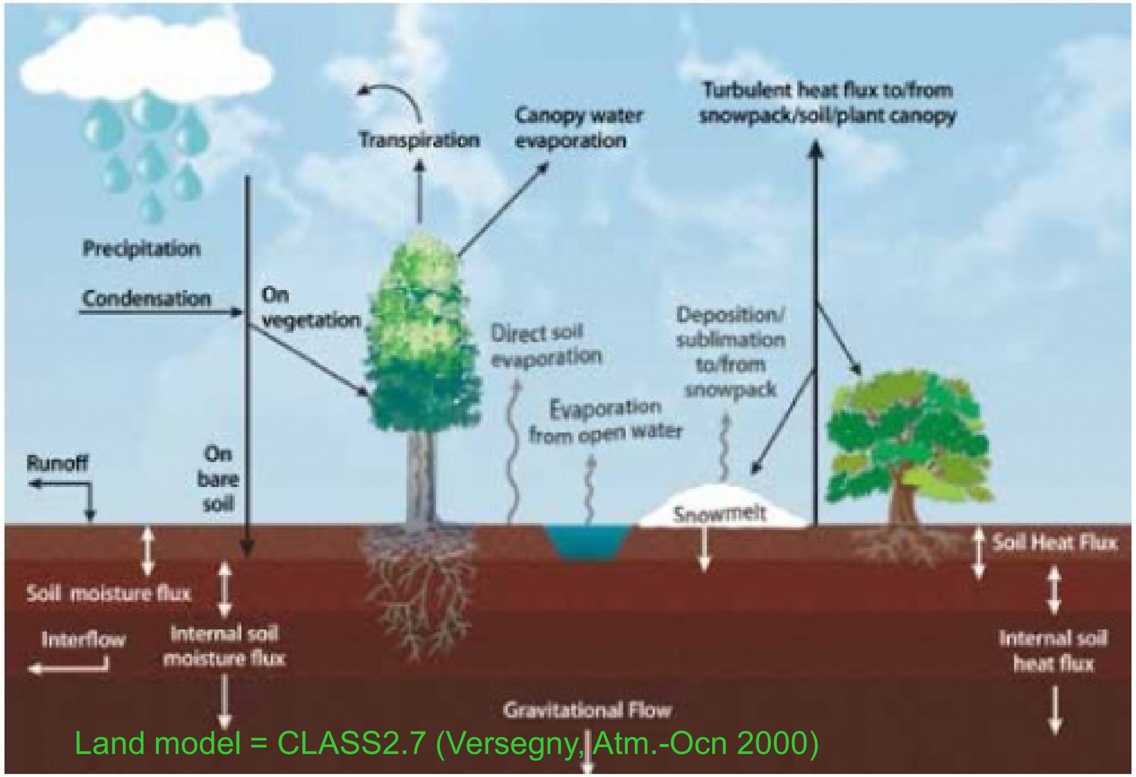


Figure 2. Most frozen ground in the United States is seasonally frozen ground. The shaded areas on the map, between the dotted lines, mark the average depth that the soil freezes to in the winter.

https://nsidc.org/cryosphere/frozenground/whereis_fg.html

CLASS soil layers: 10 cm   25 cm   3-4 m

CanSIPS Land initialization



www.eoearth.org/view/article/152990

Direct atmospheric initialization through assimilation of gridded 6-hourly T, q, u, v using incremental analysis update

<u>Indirect</u> land initialization through response to model atmosphere

Is soil moisture initialized skillfully?

→ not observed well in hindcast period, but does appear to agree with available analyses and drought reports

DROUGHT THREATENS TURKISH AGRICULTURE

NewArticle Published: 09 February 2014, Sunday Updated: 09 February 2014, Sunday

As Turkish farmers around the country watch with dismay the dwindling water levels, Forestry Minister Eroğlu warns the periodic **drought Turkey** faces every 7 years could actually be happening now

SABAH 9 Feb 2014

MailOnline 21 Jan 2014

The largest freshwater lake in China which covers an expanse twice the size of London has dried up because of an ongoing drought.

Poyang Lake in rural Jiangxi province is one of the country's most popular tourist attractions.

But the combination of drought and a new water storage facility upstream at the Three Gorges reservoir - the world's biggest dam - has caused water levels to drop to dangerously low levels.

© HAP/Quirky China News/REX

Dry land: The pavilion and tower in the distance used to be based in the centre of China's largest lake which has dried up because of drought

The New York Times 1 Feb 2014

Severe Drought Has U.S. West Fearing Worst

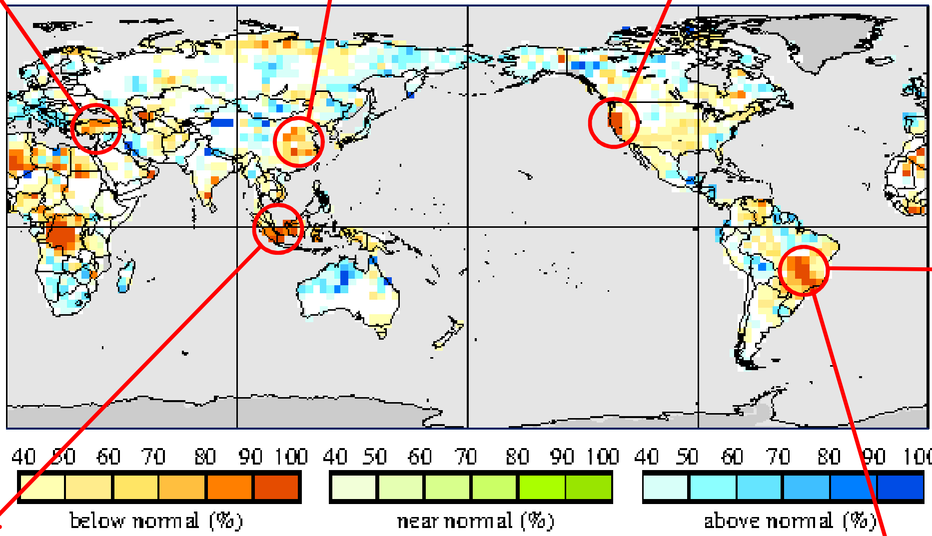
LOS ANGELES — The punishing drought that has swept California is now threatening the state's drinking water supply.

With no sign of rain, 17 rural communities providing water to 40,000 people are in danger of running out within 60 to 120 days. State officials said that the number was likely to rise in the months ahead after the State Water Project, the main municipal water distribution system, announced on Friday that it did not have enough water to supplement the dwindling supplies of local agencies that provide water to an additional 25 million people. It is first time the project has turned off its spigot in its 54-year history.

State officials said they were moving to put emergency plans in place. In the worst case, they said drinking water would have to be brought by

Max Whittaker for The New York Times

Probabilistic soil moisture forecast Feb 2014 lead 0



Evidence CanSIPS soil moisture initialization is somewhat realistic

Map of Brazilian coffee growing regions

Arabica Robusta

Source: Souza 2008, p. 226

Bloomberg NEWS

Drought Threatens S.E. Asia Food Price Gains Amid Haze 28 Feb 2014

By Jasmine Ng | Feb 28, 2014 3:52 AM PT | 2 Comments Email Print

The drought parching **Singapore** and swaths of **Malaysia** and Indonesia threatens to raise food prices, slow economic growth and disrupt water supply in the region, home to the world's oldest tropical rain forests.

Areas around **Kuala Lumpur**, Malaysia's capital, started water rationing this month. Neighboring Singapore, which had a record 27 days without rain from Jan. 13, is

Coffee to Soybeans Surge as Brazil Drought Damages Crops 25 Feb 2014

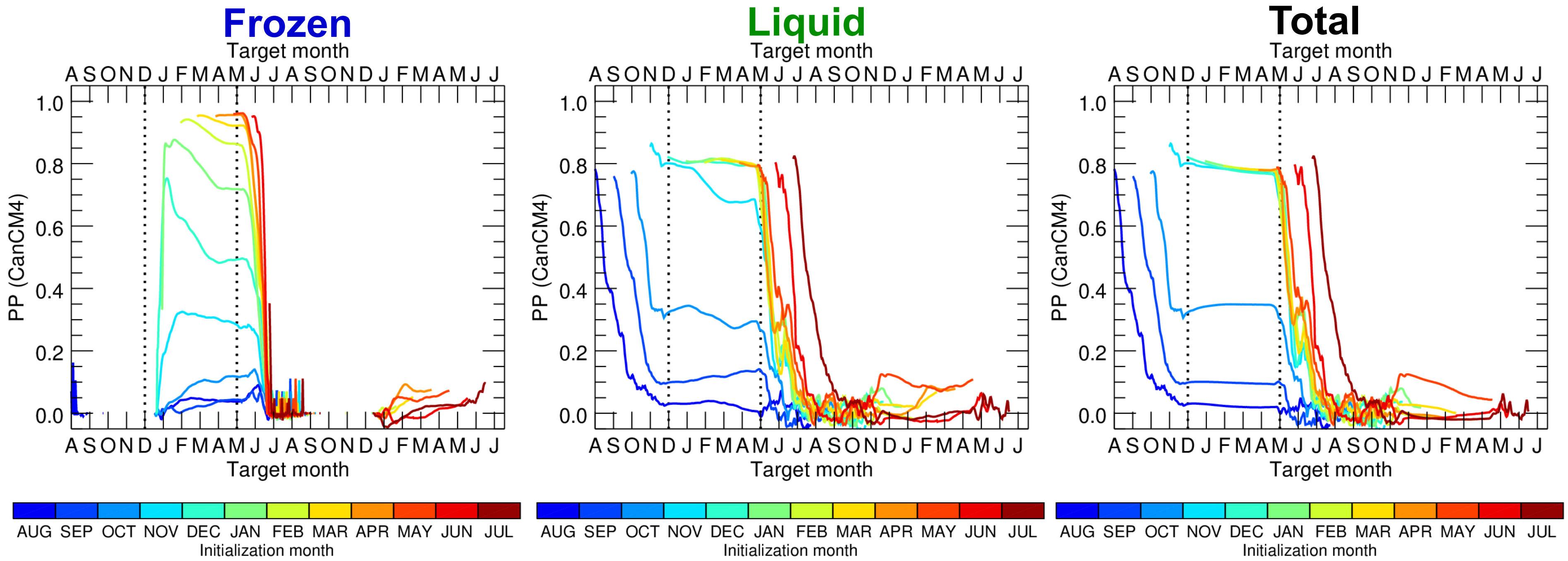
By Marvin G. Perez, Megan Durisin and Liyan Chen | Feb 18, 2014 7:13 PM PT | 0 Comments Email Print

Coffee jumped the most in a decade, soybeans reached the highest since December and sugar rallied as drought scorches fields in **Brazil**, the world's biggest exporter of the crops.

The Standard & Poor's GSCI Agriculture Index of eight commodities capped a seventh straight gain yesterday, the longest streak since 2011. Rain in growing regions will be 75 percent less than normal in the next five days, deepening a moisture deficit after the driest January since 1954, David Streit, an agricultural meteorologist at Commodity Weather Group, said in a phone interview from Bethesda,

Potential predictability of frozen soil moisture

Soil moisture PP for grid cell in Labrador, Canada



→ ***High frozen soil PP in cold season contributes to persistent cold-season PP***

after Sospedra-Alfonso and Merryfield, J. Climate 2018

Summary

- Application of coupled/earth system models to seasonal forecasting presents opportunities for useful predictions beyond standard atmospheric variables

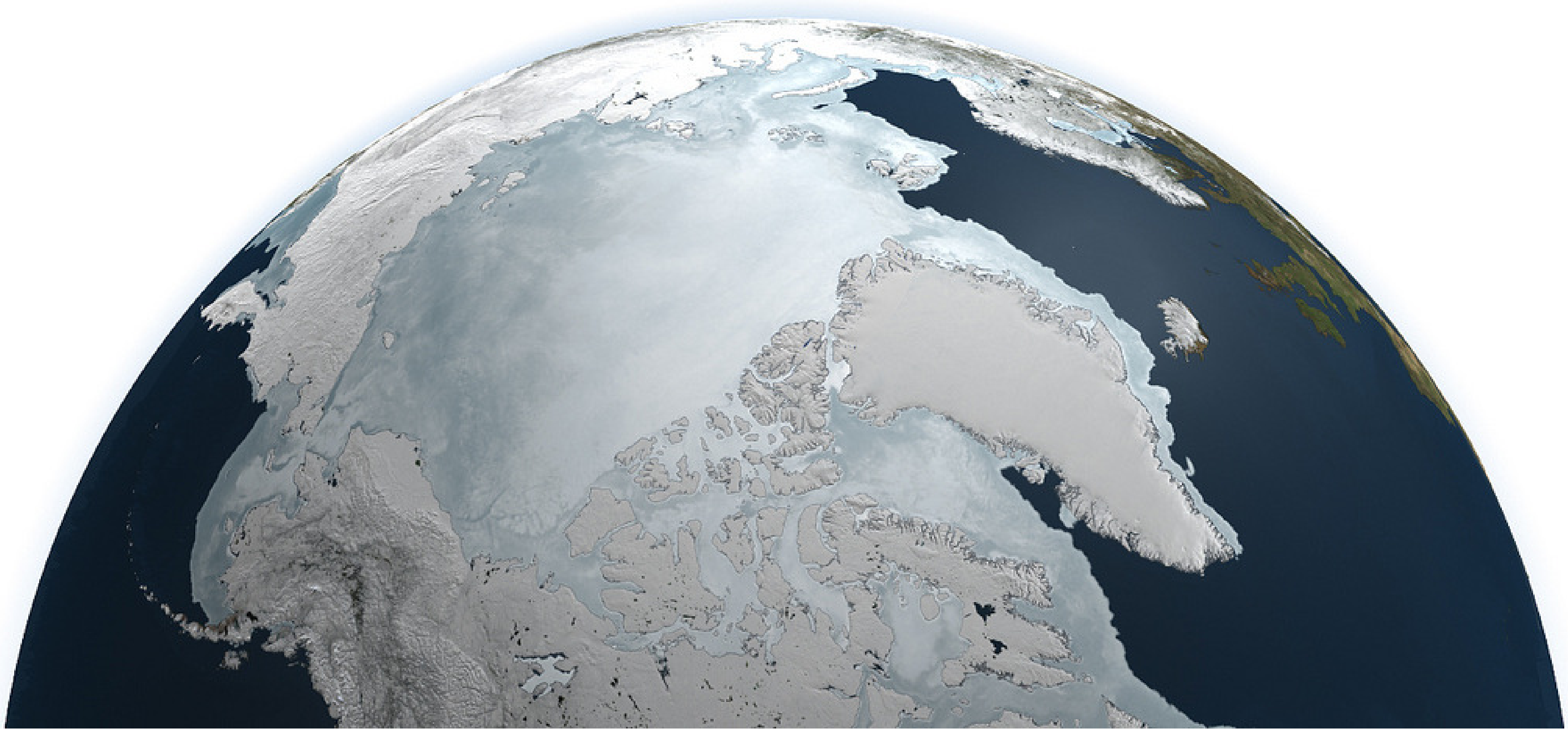
- This includes cryospheric variables including sea ice, snow water equivalent and possibly seasonally frozen ground

- Availability of accurate observations poses challenges for forecast initialization and verification

- Multi-product datasets may be tend to be more accurate than single products (similar advantage to multi-model ensemble forecasts)

Skill depends on quality both of forecasts and verifying observations!

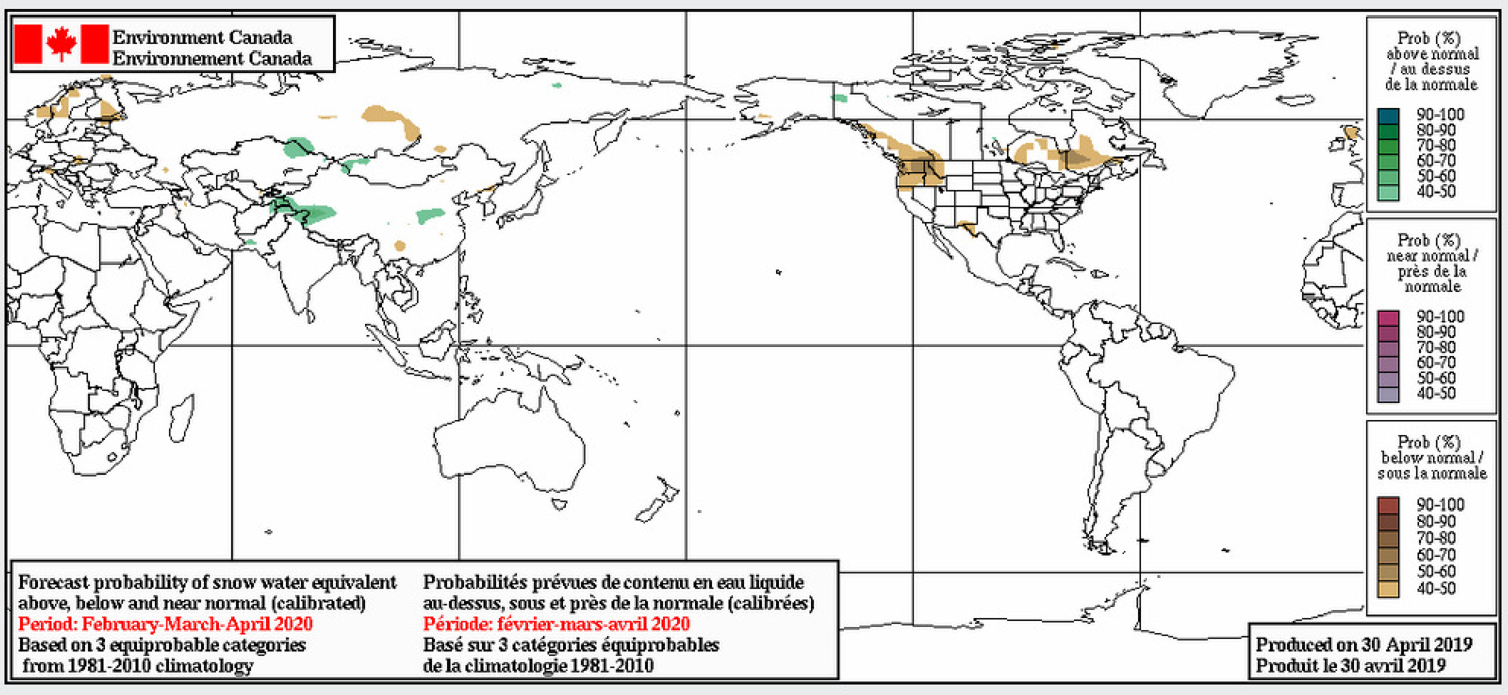
Спасибо!



Extra slides

Operational seasonal forecasts for SWE

Global seasonal forecasts



Current forecasts

Select variable:

Snow water equivalent

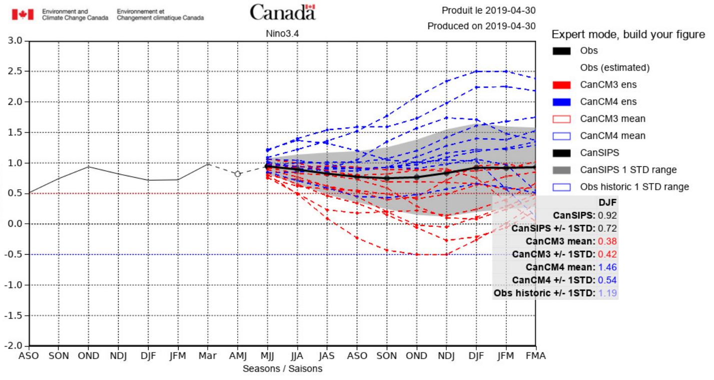
Select period:

Feb-Mar-Apr ==> 10-12 month

Output options

- ◉ Forecast map
- ○ Skill map
- ○ Reliability

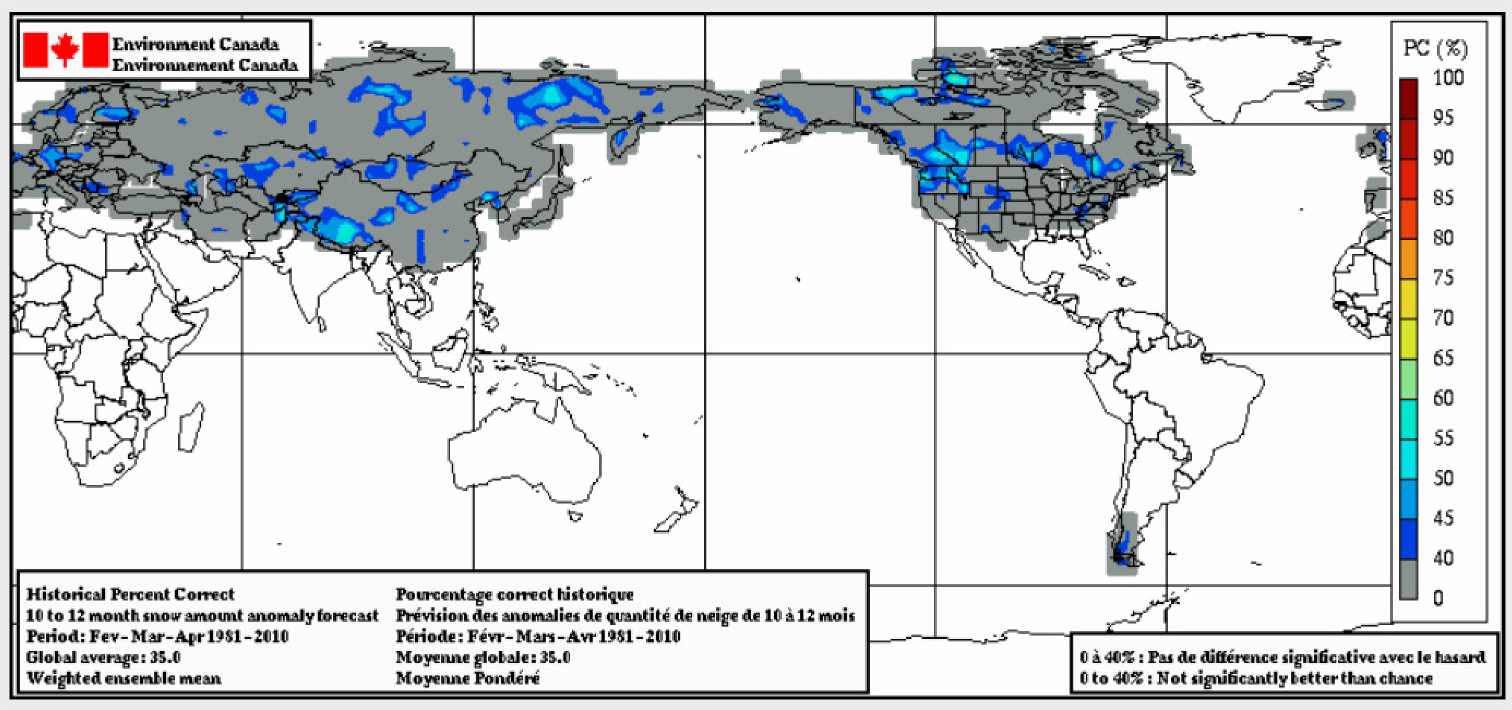
Nino3.4 forecast →



http://climate-scenarios.canada.ca/?page=cansips-global

Operational seasonal forecasts for SWE

Global seasonal forecasts



Current forecasts

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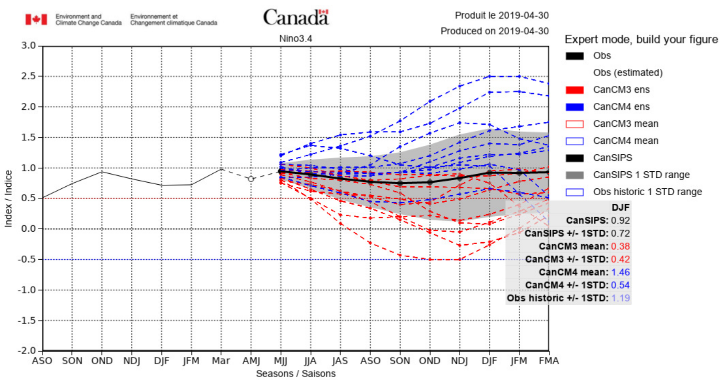
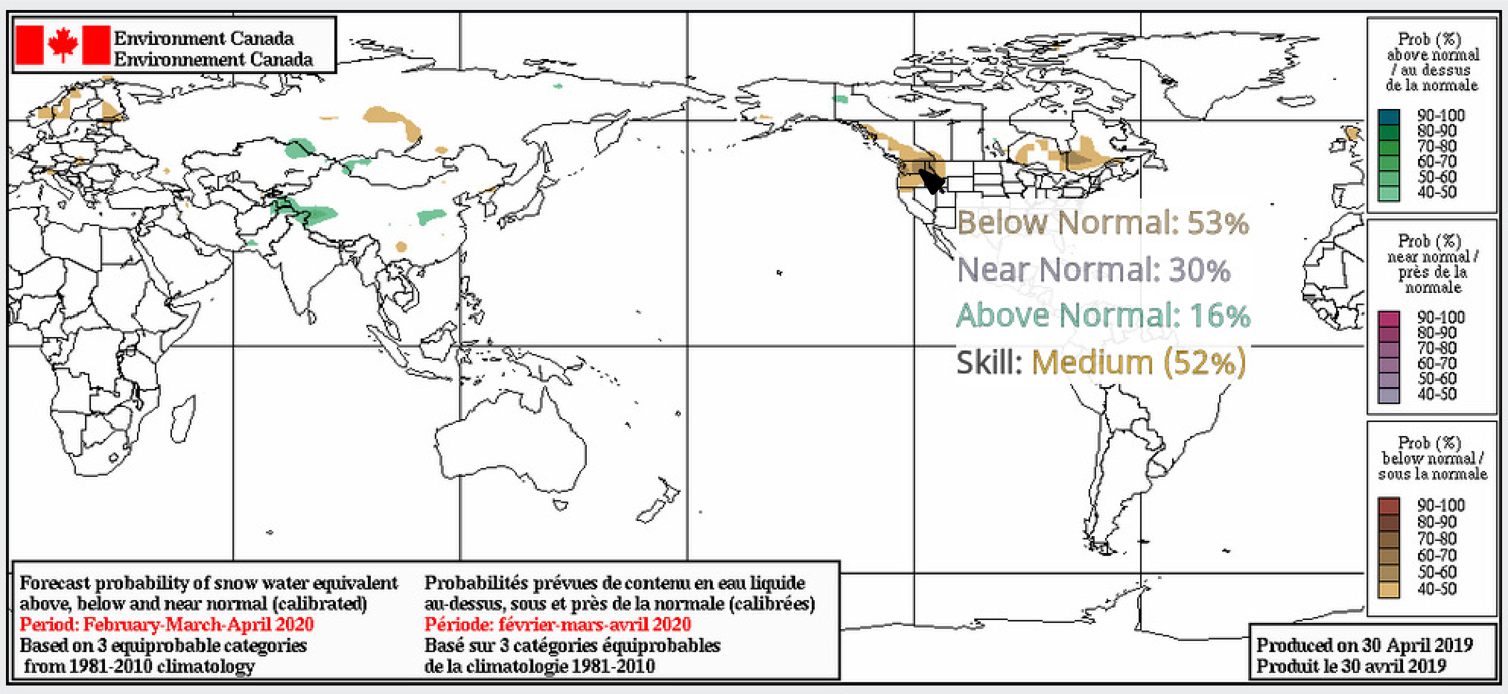
Nino3.4 forecast →



http://climate-scenarios.canada.ca/?page=cansips-global

Operational seasonal forecasts for SWE

Global seasonal forecasts



Current forecasts

Select variable:

Snow water equivalent

Select period:

Feb-Mar-Apr ==> 10-12 month

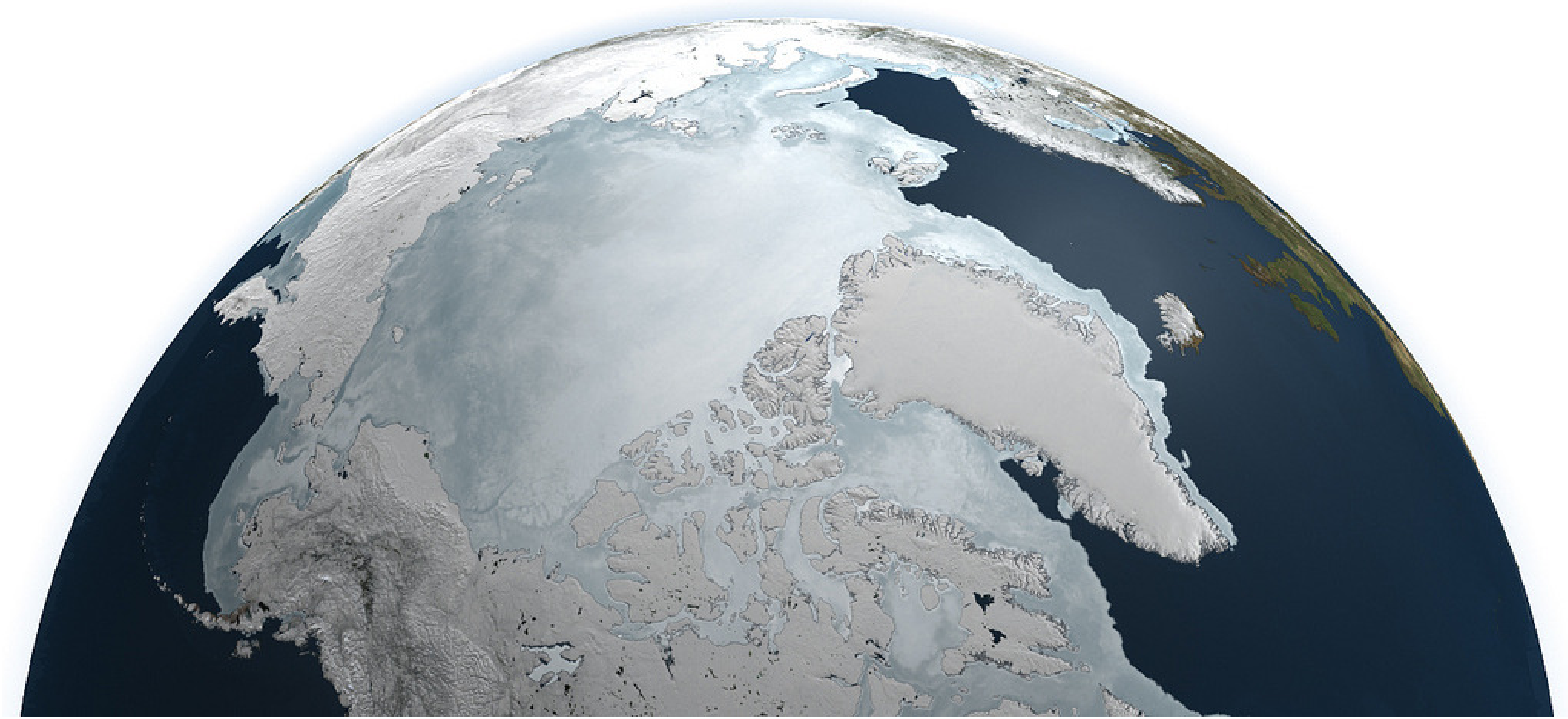
Output options

- (•) Forecast map
- ( ) Skill map
- ( ) Reliability

http://climate-scenarios.canada.ca/?page=cansips-global

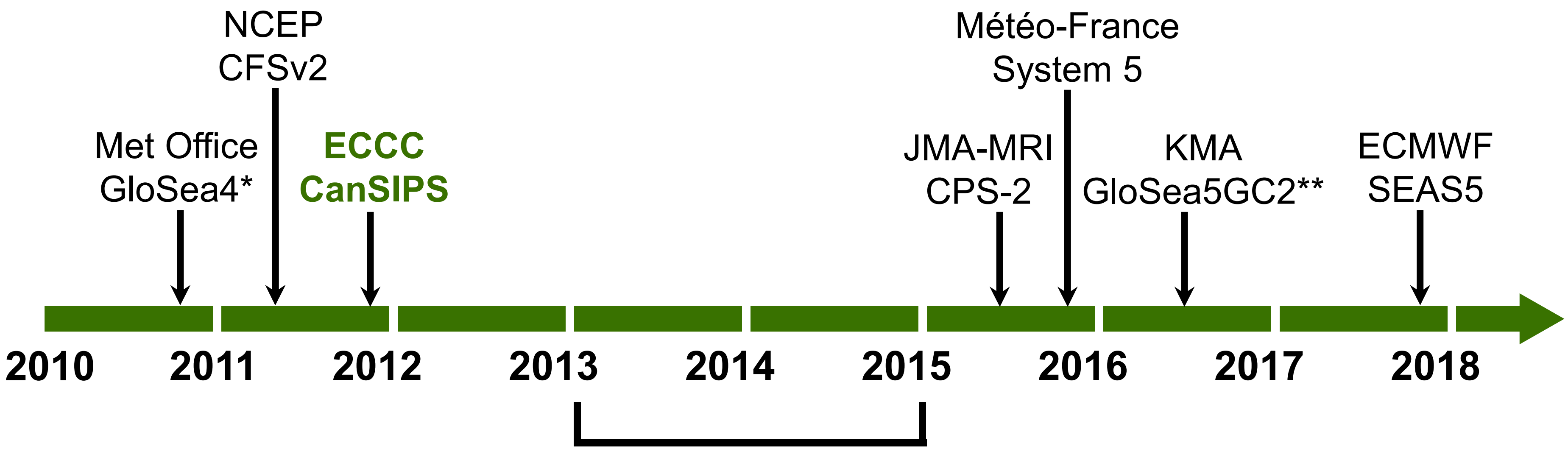
Seasonal forecasting challenges specific to sea ice

1) **Initialization**, especially of ice thickness
2) **Consistency** of initialization between hindcasts & real-time forecasts
3) **Bias correction** for concentration variable defined on [0,1]
4) **Fitting and calibration** of distribution defined on [0,1]



Timeline for seasonal sea ice forecasting

Scientific literature



Forecasts of pan-Arctic sea ice extent/area

(deterministic forecasts of anomalies)

Wang et al. (2013) CFSv2
Sigmond et al. (2013) CanSIPS
Merryfield et al. (2013) CanSIPS + CFSv2
Chevallier et al. (2013) pre-MF System 5
Peterson et al. (2014) GloSea4