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Understanding the climate prediction system

- Overview of global climate model
- Dynamical seasonal prediction in APCC

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Part 1:
What is the climate prediction system?!

Climate prediction system

1. Statistical method
- Use observed relationship of climate system to predict future
- Linear

2. Dynamical method
- Based on "***numerical method***" of climate system
- Nonlinear

Dynamical forecast!

How predict the future status??

Numerical weather prediction (NWP)

- Prediction of atmospheric conditions based on quantitative calculation of variations in line with the laws of physics

Dynamical forecast!

What is the Numerical weather prediction (NWP)

To forecast weather status in advance with computer model that solves the atmospheric flow numerically

The motions of the atmosphere are governed by physical laws expressed as the equations of hydrodynamics and thermodynamics. These equations determine the time rate of changes of meteorological variables, such as wind, pressure, temperature, and water vapor and liquid water contents, which are basic elements of the weather. Future evolution of the weather is predicted by integrating these equations numerically with respect to time, starting from an initial state of the atmosphere on high-speed electronic computers

Dynamical forecast!

What is the Numerical weather prediction (NWP)

Car

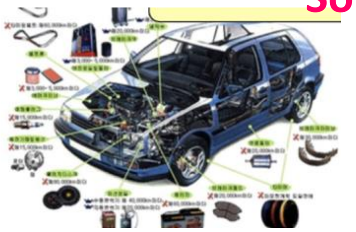
Dynamical prediction system

#1 Dynamics

Engine

#2 Physics

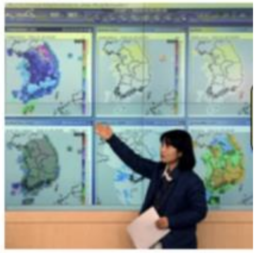
Software



#3 Initialization

Gasoline

Driver



Forecaster

High quality prediction

- Initial condition (#3) should be accurate
- Model (#1, 2) should represent the atmosphere realistically
- Well understanding and analyzing the model results are needed

Dynamical forecast!

#1 Model dynamics

Solve the governing equations in a grid system

V. Bjerknes (1904) pointed out for the first time that there is a complete set of 7 equations with 7 unknowns that governs the evolution of the atmosphere:

Newton's second law or conservation of momentum

(3 equations for the 3 velocity components);

$$\frac{D\mathbf{U}}{Dt} = -2\boldsymbol{\Omega} \times \mathbf{U} - \frac{1}{\rho}\boldsymbol{\nabla} p + \mathbf{g} + \mathbf{F}_r \qquad (1\text{-}3)$$

The continuity equation or conservation of mass;

$$\frac{1}{M}\frac{dM}{dt} = 0 \qquad \frac{\partial \rho}{\partial t} = -\nabla.(\rho \mathbf{v}) \qquad (4)$$

Dynamical forecast!

#1 Model dynamics

The equation of state for ideal gases

$$p\alpha = RT \qquad (5)$$

The first law of thermodynamics or conservation of energy

$$Q = C_v \frac{dT}{dt} + p\frac{d\alpha}{dt} \qquad \frac{ds}{dt} = C_p \frac{1}{\theta}\frac{d\theta}{dt} = \frac{Q}{T} \qquad (6)$$

Conservation equation for water mass

$$\frac{dq}{dt} = E - C \qquad \frac{\partial \rho q}{\partial t} = -\nabla.(\rho \mathbf{v} q) + \rho(E - C) \qquad (7)$$

7 equations, 7 unknown *(u, v, w, T, p, ρ and q)*

: Governing Equations- Written as computer program code (**NWP**)

Dynamical forecast!

#1 Model dynamics

Richardson

Proposed to divide the earth's surface into a grid, with each grid cell the base of a vertical column of the atmosphere in a three-dimensional grid of atmospheric boxes. ***Each grid box about 200 km. Each column was divided into five layers at heights of about 800, 600, 400 and 200hPa.*** *Computed only the initial tendency at a single point for pressure at the base of each layer, temperature at the stratosphere, water content at the lower four layers and the two components of horizontal wind.*

His calculation of change of pressure at the point considered was ***145hPa in 6hr, an obviously unrealistic value.***
His forecast failed as a result of short-period oscillations called gravity waves that created "noise" in the observed data set, there by ***causing error in the initial conditions*** *used in his forecast.*

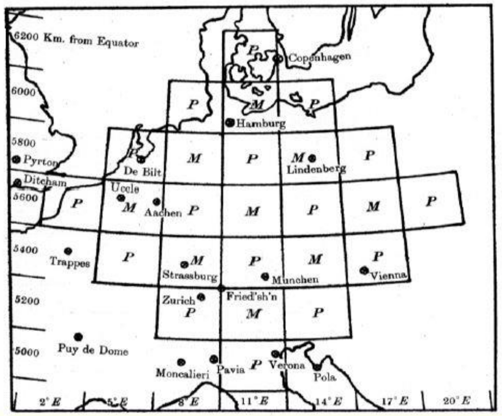
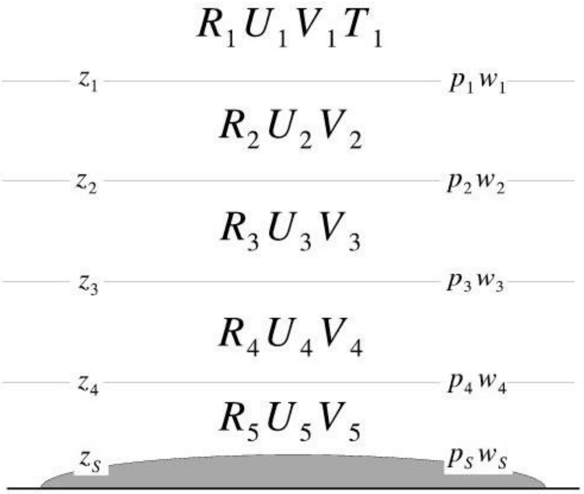


Figure 2. Grid used by Richardson in 1922 to calculate the pressure change in central Germany. X-axis shows the longitude and Y-axis shows the distance (in km) from the equator. Each grid box is 3° in the longitudinal direction and 200 km in the latitudinal direction. (Source: [9])

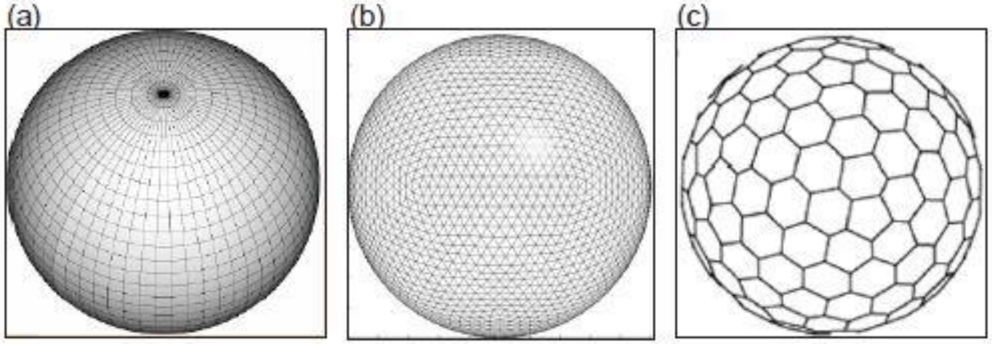


Dynamical forecast!

#1 Model dynamics

Richardson's effort *of predicting weather using grid points set the stage for future development of grids in different shapes.*
In order to accommodate the spherical shape of the earth and represent the equations more accurately and efficiently, there are different grid shapes used in numerical models.

1) *Suitability for cloud-scale to global-scale*
2) *Efficiency on different computer architectures and scalability on massively parallel computers*
3) *Conservation of mass and other quantities*
4) *Capability of local grid refinement and regional domains*



Eg., rectangular, triangular, and hexagonal…

Figure 4. Examples of (a) rectangular or latitude-longitude grid, (b) triangular grid and (c) hexagonal grid.

Dynamical forecast!

#1 Model dynamics

1) Rectangular/latitude-longitude grid

Most commonly used grid in the NWP models
*It is simple in nature but suffers from "**the polar problem**" where the lines of equal longitude, known as meridians, converge to points at the poles*
The poles are unique points and may cause violation of global conservation laws within the model. To maintain computational stability near the poles, small integration time-steps could be used, but at great expense.
To avoid the polar problem of the grid-point models, the application of quasi-uniform grids was proposed (e.g. NCEP GFS model)

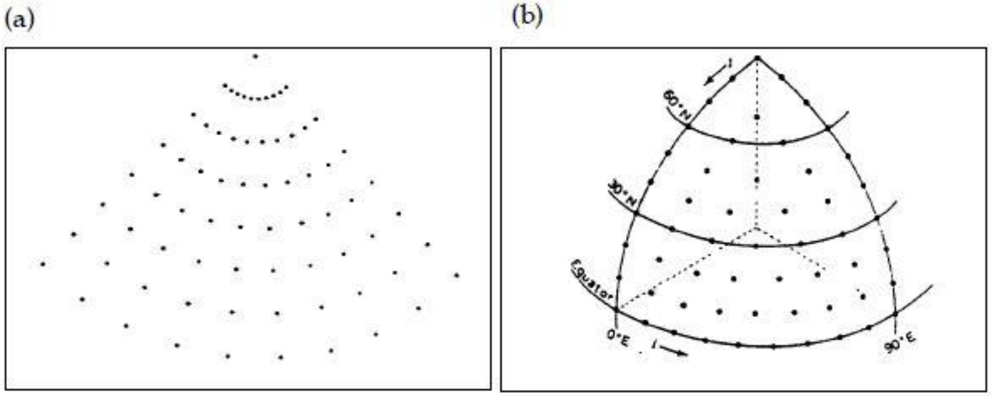


Figure 5. (a) Demonstration of the polar problem in which the meridians converge to a single point at the poles and (b) its remedy using the Kurihara grid.

Dynamical forecast!

#1 Model dynamics

2) Triangular grids/ Hexagonal grids

Not used as often in models as are these grids because it is high complex to solve the physics parameterization

*The main advantage of the unique grid is **that all the grid cells are nearly the same size**.*

*The uniform cell size allows for computational **stability and faster** calculation.*

➔ In this reason, some operational institutes try to use these grids system recently.

However, the method of distribution of grid points over the sphere is yet to be solved in a fully satisfactory manner

Dynamical forecast!

#1 Model dynamics

Vertical coordinates

Vertical structure is as important in defining the model's behavior as the horizontal configuration and model type.

Pressure coordinate

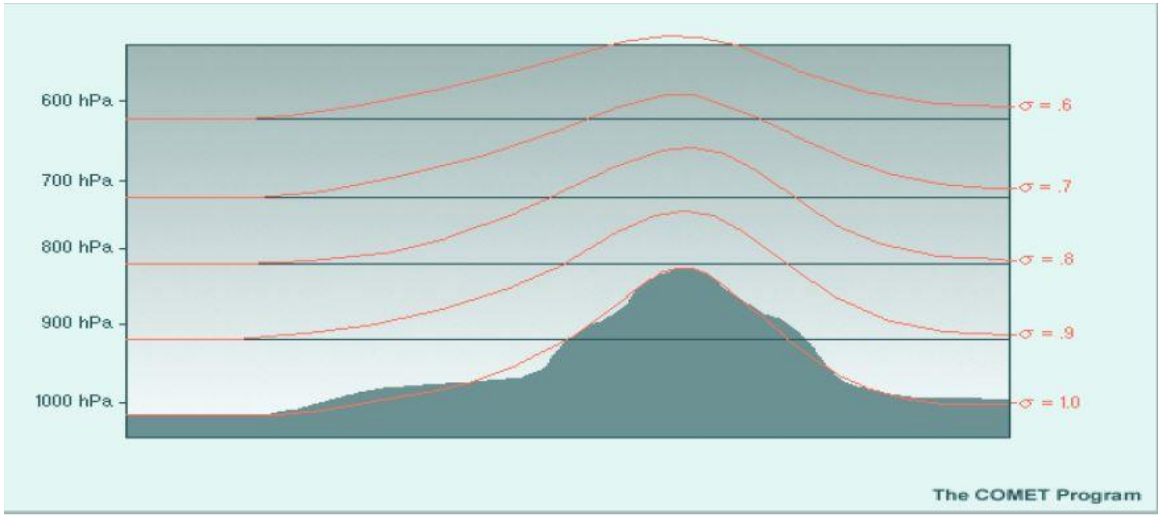
The equations of motion have their simplest form in pressure coordinates. Unfortunately, pressure coordinate systems are not particularly suited to solving the forecast equations because, like height surfaces, they can intersect mountains and consequently 'disappear' over parts of the forecast domain.
To address the problem of discontinuous forecast surfaces, Phillips (1957) developed a terrain-following coordinate called the sigma coordinate.

Dynamical forecast!

#1 Model dynamics

Sigma coordinate

Model wind forecasts depend upon accurate calculation of the pressure gradient force, which is very simple to calculate in pressure coordinates when the height is known. However, when sigma surfaces slope, the PGF must be expanded from its simple pressure coordinate form to include the effects of the slope. ***This error can become very large in areas with steep mountain slopes. This can cause substantial errors in wind forecasts and affect the entire depth of the model.***



Dynamical forecast!

#1 Model dynamics

Hybrid Sigma-Pressure coordinate

To reduce the error in sigma coordinate, Hybrid coordinate is developed.

In this system, the upper regions of the atmosphere are discretized by pressure only. Lower vertical levels use the sigma vertical coordinate smoothly merged in, with the lowest levels being pure sigma.

Recently, most commonly used this coordinate system in the NWP/Climate models

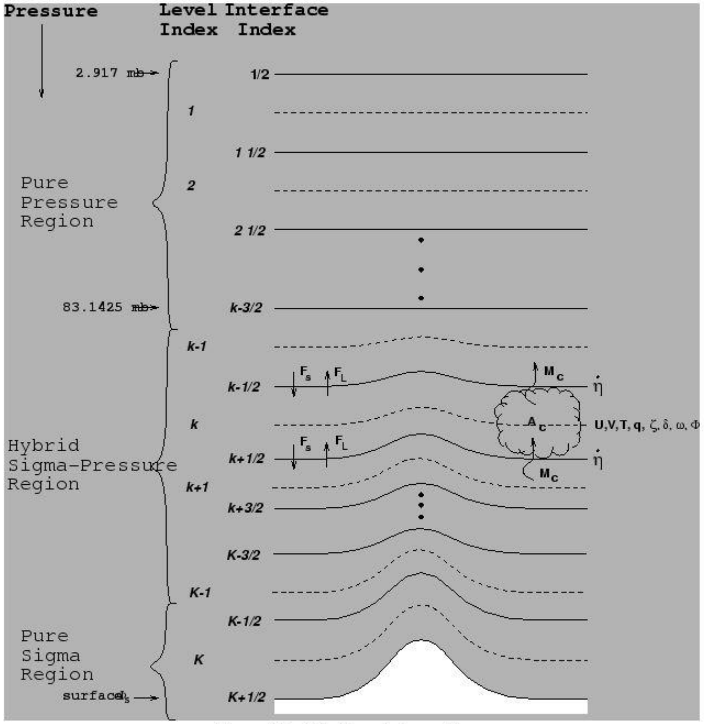


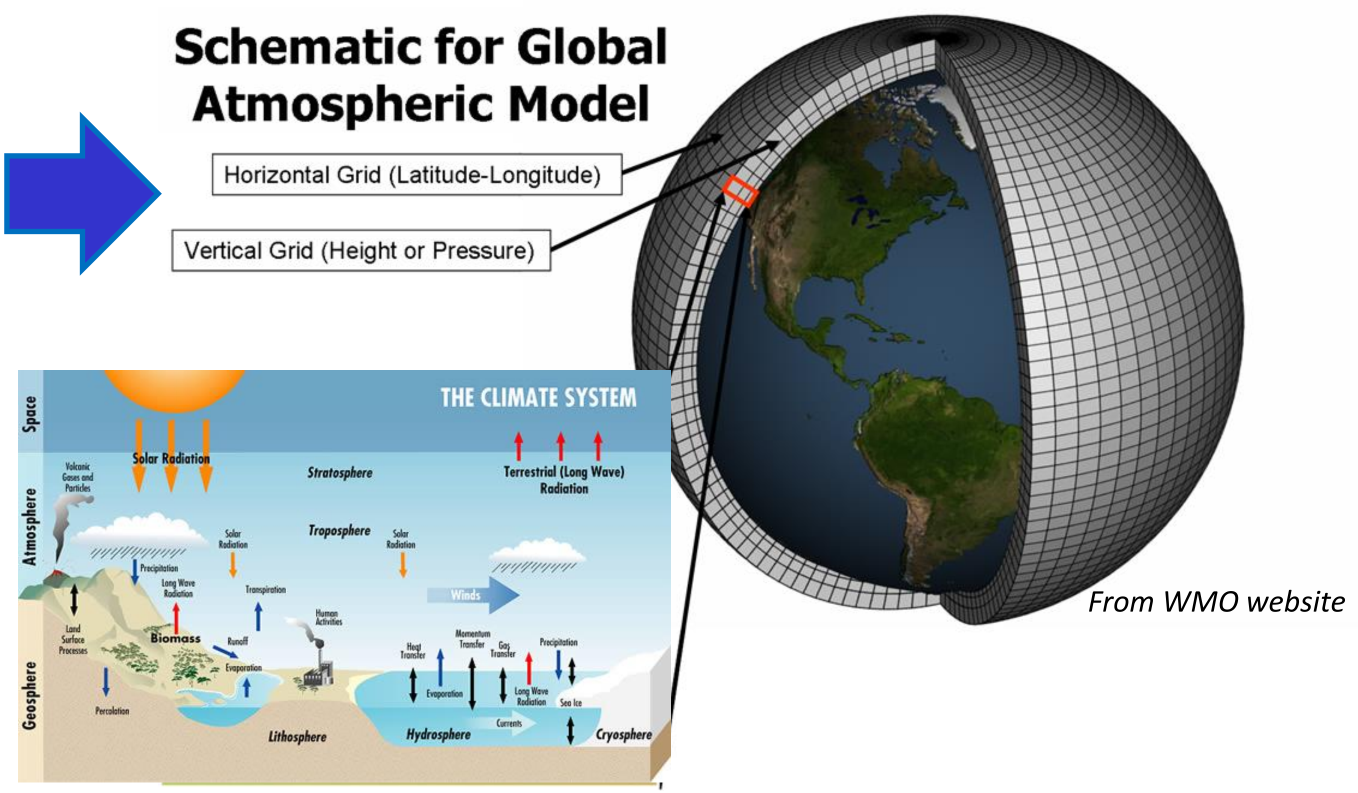
Figure 3.1: Hybrid vertical coordinate

Dynamical forecast!

#1 Model dynamics

Dynamics

u, v, w, T, p, ρ,q
(3D Coordinate)



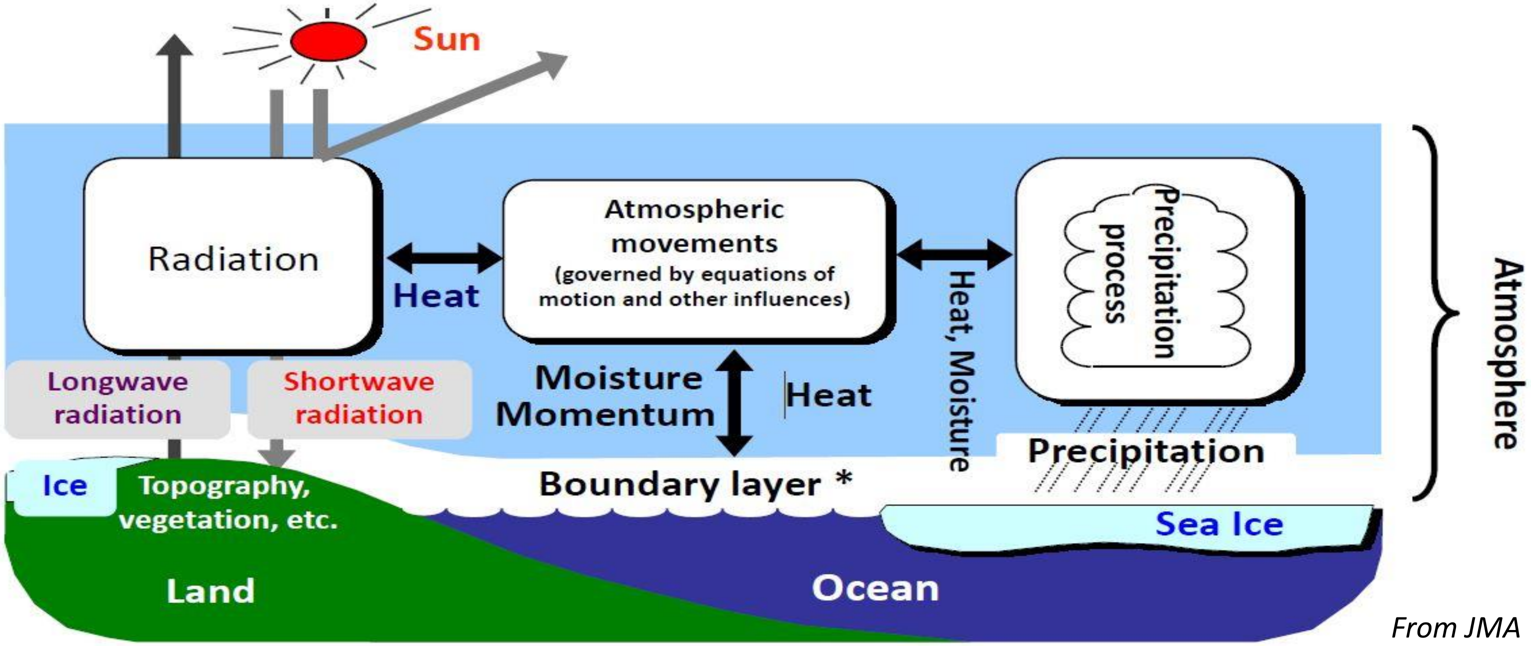
From WMO website

Physics

Representation of atmospheric phenomenon
(e.g. radiation processes, precipitation…)

Dynamical forecast!

#2 Model physics



From JMA website

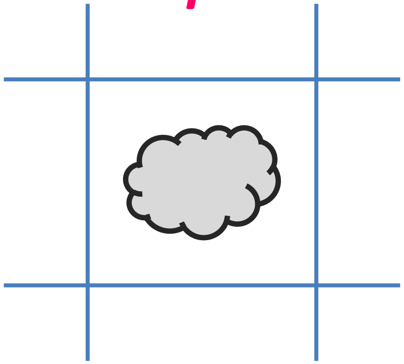
#2 Physics

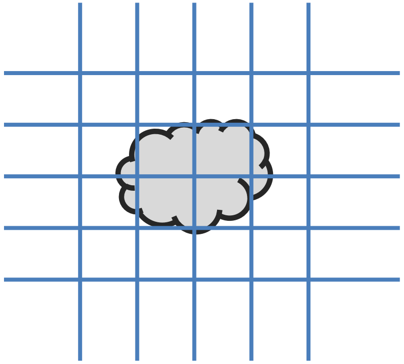
- **Component models**
  - **Land surface**
  - **Radiation**
  - **River routing**
- **Parameterization**
  - **Planetary boundary layer**
  - **Precipitation/Cloud**
  - **Cloudiness**
  - **Orographic drag**

Dynamical forecast!

#2 Model physics

Sub-grid scale parameterization ***(e.g. deep convection parameterization)***





Grid scale > real processes
: Unresolved, should be parameterized by functional relations

Grid scale < real processes
: Resolved directly by physical processes

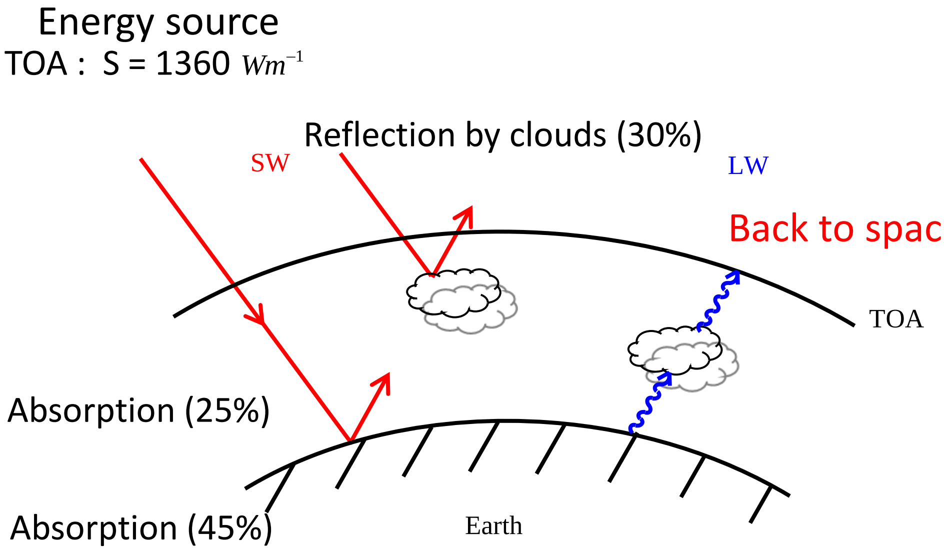
: Weather and climate model gridboxes have sides of between 5 km and 300km. A typical cumulus cloud has a scale of less than 1 km, and would require a grid even finer than this to be represented physically by the equations of fluid motion. Therefore, the processes that such clouds represent are parameterized, by processes of various sophistication.

* Parameterization : The formulation of physical process in terms of the model variables as parameters. (constants or functional relations)

Dynamical forecast!

#2 Model physics

Radiative transfer model



Energy source
TOA : S = 1360 Wm^{-1}

Reflection by clouds (30%)

Back to space by terrestrial infrared radiation

Absorption (25%)

Absorption (45%)

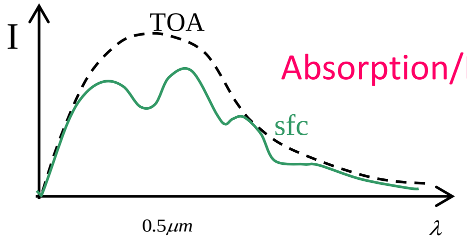
Earth is Tilted!
At low latitude : energy gain
At high latitude : energy loss
➔ To balance, Large-scale circulation with various climate variability !!

Dynamical forecast!

#2 Model physics

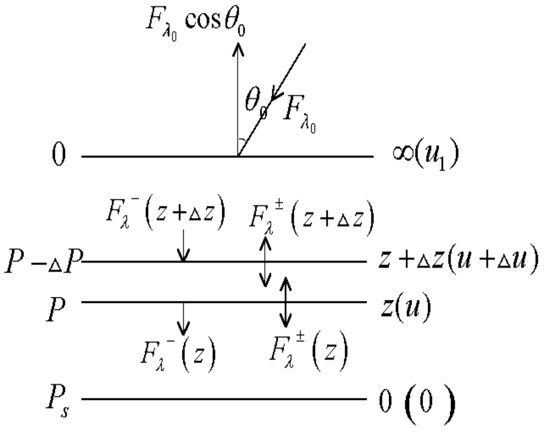
Radiative transfer model

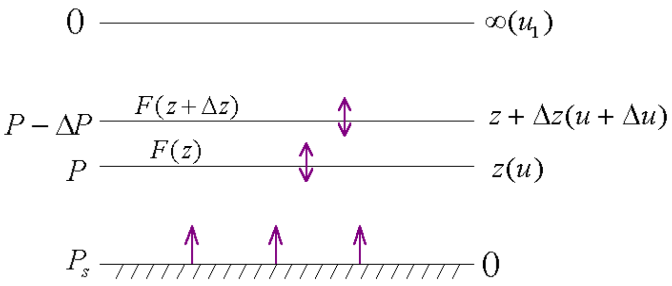
Solar radiative transfer



$$F = S\left(\frac{dm}{d}\right)^2 \cos\theta_0 \qquad (\theta_0 \text{ :Zenith angle})$$

(Insolation)





$$F(z) = F^{\uparrow}(z) - F^{\downarrow}(z)$$

$$\Delta F = F(z+\Delta z) - F(z)$$

$$\left.\frac{\partial T}{\partial t}\right|_{IR} = -\frac{1}{c_P \rho}\frac{\Delta F}{\Delta P} = -\frac{g}{c_P}\frac{\Delta F}{\Delta u}$$

Variation ratio of temperature

In shortwave radiation: absorption, emission, reflection of fluxes in all grid

In longwave radiation: variation ratio of temperature

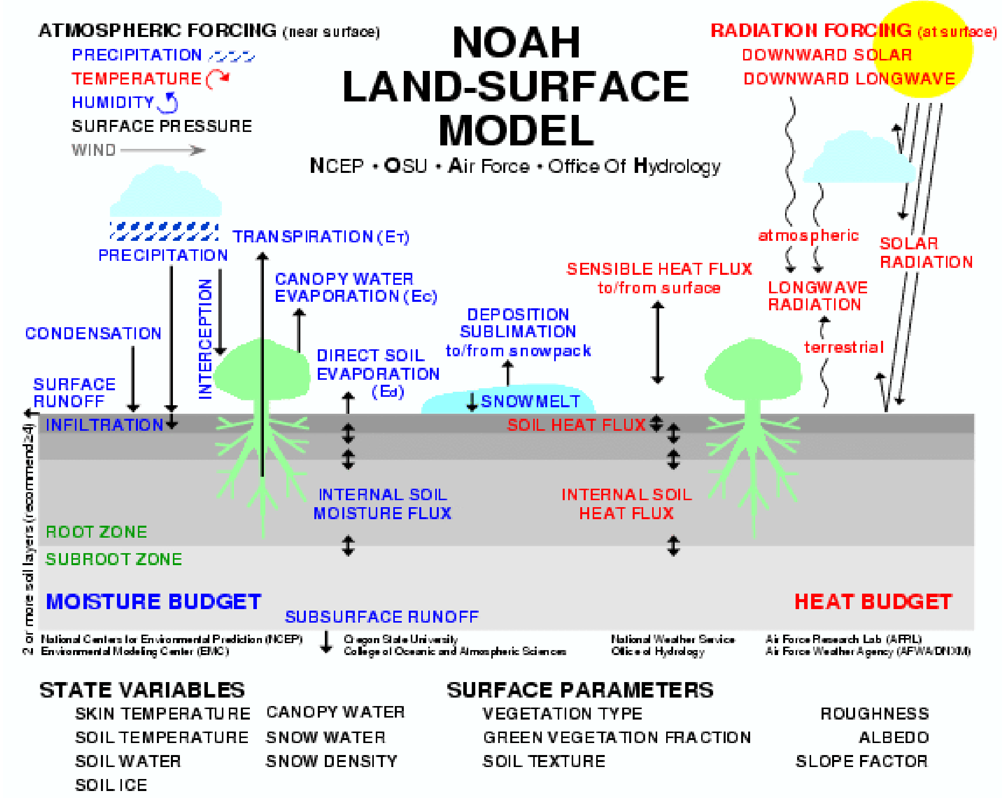
→ All processes is interacted hydrophysics processes

Dynamical forecast!

#2 Model physics

Land surface model

: compute surface fluxes and
update surface temperature and humidity
by solving soil model and surface energy
budget



Soil thermodynamics

$$C(\Theta)\frac{\partial T}{\partial t} = \frac{\partial}{\partial z}\left[K_T(\Theta)\frac{\partial T}{\partial z}\right]$$

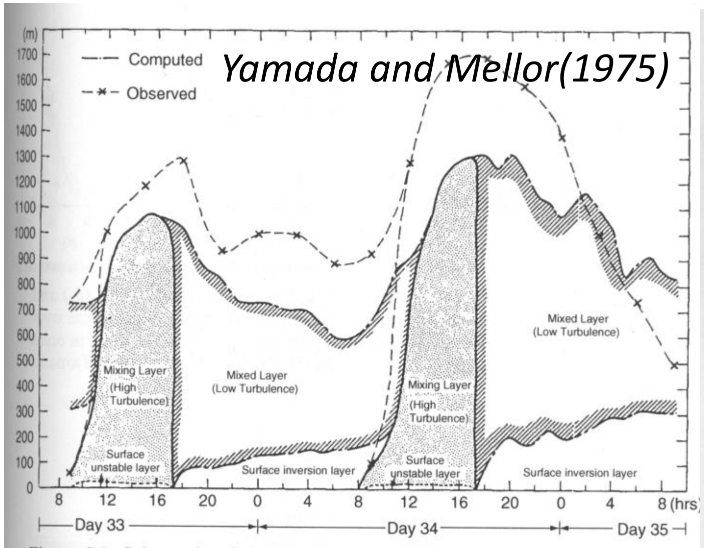
heat capacity with the ground heat flux as the surface boundary condition, and **prescribed deep soil temperature**

Dynamical forecast!

#2 Model physics

Vertical diffusion parameterization (Planetary boundary layer)

- computes the parameterized effects of vertical turbulent eddy diffusion of momentum water vapor and sensible heat



Yamada and Mellor(1975)

Figure 5.1. Schematic of the boundary layer evolution during days 33–35 from the Wangara experiment. During the daytime the mixing layer grows to depths above 1 km and is characterized by high levels of turbulence and a shallow and unstable surface layer. As the sun sets, the level of turbulence drops precipitously, leaving a residual layer behind. The surface inversion layer grows throughout the nighttime hours, influenced by episodic turbulence and radiational cooling. From Yamada and Mellor (1975).

Daytime flux profiles

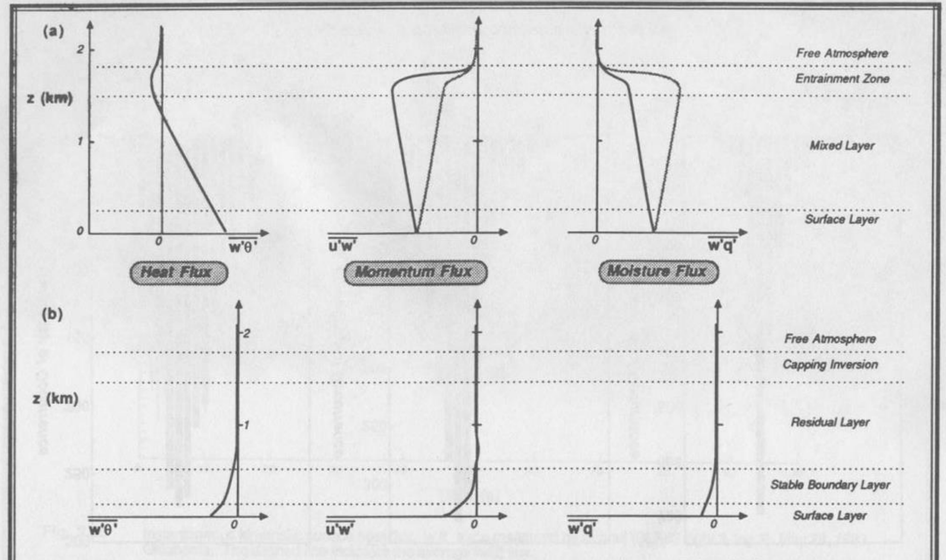


Fig. 2.15 Idealized vertical soundings of turbulent fluxes for the (a) convective mixed layer and (b) stable boundary layer.

Nighttime flux profiles

Stull (1988)

It is based on that **diurnal cycle of temperature**. Due to the difference of day and nighttime fluxes, it makes the stable and unstable layer. And wind speed is changed by mixing layer depth.

→ PBL mainly affect wind speed and temperature change

Dynamical forecast!

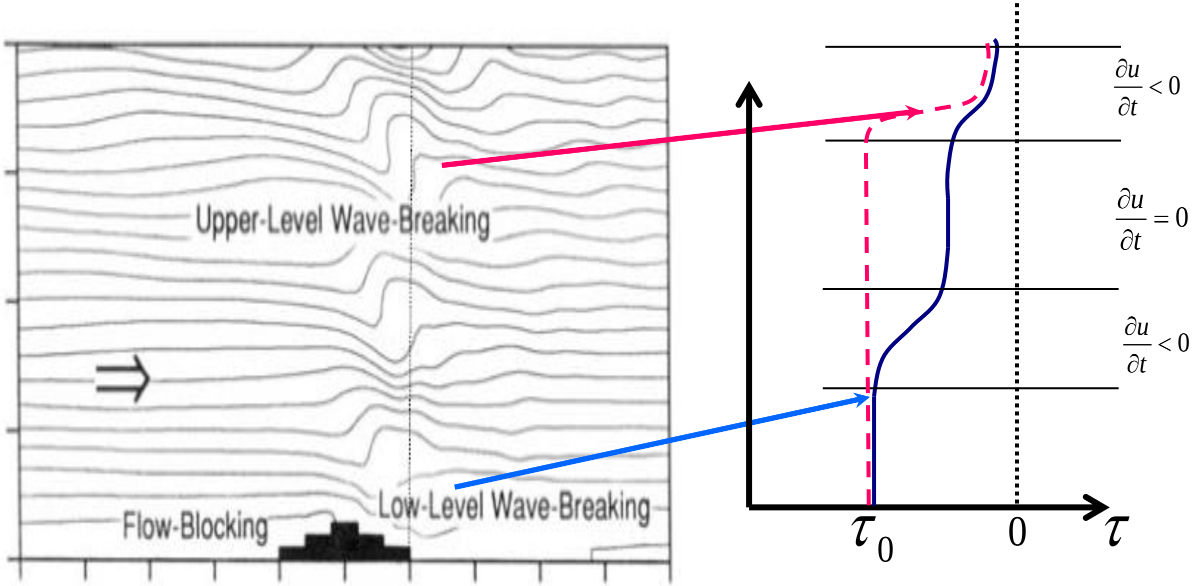
#2 Model physics

Gravity wave drag (GWD)

** GWDO : GWD induced by orography*

** GWDC : GWD induced by convection*

- This scheme includes the **effect of mountain** induced gravity wave drag from sub-grid scale orography including convective breaking, shear breaking and the presence of critical levels. Effects are strong in the presence of **strong vertical wind shear and thermally stable layer**.



$$\frac{\partial u}{\partial t} = -\frac{1}{\rho}\frac{\partial \tau_x}{\partial z}$$

$$\frac{\partial v}{\partial t} = -\frac{1}{\rho}\frac{\partial \tau_y}{\partial z}$$

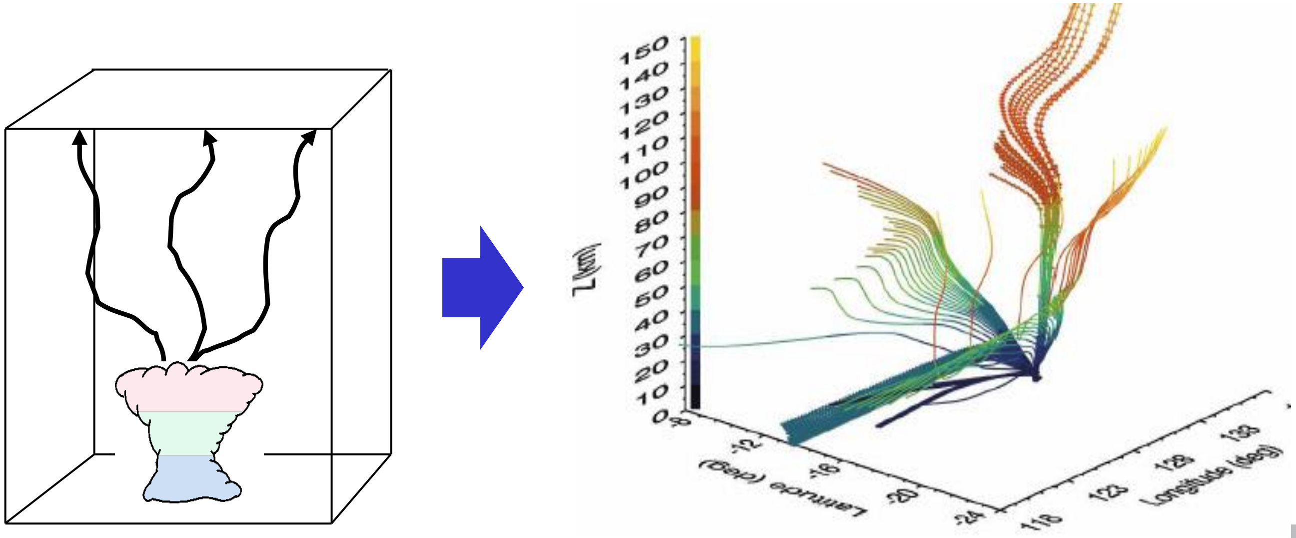
Dynamical forecast!

#2 Model physics

Gravity wave drag

Convective GWD parameterizations

- Chun and Baik (1998, 2002): The momentum flux spectrum for the ***convective GWD*** parameterization was first analytically formulated
- Chun et al. (2008): A nonlinear source effect was included in the CGWD parameterization of Song and Chun (2005) that had taken account of diabatic source alone
- Song and Chun (2008): GW propagation properties were explicitly calculated and a three-dimensional propagation of GWs was realistically represented



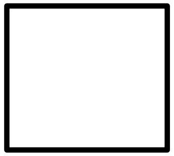
Dynamical forecast!

#2 Model physics

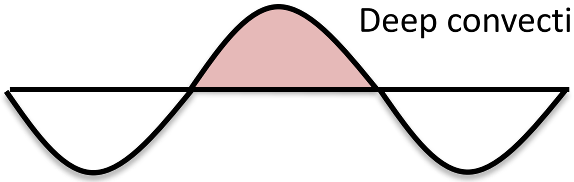
Precipitation processes

In real atmosphere, dynamical motion -> RH > 1 => clouds form -> produces rain

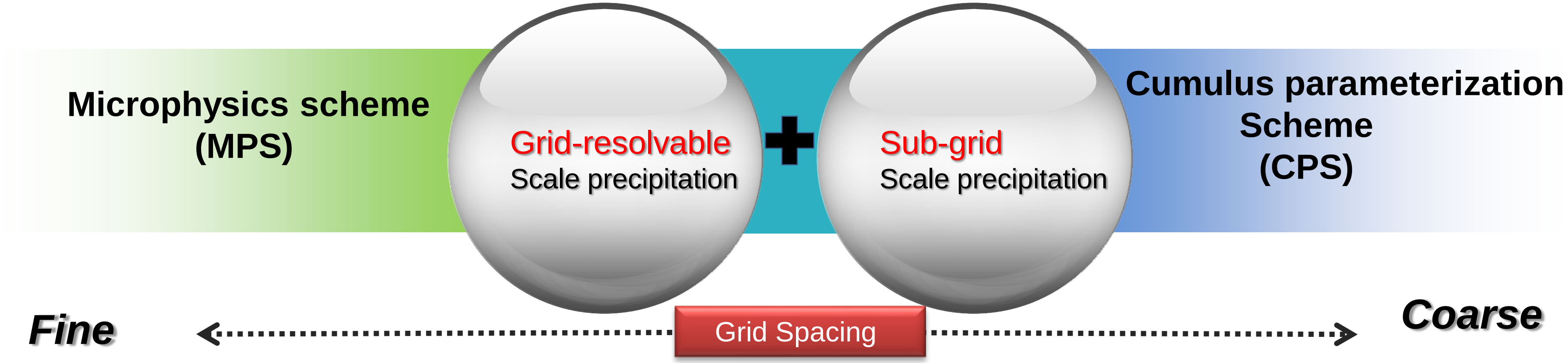
In modeled atmosphere, RH < 1



$\overline{RH} < 1$



Thus, we need the ***cumulus parameterization*** scheme to account for releasing conditional instability due to subgrid scale motion



Dynamical forecast!

#2 Model physics

Microphysics processes

Non-convective precipitation
large-scale precipitation
grid-resolvable scale precipitation
explicit moisture scheme
cloud scheme
microphysics scheme

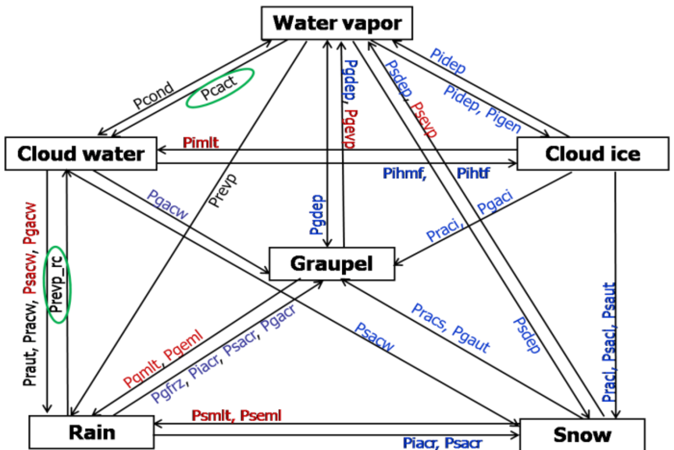
- Remove supersaturation after deep and shallow convection, and feedback to large-scale (accretion, collision, or coalescence)

Bulk microphysics :

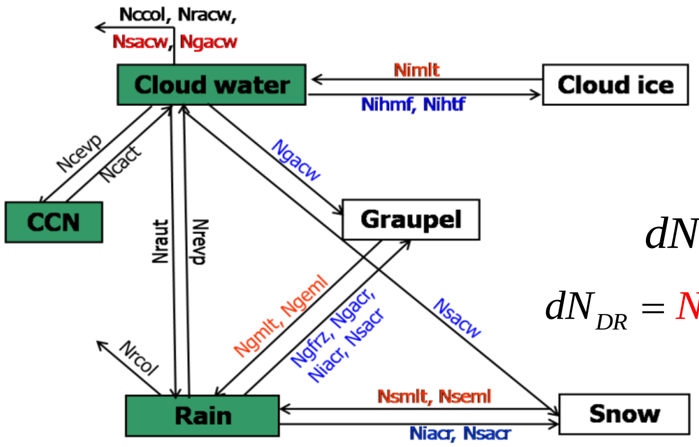
hydrometeors with size distribution in inverse-exponential function

- Single moment : predict mixing ratios of hydrometeors
- **Double moment** : + number concentrations
- Triple moment : + reflectivity

Mixing ratio (q)



Number concentration (N)



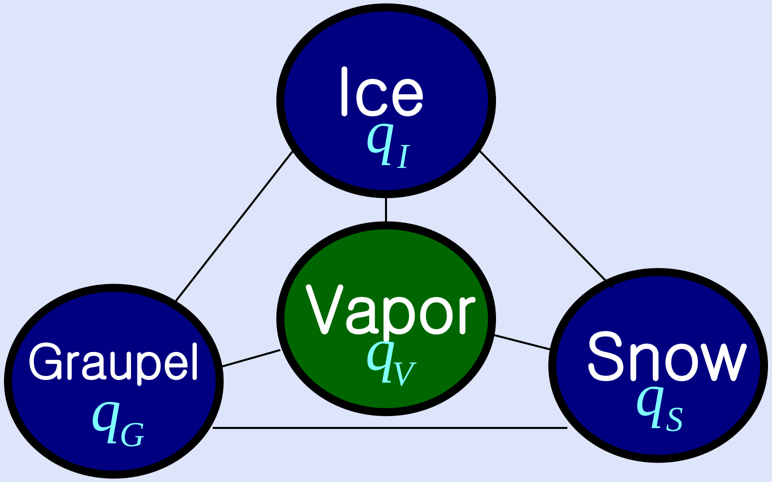
$$dN_{DR} = N_{0R} \exp(-\lambda_R D_R) dD_R$$

$$dN_{DR} = N_R \lambda_R^2 (N_R) D_R \exp(-\lambda_R D_R) dD_R$$

Dynamical forecast!

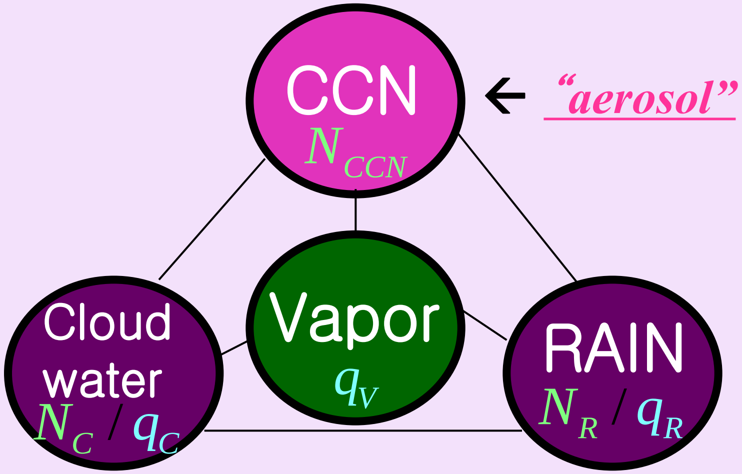
WSM versus WDM

Cold rain processes :
(Hong et al. 2004; Hong and Lim 2006)



q for 4 hydrometeors will be predicted (Single Moment)

Warm rain processes :
(Khairoutdinov and Kogan 2000; Cohardt and Pinty 2000)



N,q for 2 hydrometeors will be predicted (Double Moment)

N: Cloud water, Rain, CCN

q: Cloud water, Rain, Ice, Snow, Graupel, Vapor

WDM6

(Lim and Hong, 2010)

Dynamical forecast!

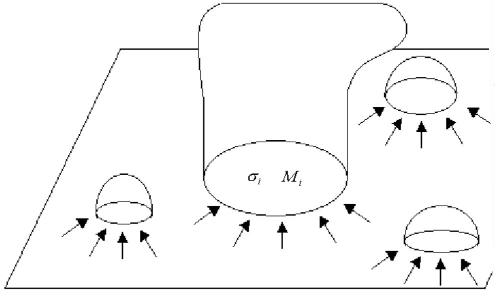
#2 Model physics

Convective precipitation parameterization

Parameterized convection
Cumulus convection
Subgrid scale precipitation
Implicit precipitation

- represents deep precipitating convection and feedback to large-scale
- must formulate the collective effects of subgrid scale clouds in terms of the prognostic variable of grid scale

Convective scheme ➔ Hydrometer from Microphysics processes ➔ Final precipitation!



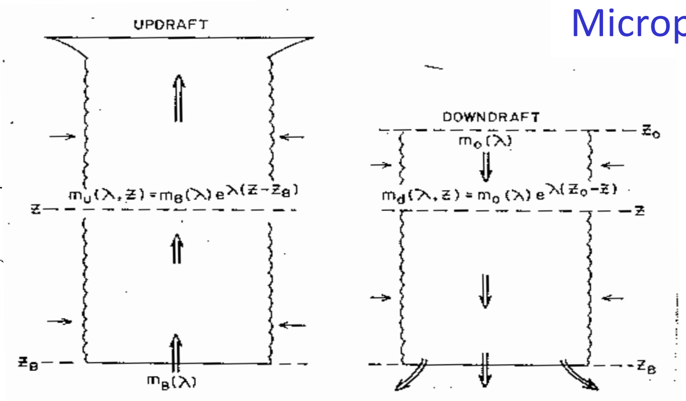


FIG. 4.10. Model for updraft and downdraft of cloud type λ (from Johnson 1976).

- ●Entrainment : $\frac{\partial M_i}{\partial z} + \rho \frac{\partial \sigma_i}{\partial t} > 0, \quad S_{ib} = S$
- ●Detrainment : $\frac{\partial M_i}{\partial z} + \rho \frac{\partial \sigma_i}{\partial t} < 0, \quad S_{ib} = S_i$

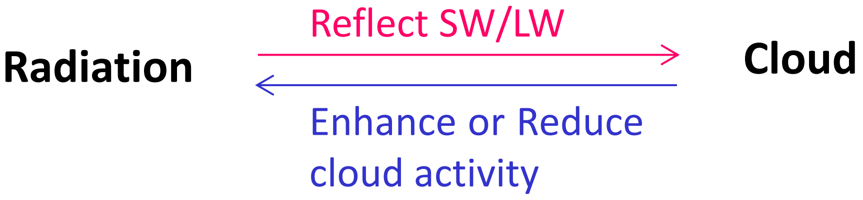
- CPS computes the warming (cooling) rate in the grid box due to adiabatic descent (ascent) with entrainment or detrainment of hydrometer.

Dynamical forecast!

#2 Model physics

Cloudiness
Cloud fraction
Radiative cloud
Cloud-radiation interaction

Cloudiness parameterization



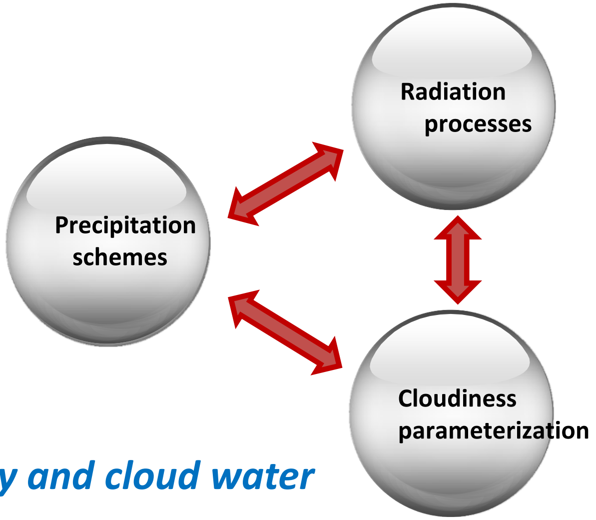
Radiation

Reflect SW/LW

Cloud

Enhance or Reduce cloud activity

: Need to the **cloud fraction** in radiation processes



Radiation processes

Precipitation schemes

Cloudiness parameterization

Diagnostic methods

Cloudiness is ***function of relative humidity, or of both relative humidity and cloud water***

- ***Widely used in weather prediction and climate models***

$$C_f = RH^{1/4}\left[1-\exp\left(\frac{-100q_t}{[(1-RH)\,q_s]^{0.49}}\right)\right]$$

Ice-cloud radiation

Cloud properties: direct input to radiation code

→ effective radii of cloud droplet, ice particle, cloud water path

Dynamical forecast!

#2 Model physics

Resolution issue!

High resolution ➔ Increased grid resolved processes ➔ Improvement prediction skill

Computing power ➔ One of reason to need the Supercomputer!!

Dynamical forecast!

#2 Model physics

Resolution issue!

Cut-off horizontal grid length for parameterizations

- PBL : ~50 m (Mirocha, 2008 WRF workshop)
- GWDO : ~ 3 km (hydrostatic approximation)
- GWDC: ~ 3 km (go with CP)
- Cumulus parameterization : ~ 3 km (Shin and Hong 2009)

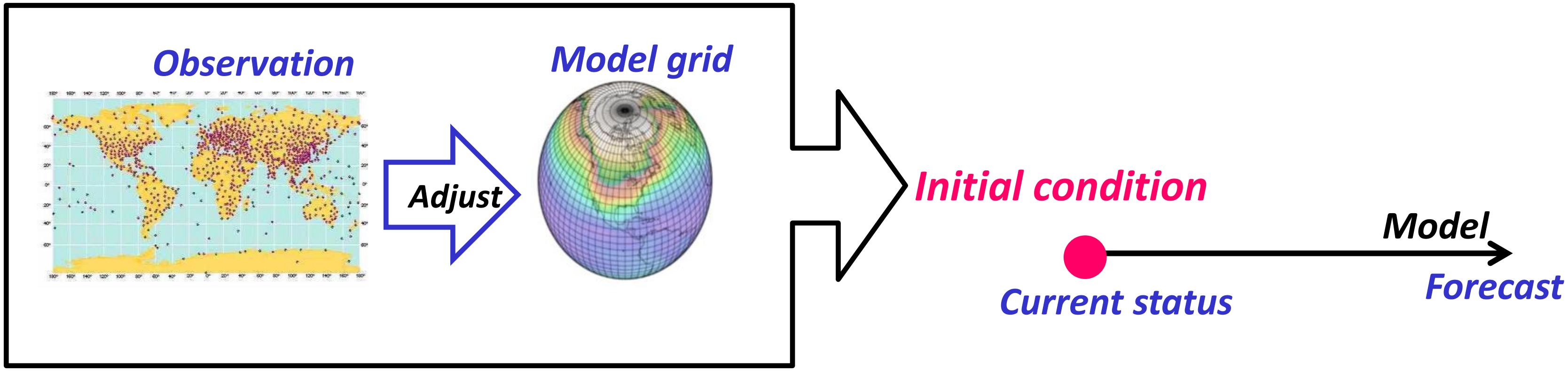
➔ ***Subgrid-scale parameterization for physics may be necessary even at 1 km or smaller since the finite model grid cannot resolve all the nature explicitly***

Dynamical forecast!

#3 Initialization

Estimating Current status of climate system

- Preparing the beginning initial state of GCM with available observation
  - Balance between Wrong GCM vs Wrong OBS.
  - Balance between components (Atm, Ocn, Land, Sea-ice…)



Observation

Adjust

Model grid

Initial condition

Model

Current status

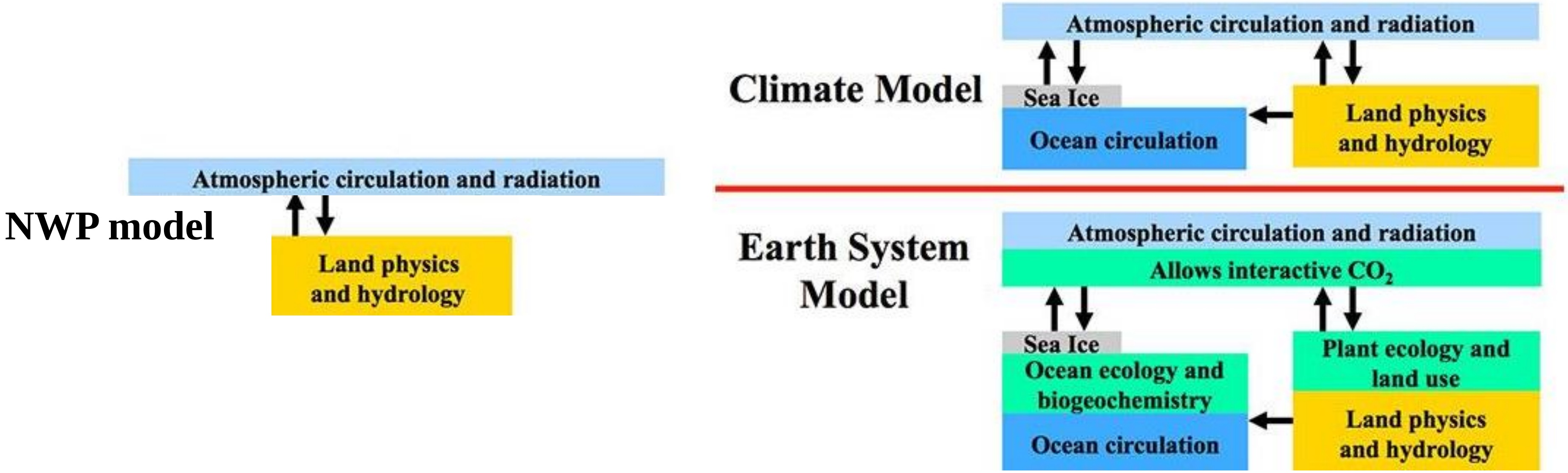
Forecast

How well MJO (ENSO) can be predicted relies on how well a model can be initialized especially in the atmosphere (upper ocean)

→ atmospheric (ocean) initialization is important!!

What is climate model?

- **Representing dynamics, physics processes of atmosphere, land, ocean, sea-ice and their coupled behaviour well**



- A coupled climate model is a computer code that estimates the solution to differential equations of fluid motion and thermodynamics to obtain time and space dependent values for temperature, winds and currents, moisture and/or salinity and pressure in the atmosphere and ocean.
- Components of a climate model simulate the atmosphere, the ocean, sea, ice, the land surface and the vegetation on land and the biogeochemistry of the ocean.

An Earth System Model (ESM) is a coupled climate model that also explicitly models the movement of carbon through the earth system.

Uncertainties and limitation

What limits forecast skill?

- Model Error

  - models physics are simpler than the real world

  - resolutions are coarse (~100-200 km), so small-scale processes can be easily missed

- Errors in the initial conditions

  e.g. measurement errors, gaps in the observing network, how observational data are used in models… etc

- Atmos/Ocean Chaos – small un-measurable errors keep growing in a chaotic way, making forecasts diverge from the reality

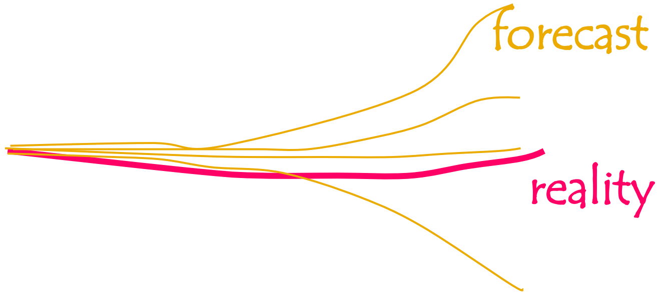
- Not all the interactions in the climate system are currently fully understood

  – there may be sources of predictability that have not been found so not been included in the model

Any Question?

How can improve the prediction skill?

Ensemble Forecasts



Make multiple forecasts by

Introducing small differences to the initial conditions within the range of possible observational errors – multi-member ensemble forecasts

Combining different models, some model errors can be canceled
- multi-model ensemble forecasts

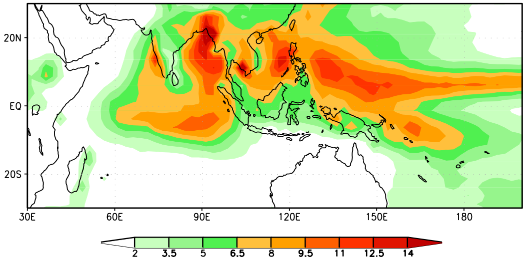
Ensemble forecasts can incorporate degree of uncertainty (chaos + errors) through probabilistic forecasts

How can improve the prediction skill?

System improvement

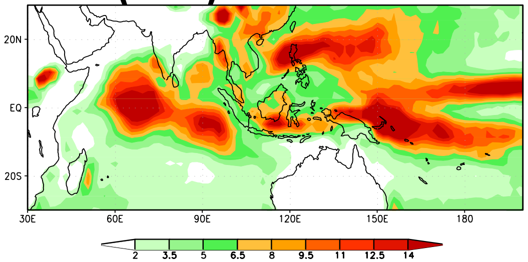
Air-sea interaction (ocean model coupling)

CMAP

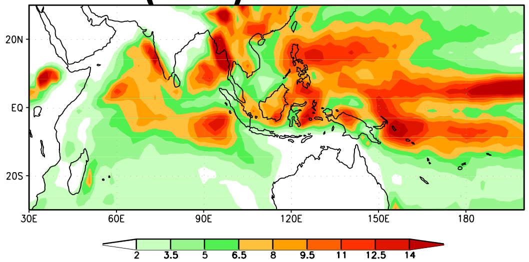


AGCM: Atmosphere-only model
CGCM: Atmosphere-Ocean coupled model

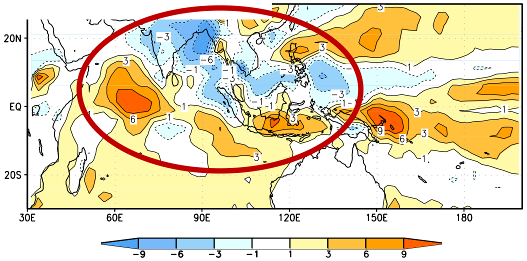
AGCM (0.78)



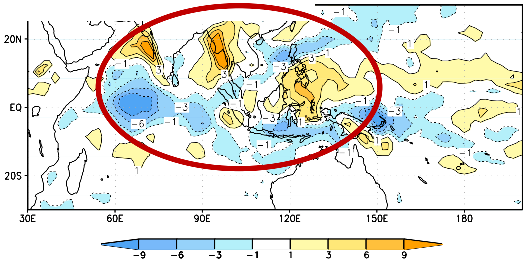
CGCM (0.83)



AGCM - CMAP



CGCM - AGCM



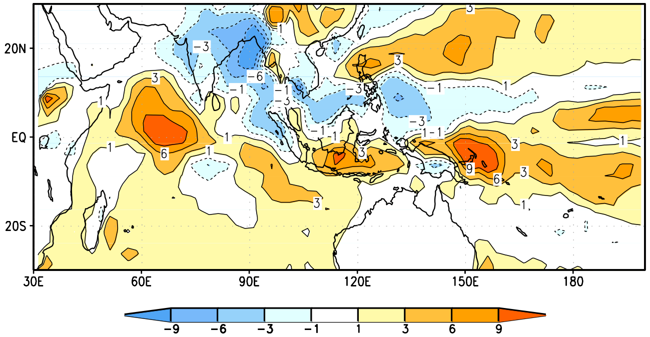
Ham et al. 2014

How can improve the prediction skill?

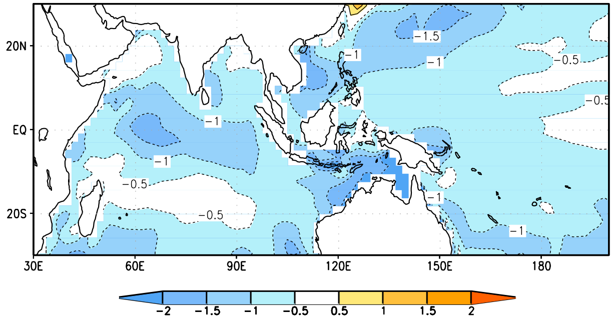
System improvement

Air-sea interaction (ocean model coupling)

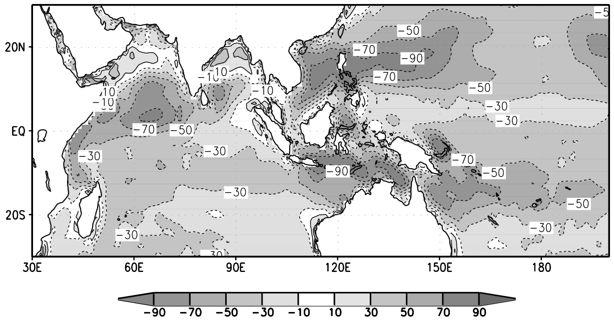
Precipitation (AGCM – OBS)



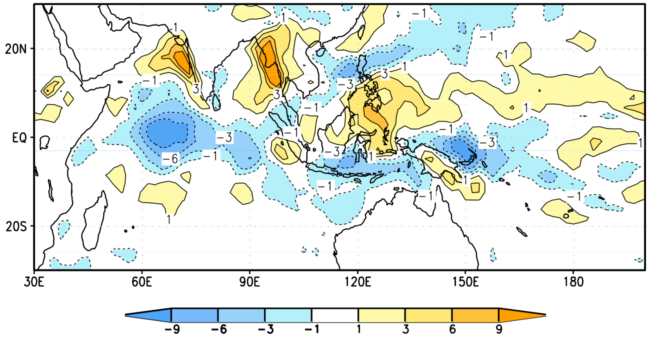
SST (CGCM – AGCM)



NET sfc heat flux (AGCM – OBS)



Precipitation (CGCM – AGCM)



Net sfc heatflux

downSW – upSW –upLW + downLW – SH –LH

➔ Positive: warming, Negative: cooling

<u>SST – Precipitation Negative feedback</u>

Precipitation positive bias

→ SH decrease (SW reduce due to cloud)

→ SST cooling

→ Reduce precipitation

How can improve the prediction skill?

System improvement

Air-sea interaction (ocean model coupling)

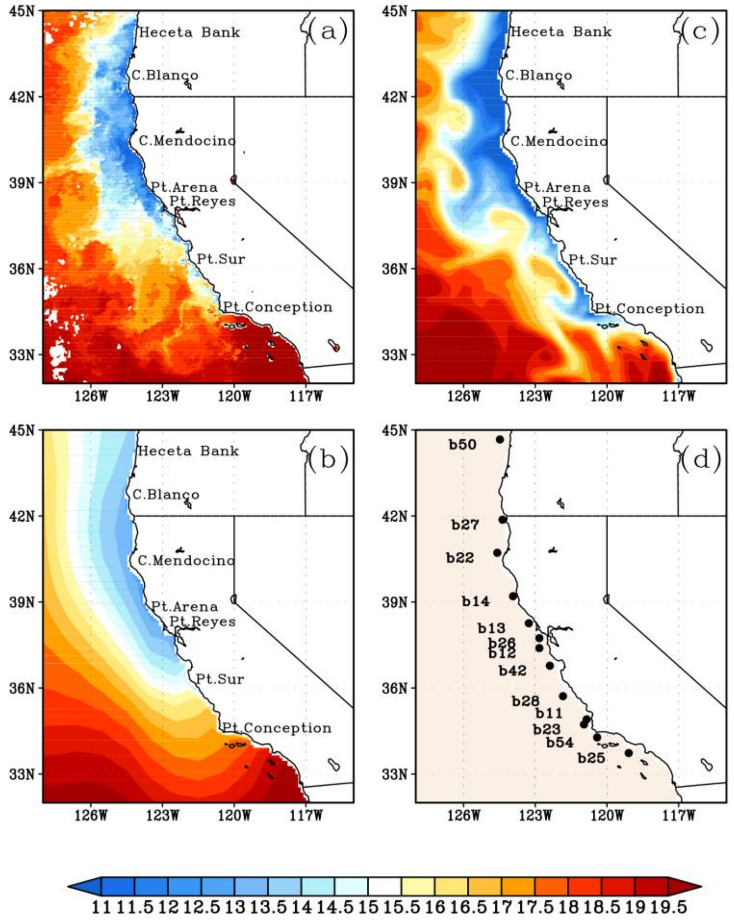


Fig. 4 August 2005 monthly mean SST ($(^\circ C)$) from (a) the 4-km AVHRR, (b) NCEP, and (c) the CPL run. The distribution of buoy stations is displayed in (d).

Courtesy of Li et al. 2012

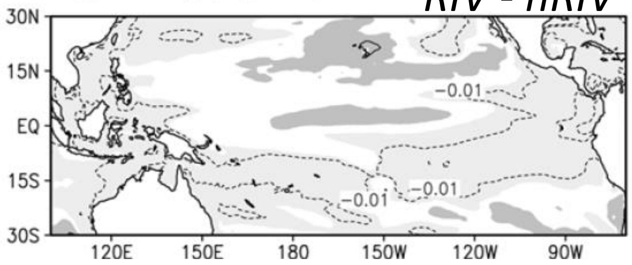
How can improve the prediction skill?

System improvement

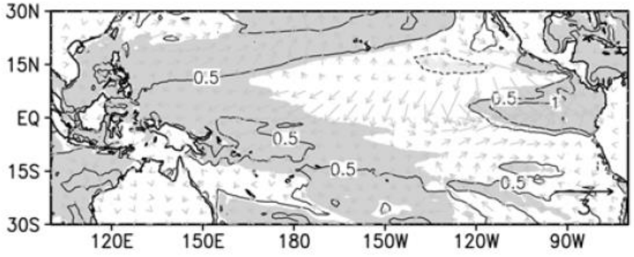
Air-sea interaction (river routing model coupling)

(a) Salinity (log-scale)

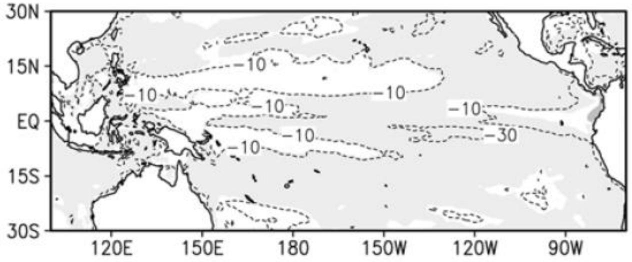
RIV - nRIV



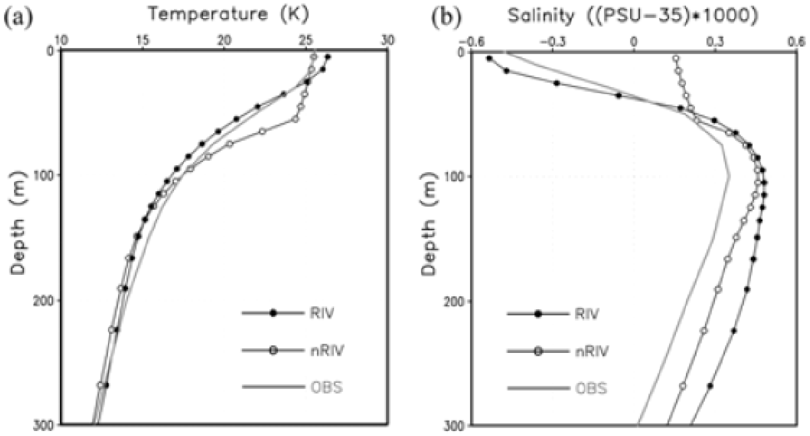
(b) SST



(c) MLD



Shading region shows the 95% significance level



❖ The noticeable reduction of salinity in the coastal regions due to the increased runoff

➔ Increased in SST over the eastern equatorial Pacific, upwelling region

➔ Decrease in the upwelling of cold sea water due to the reduction of trade wind

➔ The resultant shallow mixed layer depth can cause the anomalous warming

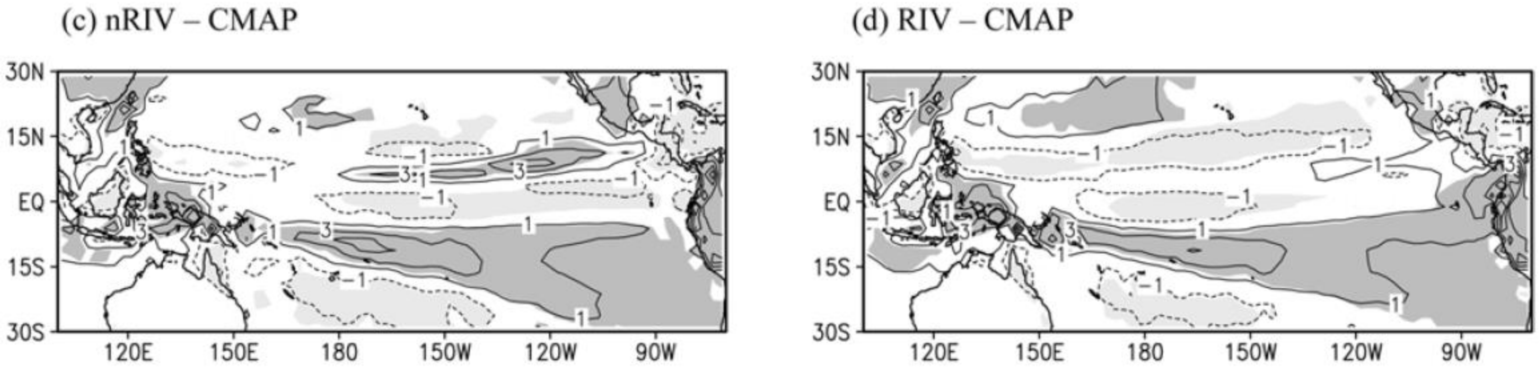
Ham et al. 2012

How can improve the prediction skill?

System improvement

Air-sea interaction (river routing model coupling)

Precipitation biases



Ham et al. 2012

- ❖ nRIV: exaggerated precipitation over the central tropical ocean, underestimated it over the eastern equatorial Pacific

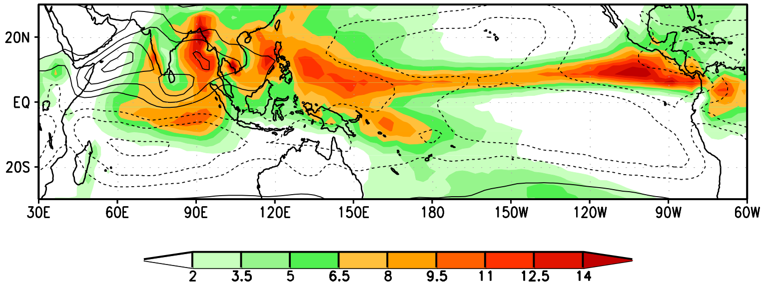
➔ RIV experiment show a better agreement with the observed than nRIV run, due to a decrease in it over the central tropical ocean.

How can improve the prediction skill?

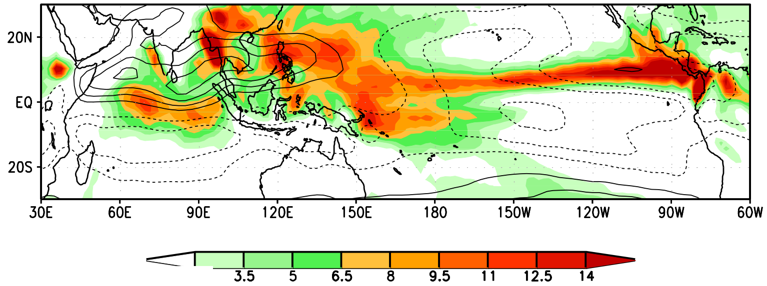
System improvement

Physics (convective parameterization)

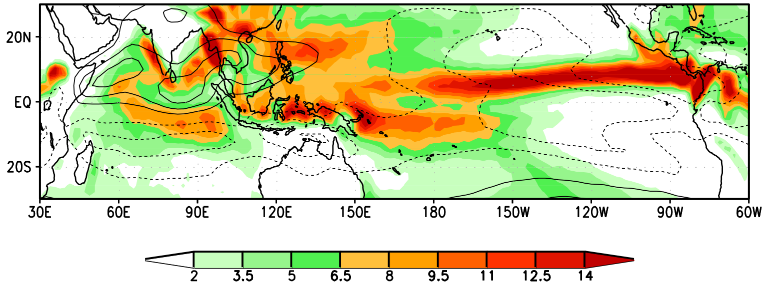
CMAP & RA2



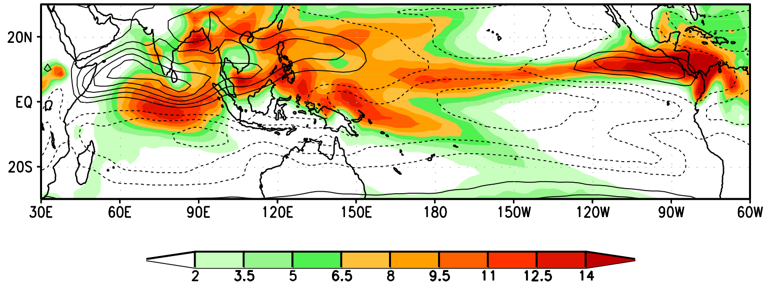
KF2 (0.87)



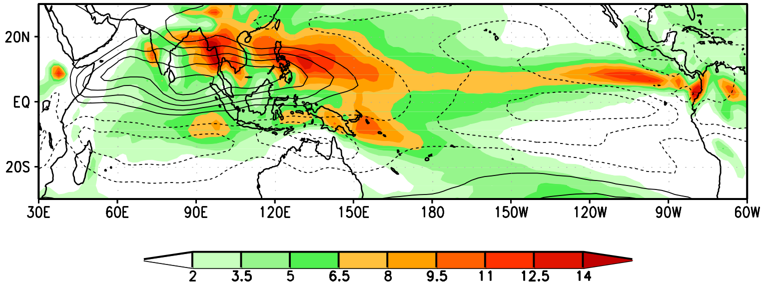
SAS (0.83)



CCM (0.83)



RAS (0.84)

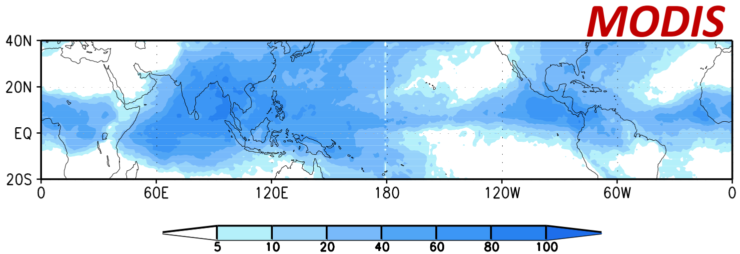


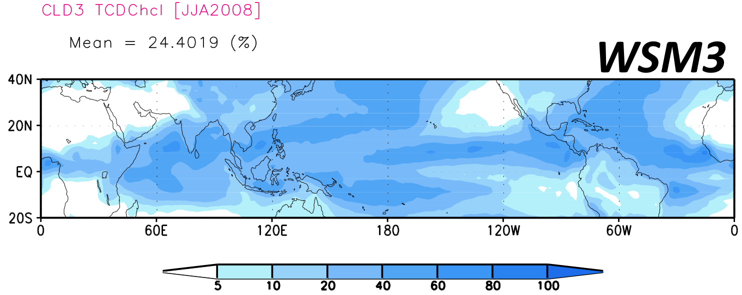
eight extended boreal summers [May-September (MJJAS)] from 1997 to 2004 (SMIP type)

How can improve the prediction skill?

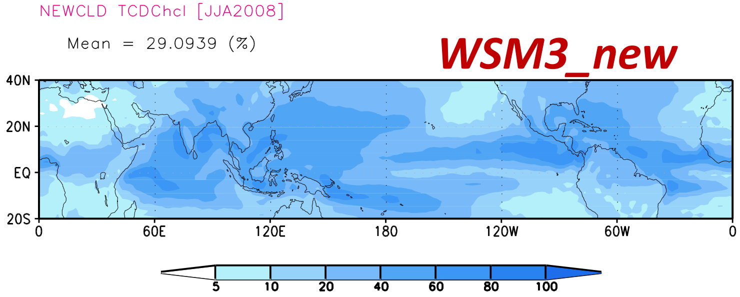
System improvement

Physics (cloudiness development)




CLD3 TCDChcl [JJA2008]

Mean = 24.4019 (%)


NEWCLD TCDChcl [JJA2008]

Mean = 29.0939 (%)

$$C_f = RH^{\alpha}\left[1 - \exp\left(\frac{-\beta q_t}{[(1-RH)\,q_s]^{\gamma}}\right)\right] \quad \Rightarrow \quad C_{total} = 1 - \exp\left(\alpha(q_{MPS} + q_{CPS})RH^{\beta}\frac{e_{sw}}{e_{si}}\right)$$

Cloud amount from the WSM3 experiment show a underestimation over the western Pacific.

New experiment shows significant improvement compared to the WSM3 result.

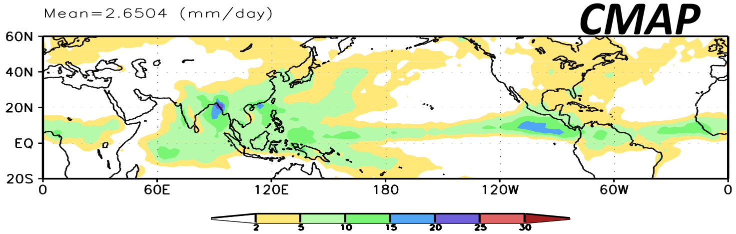
→ New explicit cloudiness parameterization leads to increase in cloud amount over the western Pacific and Maritime continental region.

Ham et al. 2013

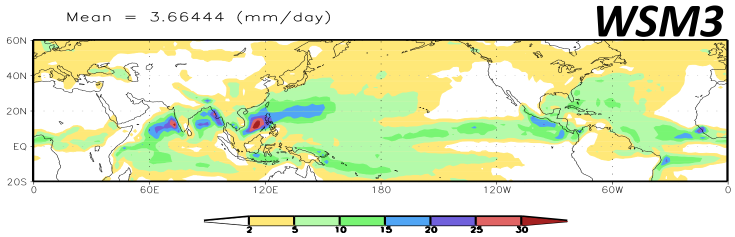
How can improve the prediction skill?

System improvement

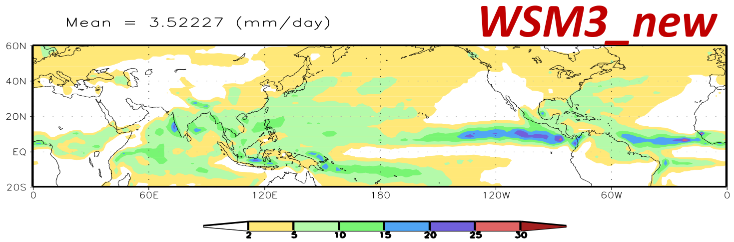
Physics (cloudiness development)



CMAP



WSM3



WSM3_new

Ham et al. 2013

Precipitation from the WSM3 experiment show a overestimation over the western Pacific.

New experiment shows significant improvement compared to the WSM3 result.

→ New explicit cloudiness parameterization leads to decrease in precipitation over the western Pacific and Maritime continental region.

How can improve the prediction skill?

System improvement

Coupling other component, physics, Initialization

- **NCEP CFSv1 → CFSv2**

  Resolution, Initialization system, Land model, Sea-ice model, CO2 mixing ratio, changing physics schemes (radiation package, cloud optical thickness, convective gravity wave drag, etc.)

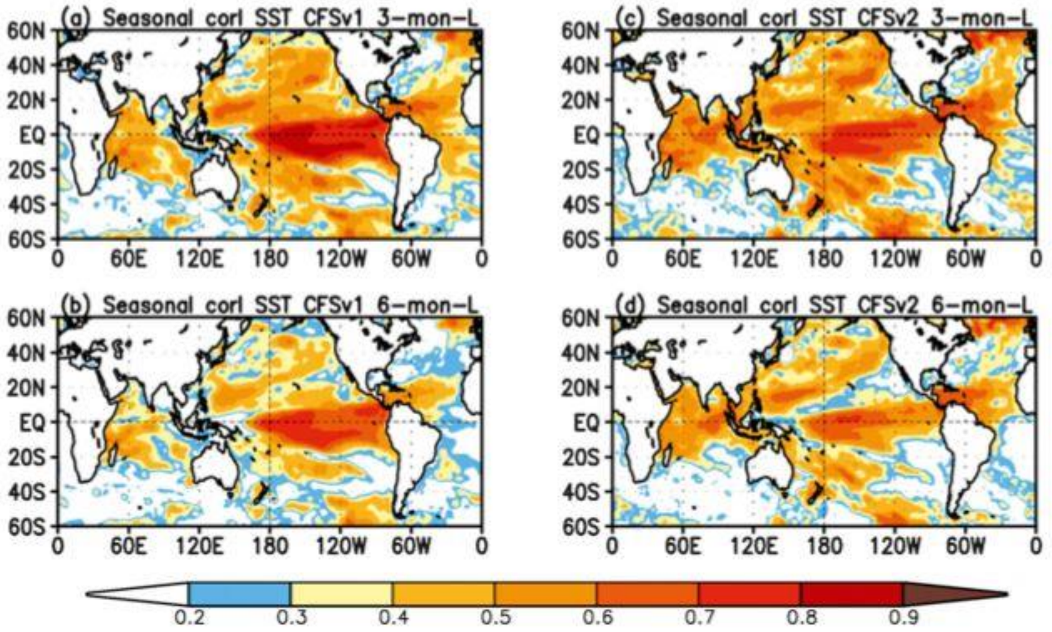


FIG. 2. Anomaly correlation of 3-month-mean SST between model forecasts and observation: (a) 3-month lead CFSv1, (b) 6-month lead CFSv1, (c) 3-month lead CFSv2, and (d) 6-month lead CFSv2. Contours are plotted at an interval of 0.1.

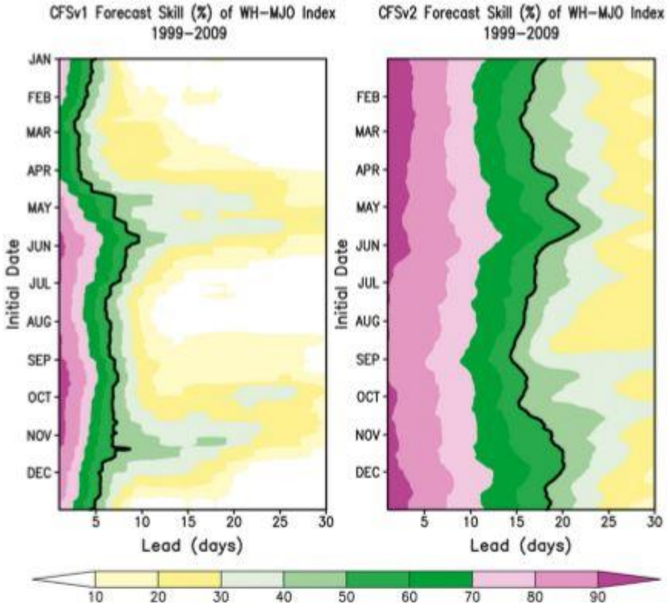


FIG. 1. The bivariate anomaly correlation (BAC) × 100 of CFS in predicting the MJO for period 1999–2009, as expressed by the Wheeler and Hendon (2004) index (two EOFs of combined zonal wind and OLR), for (left) CFSv1 and (right) CFSv2. Both are subjected to systematic error correction. The black lines indicate the 0.5 level of BAC.

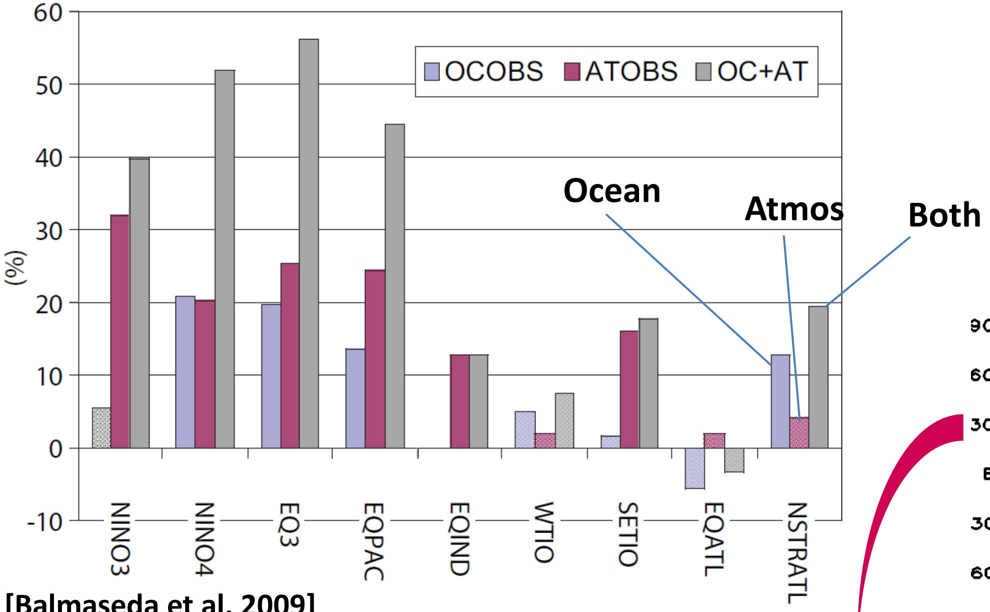
Courtesy of Saha et al. 2014

How can improve the prediction skill?

Improved Initial Condition

From Prof. M.I. Lee

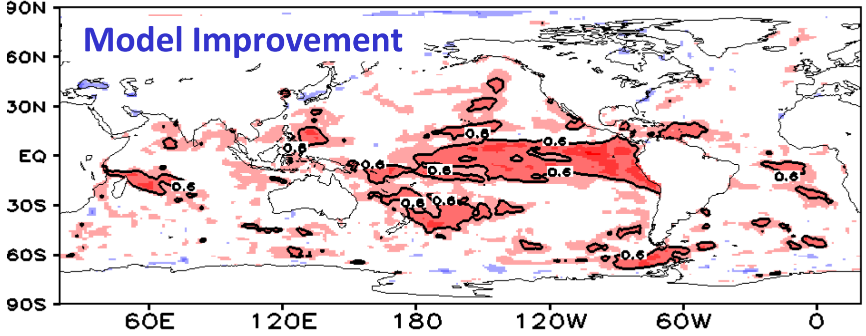
Impact of initialization on forecast skill (ECMWF)



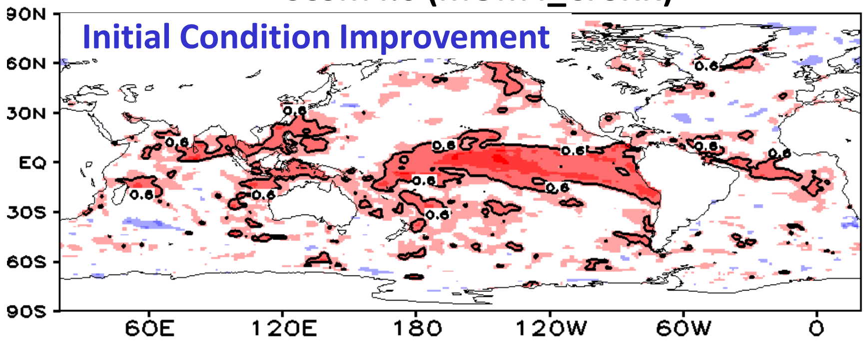
[Balmaseda et al. 2009]

Prediction Skill of SST Anomaly (4mon-lead)

CCSM4.0 (MOM3_ODA)



CCSM4.0 (MOM4_CFSRR)



Same ocean model

Initial Condition change:

from GFDL-OI (MOM3_ODA)

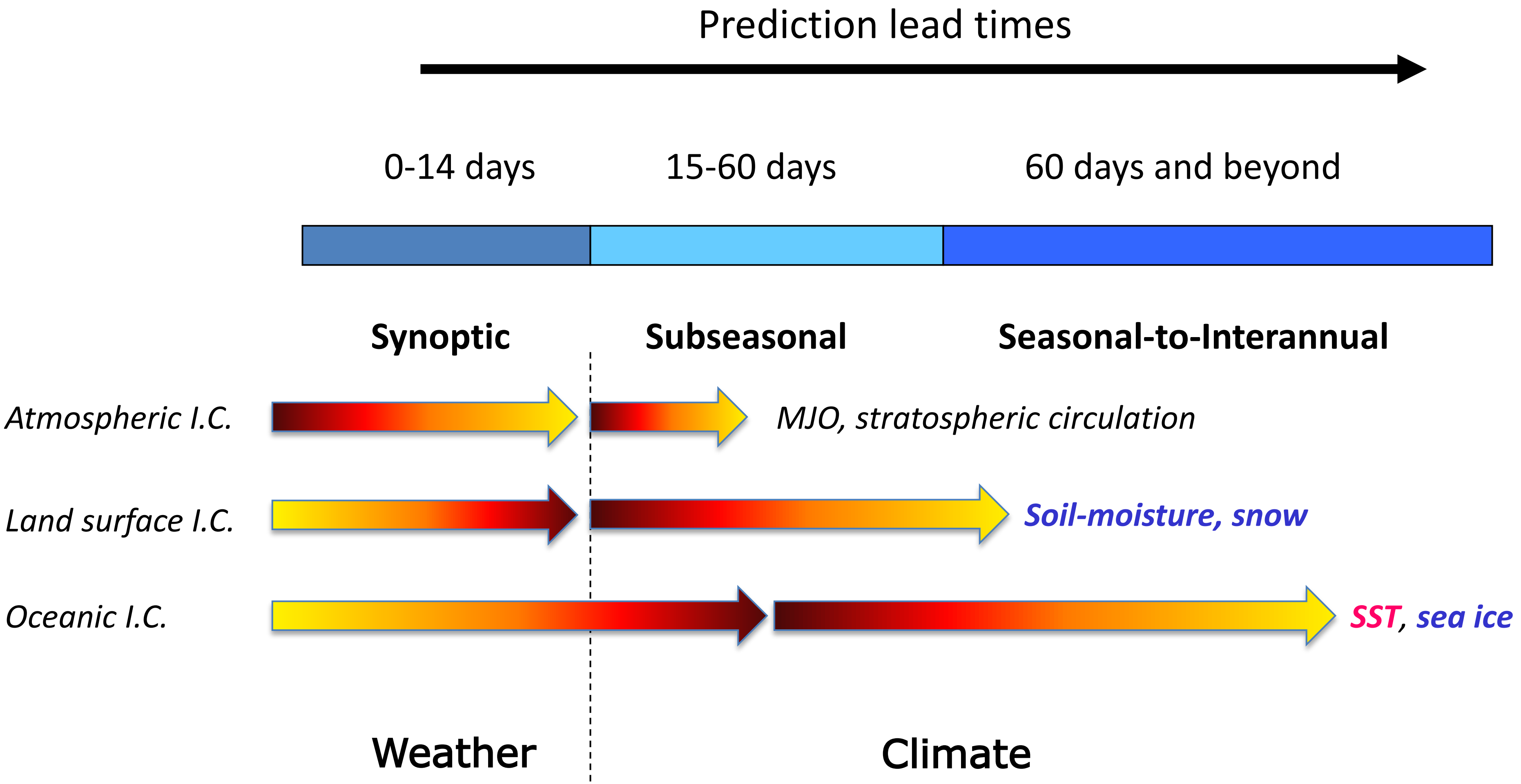
to CFSR (based on MOM4, coupled)

[Kirtman et al., 2014, BAMS]

How can improve the prediction skill?

Improved Initial Condition

From Prof. J.H. Jeong



Prediction lead times

0-14 days | 15-60 days | 60 days and beyond

Synoptic | **Subseasonal** | **Seasonal-to-Interannual**

Atmospheric I.C. — *MJO, stratospheric circulation*

Land surface I.C. — ***Soil-moisture, snow***

Oceanic I.C. — ***SST, sea ice***

Weather | **Climate**

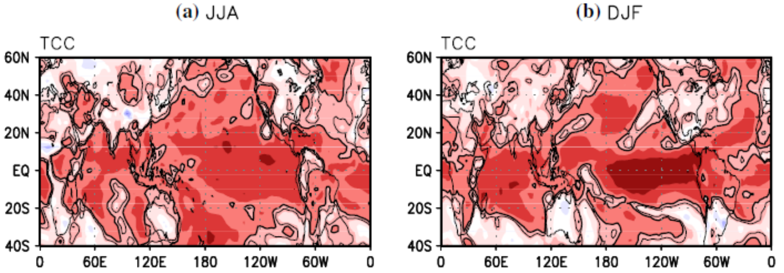
Current Climate prediction model: SST, Atmospheric circulation
Important forcing for climate prediction: Slow-varying soil-moisture, snow, sea ice (NOT many)

How can improve the prediction skill?

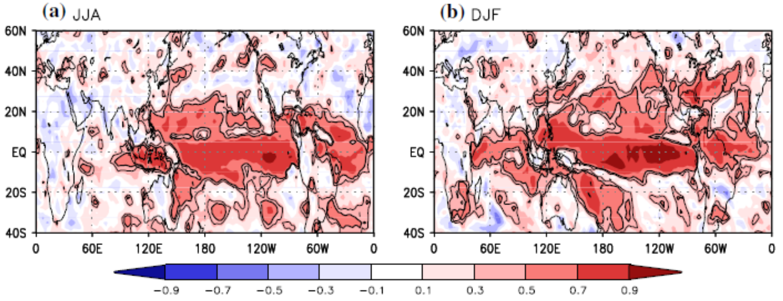
Improved Initial Condition

From Prof. M.I. Lee

APCC/CliPAS MME Skill for 2m Air Temperature (1981-2003)



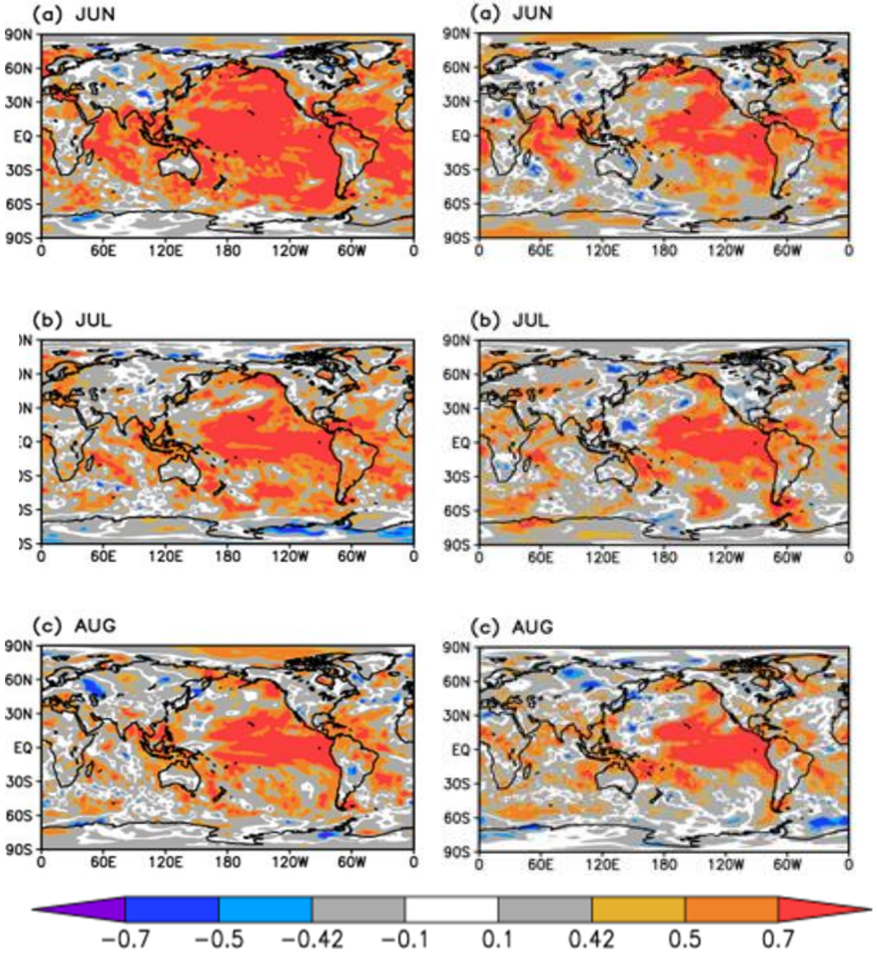
APCC/CliPAS MME Skill for Precipitation (1981-2003)



Wang et al. 2008 (Climate Dynamics)

Almost climate model show the low prediction skill in land area for temperature as well as precipitation.

GloSea4(left) and GloSea5(right) hindcast skill
(initialized at May)

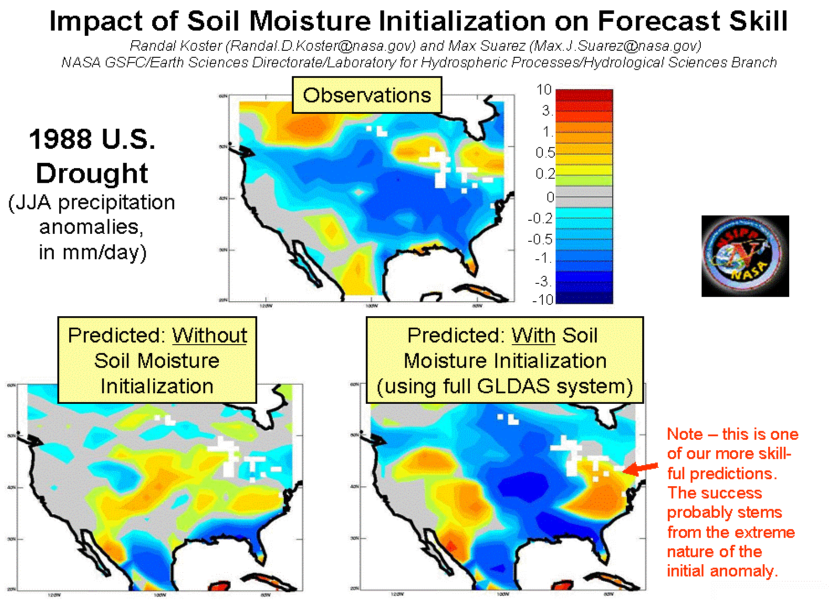


Lee et al. 2014 (APJAS)

How can improve the prediction skill?

Improved Initial Condition

From Prof. J.H. Jeong



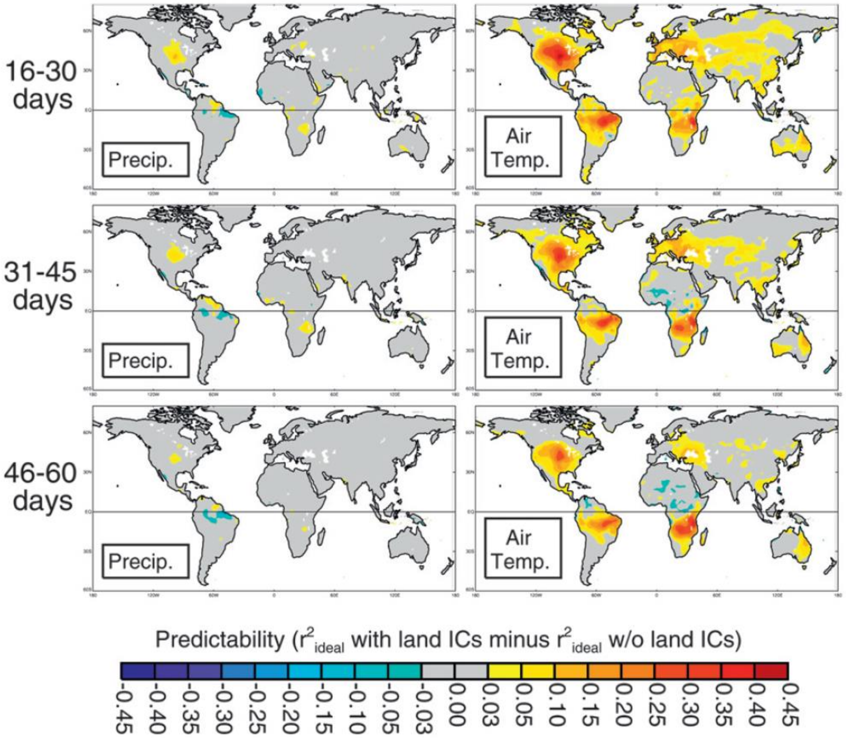
Impact of Soil Moisture Initialization on Forecast Skill

Randal Koster (Randal.D.Koster@nasa.gov) and Max Suarez (Max.J.Suarez@nasa.gov)
NASA GSFC/Earth Sciences Directorate/Laboratory for Hydrospheric Processes/Hydrological Sciences Branch

1988 U.S. Drought
(JJA precipitation anomalies, in mm/day)

Note – this is one of our more skillful predictions. The success probably stems from the extreme nature of the initial anomaly.

Koster et al. (2004; J Climate)



Predictability (r^2_{ideal} with land ICs minus r^2_{ideal} w/o land ICs)

Koster, Jeong et al. (2011; J Hydromet.)

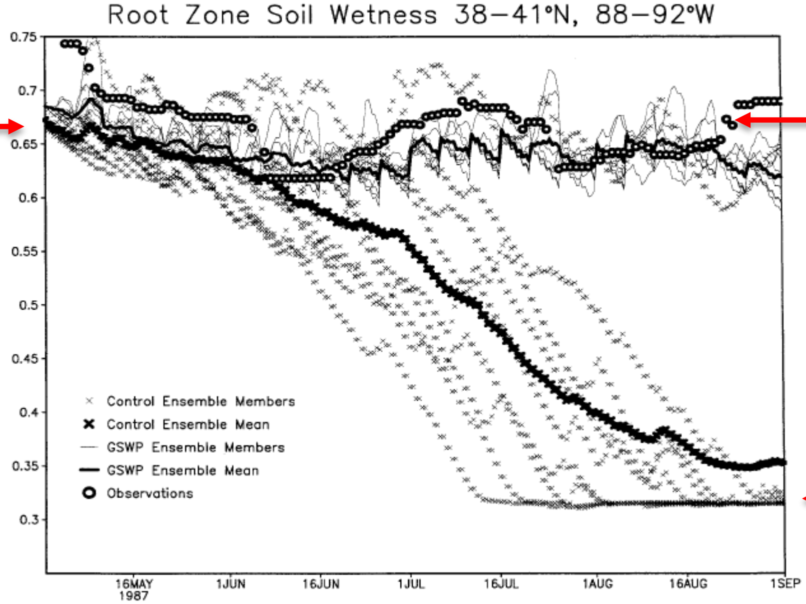
Soil moisture is important factor in climate prediction
: with soil moisture initalization lead to the improved prediction skill for temperature
: land initialization can affect predictability of temperature as well as precipitation

How can improve the prediction skill?

Improved Initial Condition

From Prof. J.H. Jeong

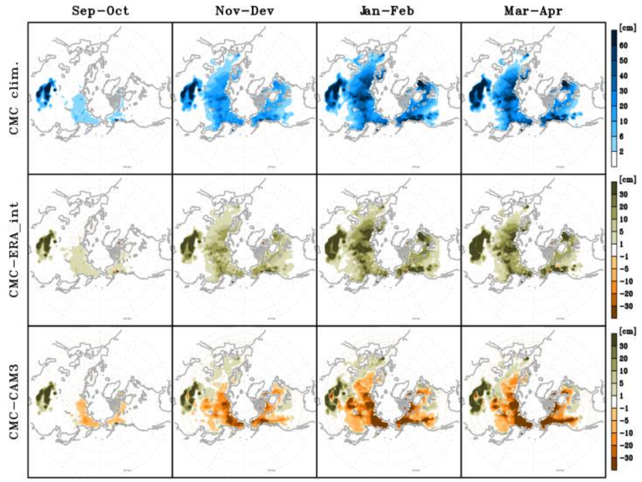
Initialized here, say perfectly, but



Real world

Model's world

FIG. 4. Comparison of the evolution of root zone soil wetness for individual ensemble members (light) and the ensemble mean (bold) for –Aug 1987 at a grid cell over Illinois. Also shown is the top 1-m soil wetness averaged for 12 nits are fraction of saturation.



Obs snow

Obs-ERAi

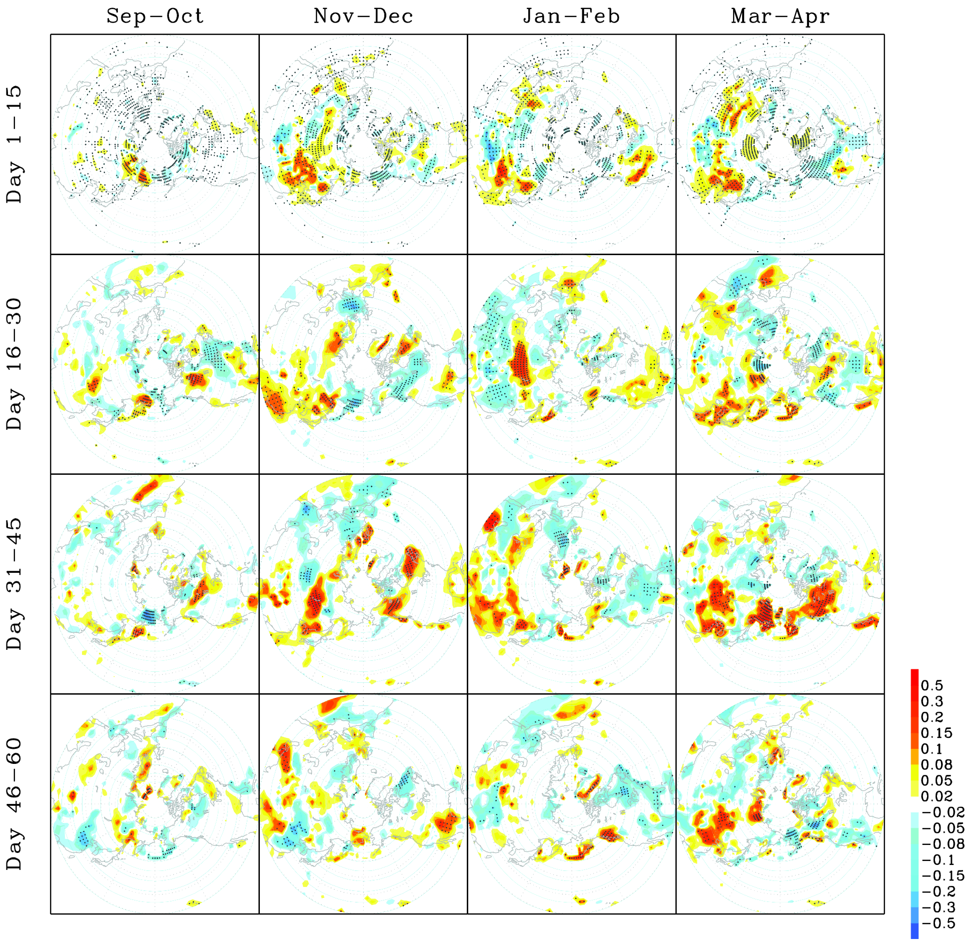
Obs-CAM3(model)

Due to large biases, directly initialization is not reasonable
→ Anomaly initialization is needed
→ It can consider the observed characteristics to the model with reducing unbalance between model and real world

How can improve the prediction skill?

Improved Initial Condition

From Prof. J.H. Jeong



Jeong et al. (2013; J Climate)

Recently, snow depth initialization is also issue for climate prediction model

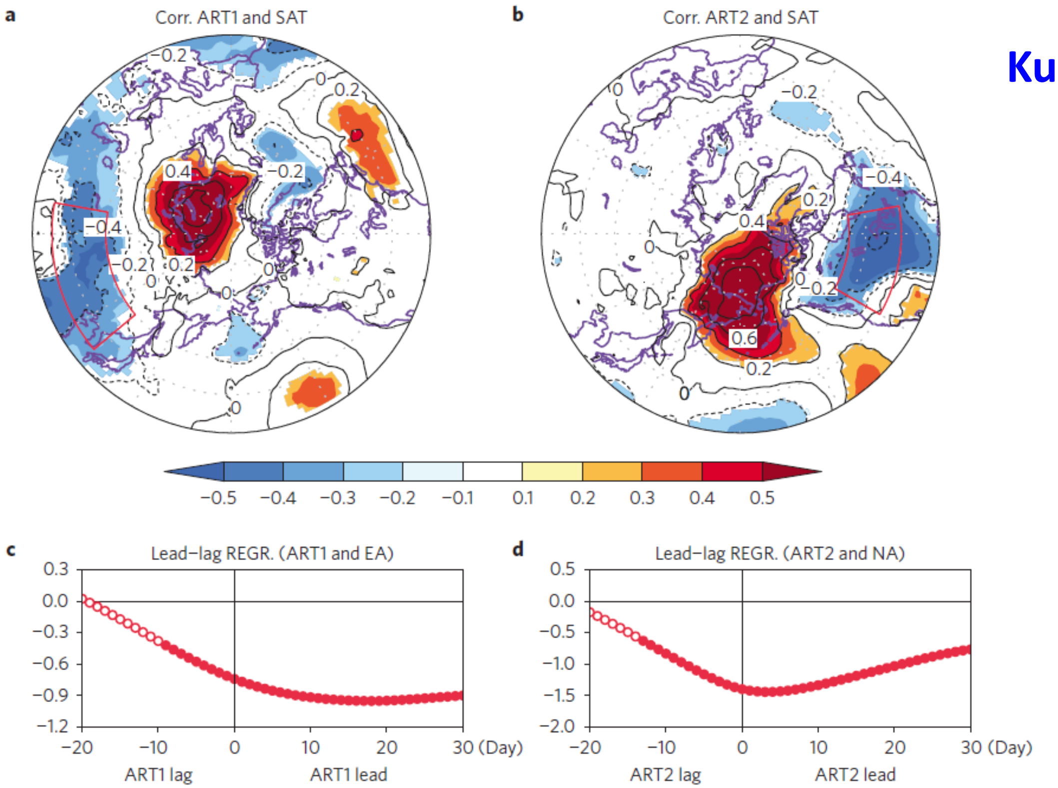
Jeong et al. 2013

- **Snow depth initialization** can lead to positive effect over East Asia or North America, others

How can improve the prediction skill?

Improved Initial Condition

From Prof. J.H. Jeong



Kug et al. (2015; Nature Geoscience)

Warm anomaly over Kara-Barents sea leads to cold anomaly over the East Asia after 2 weeks.

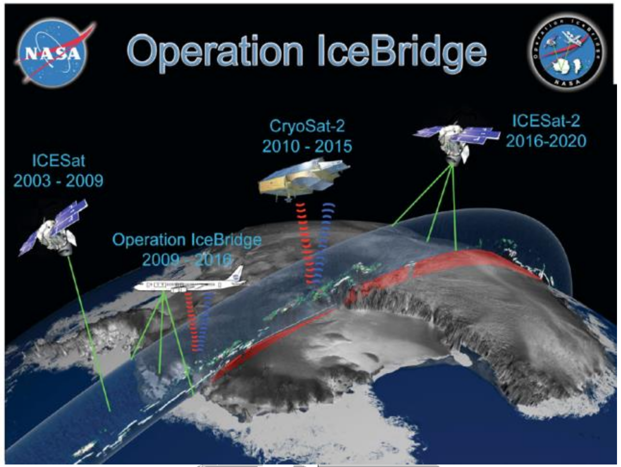
Interaction between Sea-ice and temperature anomaly is already well known system. However, there are huge biases over the High latitude region in the climate model system. ➔ Need to suitable initialization for **Sea-ice**

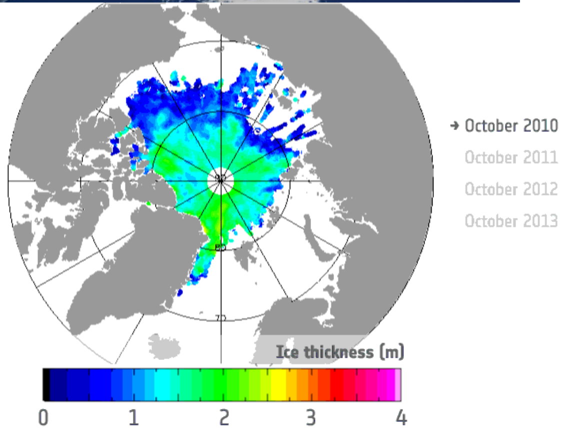
How can improve the prediction skill?

Improved Initial Condition

From Prof. J.H. Jeong

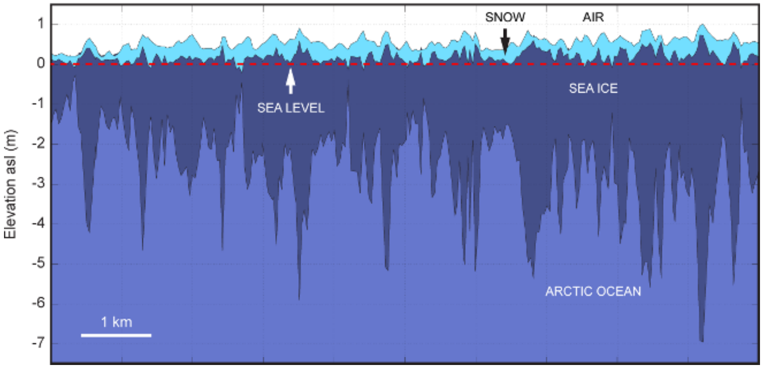
Satellites for sea-ice observation

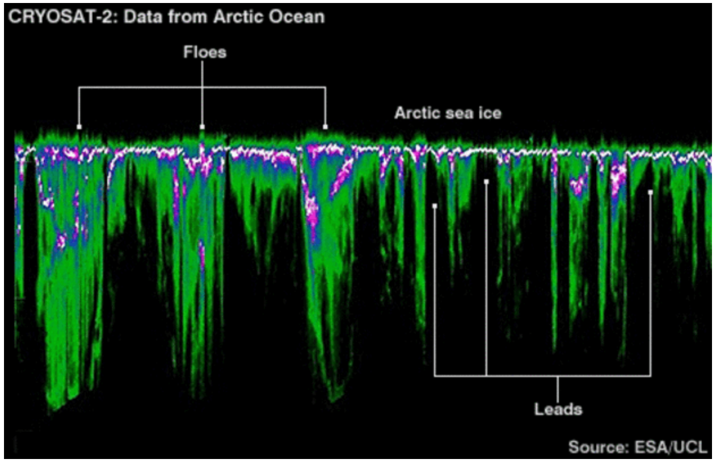




Sea-ice cover

Sea-ice Depth information





Source: ESA/UCL

Sea-ice cover: relative well known due to the satellites research
Sea-ice depth information is still poor understood

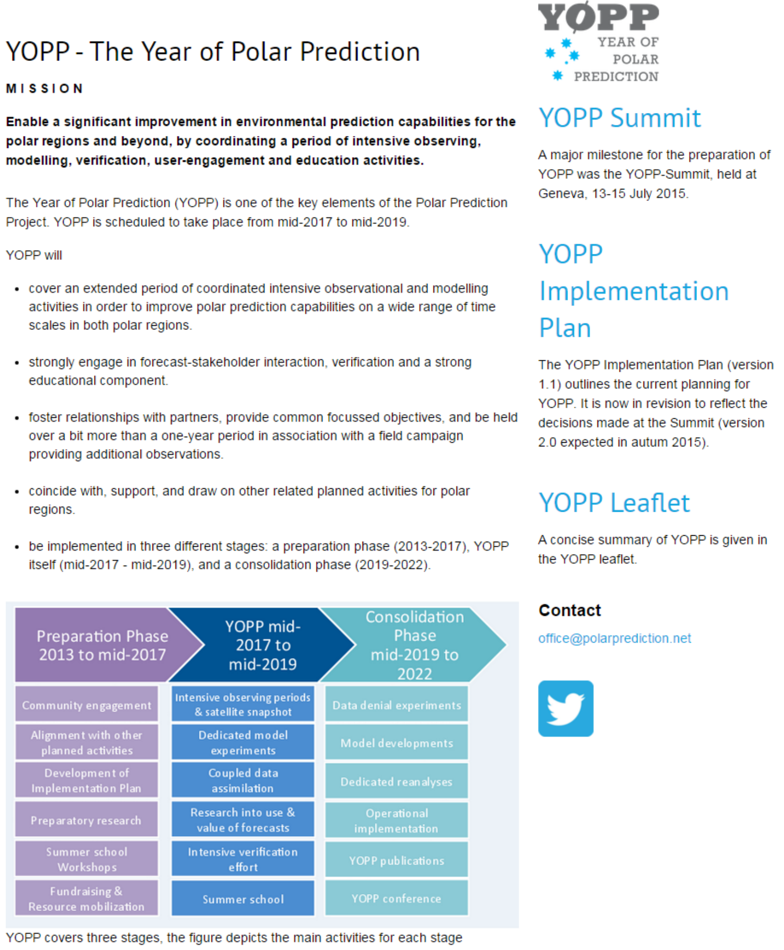
How can improve the prediction skill?

Improved Initial Condition

From Prof. J.H. Jeong

Sea Ice Historical Forecast Project (Ice-HFP)

Tremendous advance in improving and exploiting the initialization of the oceanic and atmospheric components of seasonal forecast systems has been made in the past decade, particularly with the advent of enhanced knowledge of the world's oceans through ARGO. Utilizing the increased knowledge of sea ice conditions within seasonal prediction systems remains an untapped and unknown reservoir of potential predictability. Current seasonal prediction systems range from prescribed sea ice climatologies to fully thermodynamic and dynamic interactive sea ice initialized from an observed state. To gain understanding of the potential impact of sea ice initialization on the atmosphere, it is necessary to perform model comparisons with and without sea ice initialization.



YOPP - The Year of Polar Prediction

MISSION

Enable a significant improvement in environmental prediction capabilities for the polar regions and beyond, by coordinating a period of intensive observing, modelling, verification, user-engagement and education activities.

The Year of Polar Prediction (YOPP) is one of the key elements of the Polar Prediction Project. YOPP is scheduled to take place from mid-2017 to mid-2019.

YOPP will

- cover an extended period of coordinated intensive observational and modelling activities in order to improve polar prediction capabilities on a wide range of time scales in both polar regions.
- strongly engage in forecast-stakeholder interaction, verification and a strong educational component.
- foster relationships with partners, provide common focussed objectives, and be held over a bit more than a one-year period in association with a field campaign providing additional observations.
- coincide with, support, and draw on other related planned activities for polar regions.
- be implemented in three different stages: a preparation phase (2013-2017), YOPP itself (mid-2017 - mid-2019), and a consolidation phase (2019-2022).

Preparation Phase 2013 to mid-2017	YOPP mid-2017 to mid-2019	Consolidation Phase mid-2019 to 2022
Community engagement	Intensive observing periods & satellite snapshot	Data denial experiments
Alignment with other planned activities	Dedicated model experiments	Model developments
Development of Implementation Plan	Coupled data assimilation	Dedicated reanalyses
Preparatory research	Research into use & value of forecasts	Operational implementation
Summer school Workshops	Intensive verification effort	YOPP publications
Fundraising & Resource mobilization	Summer school	YOPP conference

YOPP covers three stages, the figure depicts the main activities for each stage

YOPP Summit

A major milestone for the preparation of YOPP was the YOPP-Summit, held at Geneva, 13-15 July 2015.

YOPP Implementation Plan

The YOPP Implementation Plan (version 1.1) outlines the current planning for YOPP. It is now in revision to reflect the decisions made at the Summit (version 2.0 expected in autum 2015).

YOPP Leaflet

A concise summary of YOPP is given in the YOPP leaflet.

Contact

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Yet, the impacts of sea ice on seasonal predictability have not been assessed systematically.
Several international projects are going on….

Part 2:
APCC dynamical seasonal prediction system

- model framework
- prediction skill

APCC dynamical seasonal prediction system

What we do?

- Real-time forecasts – predicting real future with latest initial conditions

- Hindcasts/retrospective forecasts for the past decades
  - e.g. Use 1997 Jan 1st atmosphere/ocean state as initial conditions. Could model have predicted 97/98 El Nino event?
  - Systematic errors, various characteristics
  - Climatology for anomaly analyze

- Usually average in time - predict climate not weather

  (e.g. weekly, monthly & seasonal means)

APCC dynamical seasonal prediction system

- Community Climate System Model version 3 (CCSM3)
  - Community model
  - Ocean temperature nudging

- Seamless Coupled Prediction System (SCoPS)
  - Newly developed coupled system with a research group of Univ. of Hawaii
  - For predicting subseasonal to seasonal climate
  - High resolution atmosphere-ocean-land-seaice model
  - Coupled AO initialization

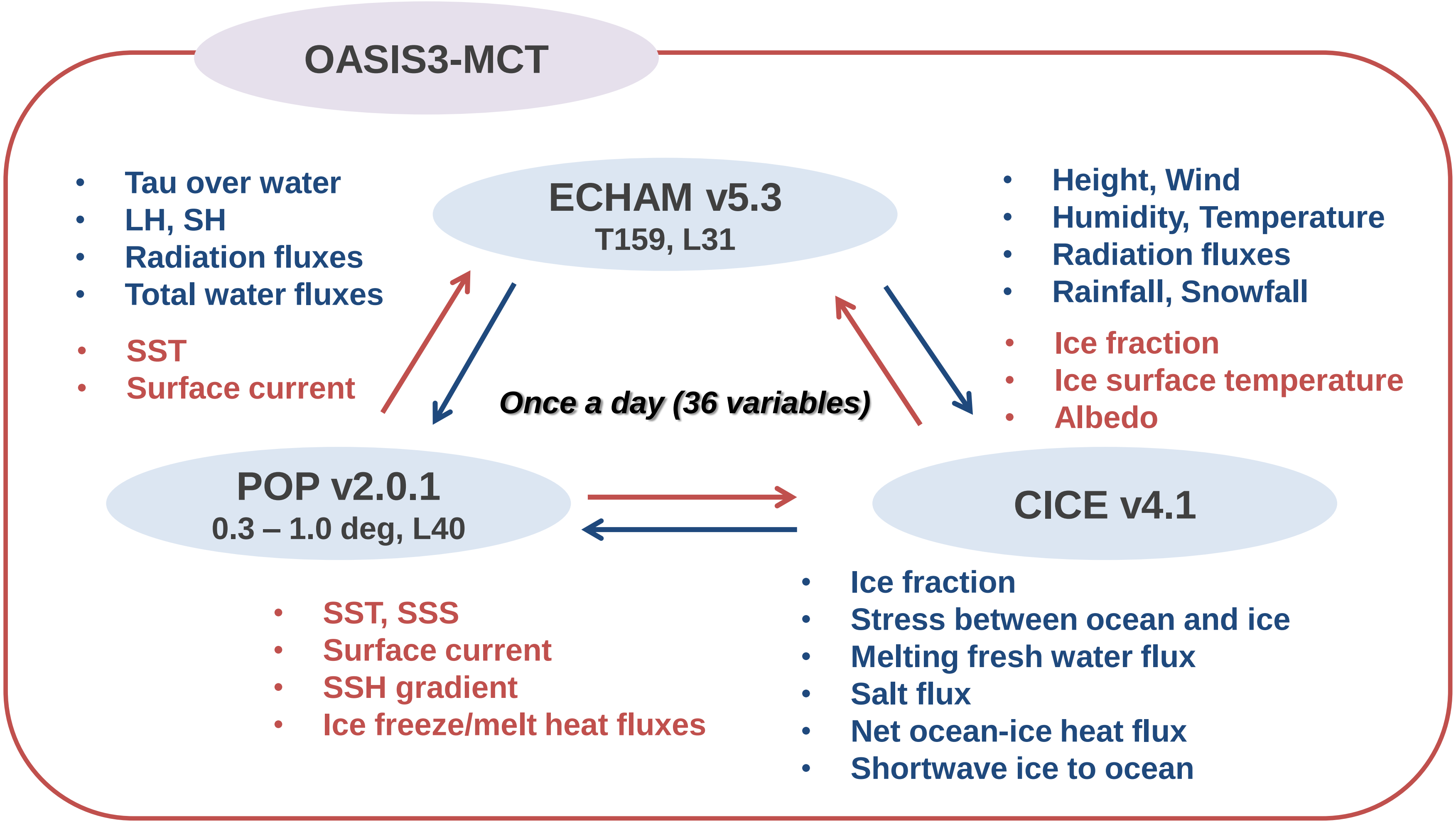
APCC dynamical seasonal prediction system

Configuration

		SCoPS	CCSM3
Model	**Atmos.**	ECHAM v5.3	CAM3
	Ocean	POP v2.0.1	POP v1.4.3
	Sea ice	CICE v4.1	CSIM4
Resolution	**Atmos.**	T159L31	T85L26
	Ocean	~1.0˚ x 0.5˚ / L40	
Initialization	**Atmos.**	3D nudging from CFSR U, V, T, Q	-
	Ocean	3D EAKF from CFSR SST and profile SST, SSS data (WOD)	3D nudging from GODAS ocean temperature

APCC dynamical seasonal prediction system

Configuration



OASIS3-MCT

- **Tau over water**
- **LH, SH**
- **Radiation fluxes**
- **Total water fluxes**

- **SST**
- **Surface current**

ECHAM v5.3

T159, L31

- **Height, Wind**
- **Humidity, Temperature**
- **Radiation fluxes**
- **Rainfall, Snowfall**

- **Ice fraction**
- **Ice surface temperature**
- **Albedo**

Once a day (36 variables)

POP v2.0.1

0.3 – 1.0 deg, L40

CICE v4.1

- **SST, SSS**
- **Surface current**
- **SSH gradient**
- **Ice freeze/melt heat fluxes**

- **Ice fraction**
- **Stress between ocean and ice**
- **Melting fresh water flux**
- **Salt flux**
- **Net ocean-ice heat flux**
- **Shortwave ice to ocean**

APCC dynamical seasonal prediction system

- 10 forecasts from SCoPS (Ensemble forecast)

Real-time forecasts

- ensemble of 10 forecasts updated monthly

Hindcasts

- 10 member ensemble forecasts initialized on the 1st , 5th of each month for 1982-2013

- Forecasts go out to 7 months

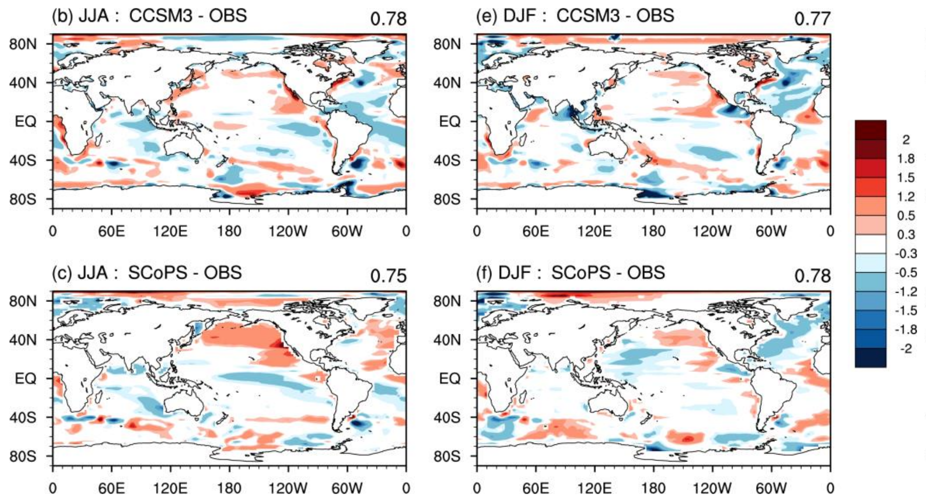
- Monthly anomalies of forecasts computed by removing the hindcast climatology as a function of lead time → model's mean bias removed from the forecasts

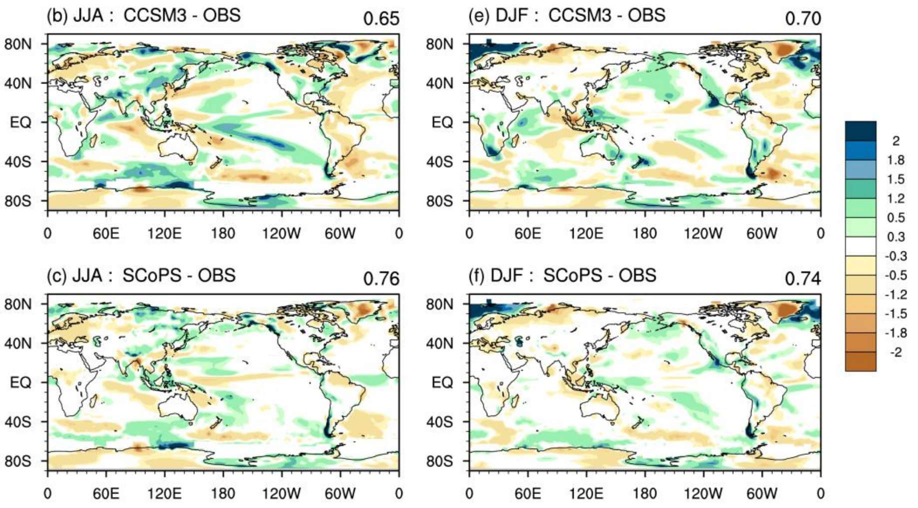
* Lead time: a time gap between the date of initialisation and the date of verification

APCC dynamical seasonal prediction system

Systematic error

Hindcast (1982-2013)





model systematic errors

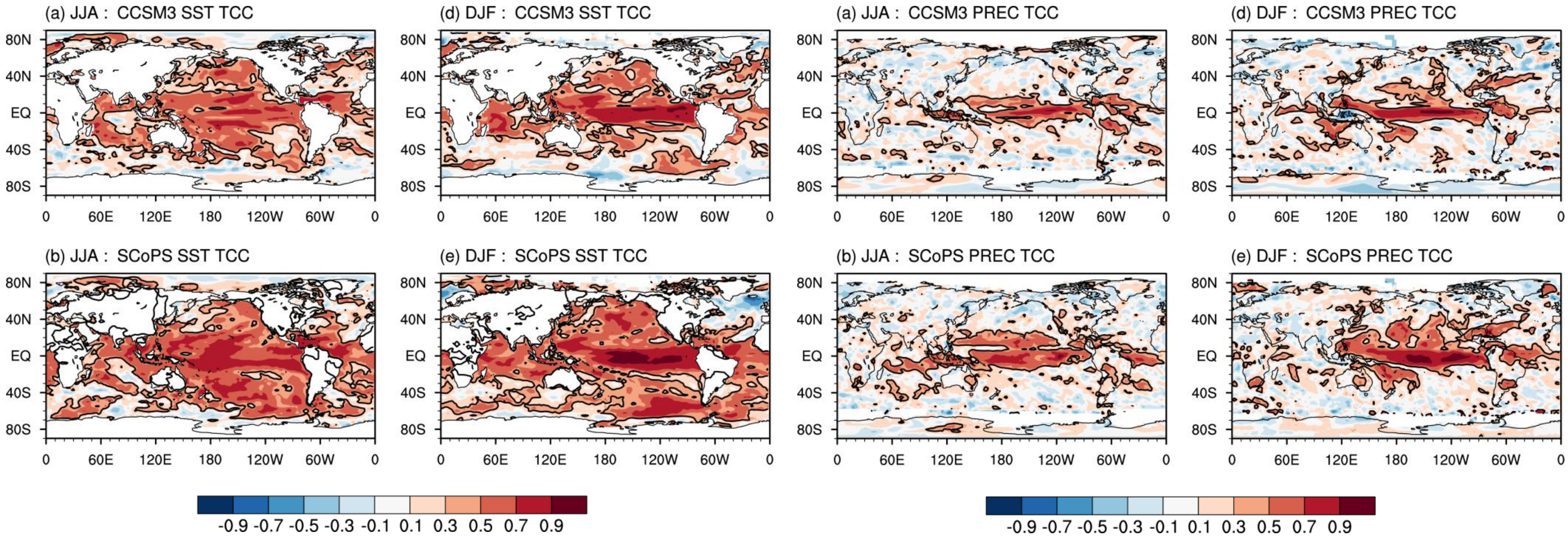
Two models show the some biases for temperature and precipitation, but it is not large.

Correlation also show about 0.6 to 0.8

APCC dynamical seasonal prediction system

Temporal Correlation Coefficients (JJA&DJF)

Hindcast (1982-2013)



For the SST, SCoPS show the higher correlation coefficient over the globe.

Also, precipitation skill is improved by SCoPS

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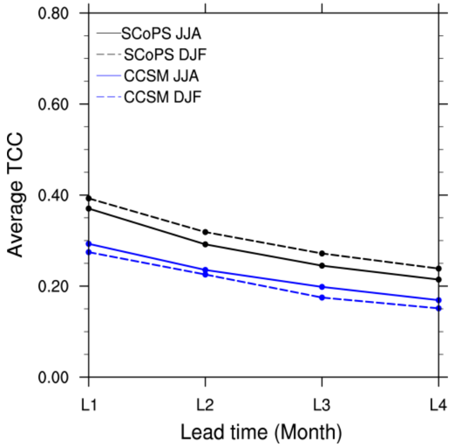
Averaged Temporal Correlation Coefficients

Hindcast (1982-2013)

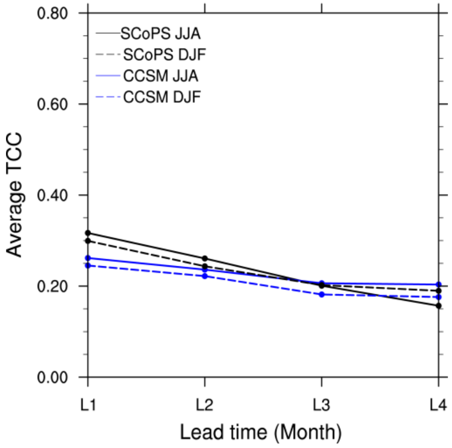
SST

(a) ACC: GLOBAL SST



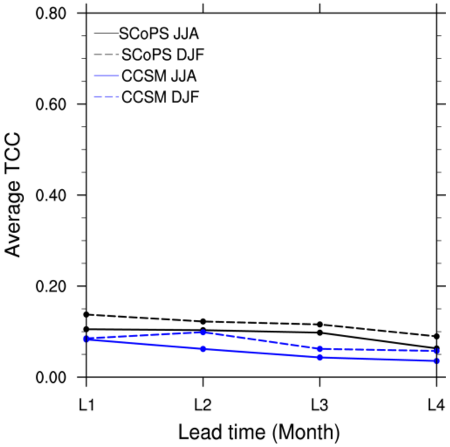
2mTemp

(c) ACC: Global 2M_TEMP



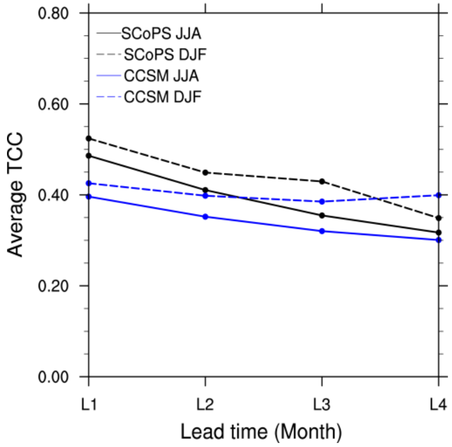
Precipitation

(e) ACC: Global Precipitation

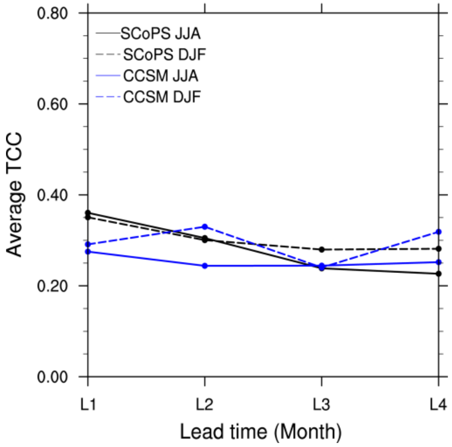


Global

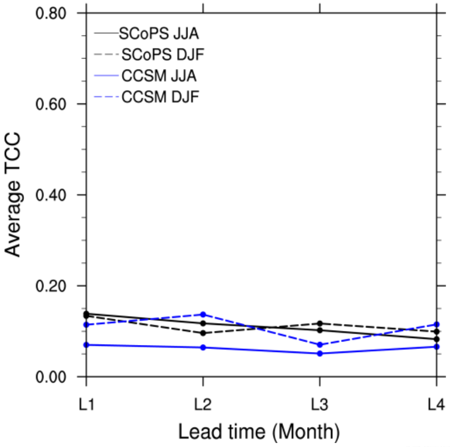
(b) ACC: East Asia SST



(d) ACC: East Asia 2M_TEMP



(f) ACC: East Asia Precipitation



East Asia

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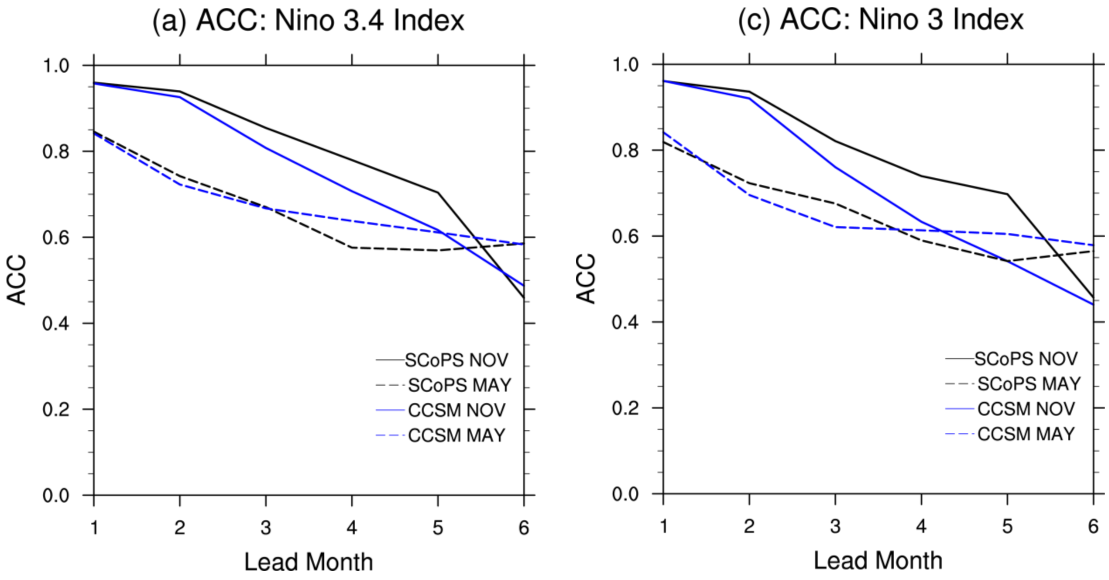
Hindcast (1982-2013)

ACC of NINO index

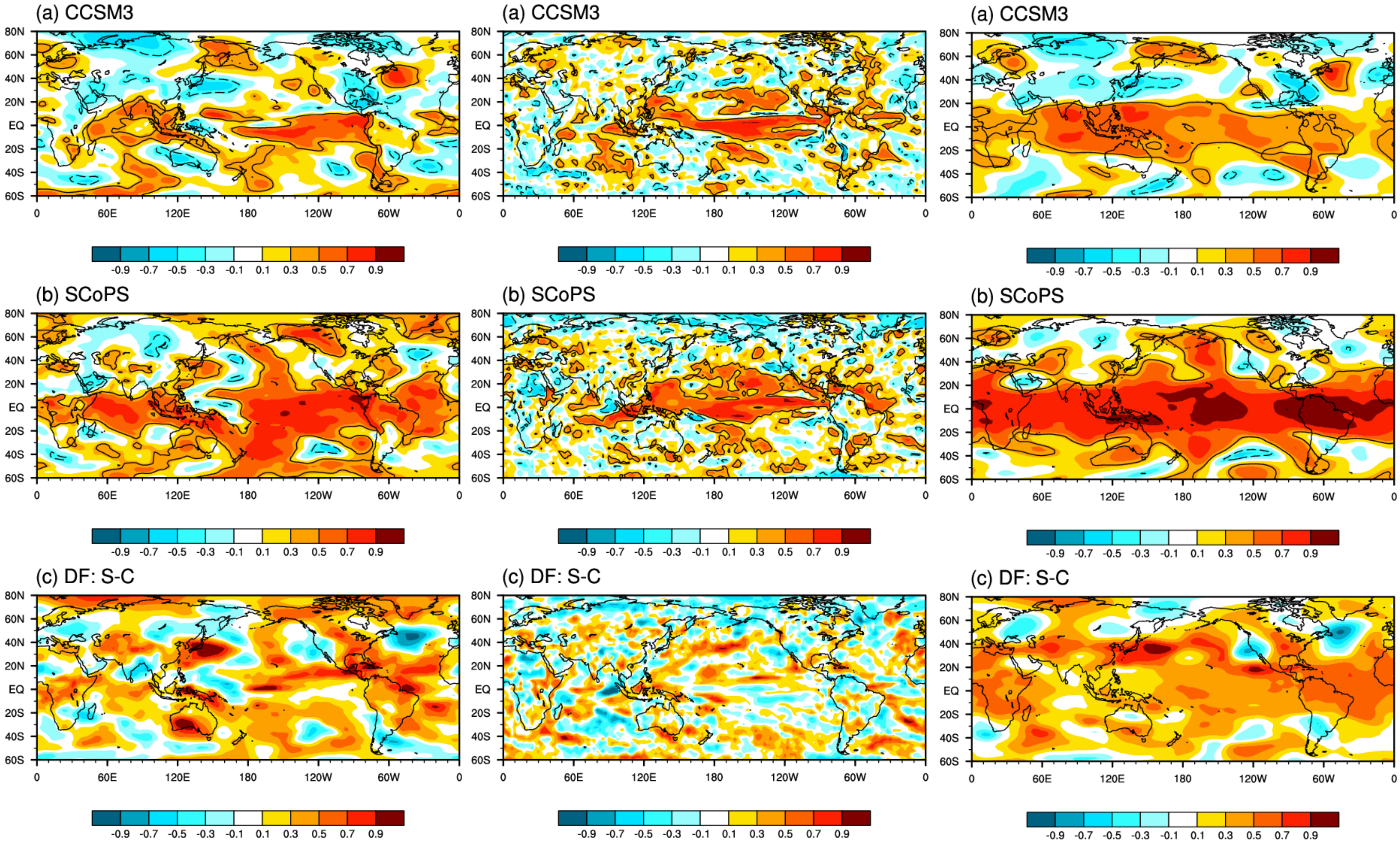


APCC dynamical seasonal prediction system

Temporal Correlation Coefficients

Realtime Forecast (2014-2016)

T850 **PREC** **Z500**



APCC dynamical seasonal prediction system

- SCoPS

  : APCC operation seasonal prediction model (monthly)

  : APCC MME participant model

- Plan to

  : Improvement of initialization system in SCoPS

Thank you for your time !!

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