APEC CLIMATE CENTER

Introduction to PICASO

- Day 1, Afternoon Session 2
- Yun-Young Lee

I. Climate Prediction & Services

Climate Services

Anticipated Change → Assessing impact → Action

Seasonal prediction

Prediction of weather statistics for a couple of seasons

letters to nature

Forecasting Andean rainfall and crop yield from the influence of El Niño on Pleiades visibility

Benjamin S. Orlove*†, John C. H. Chiang† & Mark A. Cane†

Food and Agriculture Organization of the United Nations

CLIMATE-SMART AGRICULTURE

Using seasonal forecasts to support farmer adaptation to climate risks

Prob. Forecast & Economic Values

Forecast says "above normal 40%, below normal 60%" (information).

Should I save some water for this dry season?

- Reserving water costs $20

(Farmer A) My crop is very sensitive to drought…

If drought occurs, my crop will die if there is no reserved water - $100

(Farmer B) Nahh… My crop loves drought…

Although, drought may cost extra $10 for harvesting

You can make a clever choice:

(Farmer A)

	Above	Below
Reserve	20	20
No Action	0	100

•

Chance
0.4
0.6

=

Cost
20
60

(Farmer B)

	Above	Below
Reserve	20	20
No Action	0	10

•

Chance
0.4
0.6

=

Cost
20
6

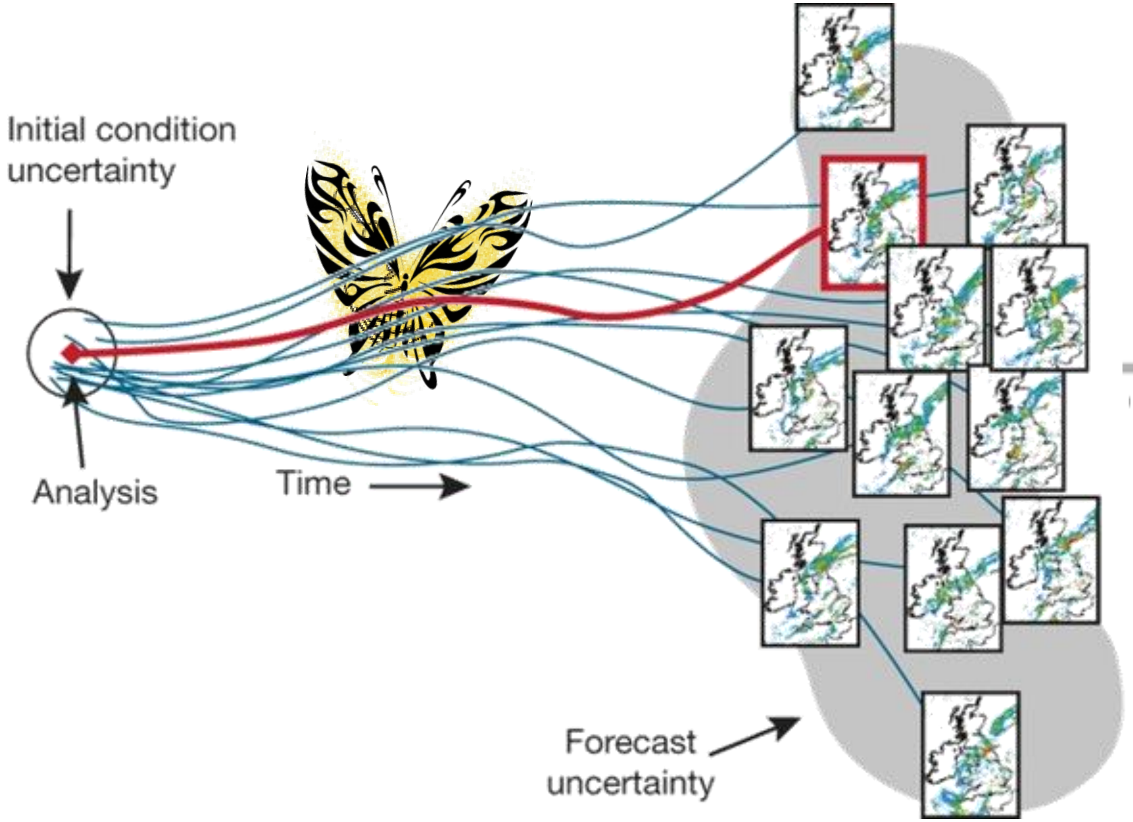
Climate information for decision making

Properties for Usable information (Cash et al. 2003, Kirchhoff et al. 2013)

- Credibility : Quality of information, Provider's reputation
  - Forecast accuracy
- Salience : fitness to context of user
  - Scale, Variables, Products
- Legitimacy : cleanness of information from other factors
  - Objectivenss, Openness

Co-production by "producers" and "users"

Is a perfect forecast possible?



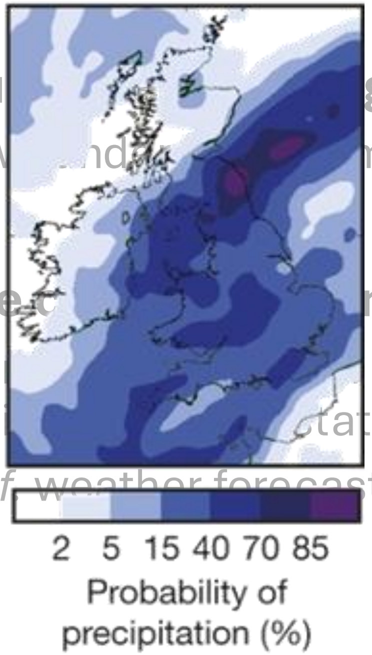
Perfect? (accurate + precise)

Ou g of climate system.

- W nd me of it, not all of it.

The m is nonlinear.

- S in the initial condition leads to totally di tates.
- *cf.* weather forecast



Still, there is 'some' portion that can be predicted.

Benefit of Multi Model Ensemble

Single model prediction:

$$y = Ax + \varepsilon_m + \varepsilon_s + \cancel{\varepsilon'}$$

future rainfall

predictable part

models' lies

our limitation

nature's tricks

Multi-Model Ensemble (MME) prediction:

$$y = Ax + \cancel{\varepsilon_m} + \varepsilon_s + \cancel{\varepsilon'}$$

future rainfall

predictable part

~~models' lies~~

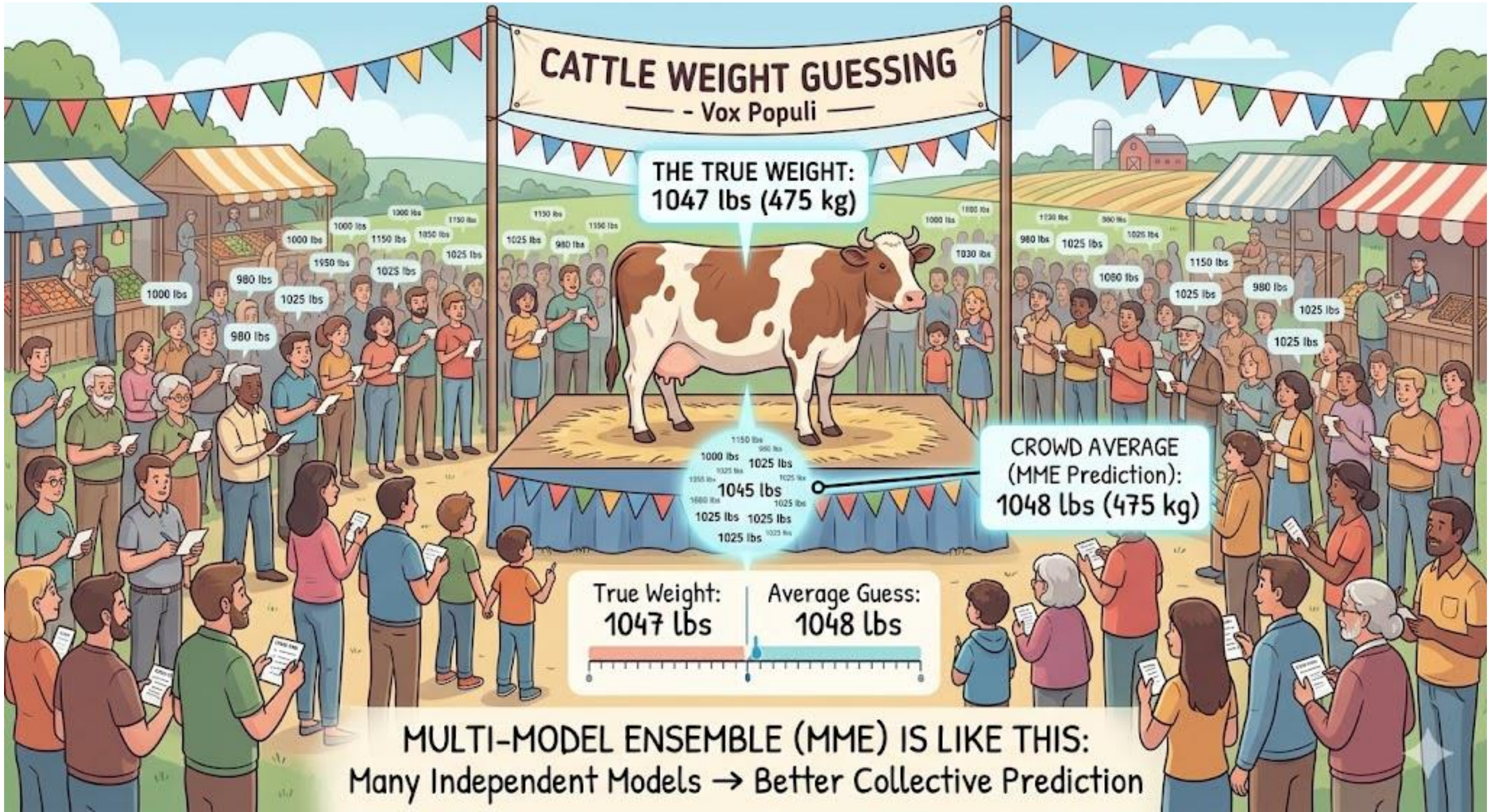
our limitation

~~nature's tricks~~

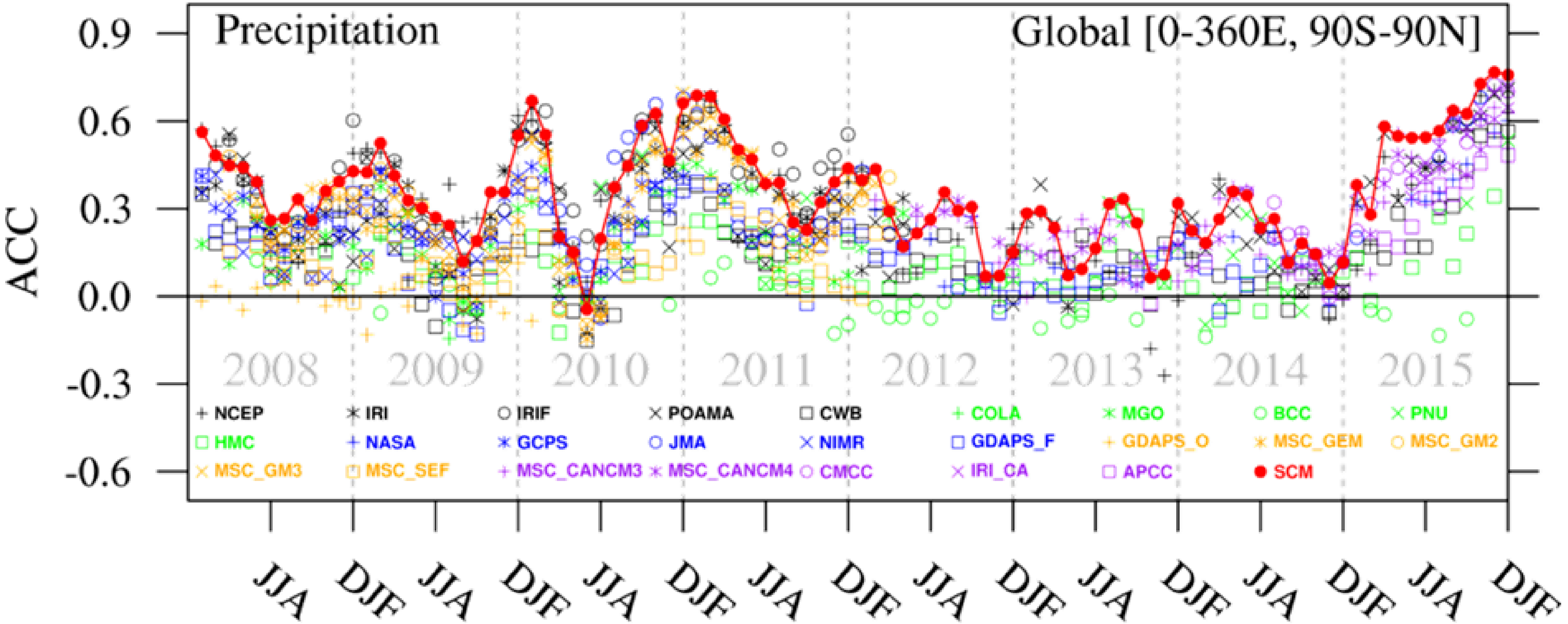
- The ensemble prediction is to consider intrinsic uncertainty associated with initial uncertainty and chaotic behavior of dynamical system.
- The multi-model ensemble is to consider model dependent uncertainty by combining different model forecasts.

Beauty of Democracy

- Independent Rational individuals :
  - Best decision for the society (in general)



How about the skill? (Single *vs* MME)



$$\boxed{R_{MM} = \frac{\langle R \rangle}{\sqrt{V(\langle y \rangle)}} = \frac{\langle R \rangle}{\sqrt{\langle r \rangle}}}$$

$$\langle R \rangle = \frac{1}{M} \sum_i R_i$$

$$\langle r \rangle = \frac{1}{M^2} \sum_i \sum_j \frac{\overline{y_i y_j}}{V}$$

Independent and good models :
Best forecast result (on average)

Operational Seasonal Forecast Models

Country	Institution	Model	Country	Institution	Model
USA	**NCEP***	CFSv2 (100km)	Canada	**MSC***	CANSIPv2 (150km)
USA	**NASA**	GEOS-S2S-2.1 (55km)	Russia	**MGO**	MGO_AM (300km)
USA	GFDL	GFDL_FLORB (50km)	Russia	**HMC***	HMC_GCM (150km)
USA	NCAR	CCSM4 (120km)	China	**BCC***	BCC_CSM (125km)
UK	**UKMO***	GloSea5 (60km)	Brazil	CPTEC*	CPTEC_GCM (100km)
EU	ECMWF	SEAS5 (36km)	South Africa	SAWS*	SAWS_EPS (300km)
Germany	DWD*	GCFS2 (100km)	Taiwan	**CWB***	GFST119 (120km)
France	**Meteo France ***	MF_SYS7 (50km)	Korea	**KMA ***	GloSea5 (60km)
Italy	**CMCC**	CPS3 (100km)	Korea	**APCC**	SCOPS (80km)
Japan	**JMA ***	JMA-CPS2 (80km)	Korea	**PNU-RDA**	PNU_CGCM (300km)
Japan	**JAMS**TEC	SINTEX-F (125km)	Australia	**BoM***	ACCESS-S2 (60km)

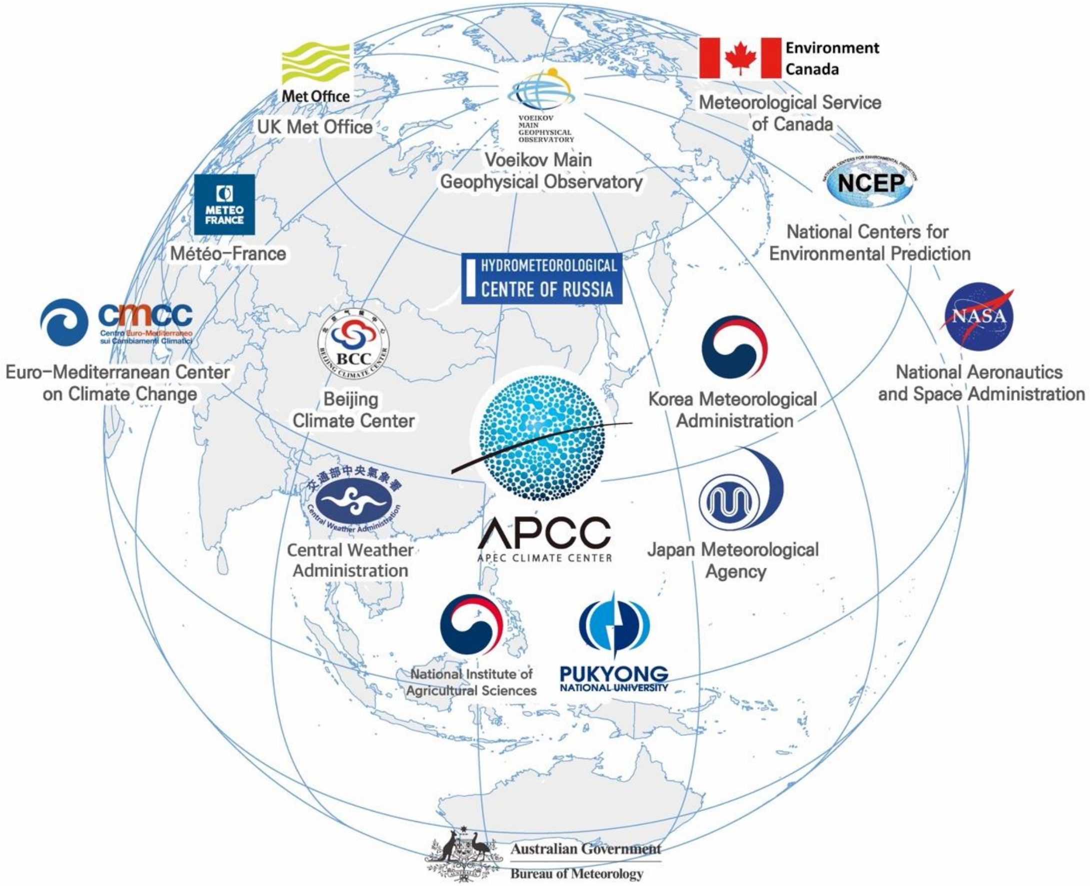
and More..

APEC Climate Center

- Established in 2005 by indorsement of 21 APEC economies

  aims "enhancement economic opportunities, reduction of economic loss and protection of life and properties through: exchange of data, producing skillful prediction, targeted research and capacity building… "

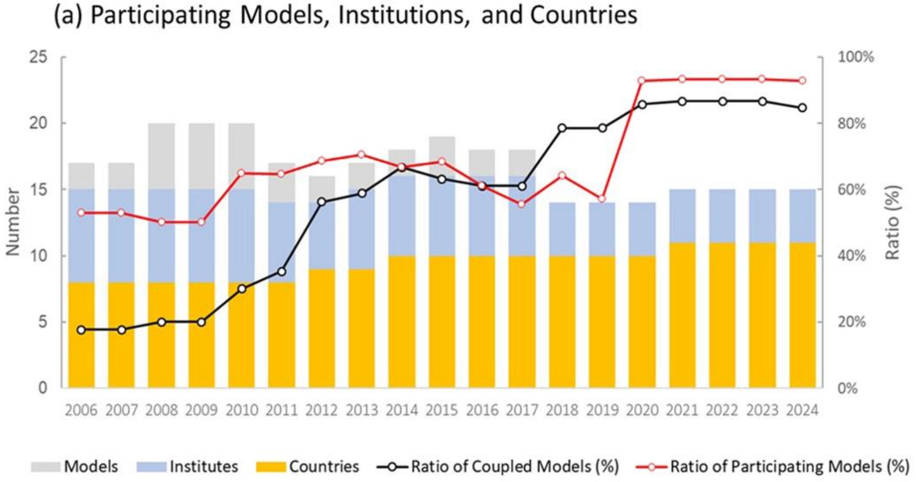
  It was institutionalization of APCN (Network) project since 1998

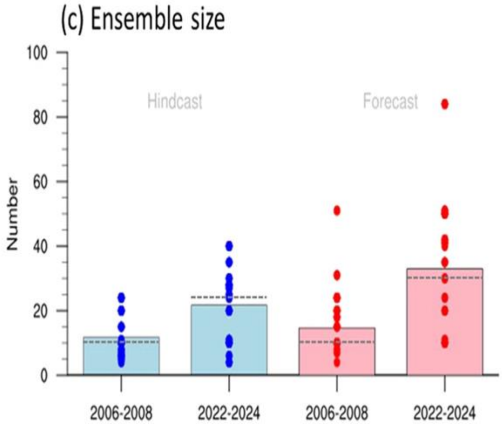


Multi Model Ensemble participating groups:
10 Countries/16 Organizations

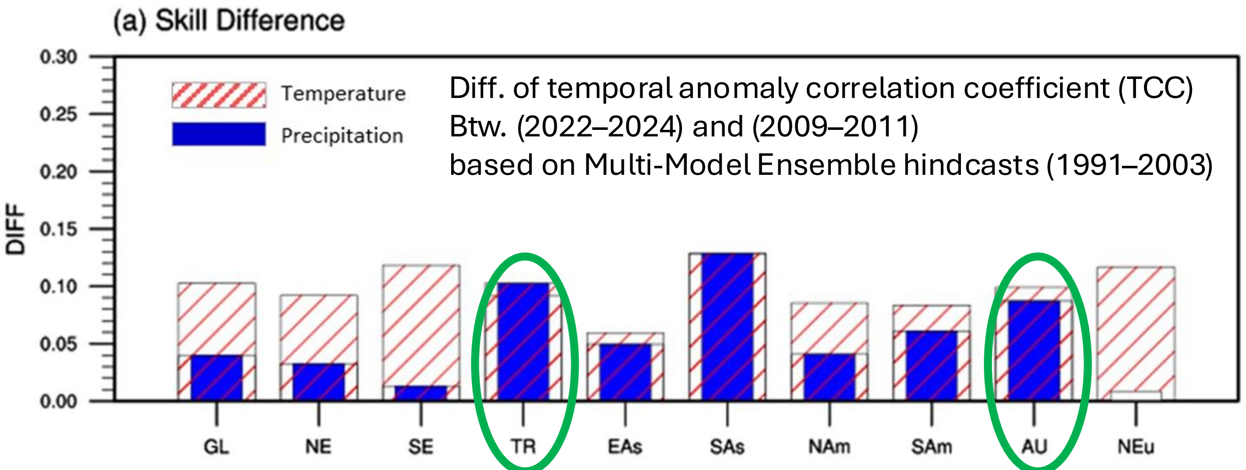
APCC-MME seasonal prediction

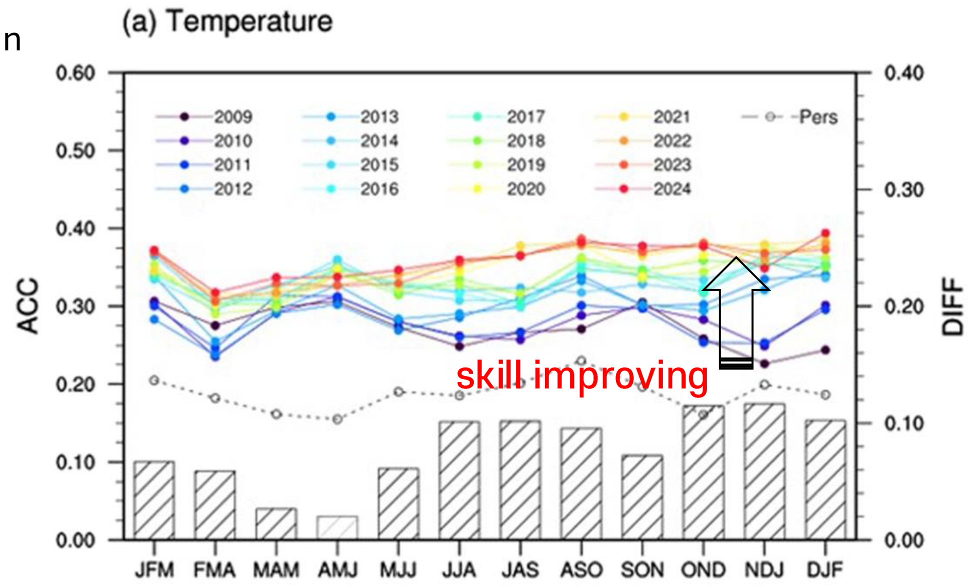
Min et al. (2025) A Diachronic Assessment of Advances in Seasonal Forecasting: Evolution of the APCC Multi-Model Ensemble Prediction System Over the Last Two Decades, GRL

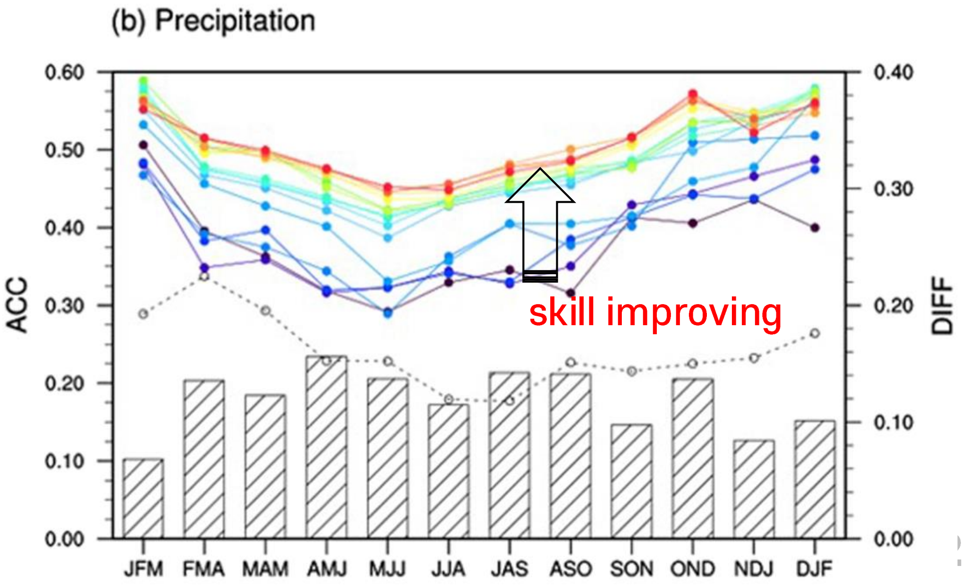




Collective improvement of prediction models
(participating group has been changed, better models, more models..)



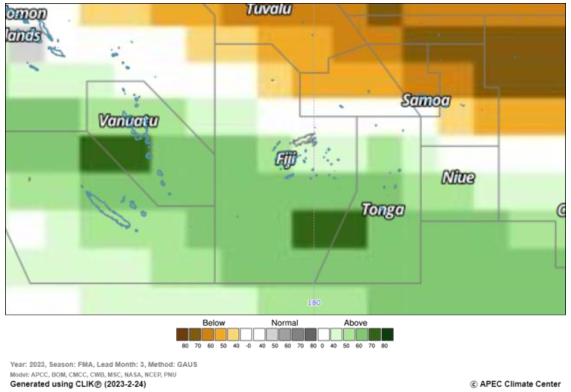




II. PICASO

Tailoring climate information

No one lives in ‘global mean’ condition!



- Transforming information to enhance salience (and credibility)
  - Scale : Climate info. >> user interest
    - ✓ Statistical Downscaling
  - Form (output) : lack of knowhow to use the info.
    - ✓ impact modeling
    - ✓ analysis of model output

PICΛSO: hybrid seasonal prediction

PICΛSO was developed through ROK-PI CliPS#1

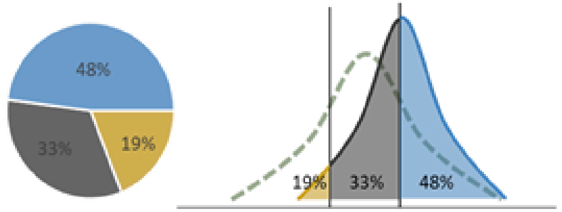
“Pacific Island Countries Advanced Seasonal Outlook”

Hybrid downscaled seasonal prediction system

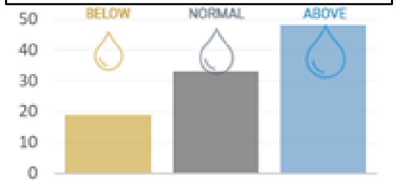
- Dynamical: Multi-Model Ensemble (APCC-MME) seasonal prediction system
- Statistical: empirically tailored by experts and customized to your station

world’s most skillful seasonal prediction system

tailored & customized



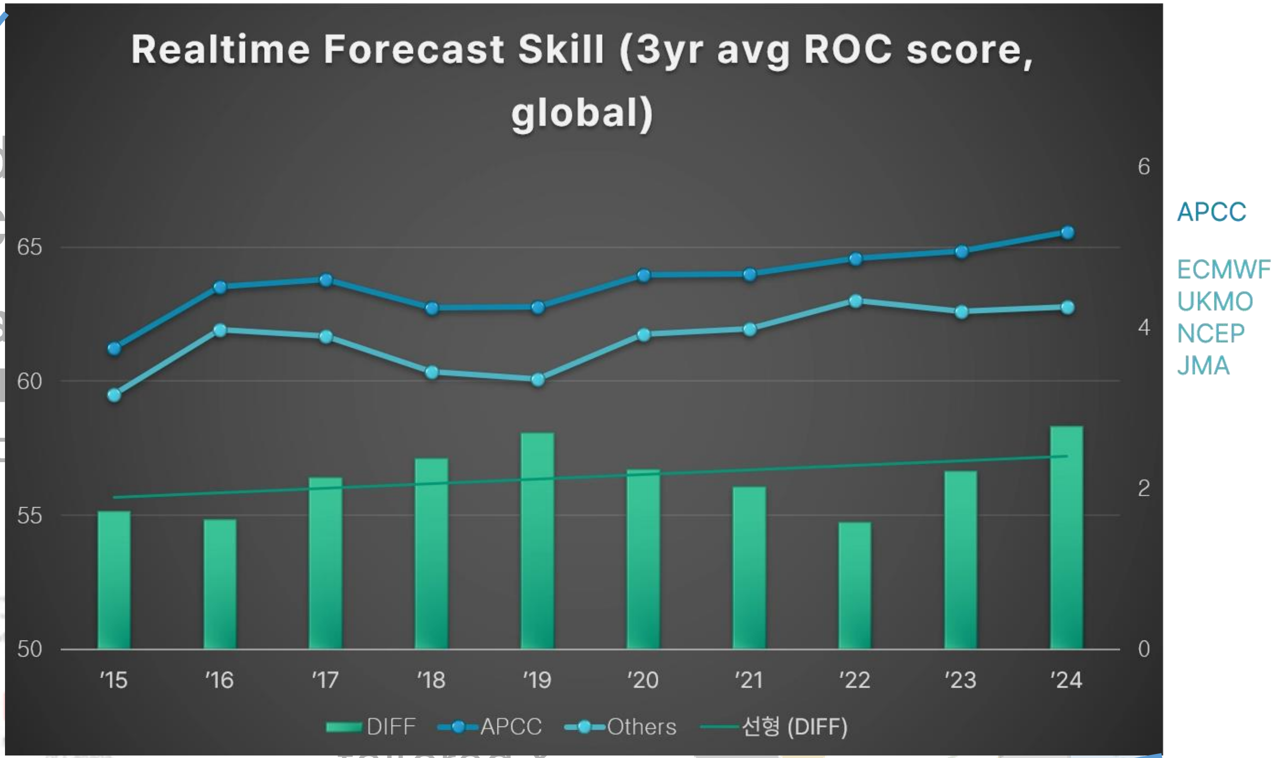
station-level



PICΛSO: hybrid seasonal prediction

PICΛSO was developed
“Pacific Island C

Hybrid downscaled sea
- Dynamical: Multi-Model
- Statistical: empirically t



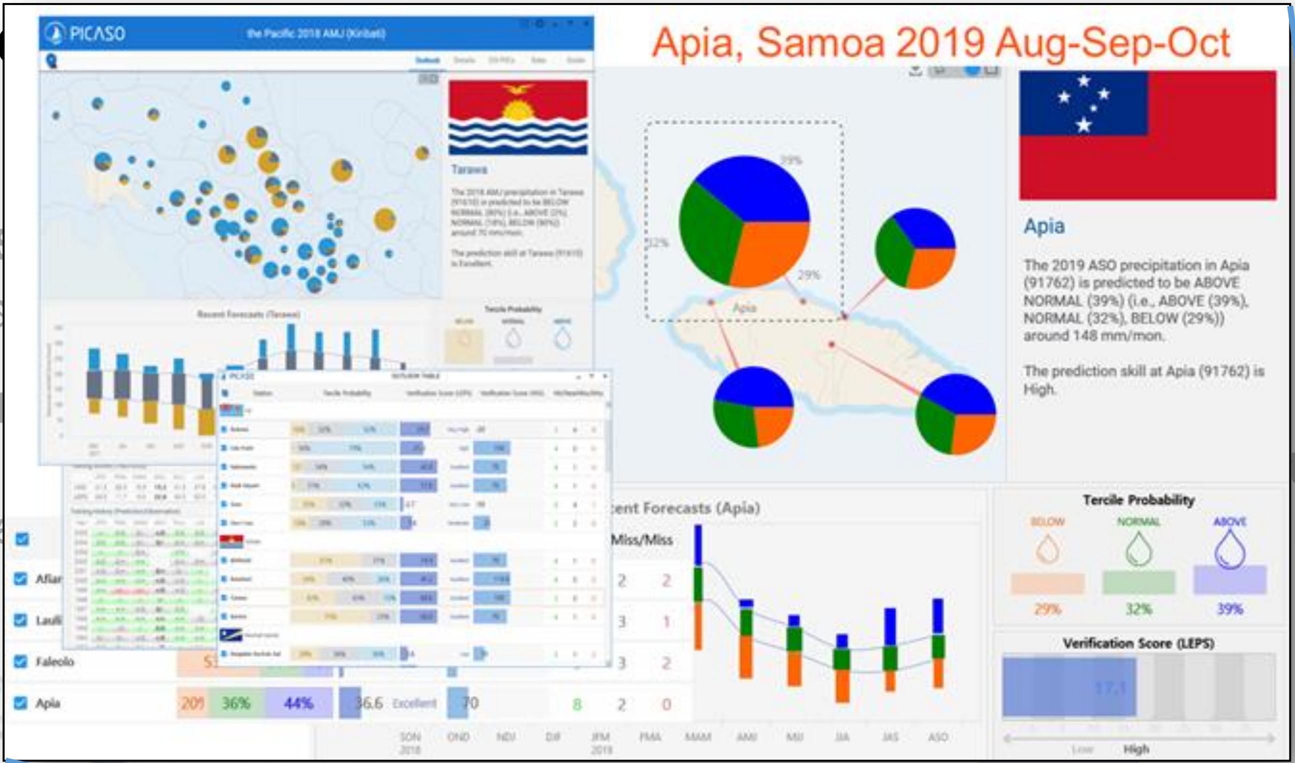
world’s most skillful seasonal prediction system

tailored &

customized

station-level

PICΛSO: hybrid s



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Hybrid dow

- Dynamic
- Statistica

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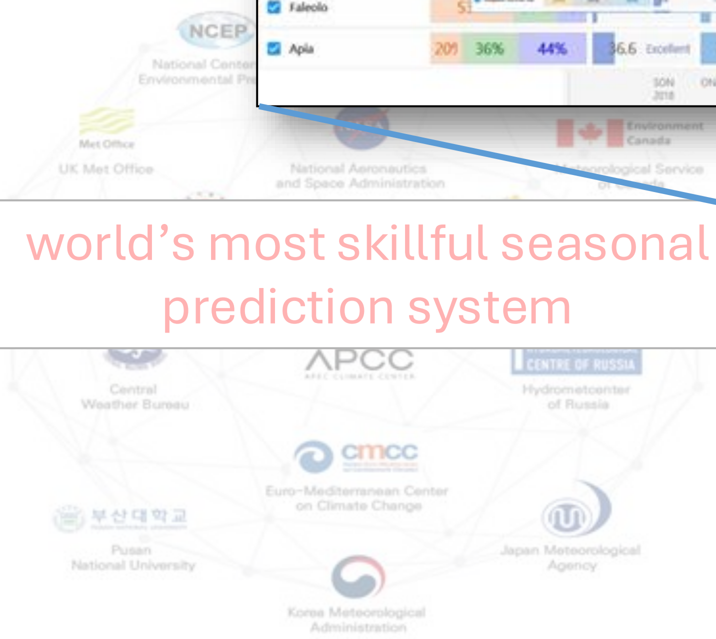
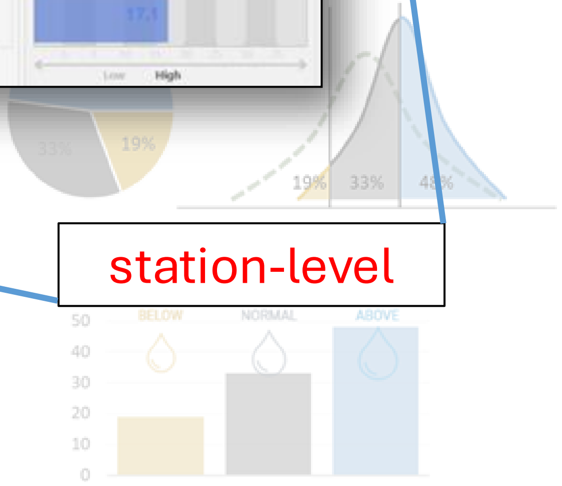


world’s most skillful seasonal prediction system

tailored &

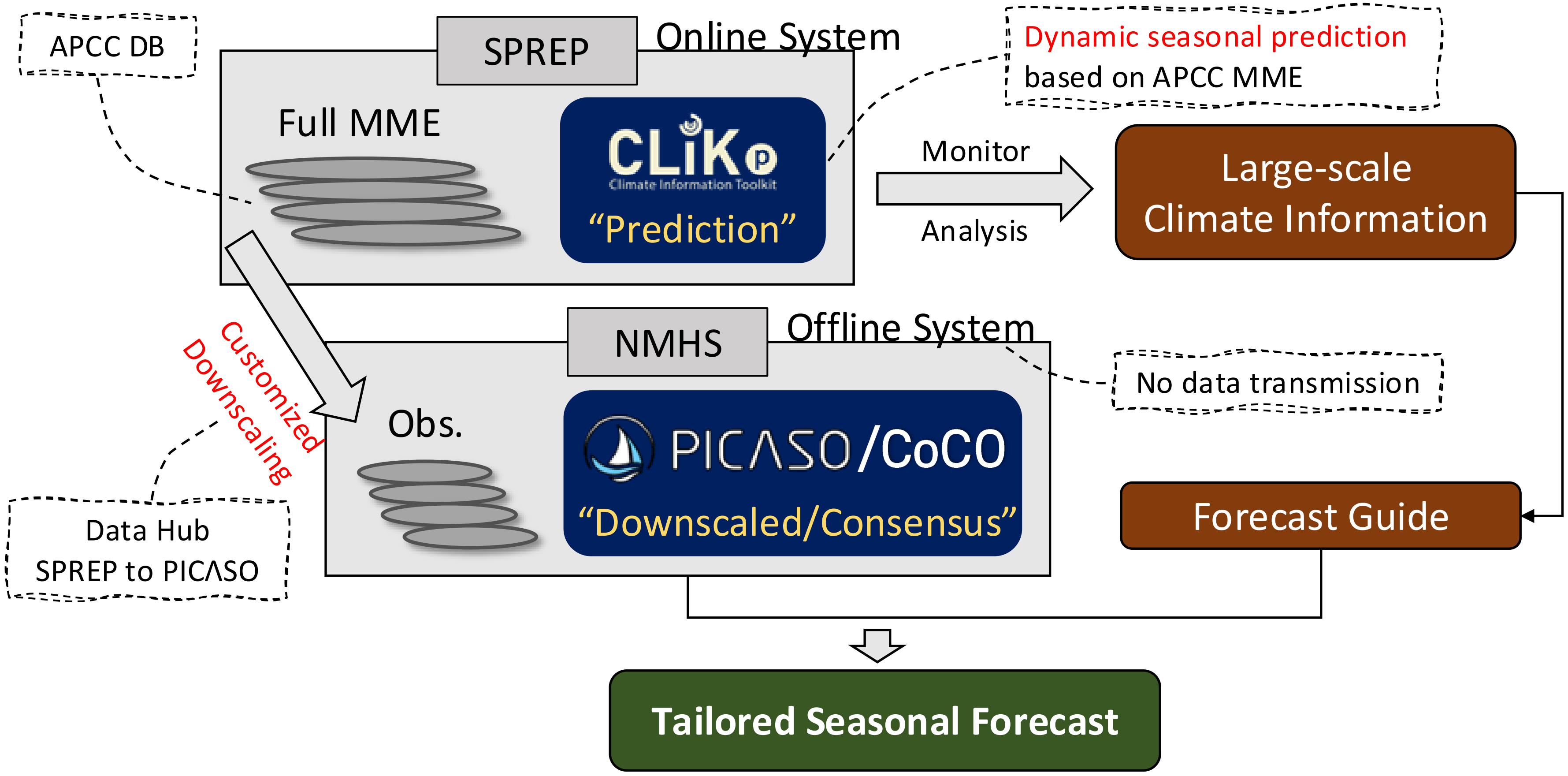
customized



station-level

System Structure

CLiK®: customized dynamic seasonal prediction based on APCC-MME



PICΛSO Strategy

Past

Now

Current Climate

Dynamical Prediction

Future

Predicted Climate → Predicted Rainfall

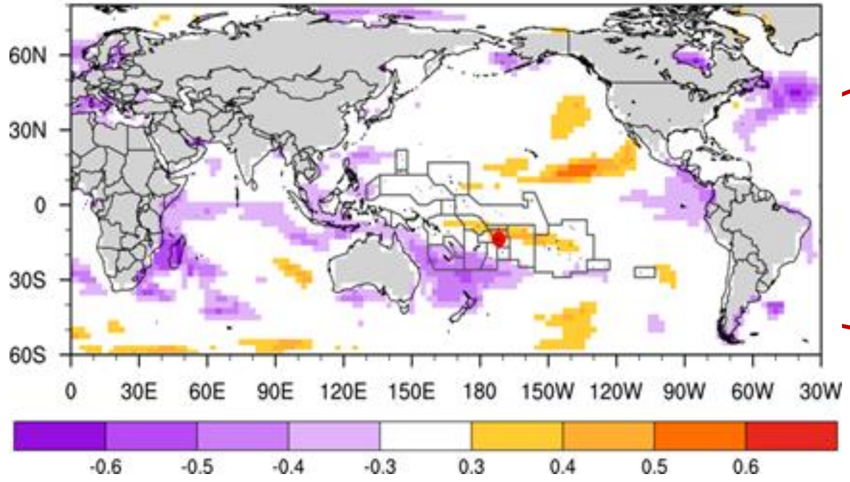
Dynamical prediction is based on
the physical laws that govern the relationship and
simulates (predicts) the "future climate."

PICΛSO further tailors "predicted climate"
onto
"predicted rainfall" at a given site.

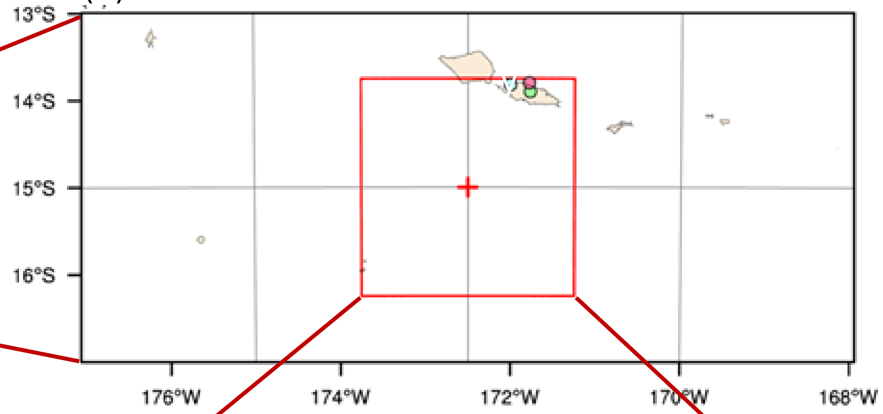
Bringing dynamical MME to your home

Why do we need tailoring?

(a) Model representation of the relationship

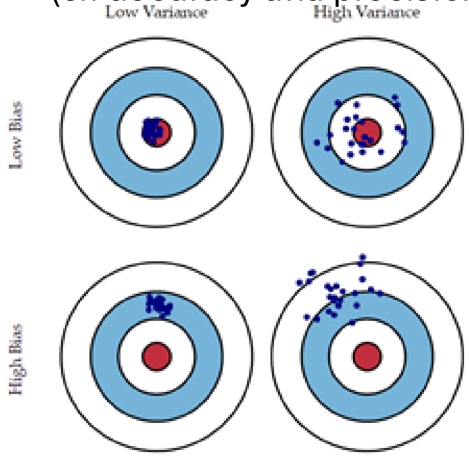


(b) Coarse model resolution

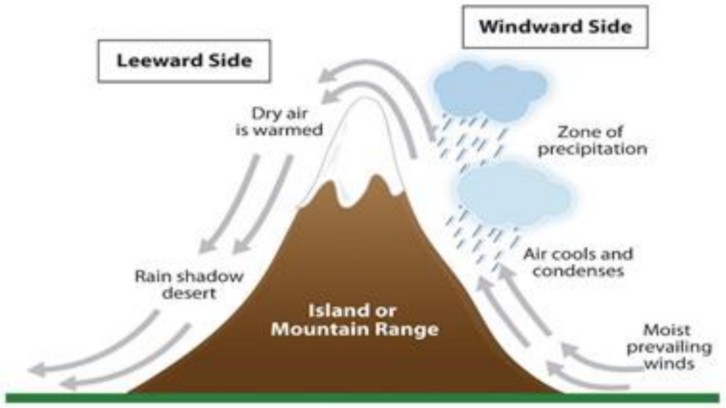


(e) Bias

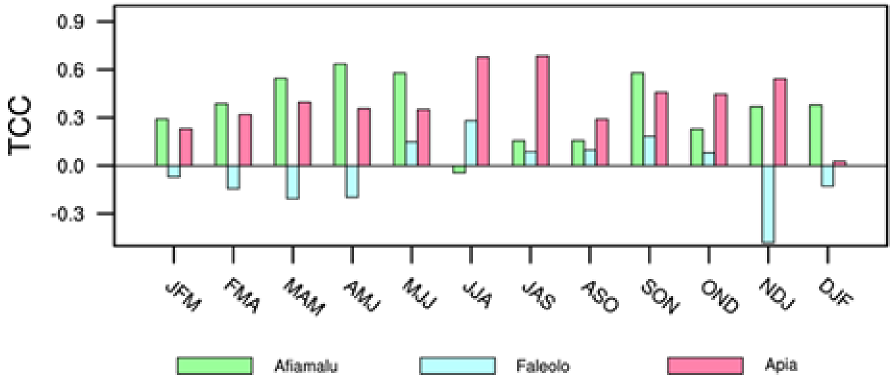
(*cf.* accuracy and precision)



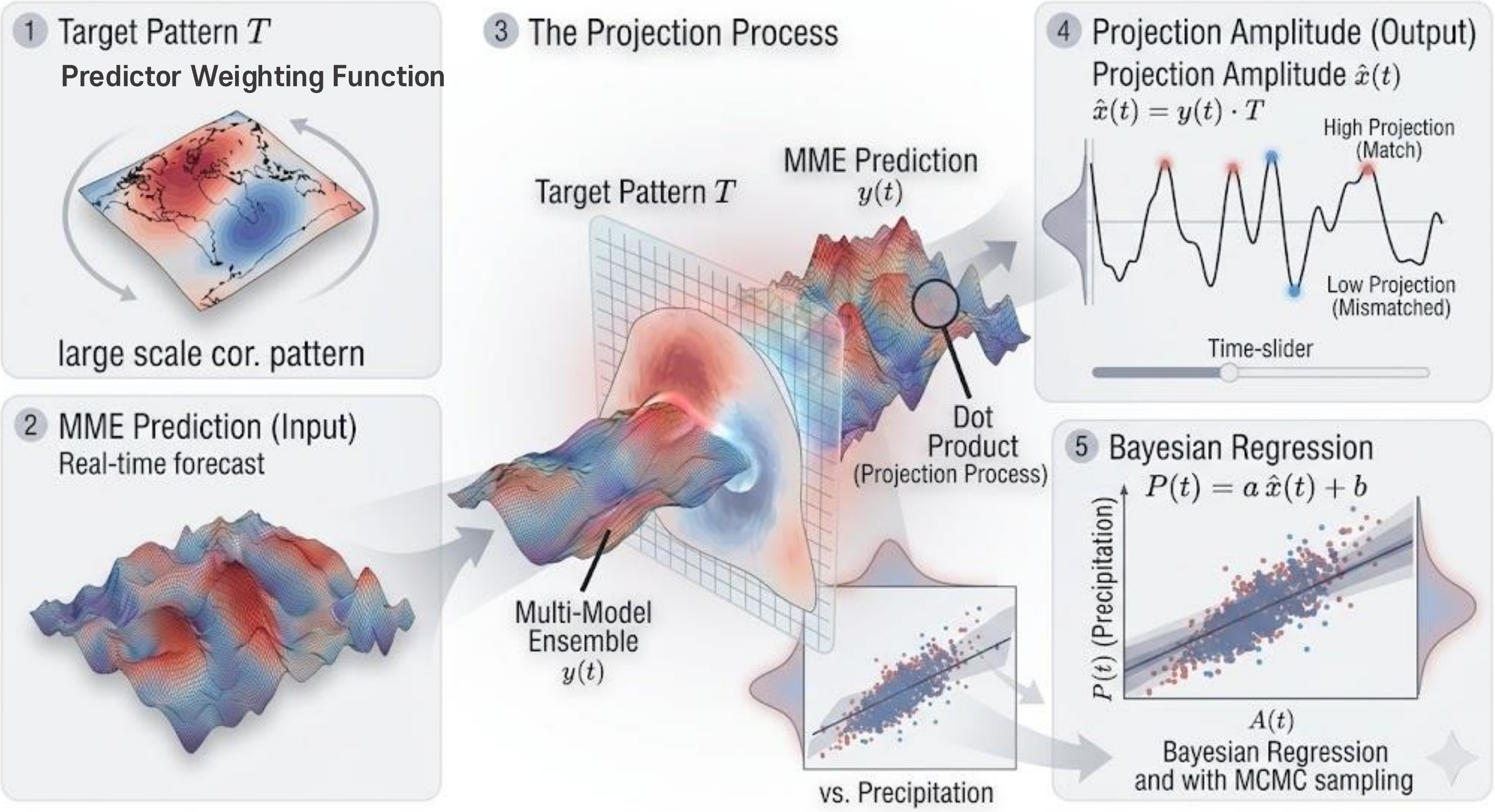
(c) An example of local effect (topography)

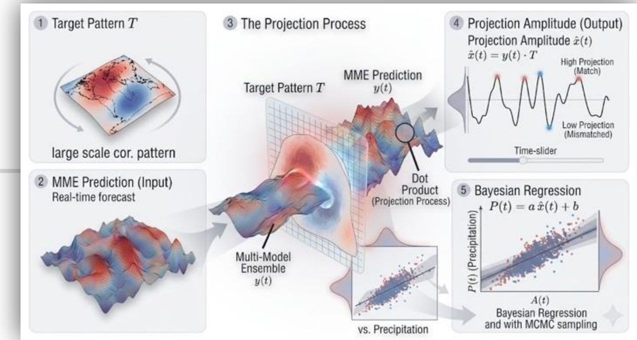


(d) Simulation skills



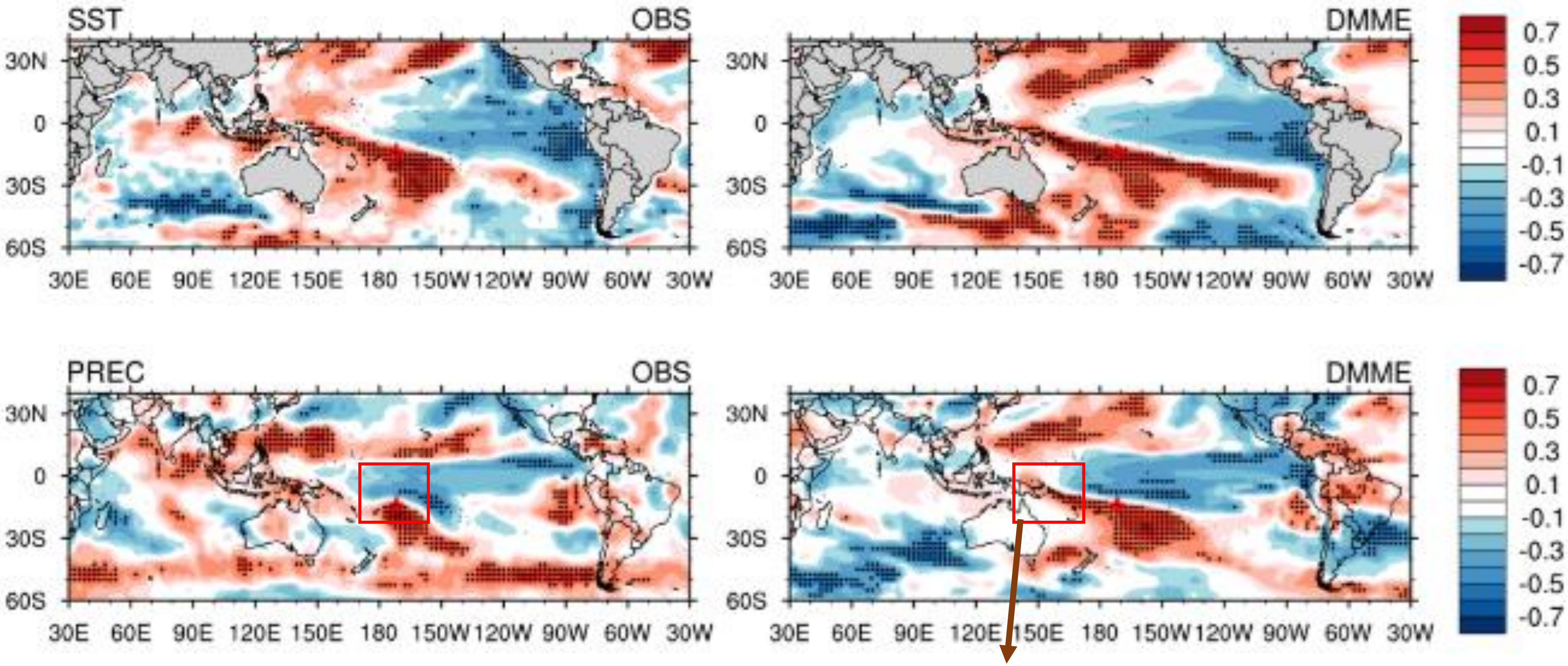
Tailoring procedure : from MME to local





❶ Identifying the Predictors (OBS *vs* MME)

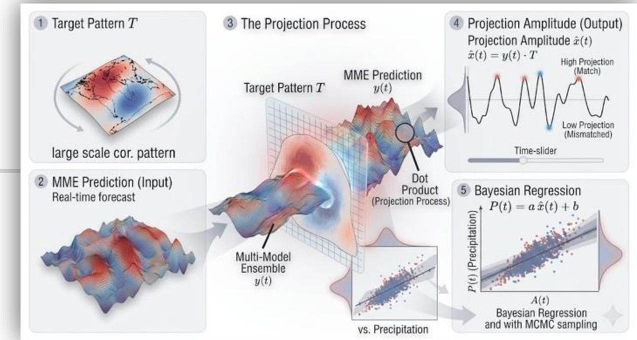
Observed relationship **Simulated relationship**



Large scale Predictor for rainfall (+)

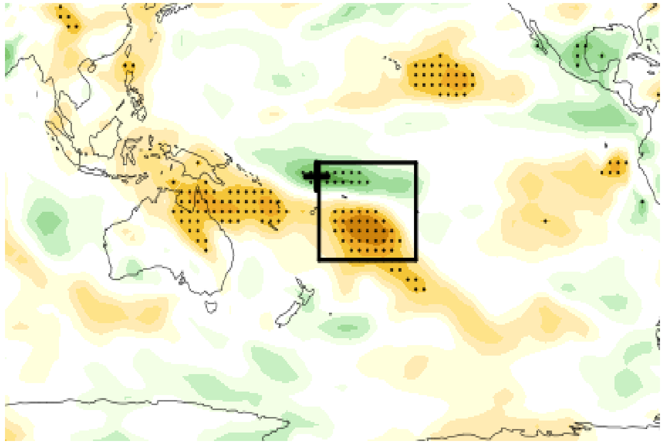
$f(y) \to \hat{x}$

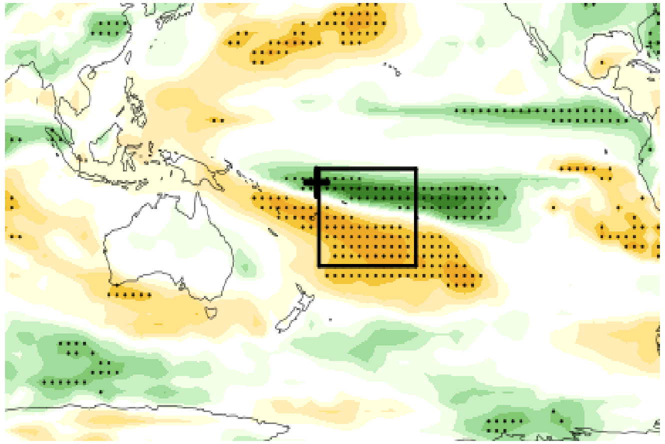
ex) Apia, Sep–Nov



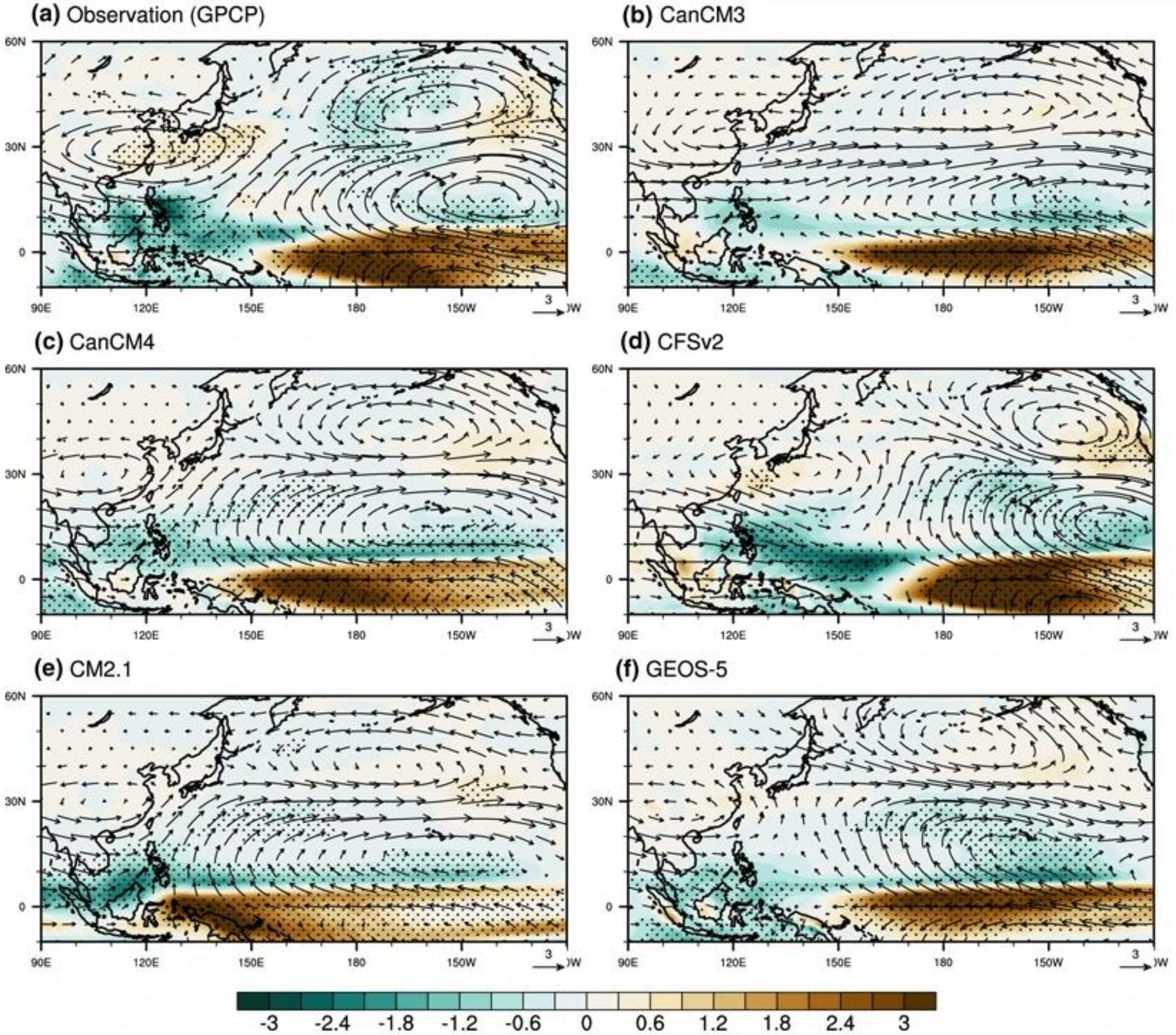
Also consider bias

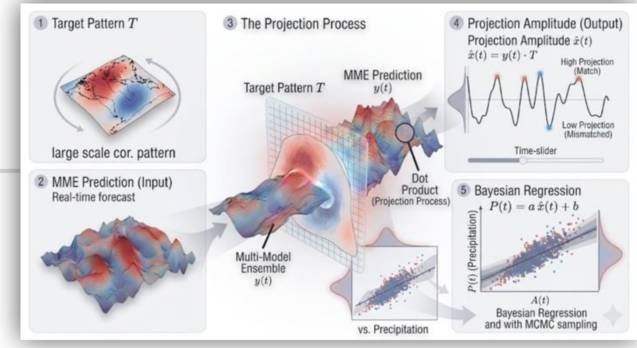
- **Correlation map of global precip. with station rainfall**





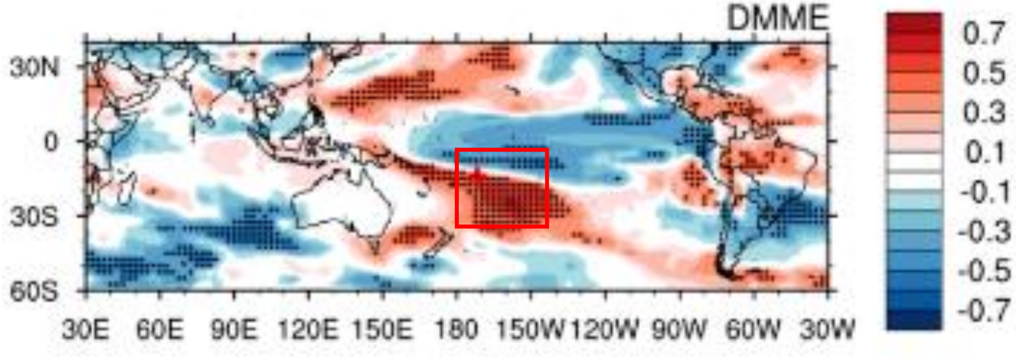
- **Rainfall associate with ENSO**





❸ Pattern Projection

Extracting the predictor ($\hat{x}$) from MME by Matrix Dot Product



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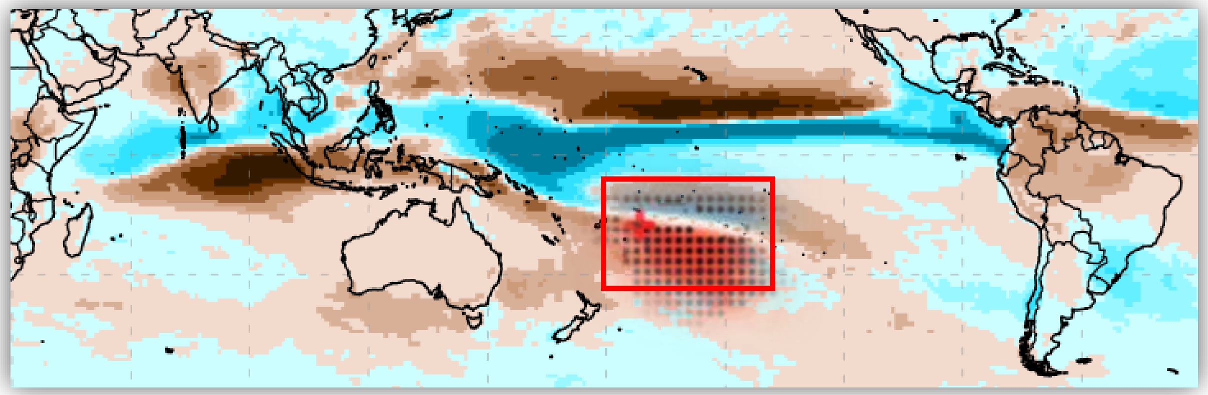
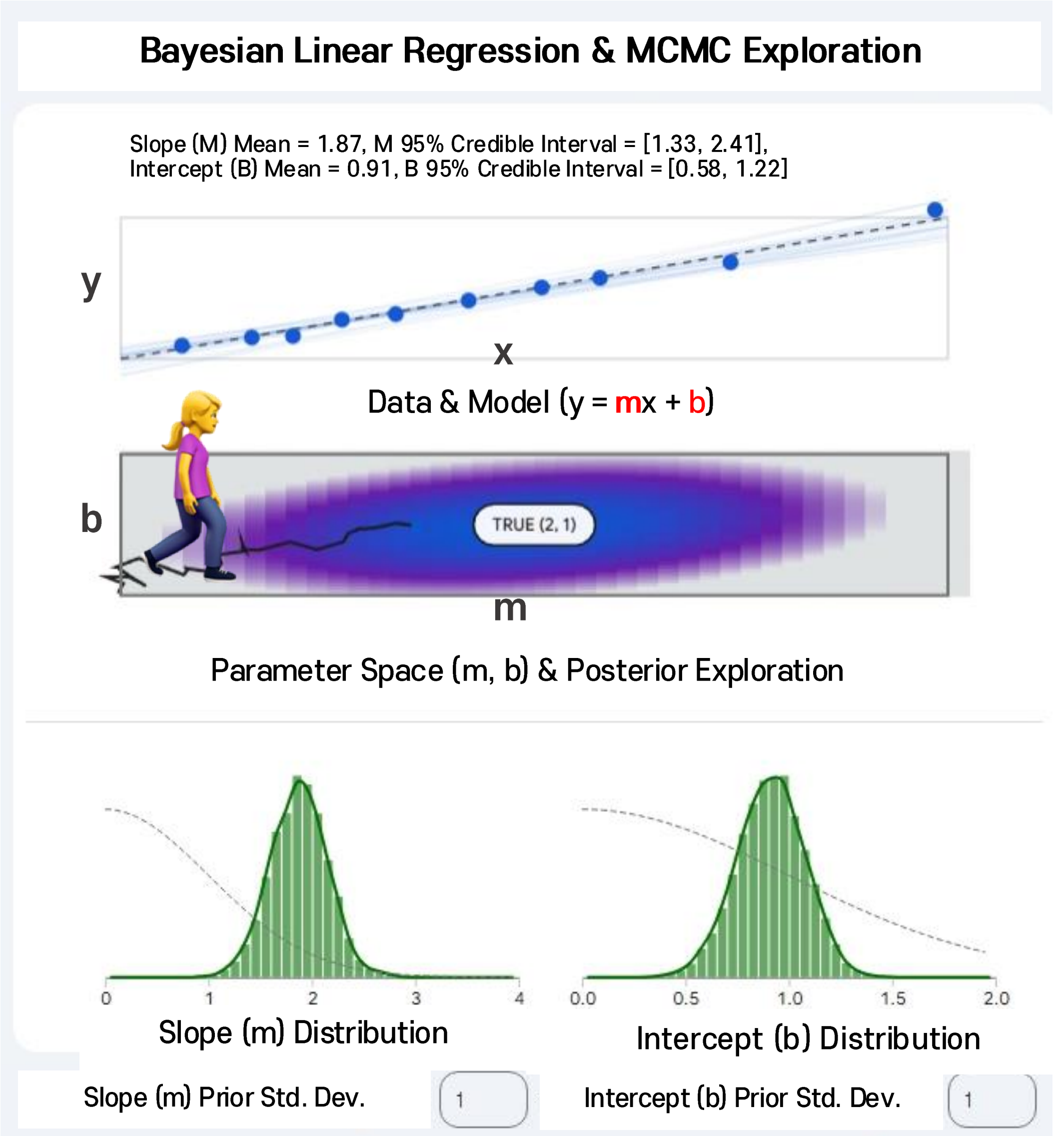


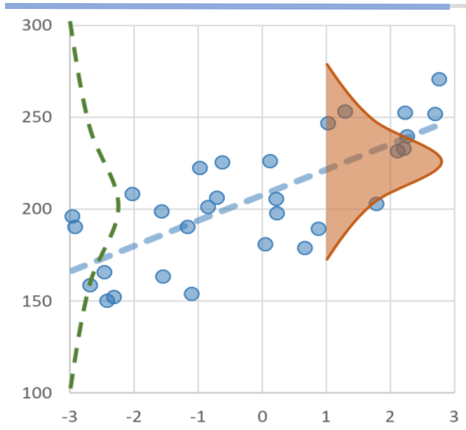
-0.2	-0.4	-0.5
0.2	0.3	0.4
0.1	0.5	0.6

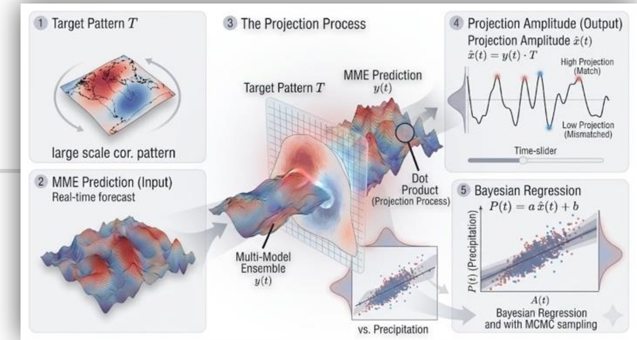
-0.3	-0.4	-0.3
-0.3	0.1	0.1
-0.2	-0.1	0.1

(-0.2x-0.3) + (-0.4x-0.4) + (-0.5x-0.3) · · · + (0.6x0.1) ➡ X

❺ Bayesian Regression by MCMC







Y = aX+b

Problem: Complex climate models make direct integration of posteriors impossible.

Solution: MCMC, A "Random Explorer" samples the parameter space to map the posterior distribution

→ **Application:** Extract parameter sets (m, b) from the map to perform ensemble predictions.

Bayesian Regression via MCMC Sampling

1.Define Priors: Set initial beliefs for parameters P(m,b).

2.Likelihood: Evaluate how well parameters explain the data.

3.Formulate **Posterior:** Posterior ∝ Likelihood × Prior.

4.MCMC Sampling: Explore parameter space via random walk to collect samples.

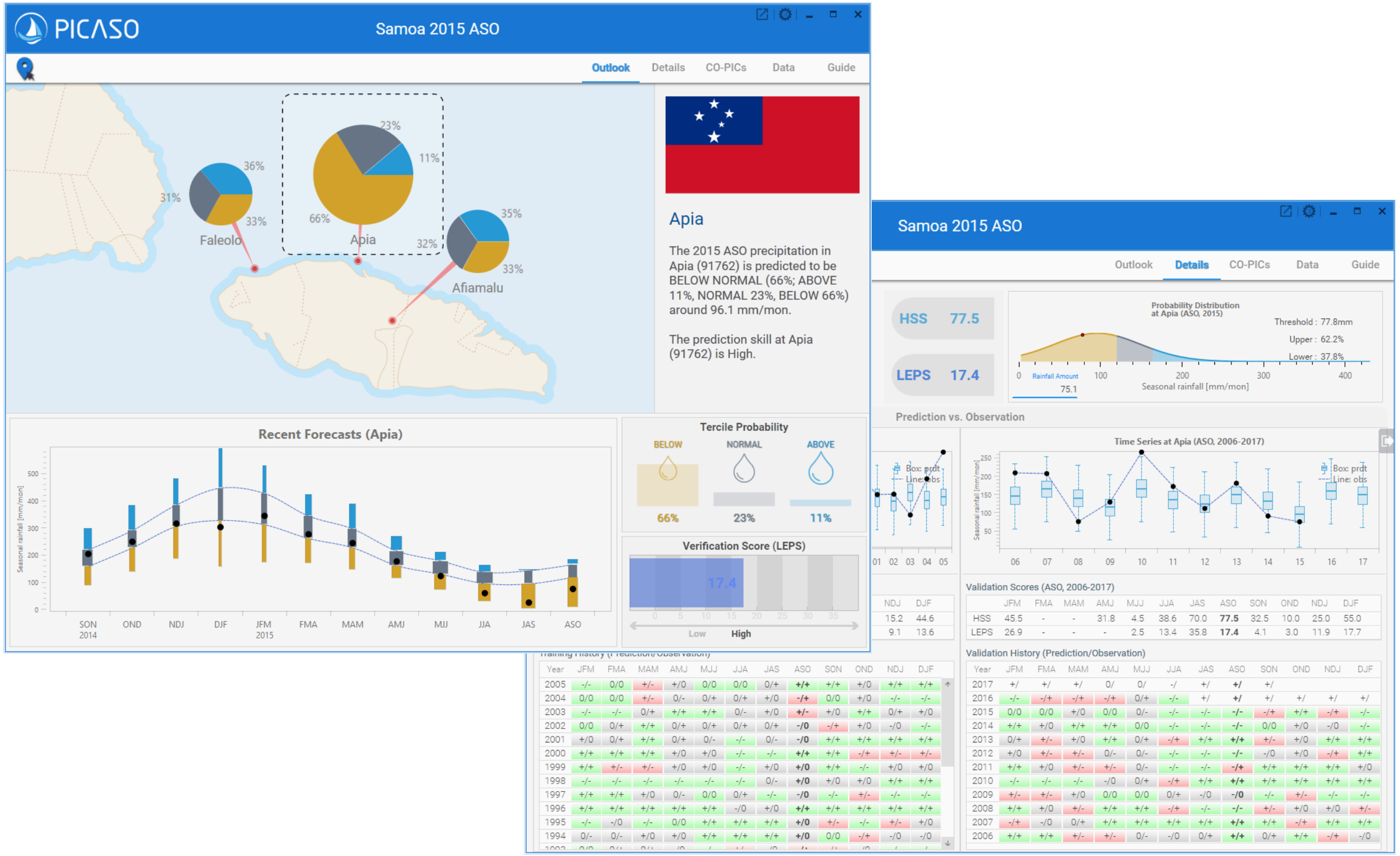
5.Approximate & Analyze: Build the final distribution and extract statistics.

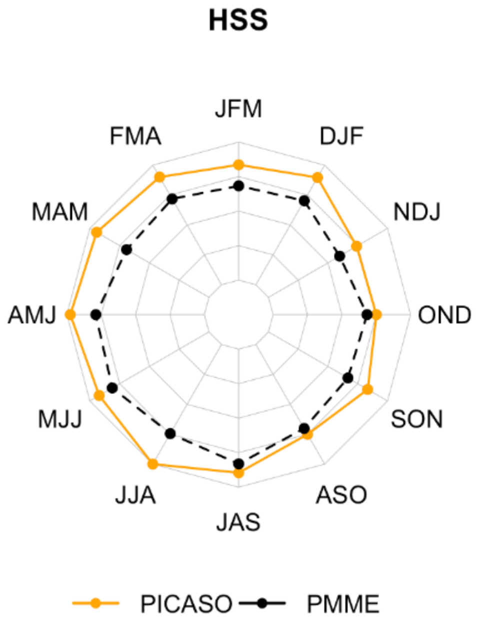
* Markov Chain Monte Carlo (MCMC, **specifically, an illustrative random walk**)

- Markov Chain: The next step depends *only* on the current state, independent of the past.
- Monte Carlo: Repeated random sampling to approximate complex probabilities.

PICASO (Pacific Island Countries Advanced Seasonal Outlook)

- Statistical Downscaling and Bias-Correction





- ✓ Covering 14 PICs
- ✓ Easy to use (hopefully)
- ✓ Minimum resource requirement (network access)

PICΛSO UX: Preview

Outlook
climate at a glance

- Tercile/Recent Forecasts
- Verification Scores
- Natural Language Outlook

Details
for experts

- Interactive Probability Scale
- Historical Forecast/Observation
- Training/Validation Scores/Table

CO-PICs
large-scale view

- ENSO/SST outlook
- Temperature/Precipitation
- Validation and Verification

Data
manage your data

- Interactive Data Management
- Import and Export

Guide
look beyond

- Detailed Application Guide
- Climate Summary

Settings
optimize the system

- Themes and Styles
- Export as PDF/PNG

Where to check information

- What is the predicted probability distribution of my location? → Outlook & Details
- How high is the prediction skill for this location/season? → Details
- Identification of predictor weighting functions → Guide
- What is the global forecast for this season? → CO-PICs + CLIKp
- I would like to generate a good-looking seasonal outlook → Settings > Exports

Thanks!

Questions/Comments?