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APEC 기후센터

2023년 APEC기후센터 기후정보서비스 사용자워크숍

기후예측 생산 및 검증

- 2023. 7. 12
- APEC 기후센터 예측운영과
- 이 현 주

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다중모델 앙상블의 이해

- 앙상블 예측이란?
- 다중모델 앙상블
- 결정론적 예측과 확률론적 예측

기후예측

6Hours **초단기 예보**

3Days **단기 예보**

10Days **중기 예보**

3Months **장기 예보**

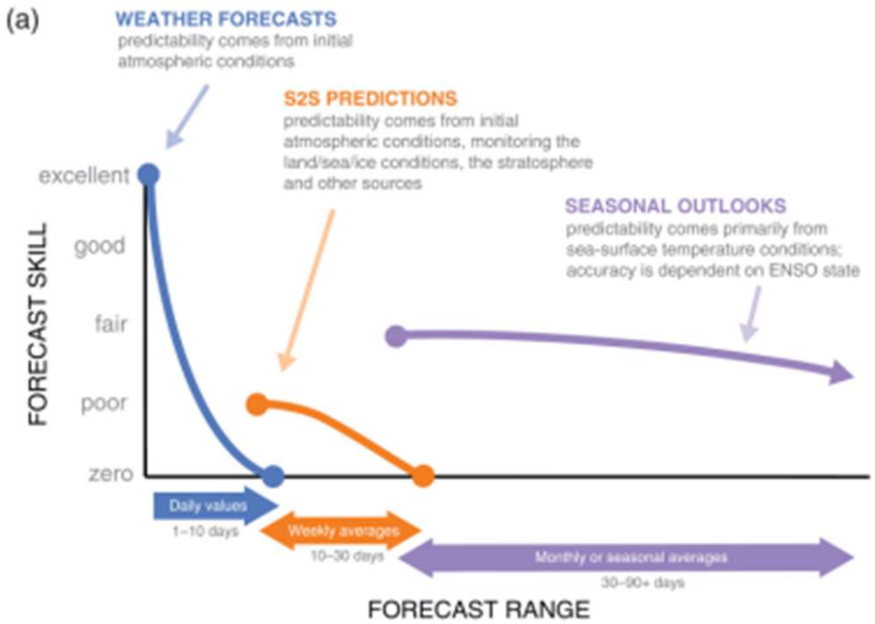
기온, 강수량

(1개월전망)
11일이후~4주까지
주별 예보
(3개월전망)
다음달~3개월
월별 예보

1Years **기후 전망**

기온, 강수량,
엘니뇨/라니냐 전망

(계절기후전망)
연 4회
(연기후전망)
연 1회



[기후예측]

- 주/월/계절 단위의 비교적 긴 시간규모에 대하여 평균 대비 경향성 예측
- 즉, 과거에서 기대할 수 있는 날씨 상태에 비해 미래의 날씨 양상이 어떠할 것인가?

기후예측 방법

경험적 방법

- 과거 자료를 이용해 대상지역 기후변동과 관련있는 인자를 추출·이를 이용한 예측
  (예: 라니냐→건조한 가을)
- 모든 경우에 적용이 가능하지 않음. 가용자료의 한계, 기후변화에 취약

역학적 방법

- (1960, 70년대) 과학적 기반 연구
- (1986) 최초 해수온 장기예측
- (90년대 후반) 기후모델 이용한 예측 시작
- (현재) 전 세계 20여개 모델 운영 중
- (50년대) 기상모델을 이용한 일기예보

- 대기/해양의 움직임을 나타내는 물리방정식을 컴퓨터 프로그램(기후모델)을 통해 해석, 미래를 예측
- 기후모델이 완벽하지 않음
  (초기조건, 모수화, 해상도 등)

* 기후모델을 이용한 기후예측은 상대적으로 늦게 시작한 예보 기술이나 현재 기후예측의 주류 기술

수치예보

모든 관측 자료

슈퍼컴퓨터 (계산)

예측값 생성

정보 전달

[수치예보 모델]

- 운동방정식
- 질량보존방정식
- 열역학 방정식
- 지배방정식

But, 단일 수치예보의 한계

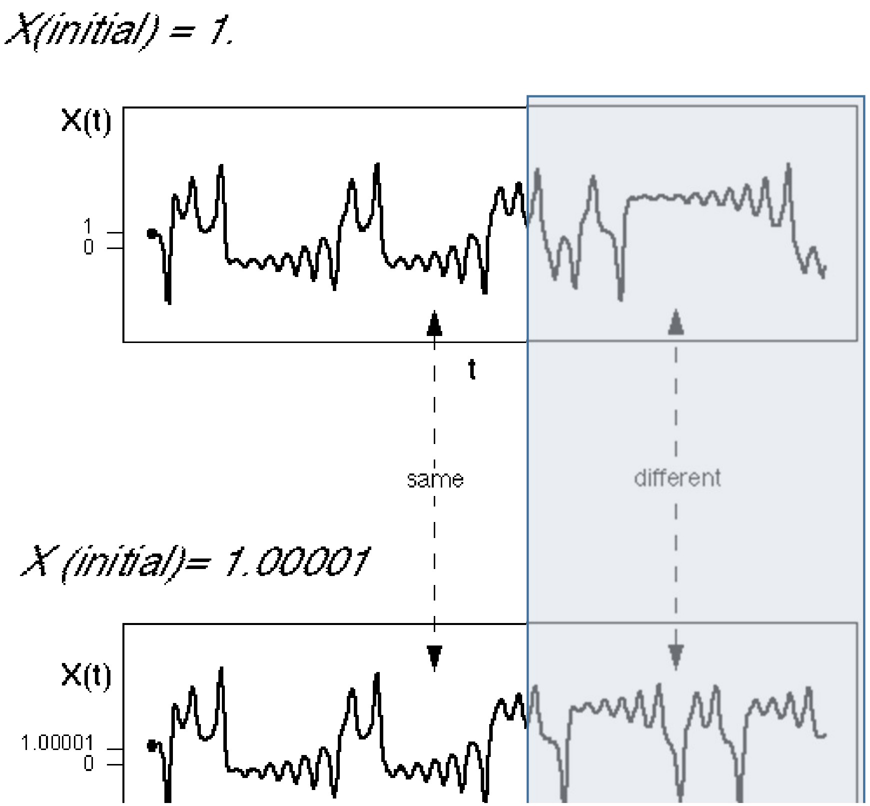
측정이 불가능한 미세한 요동 + 초기 관측값의 오차

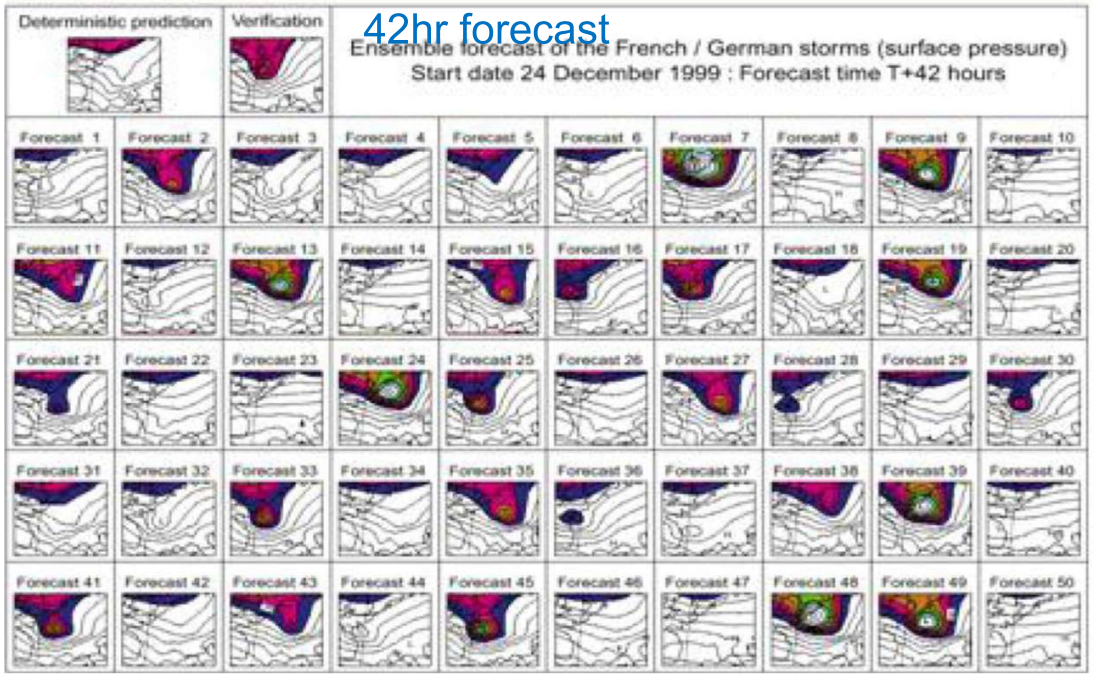
모델의 예측시간이 길어질수록 예측 편차가 커짐

하나의 모델에 의존하여 예측하면, **큰 오차 발생 가능성** 大

출처 : 기상청

카오스





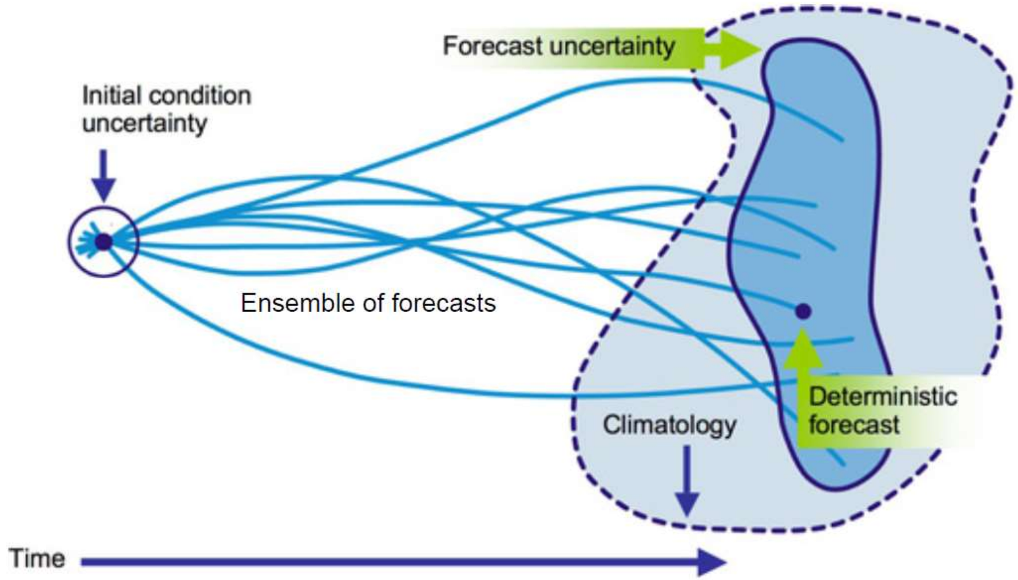
Our knowledge of climate model and initial condition **is not never perfect !**

→ **Perfect forecast is impossible.**

앙상블예측

앙상블 예측의 기본 접근법

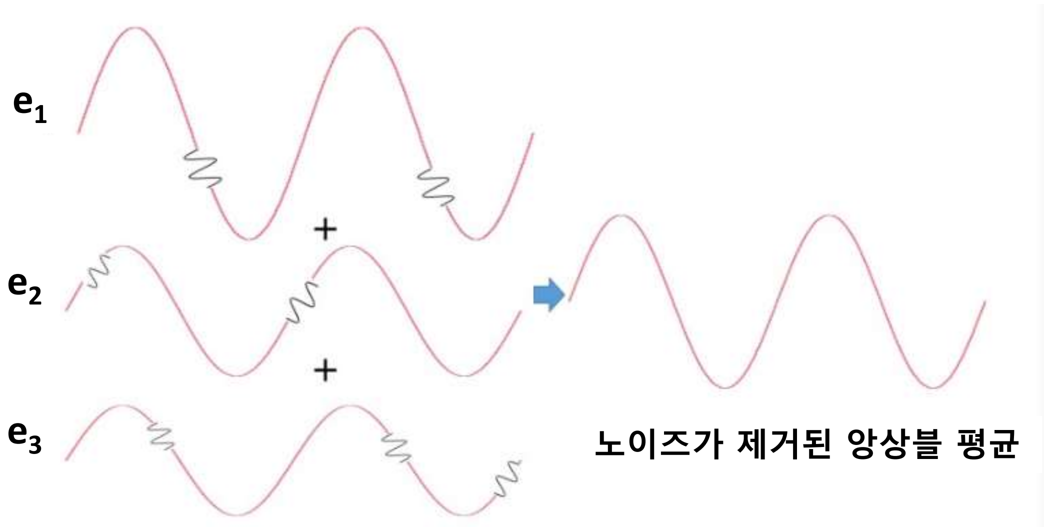
- 카오스 이론은 초기 조건과 모의결과에는 항상 불확실성 있다고 주장
- 하나의 모델을 실행시키면 가능한 다양한 해 중에서 하나의 해만 산출됨
- 서로 다른 예보 상태에 대한 확률을 추정하기 위해서는 많은 수의 모델을 실행시켜야 함
- 다양한 모의결과들은 대기의 예측 가능성에 대한 척도를 제시할 것
- 다양한 모델결과들을 분석하면 가장 가능성이 높은 대기 상태를 찾는데 도움이 될 것



극히 작은 값의 차이가 "초기값의 민감도"에 의해 커다란 차이를 만든다.

(에드워드 로렌츠, 결정론적 비주기 흐름, 1963)

앙상블예측



앙상블 멤버들의 시그널(Signal, 빨간실선)과 노이즈(Noise, 검은 실선)

Signal >> Noise : more predictable

Signal << Noise : less predictable

출처 : 기상청

다중모델 앙상블 예측

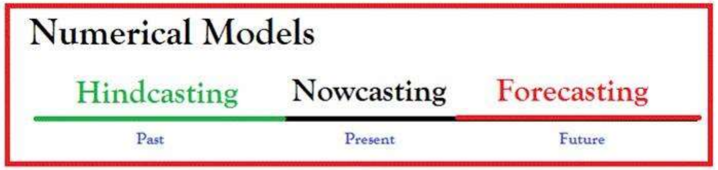
잡음 감소 (Random Noise)	계통오차 감소 (Systematic Error)
More samples : Ensembles	Cancellation of errors : Multi-Model

다중모델 앙상블(MME) 기법

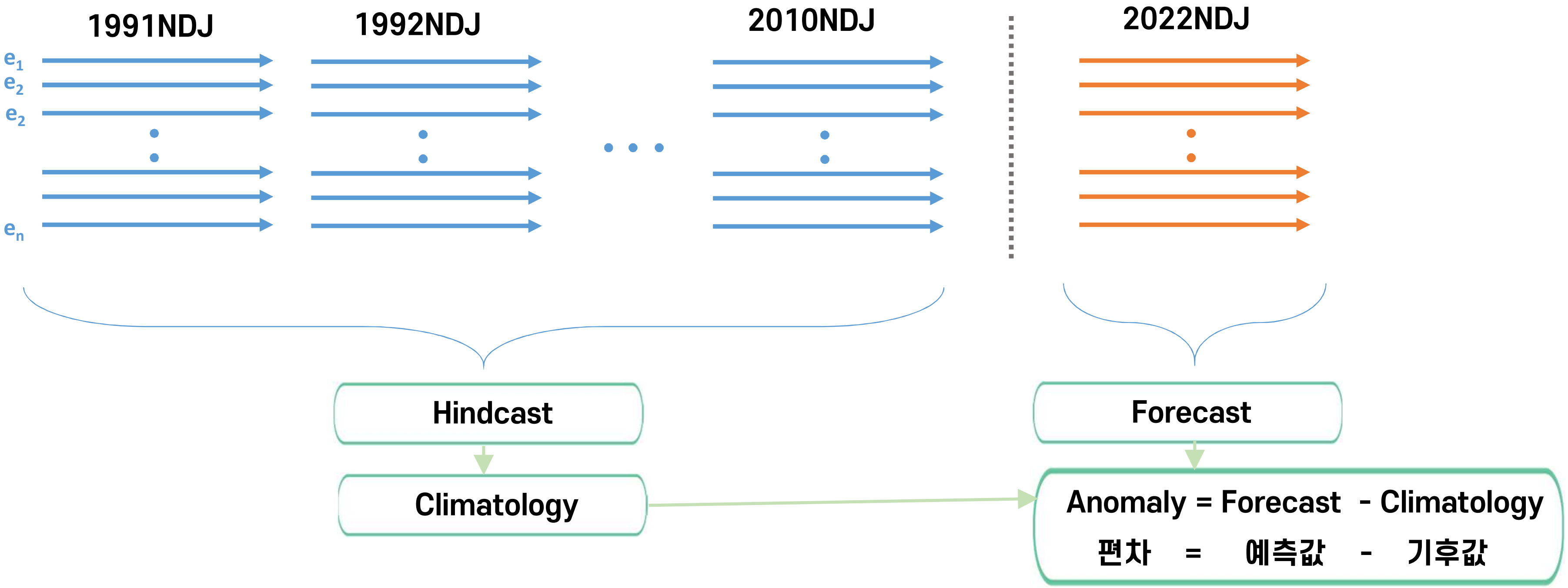
- 1990년대 시작: Krishnamurti 등
- 기후모델 분야의 집단지성
- APCC(2005~, 15개 모델), WMO-LC(2009~, 14개 모델), NMME(2011~, 6개 모델), EUROSIP(2005~, 6개 모델)

Hindcast & Forecast

<Siva Reddy, 2015, A study on global ocean analysis from an Ocean Data assimilation system its sensitivity to observations and forcing fields>



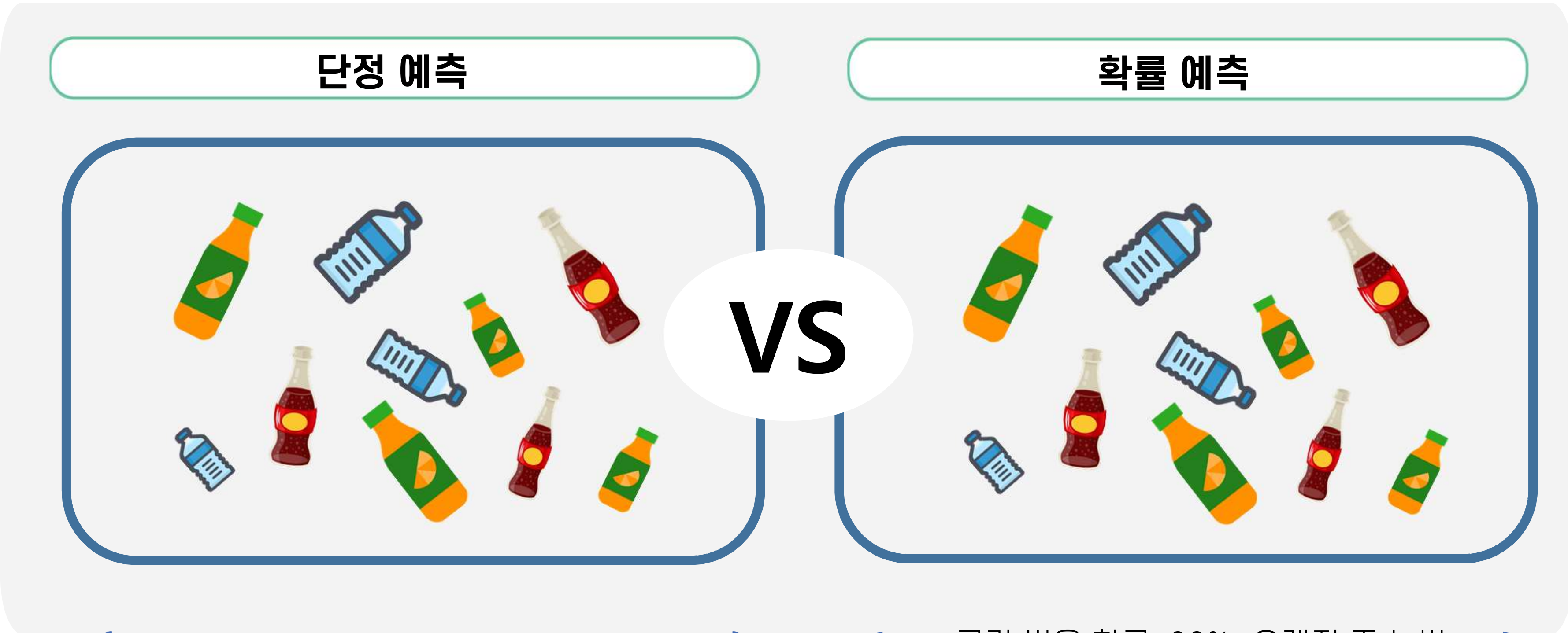
- Hindcast(Retrospective forecast)
  - 평년기간, climatology
- Forecast(real-time forecast)
  - 실제 예측



※ 개별모델별로 다름, APCCMME 공통기간 (1991-2010)사용 , 25년까지 대부분 2020년까지 확장 계획

단정 예측 vs. 확률 예측

상자에서 음료수 1개를 꺼낸다면??



[오렌지 주스를 뽑을 것으로 전망됨]

[콜라 뽑을 확률 30%, 오렌지 주스 뽑을 확률 40%, 물 뽑을 확률 30%로, 오렌지 주스를 뽑을 가능성이 높음]

출처 : 기상청

다중모델 앙상블 기법

[단정예측]

SCM	SPM	MRG	SSE
(Simple MME) Simple Composite Method	**(Calibrated MME)** Step-wise Pattern Projection Method	**(Weighted MME)** Multiple Regression Method	**(Weighted MME)** Synthetic Multi-Model Super Ensemble Method
• Simple composite of individual forecast with equal weighting	• Calibrated MME which is obtained from the adjusted (or corrected) single-model forecasts based on a stepwise pattern projection method (Kug et al. 2008)	• Empirically weighted MME with coefficient computed by multiple linear regression (Krishnamurti et al. 2000)	• Same as MRG, but with EOF-filtered dataset (Yun et al. 2003)
$P=\frac{1}{M}\sum_i F_i'$	$P=\frac{1}{M}\sum_i \hat{F}_i'$	$P=\sum_i a_i F_i'$	$P=\sum_i a_i \hat{F}_i'$

다중모델 앙상블 기법

[단정예측]

- **SCM:** simple averaged MME with equal weight

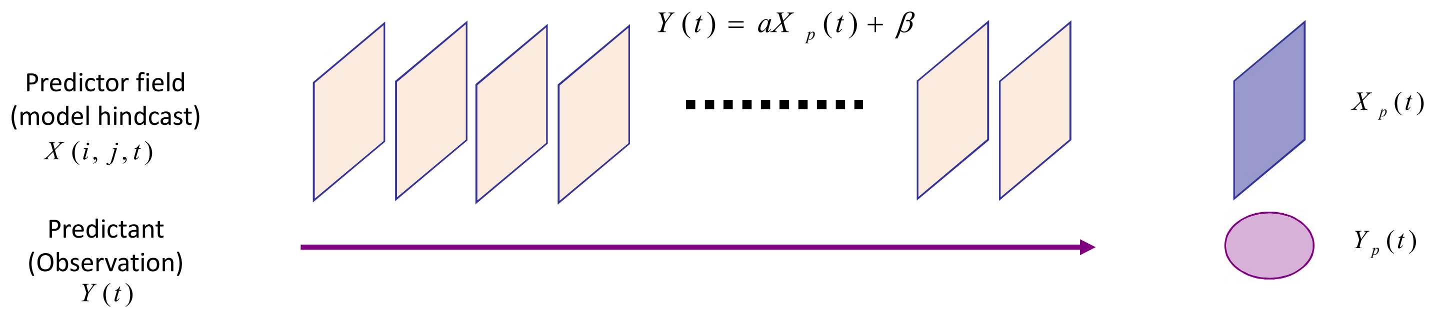
$$P = \frac{1}{M}\sum_{i=1}^{M} F_i$$

M: number of forecast models
F_i: forecast of i^{th} model

- **SPM:** simple composite of individual model forecasts, after statistical correction (downscaling) by **pattern projection method** (Kug et al. 2008)

$$P = \frac{1}{M}\sum_{i=1}^{M} \hat{F}_i$$

$\hat{F}_i$: corrected forecast of i^{th} model



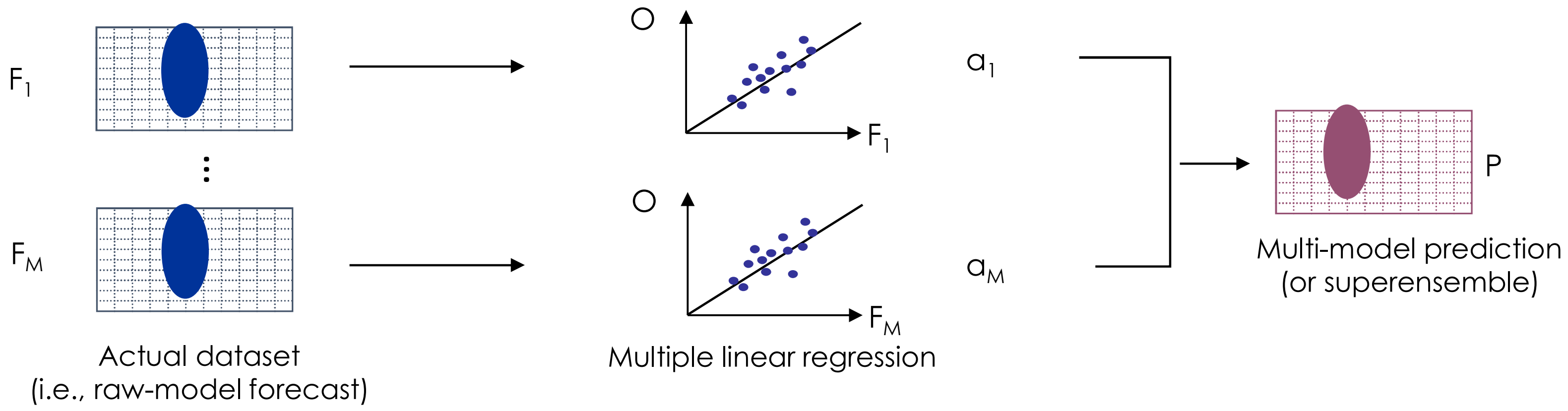
다중모델 앙상블 기법

[단정예측]

- **MRG: empirically weighted MME** with **regression coefficients** (Yun et al. 2003)

$$P = \sum_{i=1}^{M} a_i F_i$$

M: number of forecast models
F_i: forecast of i^{th} model
a_i: regression coefficients during the training period



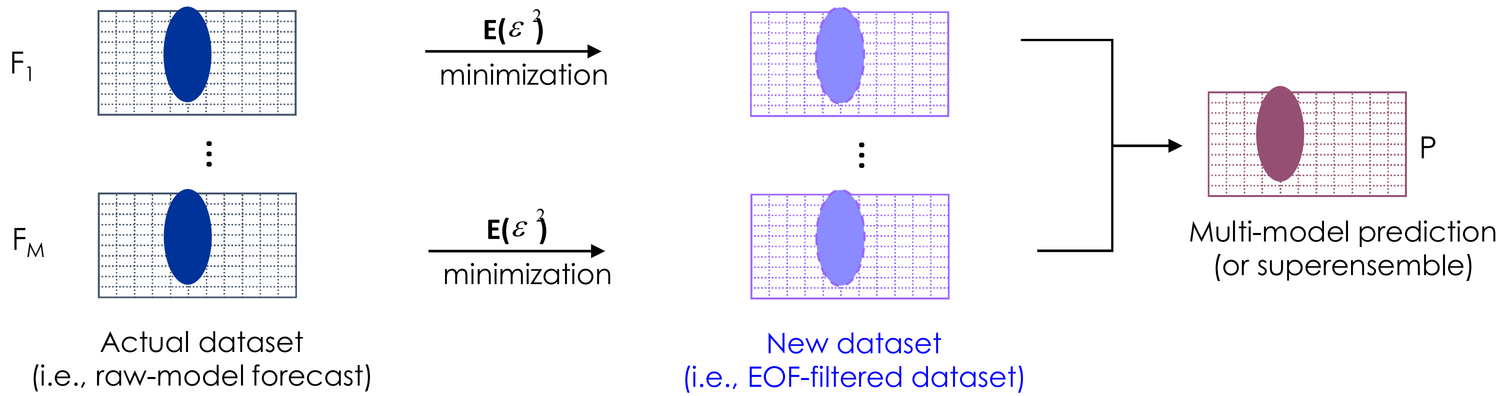
다중모델 앙상블 기법

[단정예측]

- **SSE: empirically weighted MME** with **EOF-filtering of the actual dataset** by finding a consistent spatial pattern between the observed and individual model forecast (Yun et al. 2005)

$$P = \sum_{i=1}^{M} a_i \hat{F}_i$$

M: number of forecast models
$\hat{F}_i$: corrected forecast of i^{th} model
a_i: regression coefficients during the training period



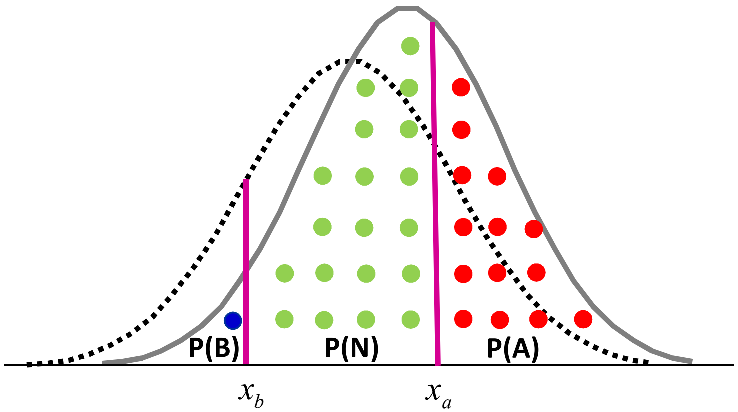
확률추정방법

모수화 vs. 비모수화 기법적용

비모수화(Non-Parametric Estimate)

Empirical ranking (or counting) method

각 카테고리 해당하는 앙상블 수를 구하여 확률을 추정하는 방법

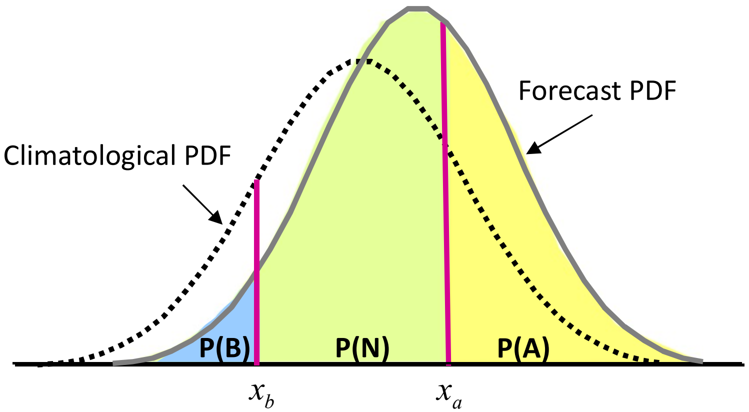


$$P(A) = \frac{N_A}{N} = \frac{\text{number of ensemble members falling into AN}}{\text{total number of ensemble members}}$$

모수화(Parametric Estimate)

Statistical fitting method

예측자료가 특정 분포도를 따른다는 가정 하에 특정 분포의 PDF로 각 카테고리의 확률을 추정하는 방법



$$P(A) = 1 - \int_{-\infty}^{x_a} F(x)dx$$

$F(x)$: theoretical PDF (e.g., Gaussian, gamma)

➢ 기술적으로 간단하며, 계산시간이 빠르며, 점근적인 분포에서 정확도가 높다(예 기온의 Gaussian PDF)

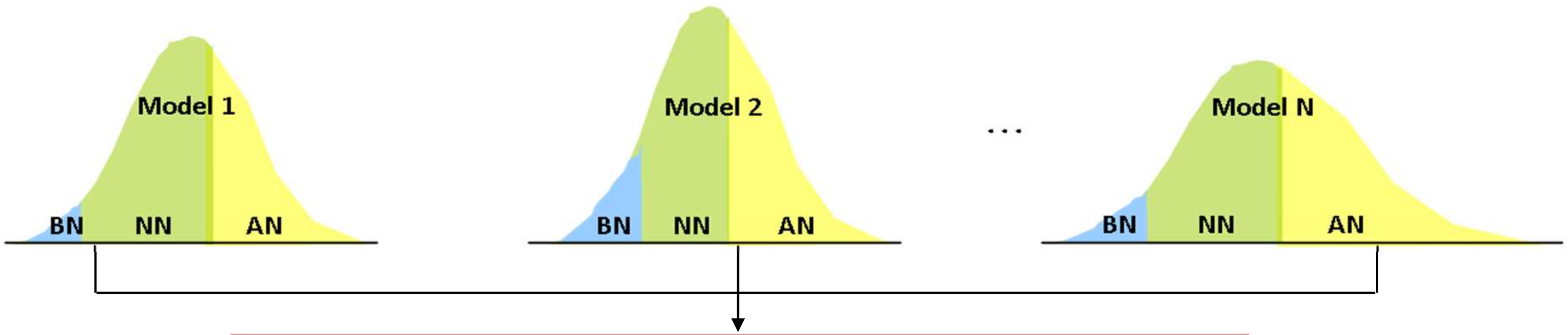
- A **Gaussian fit estimate** is more accurate than counting for **Gaussian distributed forecast variables** (Wilks 2002; Tippett et al. 2007).
- Most of operational centers use a Gaussian fitting method for tercile-based categorical probabilities of global climate variables (e.g., IRI, JMA, MSC).

AN : Above-Normal

NN : Near-Normal

BN : Below-Normal

확률 MME 기법



" Probabilistic Multi-Model Ensemble "

$$P(E) = \underbrace{\sum_{i=1}^{M} P(Model_i)}_{\text{model weight}} \times \underbrace{P(E / Model_i)}_{\text{forecast probability of an event}}$$

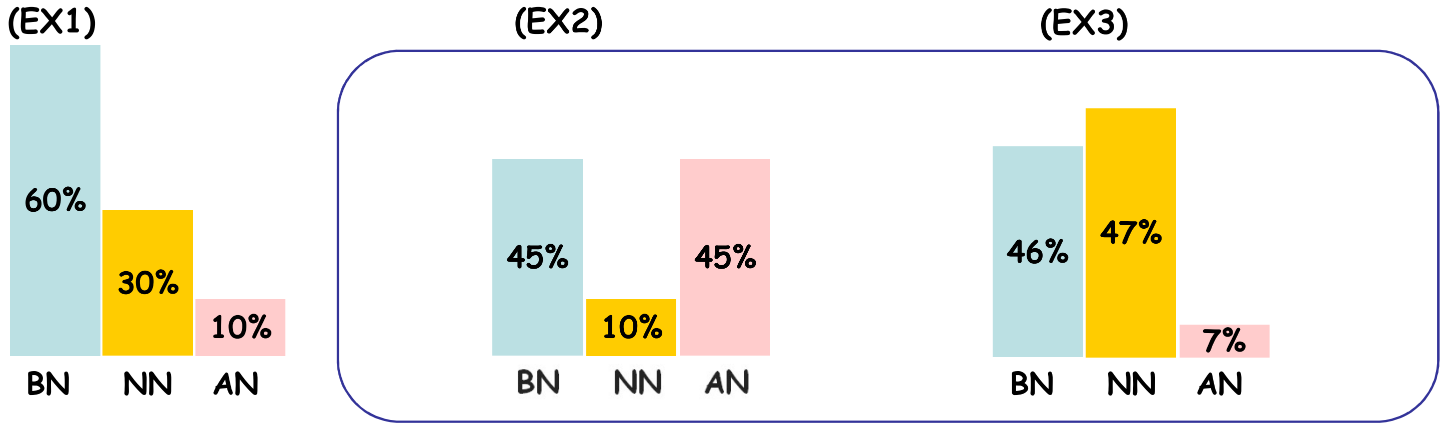
model weight **forecast probability of an event**

$$P(E) = \frac{1}{\sum_{i=1}^{M} \sqrt{n_i}} \sum_{i=1}^{M} \sqrt{n_i} P(E / Model_i)$$

n **: Ensemble size of *i* model**
M **: Total number of participating modes in MME**

- Uncalibrated multi-model ensemble, with model weights proportional to the square root of ensemble size of individual models

다중모델 앙상블 (MME) 기술



" Below Normal "   " ??? "   " Near Normal ??? "

" Chi-square Test "

$$\chi^2 = \sum_{i=1}^{k} (O_i - E_i)^2 / E_i$$

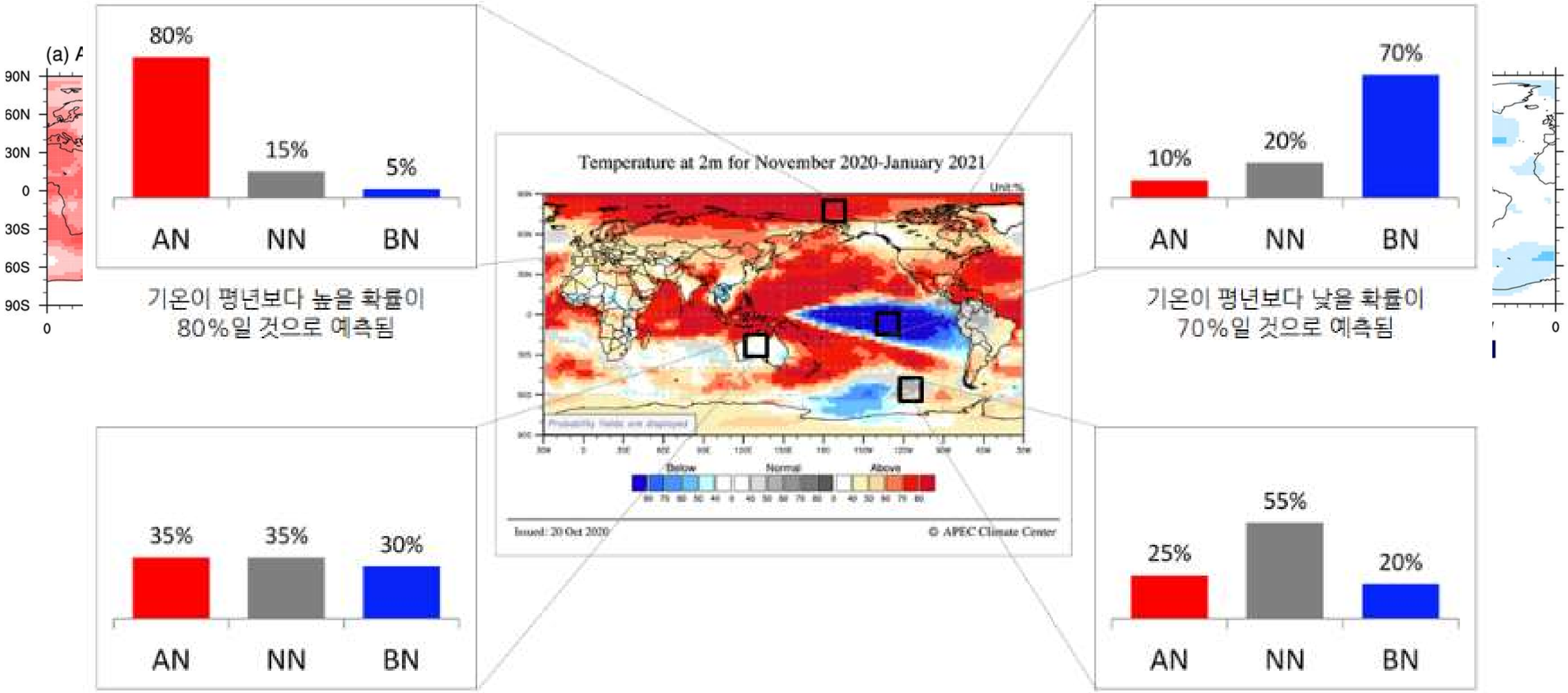
k : number of categories
O : observed frequencies in forecast
E : expected frequencies

If differences are not significant at 5% sig. level.

→ **UNCERTAINTY!!!!**

AN : Above-Normal   NN : Near-Normal   BN : Below-Normal

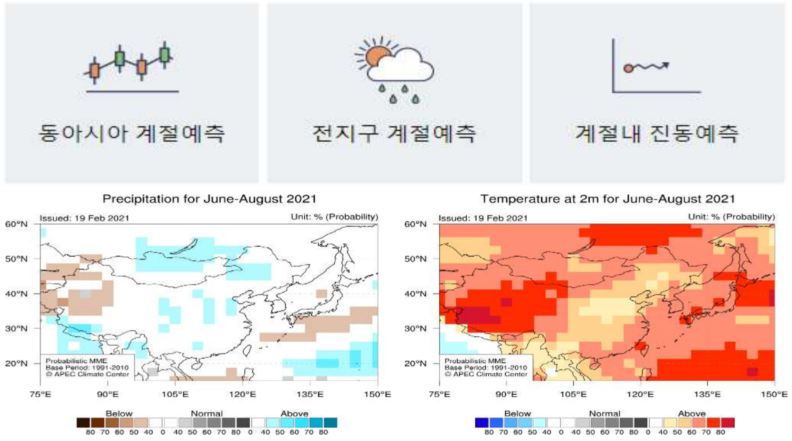
확률 예측 해석 방법

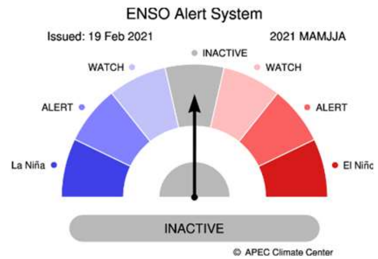


AN : Above-Normal **NN** : Near-Normal **BN** : Below-Normal

APCC 다중모델앙상블 계절예측

11개국 15개 기관
예측자료 실시간 입수





분석, 평가 및 최적 예측값 산출
(매달 향후 1~6개월 예측)

APEC기후센터 홈페이지를 통한
온라인 예측 정보 및 데이터 제공
(매월 700여 수신처)

(https://apcc21.org/ser/global/outlookSummary.do?lang-ko)

APCC 다중모델앙상블 계절예측

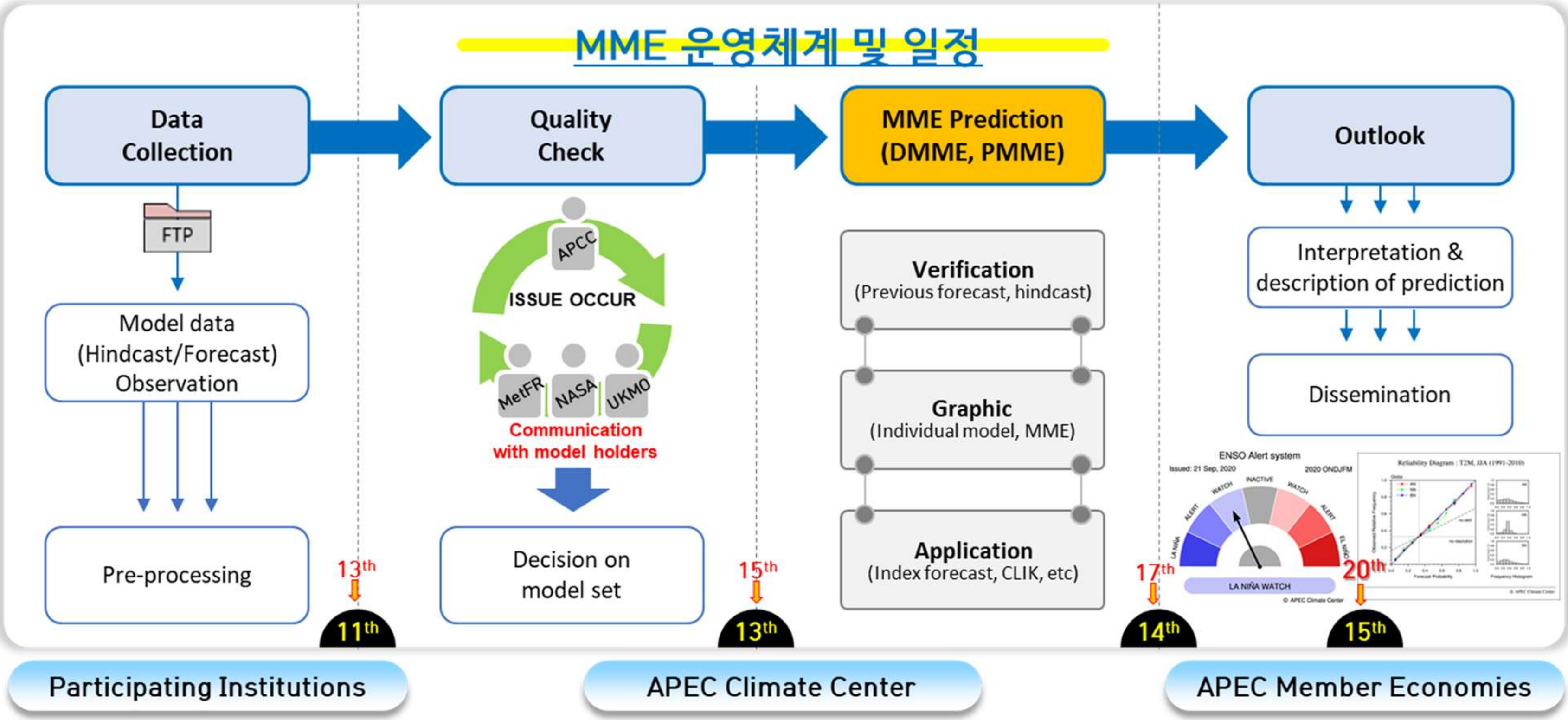
[APCC MME 참여 모델 현황 (2022년 5월 기준)

#	Institute	Model Name	SST Specification (H/F)	Masking/ OLR	Ens. (H/F)	Forecast Period	Hindcast Period	Resolution	File Type
1	APCC	SCOPS	Predicted/Predicted	O / olr	10/10	6-month	1982-2013	T159, L31	NetCDF
2	BCC	CSM1.1m	Predicted/Predicted	O	24/24	6-month	1991-2015	T106, L26	NetCDF
3	BoM	ACCESS-S2	Predicted/Predicted	O/ olr	27/11	5-month	1981-2018	N216(~60km), L85	NetCDF
4	CMCC	SPS3.5	Predicted/Predicted	O / f: olr, h: -	40/50	5-month	1993-2016	~0.5ox0.5o, 46L	NetCDF
5	CWB	TCWB1Tv1.1	Predicted/Predicted	X / olr	30/30	6-month	1982-2019	T119, L40	GRIB1
6	ECCC	CANSIPSv2.1	Predicted/Predicted	X	20/20	11-month	1980-2020	T63, L35 1ox1o , L85	GRIB2
7	HMC	SL-AV	Observed/Persistent	-	10/20	3-month	1990-2015	1.125x1.40625, L28	GRIB2
8	JMA	JMA/MRI-CPS3	Predicted/Predicted	O	10/50	6-month	1991-2020	T319, L100	GRIB2 f err: Binary
9	KMA	GLOSEA6GC3.2	Predicted/Predicted	X	12/42	6-month	1993-2016	N216, L85	GRIB2
10	MetFR	SYS 8	Predicted/Predicted	O	25/51	5-month	1993-2016	T359, L127	GRIB1
11	NASA	GEOS-S2S-2.1	Predicted/Predicted	O / olr	4/10	8-month	1981-2016	288x181, L72	NetCDF
12	NCEP	CFSv2	Predicted/Predicted	X / olr	20/20	6-month	1982-2010	T126, L64	GRIB1
13	PNU	CGCMv2.0	Predicted/Predicted	O	35/35	6-month	1980-present	T42, L18	Binary
14	UKMO	GLOSEA6	Predicted/Predicted	X	28/42	5-month	1993-2016	N216, L85	NetCDF
15	MGO	MGOAM-2	Persistent/Persistent	f: O, h: - / olr	6/10	3-month	1979-2004	T42, L14	f: GRIB1 h: NetCDF
MME						3(6)-month	1991-2010	2.5^ox2.5^o, 1.0^ox1.0^o	

모델 자체 SST masking 있음: O, 없음: X, f: forecast, h: hindcast (빨간색: 변경 모델 / 녹색: MME 참여 X)

APCC 다중모델앙상블 계절예측

현업스케쥴



계절예측 검증

- 검증이 무엇이고, 왜 필요한가?
- 결정론적 예측 검증방법
- 확률론적 예측 검증방법

Verification

• What is verification?

- **Verification** is the process of comparing forecasts to relevant observations
  : Verification is one aspect of measuring forecast **goodness**
- Verification measures the **quality** of forecasts
- For many purposes a more appropriate term is “**evaluation**”

• Why verify?

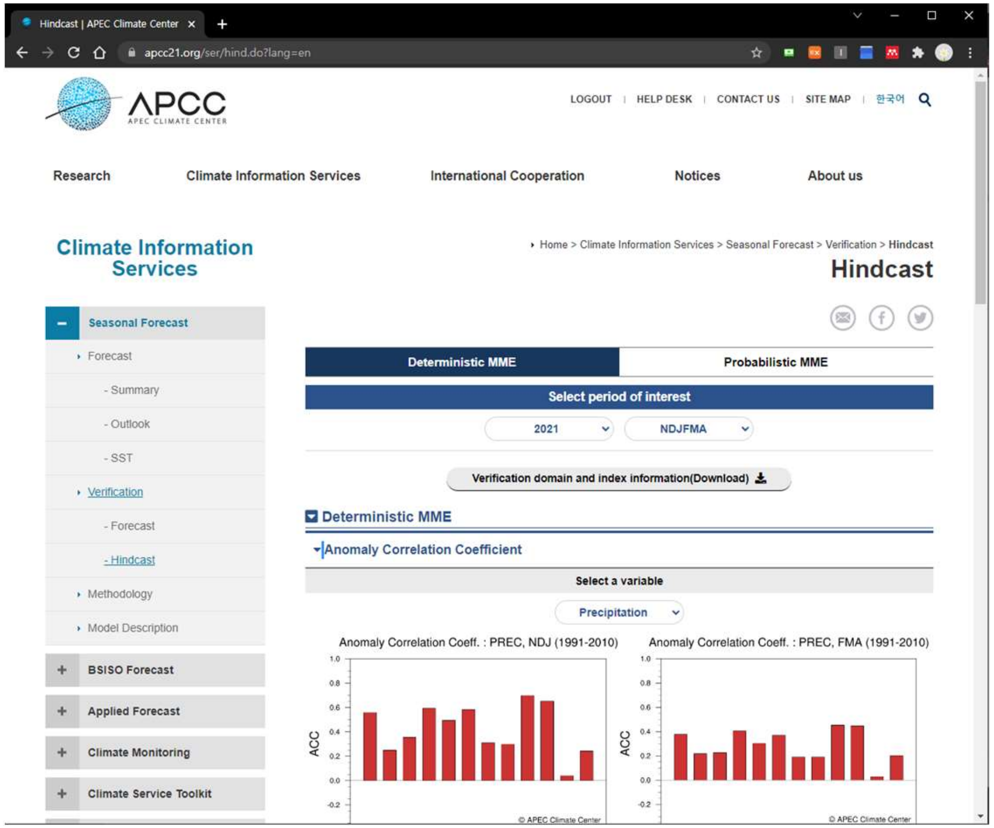
- **Administrative purpose**
  Monitoring performance
  Choice of model or model configuration (has the model improved?)
- **Scientific purpose**
  Identifying and correcting model flaws
  Forecast improvement
- **Economic purpose**
  Improved decision making
  “Feeding” decision models or decision support systems

Some other reasons

- Help operational forecasters understand model biases and select models for use in different conditions
- Help “users” interpret forecasts
- Identify forecast weaknesses, strengths, differences

Verification Skill Score

- **Skill Score**
  - **Non-categorical forecast**
    - Root Mean Square Error (RMSE)
    - Anomaly Pattern Correlation Coefficient (ACC)
    - Temporal Correlation Coefficient (TCC)
    - Mean Square Skill Score (MSSS)
    - Gilbert Skill Score (GSS)
  - **Categorical forecast**
    - Relative Operating Characteristic (ROC) score map
    - ROC Curve and Score
    - Reliability Diagram
    - Brier skill Score



(https://www.apcc21.org/ser/hind.do?lang=en)

Observation Data

• What is "truth" when verifying the forecast and hindcast?

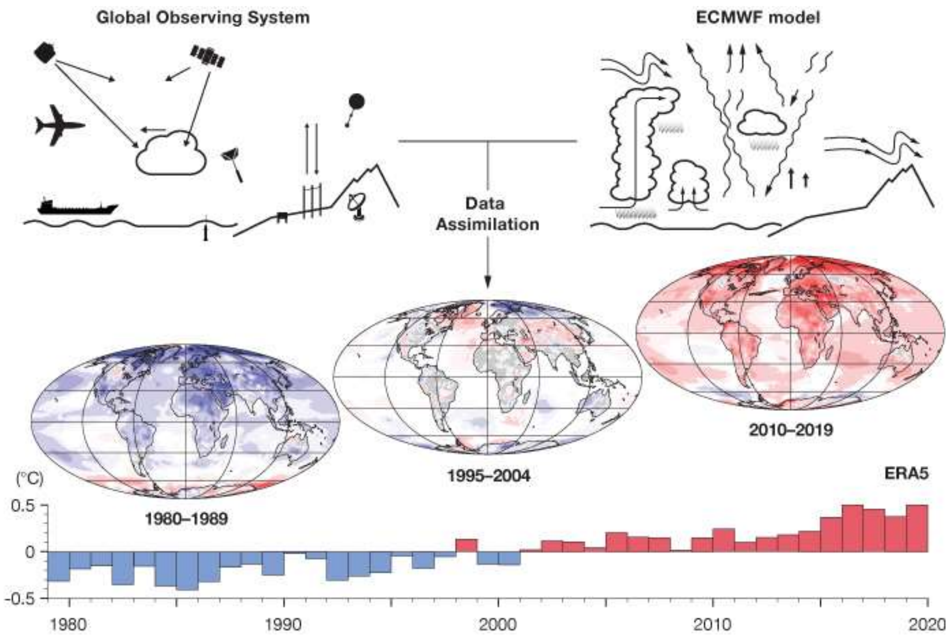
The "truth" data that we use to verify forecasts generally comes from observational data. Such as:

- Rain gauge measurements
- Temperature observations
- Satellite-derived cloud cover

• Reanalysis Data

Station observations are the best, but in the Pacific there are not enough for verification.
Use gridded 'observational' data instead.

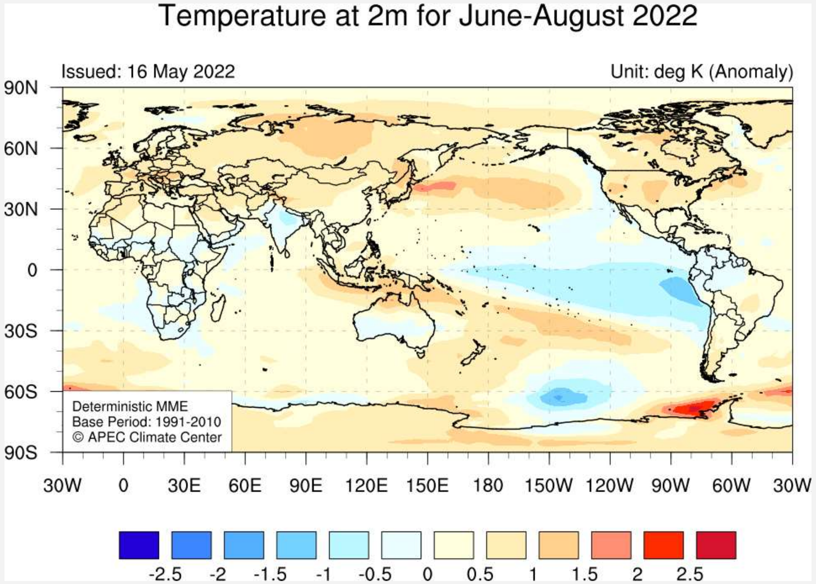
- NCEP/NCAR R1 (1948~Present)
- NCEP/NCAR R2 (1979~Present)
- ECMWF ERA5 (1950~Present)



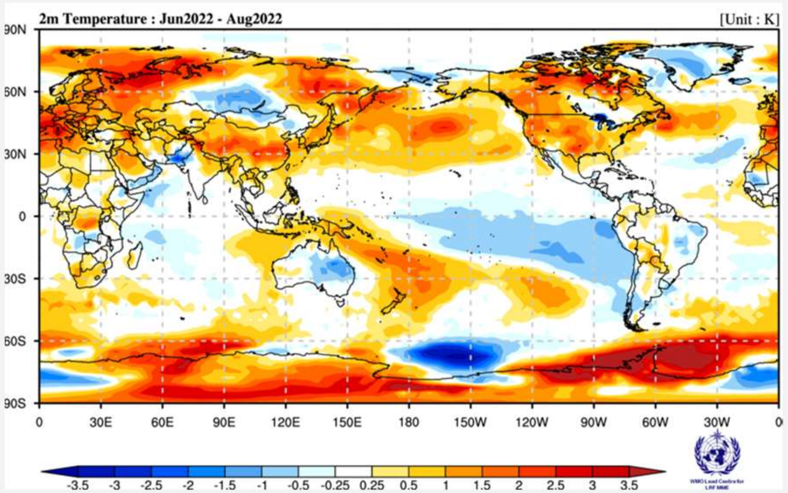
eg. A schematic of the reanalysis process

Verification for Deterministic Forecast

Real-Time Forecast



Observation



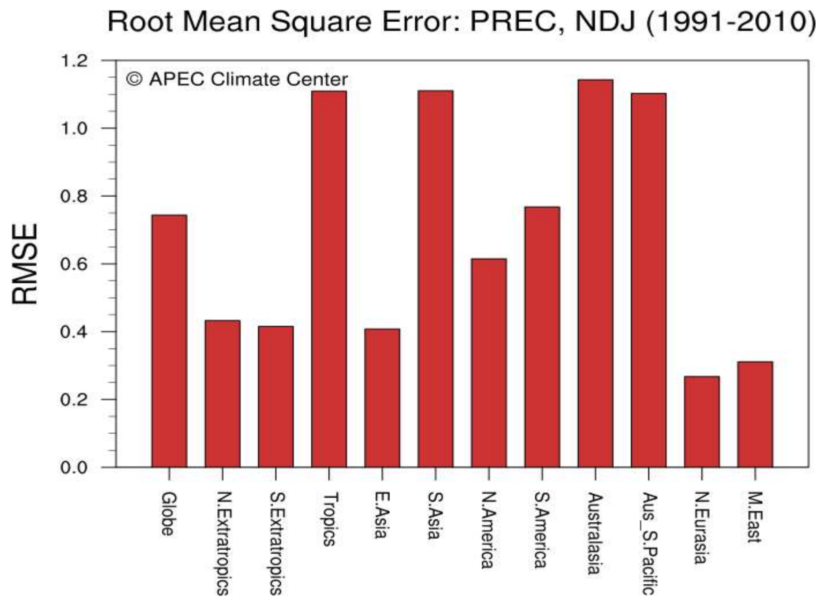
1) What is the average magnitude of the forecast errors?
2) How well did the forecast anomalies correspond to the observed anomalies?

Verification for Deterministic Forecast

RMSE [Root Mean Square Error]

$$RMSE = \sqrt{\frac{1}{W}\sum_{i=1}^{N}(F_i - O_i)^2}$$

F : forecast
O : observation
W: weighting



What is the average magnitude of the forecast errors?

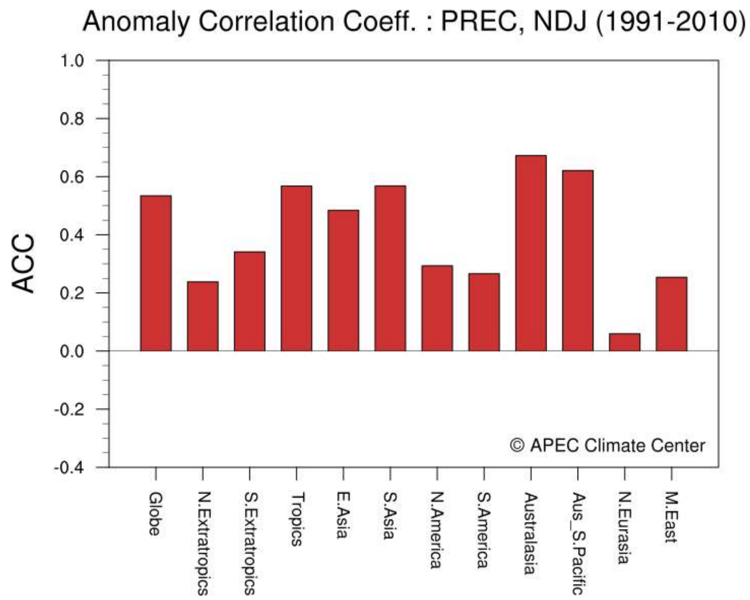
Range: 0 to ∞. Perfect score: 0.

Verification for Deterministic Forecast

ACC [Anomaly Pattern Correlation Coefficient]

$$ACC = \frac{\sum_{i=1}^{N} \omega_i (F_i - \overline{F})(O_i - \overline{O})}{\sqrt{\sum_{i=1}^{N} \omega_i (F_i - \overline{F})^2 \sum_{i=1}^{N} \omega_i (O_i - \overline{O})^2}}$$

Over bar means time average (climatology)
F : forecast
O : observation
W: weighting



How well did the forecast anomalies correspond to the observed anomalies?
Range: -1 to 1. Perfect score: 1.

<Murphy, A.H., 1988: Skill scores based on the mean square error and their relationships to the correlation coefficient. Mon. Wea. Rev. 116. 2417-2424.
WMO, 2002: Standardised verification system (SVS) for long-range forecasts LRF). Monual on the GDPS (WMO-No. 485), volume 1. >
<https://www.apcc21.org/ser/hind.do?lang=ko>

Verification for Probabilistic Forecast

The Contingency Table

Event Forecast	Event observed		
	Yes	No	Marginal total
Yes	Hit (H)	False Alarm (F)	H+F
No	Miss (M)	Correct Rejection (C)	M+C
Marginal total	H+M	F+C	H+F+M+C = N

- Hit Rate = H/(H+M)
- False Alarm Rate = F/(F+C)

Ex) Rainfall forecast

Hit : forecast said "it will rain" and it actually rains.
Miss : forecast said "it won't rain" but it rains
False Alarm : forecast said "It will rain" but it doesn't rain
Correct rejection : Forecast said "It won't rain" and it doesn't rain

Verification for Probabilistic Forecast

The Contingency Table

Event Forecast	Event observed		
	Yes	No	Marginal total
Yes	Hit (H:14)	False Alarm (F:2)	H+F
No	Miss (M:6)	Correct Rejection (C:22)	M+C
Marginal total	H+M	F+C	H+F+M+C = N

- Hit Rate = H/(H+M)
- False Alarm Rate = F/(F+C)

Ex) Rainfall forecast

Question 1) How many times rainfall actually happened?

Question 2) How many times forecaster issued rainfall?

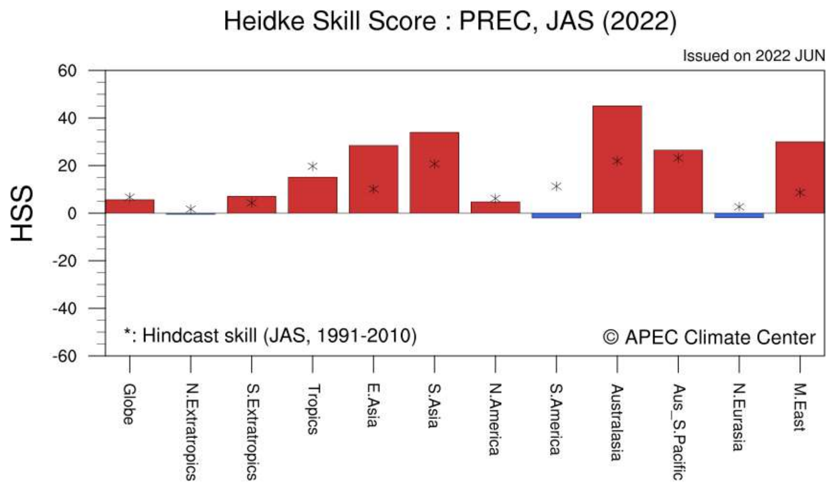
Verification for Probabilistic Forecast

HSS [Heidke Skill Score]

Event Forecast	Event observed		
	Yes	No	Marginal total
Yes	Hit (H)	False Alarm (F)	H+F
No	Miss (M)	Correct Rejection (C)	M+C
Marginal total	H+M	F+C	H+F+M+C = N

$$HSS = \frac{(H+C) - \frac{(H+F)(H+M)+(M+C)(F+C)}{N}}{N - \frac{(H+F)(H+M)+(M+C)(F+C)}{N}}$$

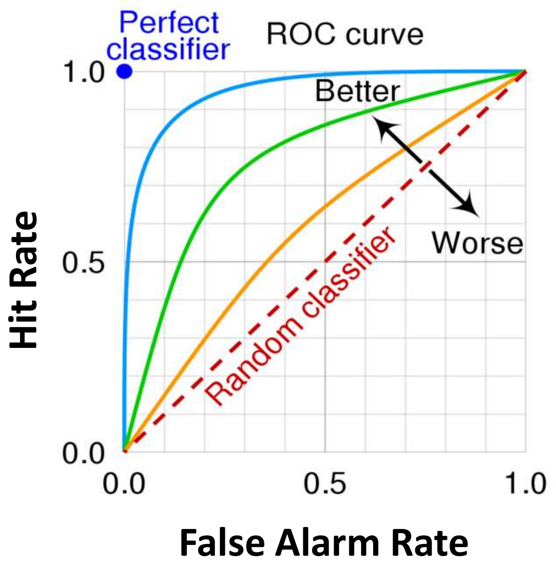
- A skill score against chance
- Relatively easy to calculate
- Range : Negative value to 1
- Perfect forecast = 1, No skill = 0

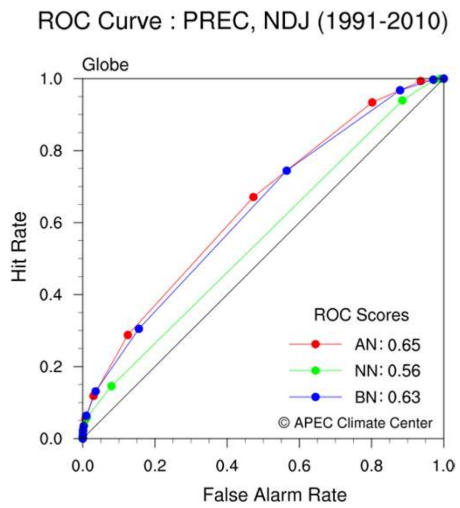


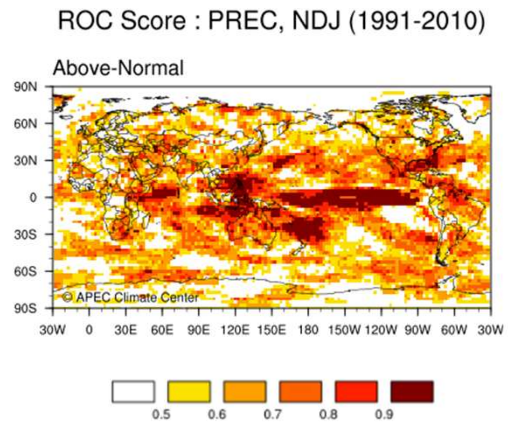
Verification for Probabilistic Forecast

ROC [Relativ Operating Characteristic] curve

- Hit Rate vs. False Alam Rate
- Hit Rate = H/(H+M)
- False Alarm Rate = F/(F+C)







What is the ability of the forecast to discriminate between events and non-events?

Range: 0 to 1. Perfect score: 1.
0.5 indicates no skill.

Fawcett, Tom(2006). "An Introduction to ROC Analysis" Pattern Recognition Letters. 27 (8): 861-874.
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