Urban Meteorology and Climate Conference

Global Precipitation Seasonal Forecast Using Teleconnection Technique

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- **Introduction**
- **Methodology and Data**
- **Results**
- **Conclusions**

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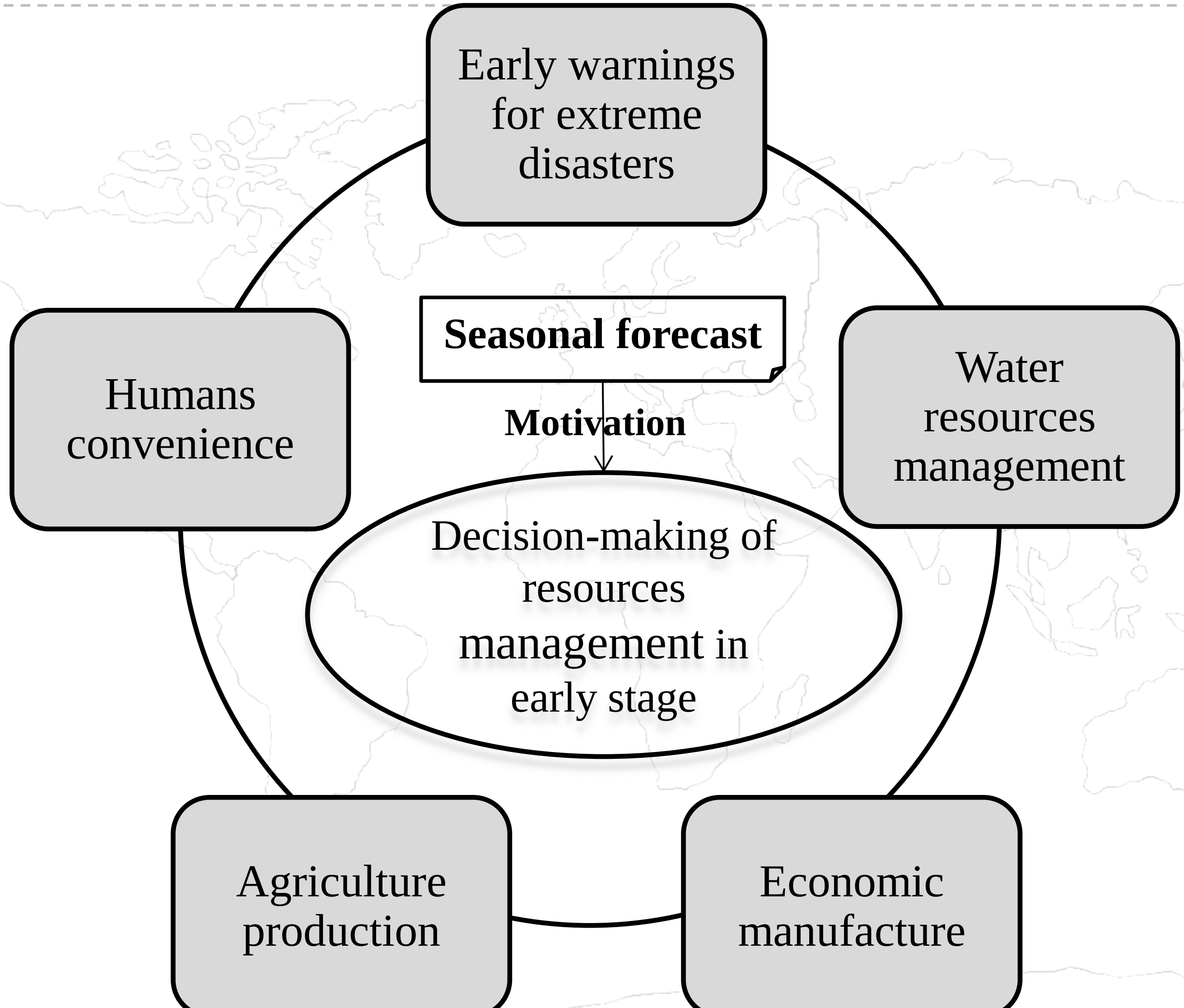
Introduction

Pic source: internet

Introduction



Pic source: internet

Introduction

The current forecast skills
unsatisfactory

→ ? →

Applied to the real world

- **Objectives:**
  - **to detect possible seasonal forecast skills of precipitation**
  - **to improve the seasonal forecast skills**

Introduction

❑ The teleconnection technique

➢ **Teleconnection**: the statistical relationships between the predictand and the predictors in remote regions (climate variability links) *(Goddard et al., 2001)*

➢ **Two different ways**: *(Chase et al. 2006)*
- coherent circulations by air-sea interactions
- disturbances related to those coherent circulations

➢ **Prominent teleconnection patterns** *(Nigam and Baxter, 2015)*
- ENSO (El Niño–Southern Oscillation)
- NAO (North Atlantic Oscillation)
- PNA (Pacific-North American pattern)
- NPO (North Pacific Oscillation)

➢ Teleconnection relationships offer **potential climate predictability** *(Chase et al., 2006)*

Research Hypothesis

Teleconnection associations based on **very few variables**, even single-variable predictors

Seasonal rainfall influenced by variables in **all three boundary forcings**, i.e. ocean, atmosphere and land

Assumption: more relevant variables considered for more reasonable precipitation forecasts

More potential variables in **ocean and atmosphere**, even in **land**, selected to investigate teleconnection relationships

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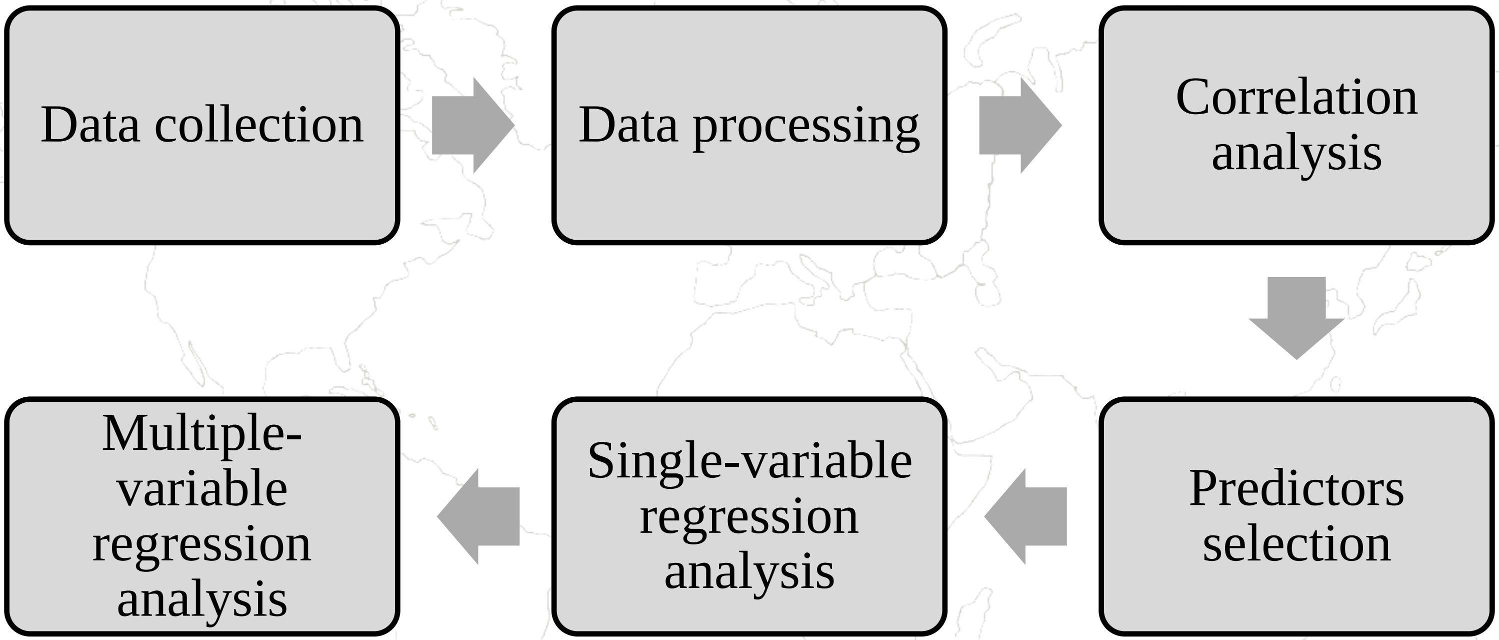
Methodology & Data



Methodology & Data

- Data Collection
  - Precipitation (**P**)
    "Global Precipitation Climatology Project (GPCP) Version 2.3 Combined Precipitation Data Set" (01/1979~08/2016)
  - Sea surface temperature (**SST**)
    "NOAA Optimum Interpolation Sea Surface Temperature V2" (12/1981~12/2016)
  - Reanalysis datasets from *European Centre for Medium-Range Weather Forecasts (ECMWF)* (01/1979~08/2016)
    - Sea level pressure (**SLP**)
    - Wind speed (**V10**)
    - Air temperature (**T2M**)
    - Total column of water (**TCW**)
    - Total column of liquid water (**TCLW**)
    - Total column of water vapor (**TCWV**)
    - **Humidity**
    - Wind shear ($|\mathbf{u}_{850}-\mathbf{u}_{200}|$) (**WISH**)
  - Time period: Jan 1982~Dec 2015
  - Temporal and spatial resolution: Monthly & $2.5^{\circ} \times 2.5^{\circ}$

Methodology & Data

- Data Collection

144 columns

72 rows

X_1	X_2	X_3	…	X_{142}	X_{143}	X_{144}
X_{145}	X_{146}	X_{147}	…	X_{286}	X_{287}	X_{288}
X_{289}	X_{290}	X_{291}	…	X_{430}	X_{431}	X_{432}
…	…	…	…	…	…	…
X_{9937}	X_{9938}	X_{9939}	…	X_{10078}	X_{10079}	X_{10080}
X_{10081}	X_{10082}	X_{10083}	…	X_{10222}	X_{10223}	X_{10224}
X_{10225}	X_{10226}	X_{10227}	…	X_{10366}	X_{10367}	X_{10368}

10,368 grids

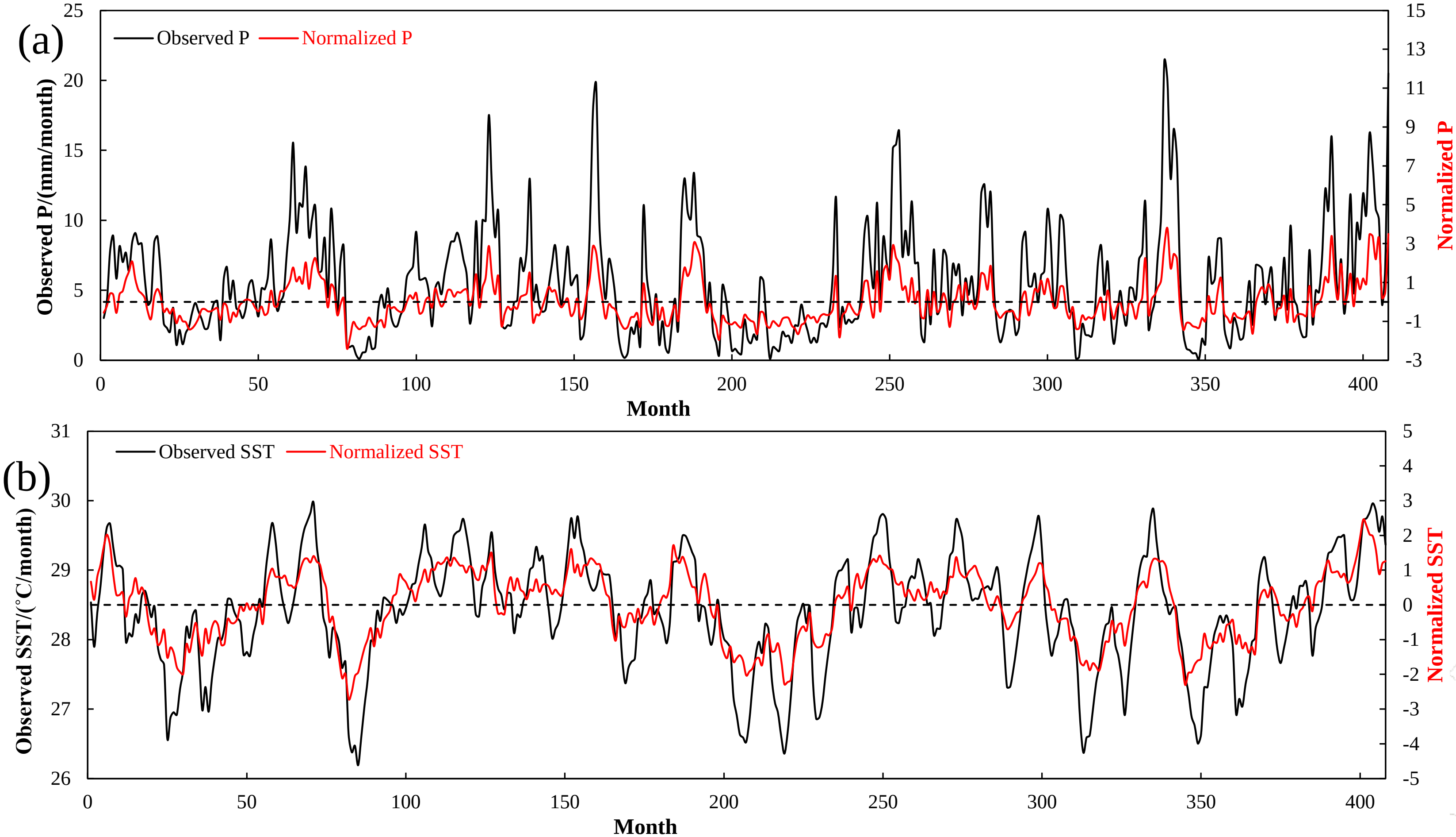
Example: $\boxed{X_{39,79}} = \boxed{X_{5551}}$

Pic source: internet

Methodology & Data

- Data processing

Normalized data = (Original data – Monthly mean) / Standard deviation

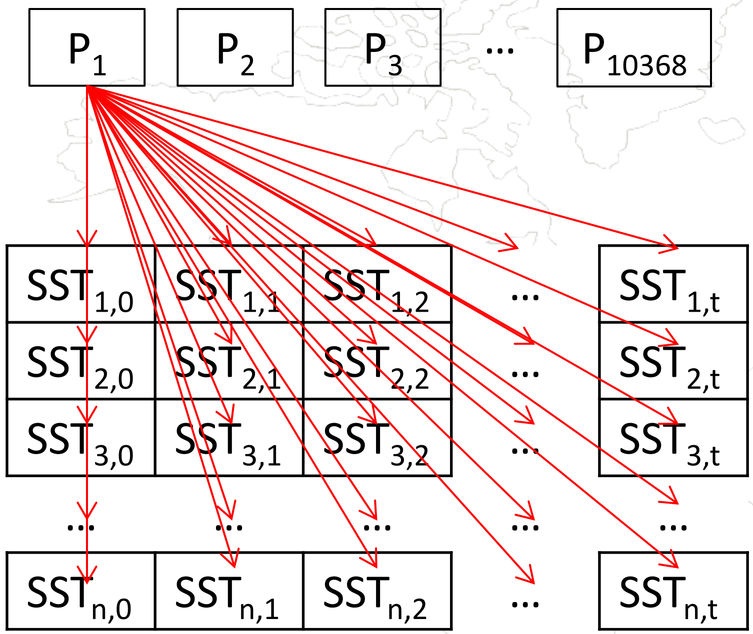


$X_{39,79}$

Methodology & Data

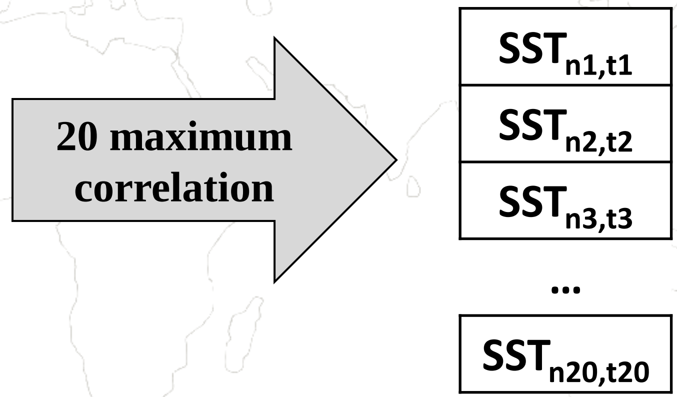
- ❑ Linear correlation analysis → **Teleconnection relationships**

Correlation coefficient



(n=144*72=10368,
t = the maximum lead-time)

- ❑ Predictors selection



($1 \le$ n1,…,n20 $\le$ 10368,
$0 \le$ t1,…,t20 $\le$ maximum lead-time)

95% confidence level

Methodology & Data

- Multiple regression analysis

$$Y = K{*}X + \varepsilon$$

Y: Predictand matrix
K: Coefficient matrix
X: Predictor matrix
Ɛ: Error

Single-variable regression:
Y: 1*402
K: 1*20
X: 20*402

Least square method

Multiple-variable regression:
Y: 1*402
K: 1*180
X: 180*402

9 variables * 20 predictors/variable

Skill core: linear correlation coefficients

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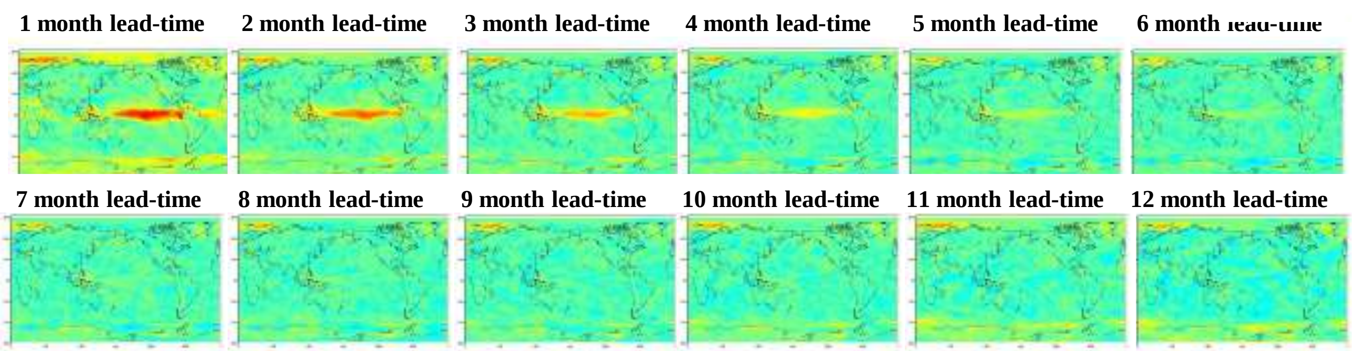
Results

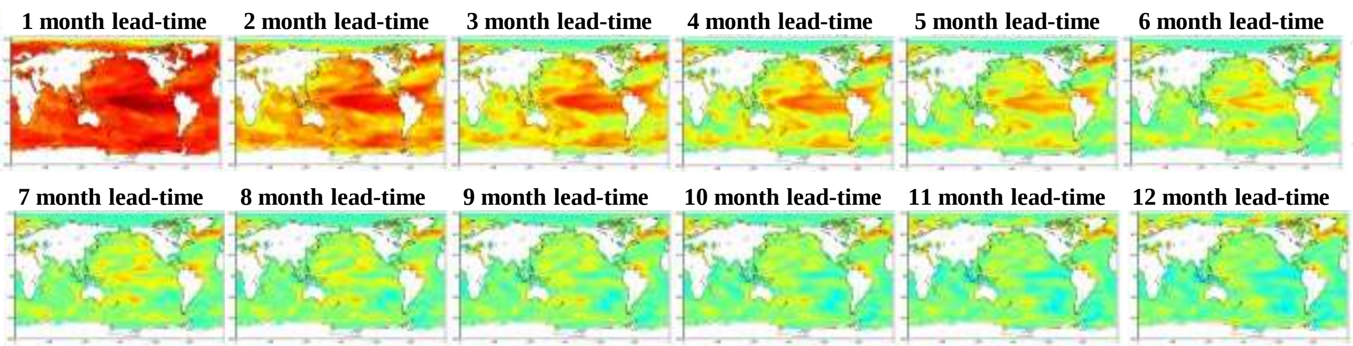
- Determination of lead-times by <u>autocorrelation analysis</u>

$$r_k = \frac{\sum_{t=k+1}^{n} (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{n} (y_t - \bar{y})^2}$$

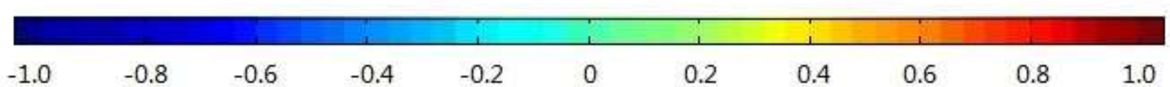
  - Memory of P anomalies



  - Memory of SST anomalies



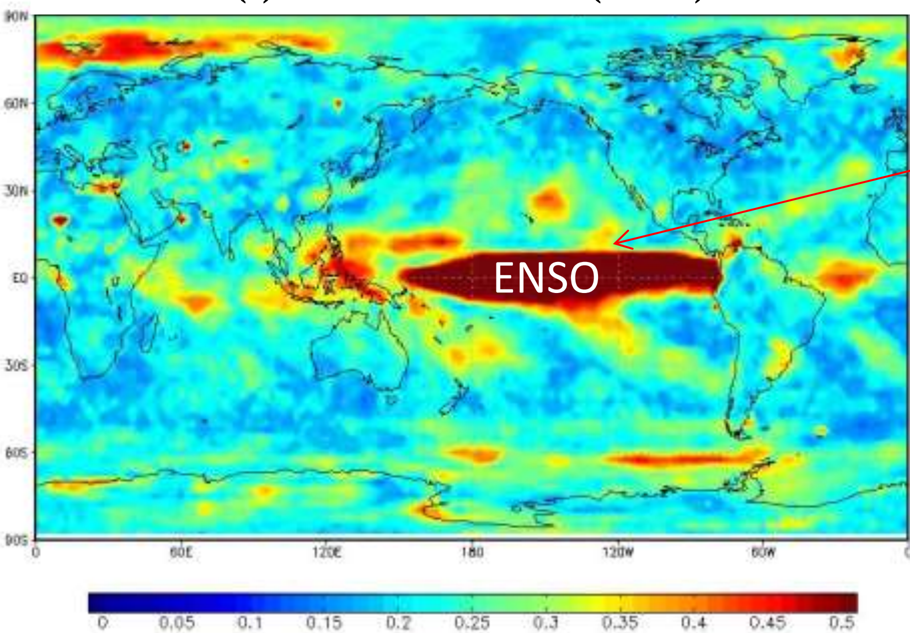
Maximum lead-time: **6 months**



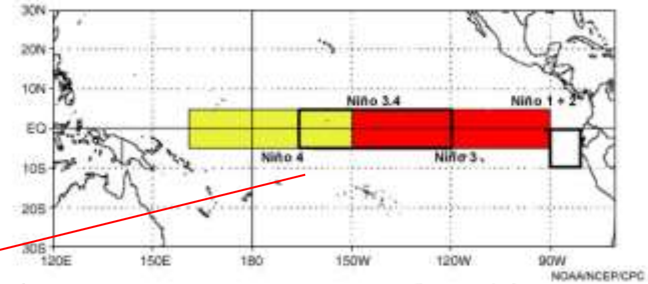
Results

- Maximum correlation results

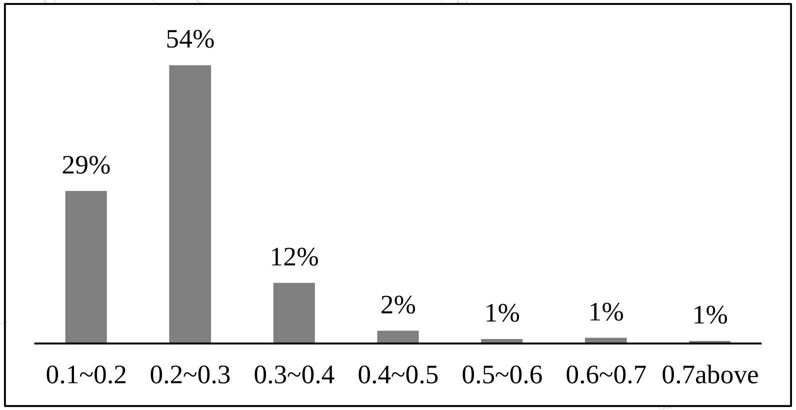
(a) Maximum correlation (P~SST)



ENSO region

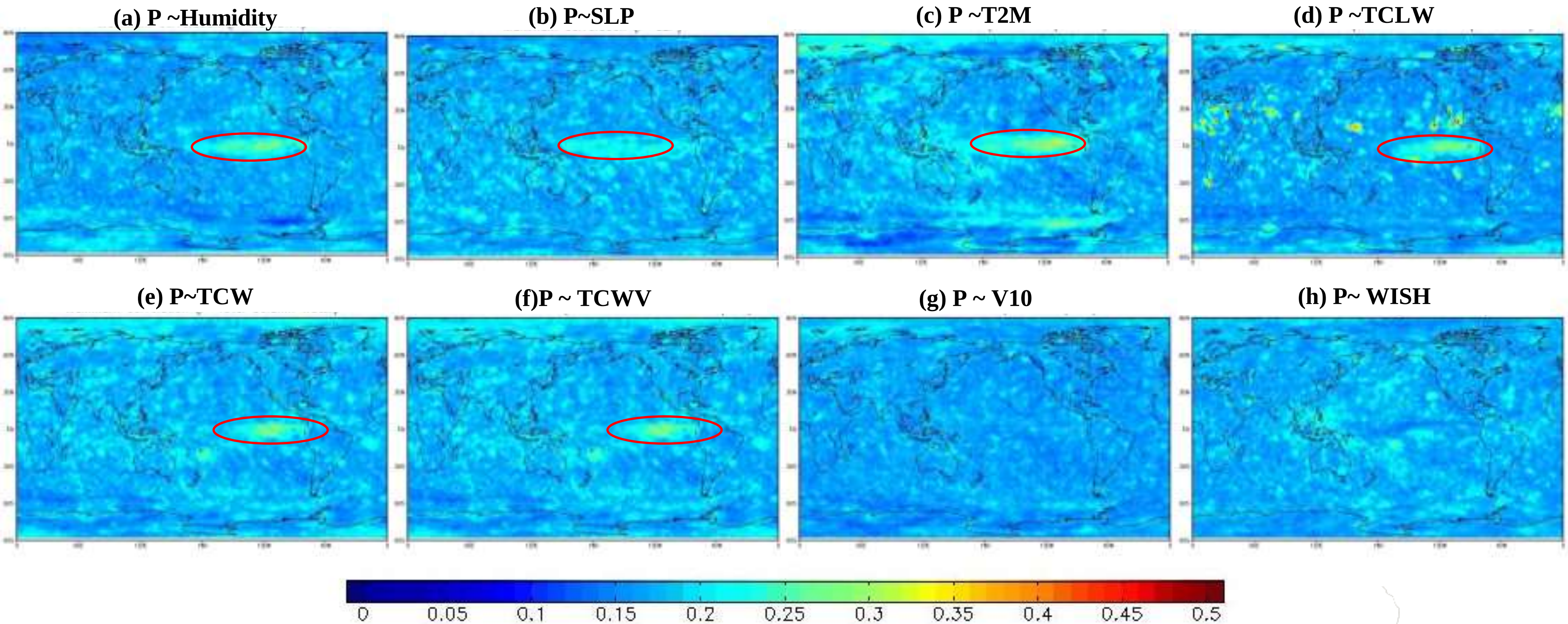


(b) statistic of the maximum correlation



Results

❑ Maximum correlation results



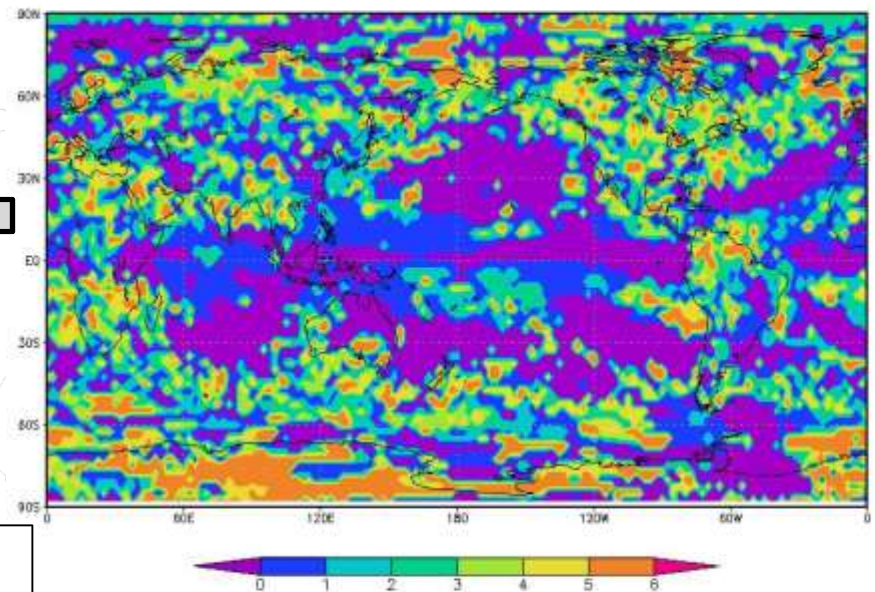
- ➢ Unsatisfactory correlation coefficients
- ➢ **ENSO-related characters** (except P~wind speed & P~wind shear)

Results

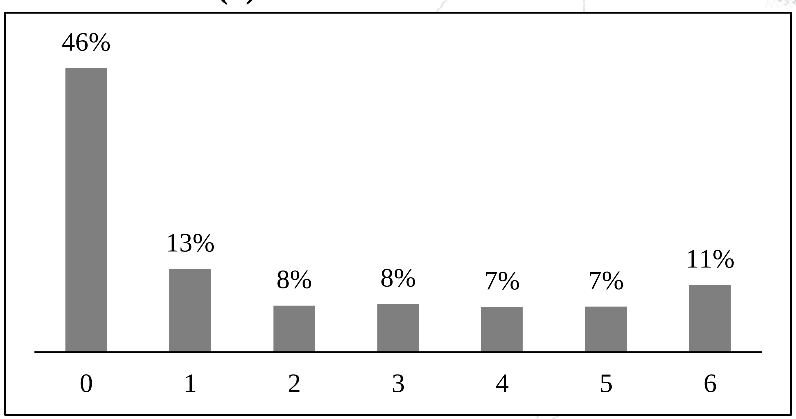
❑ Lead-time related to maximum correlation

- Most 0~1 month lead-time in **Ocean regions** , especially along **the Equator**
- Even distribution of other lead-times

(a) P ~SST



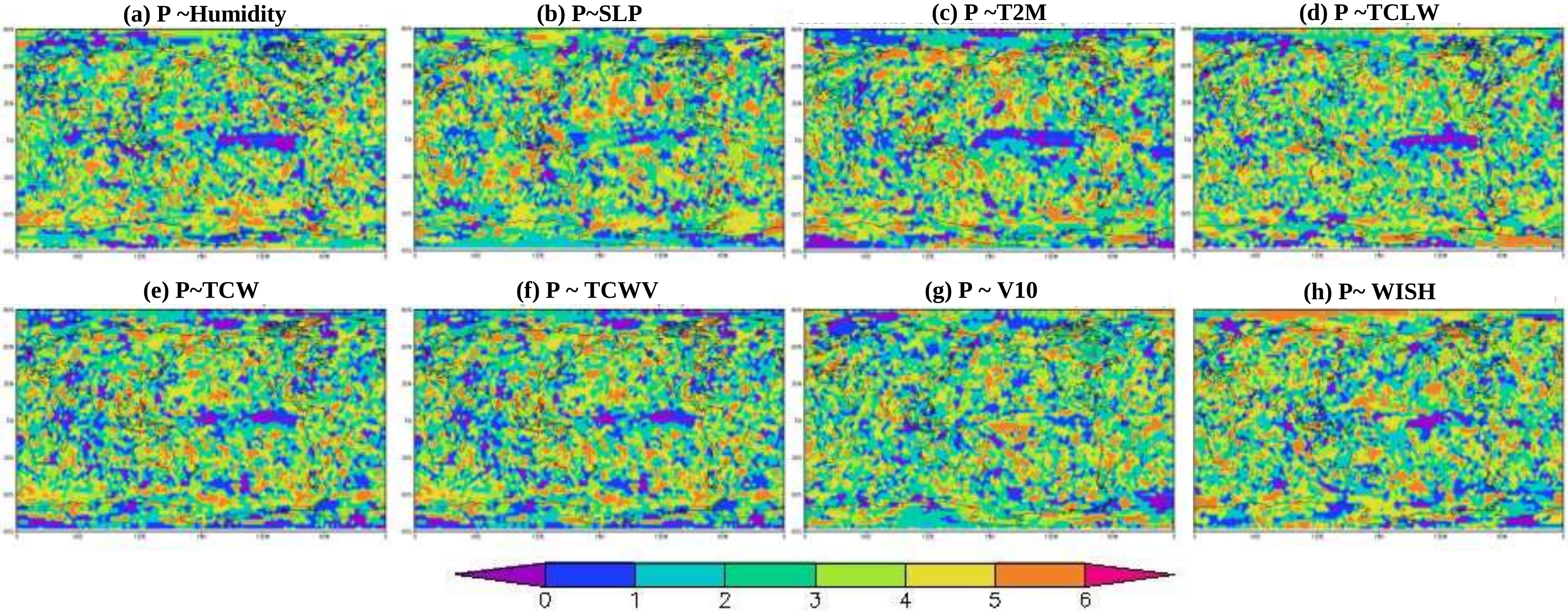
(b) statistic of lead-times



- Most frequent occurred: **0 month lead-time**
- Amount of 0 lead-time almost same with that of all other lead-times

Results

- Lead-time related to the maximum correlation

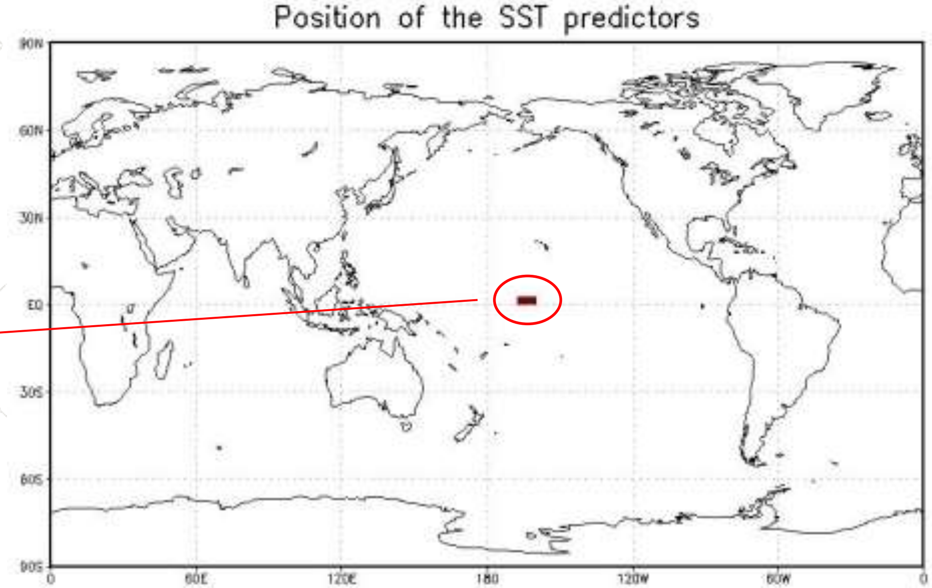


Much more **even distribution** of all the lead-times

Results

❑ Predictors selection

Position	Lead-time	Maximum Correlation
(38, 81)	0	0.74
(38, 81)	1	0.71
(37, 79)	1	0.72
(37, 79)	0	0.73
(38, 80)	1	0.71
(38, 80)	0	0.73
(37, 77)	1	0.72
(37, 77)	0	0.72
(38, 78)	0	0.72
(38, 78)	1	0.72
(37, 78)	1	0.72
(37, 78)	0	0.73
(38, 79)	0	0.73
(38, 79)	1	0.71
(37, 81)	0	0.72
(38, 82)	0	0.73
(38, 83)	0	0.72
(38, 85)	0	0.71
(38, 84)	0	0.71
(37, 80)	0	0.72

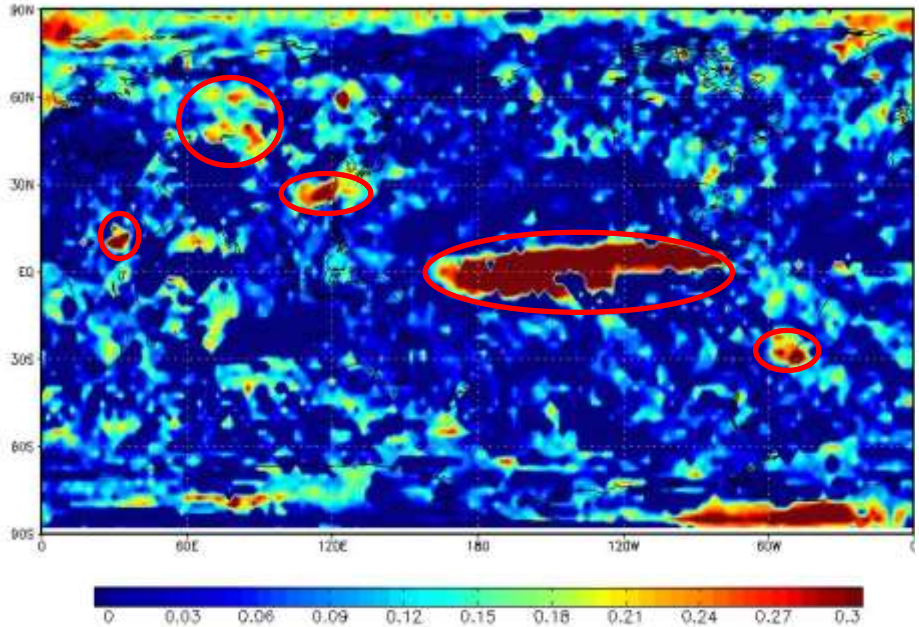


$P_{39,79}$

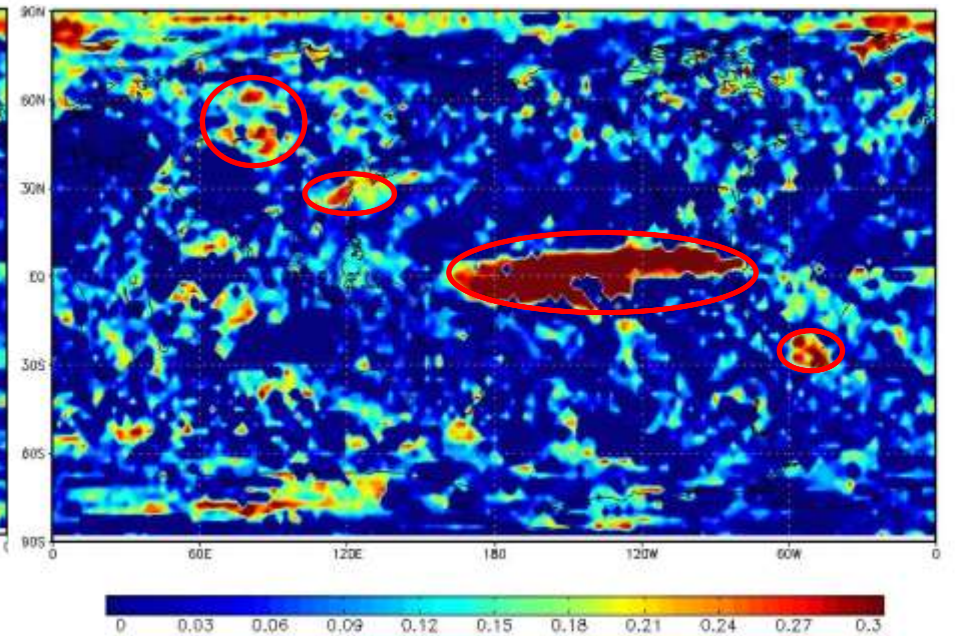
Results

❑ Forecast skill of P by regression of single-variable predictors

(a)Forecast skills of monthly P by SST predictors



(b)Forecast skills of seasonal P by SST predictors

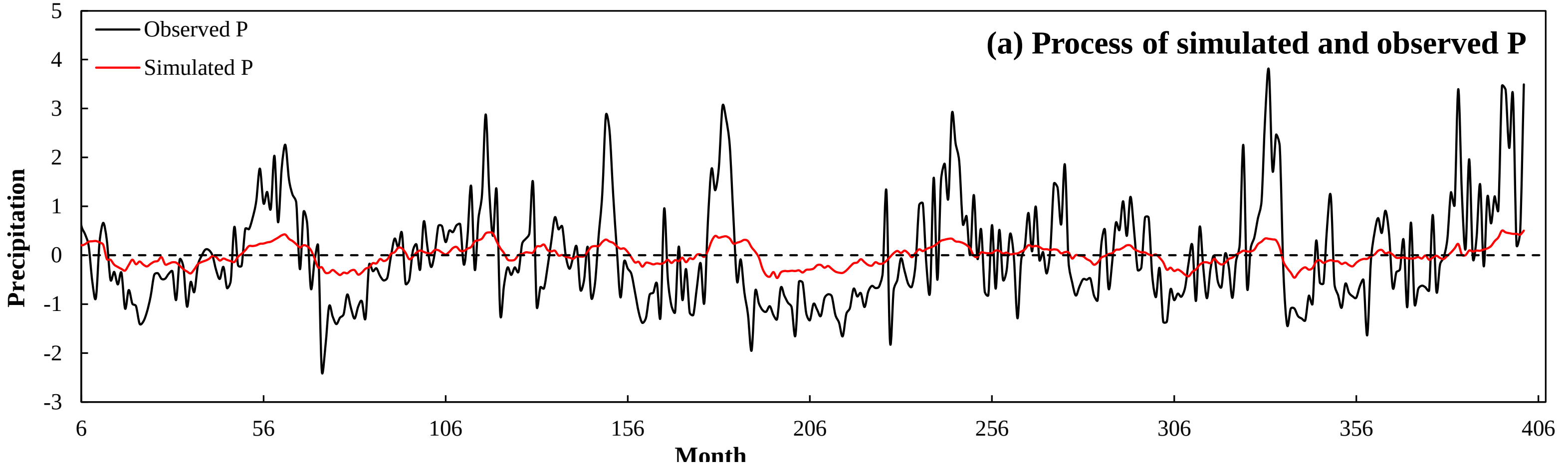


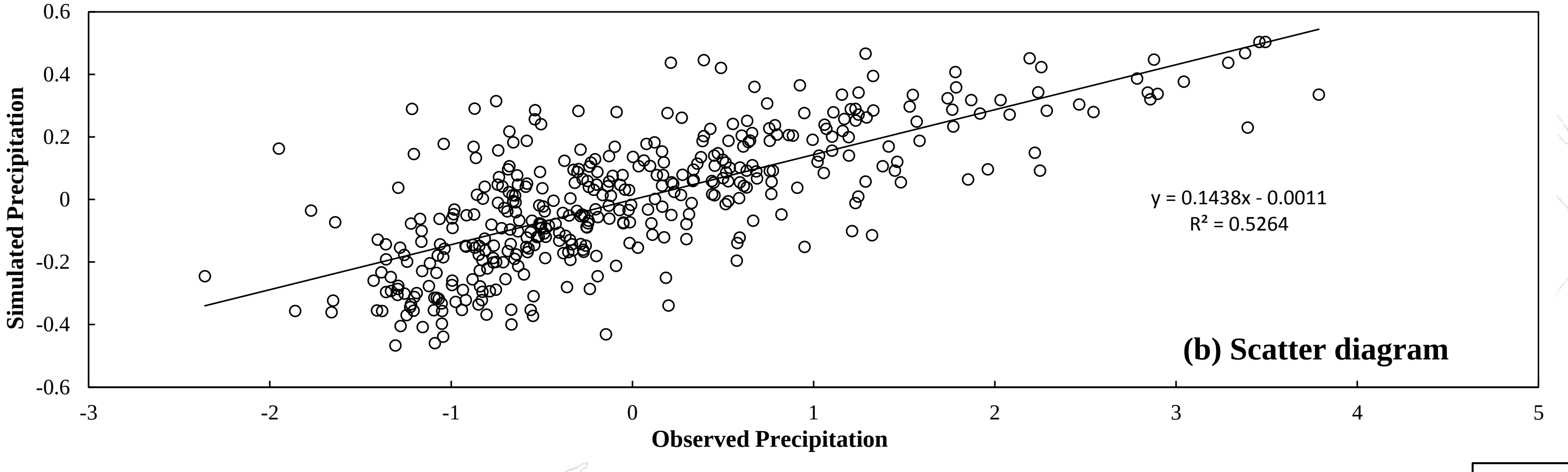
➢ **Good performances**

- Eastern Pacific Ocean (ENSO regions)
- Eastern China
- Central Africa
- Southeastern Brazil etc.

Results

- Forecast skill of monthly P by regression of SST predictors

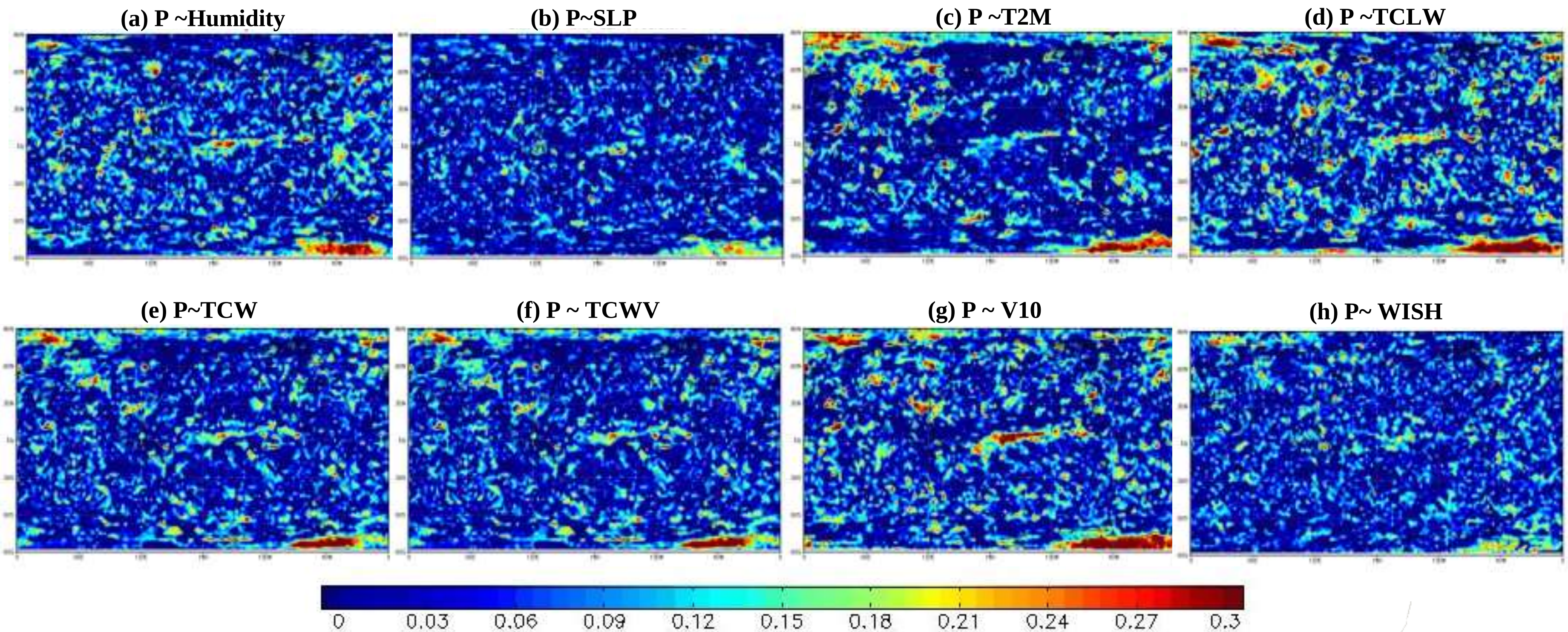




$P_{39,79}$

Results

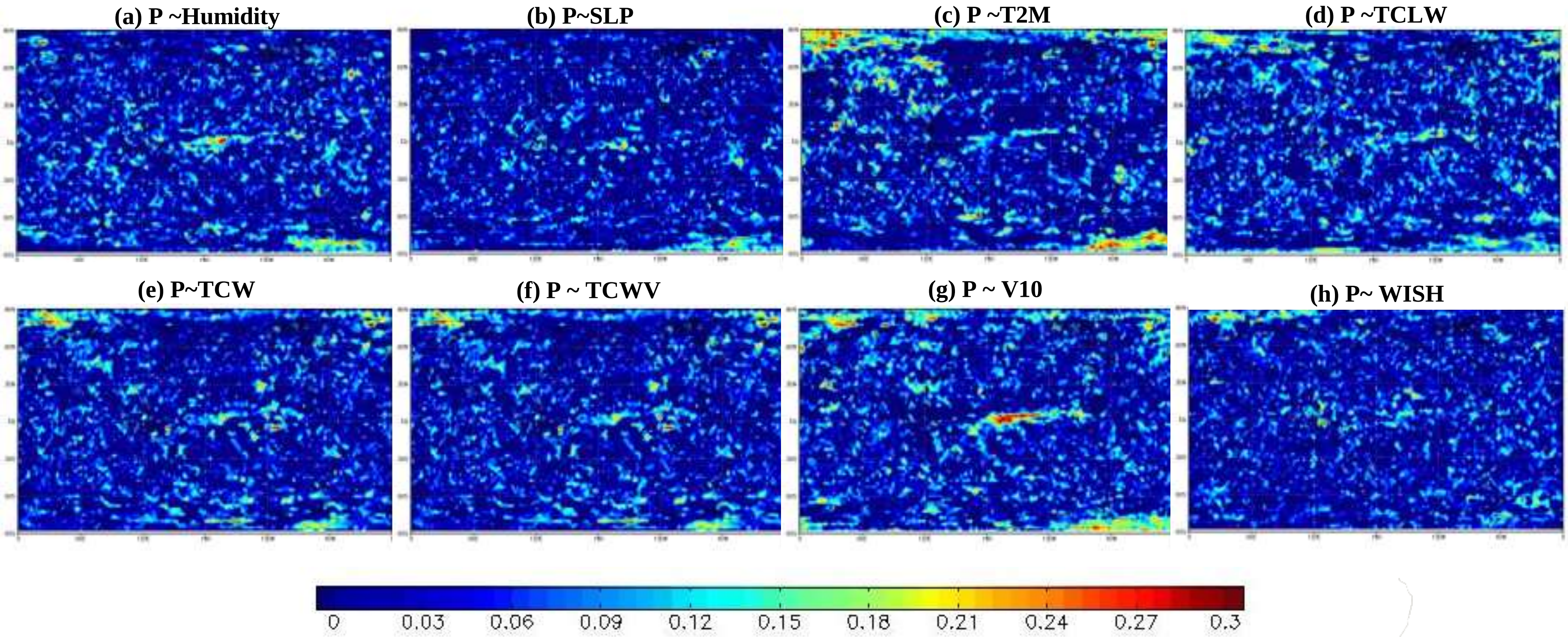
❑ Forecast skills of **monthly P** by regression of single-variable predictors



- ➢ Poor performances of most variables
- ➢ Possible predictability

Results

- Forecast skills of **seasonal P** by regression of single-variable predictors

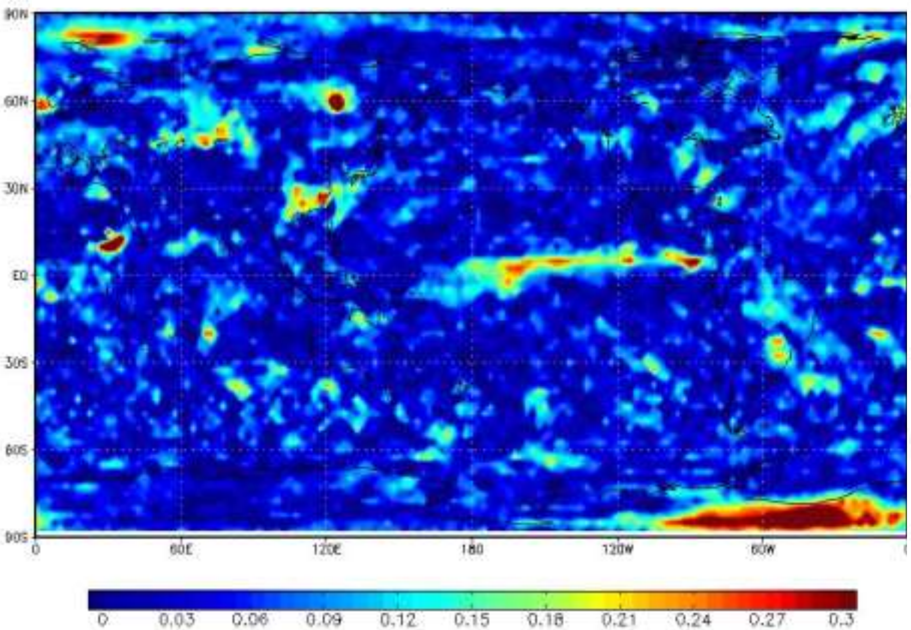


- Poor performances of most variables
- Possible predictability

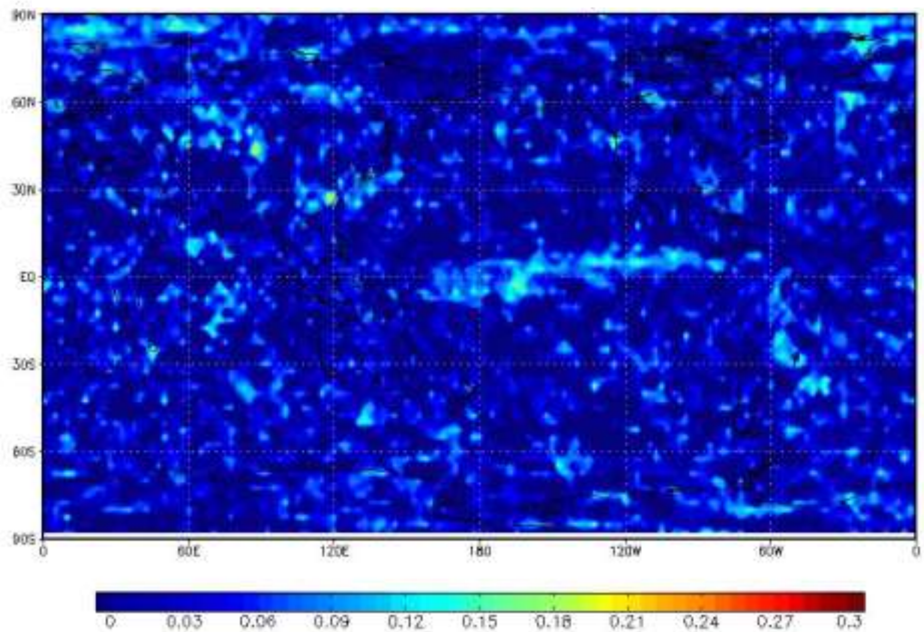
Results

❑ Forecast skill of P by regression of multiple-variable predictors

(a)Forecast skills of monthly P by multiple-variable predictors



(b)Forecast skills of seasonal P by multiple-variable predictors

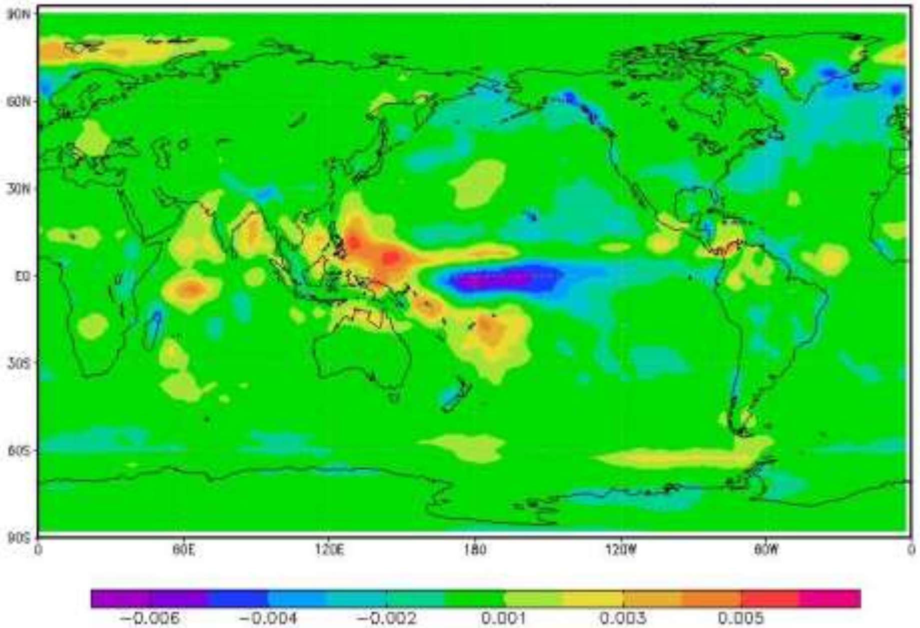


➢ Performances worse than by SST, better than by other 8 single variables

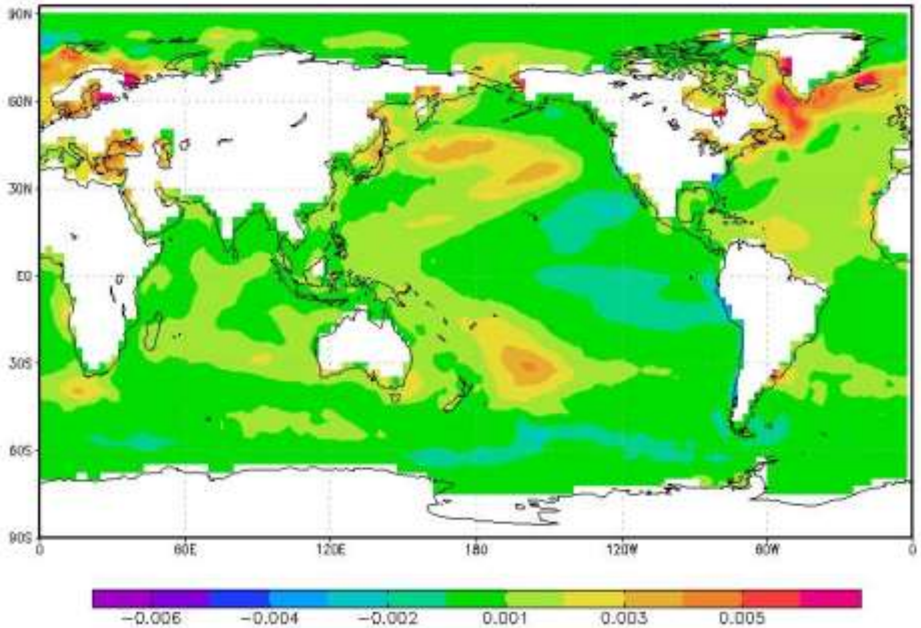
Results

❑ Possible mechanism of predictability of P by SST

(a) Linear trend of monthly P anomaly (mm/month)



(b) Linear trend of monthly SST anomaly (°C/month)

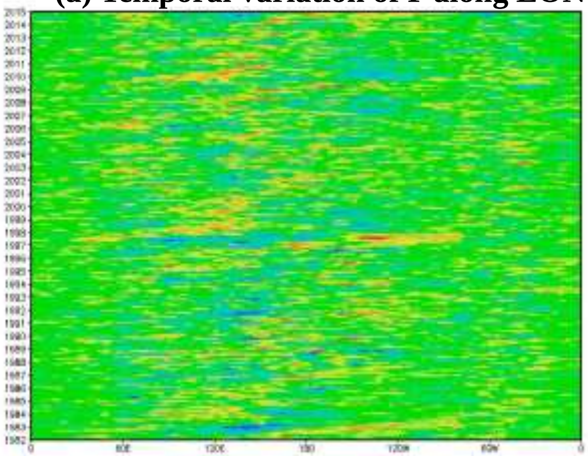


Similar trend → Impact of SST on P

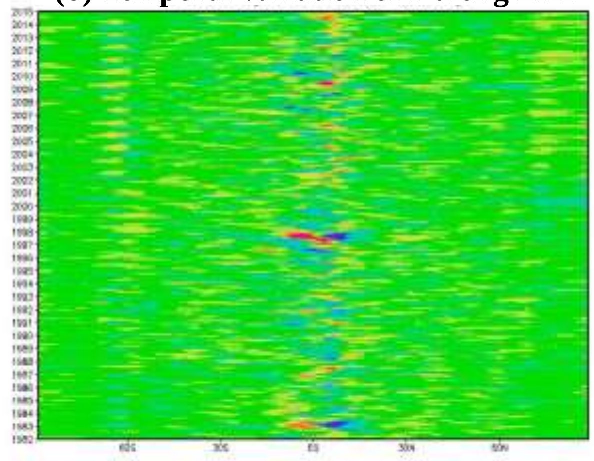
Results

❑ Possible mechanism of predictability of P by SST

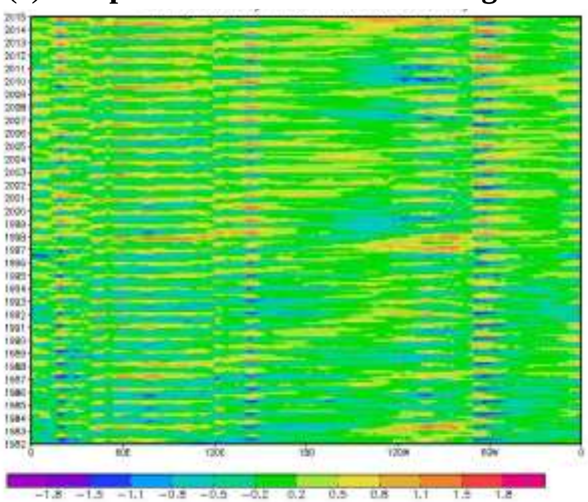
(a) Temporal variation of P along LON



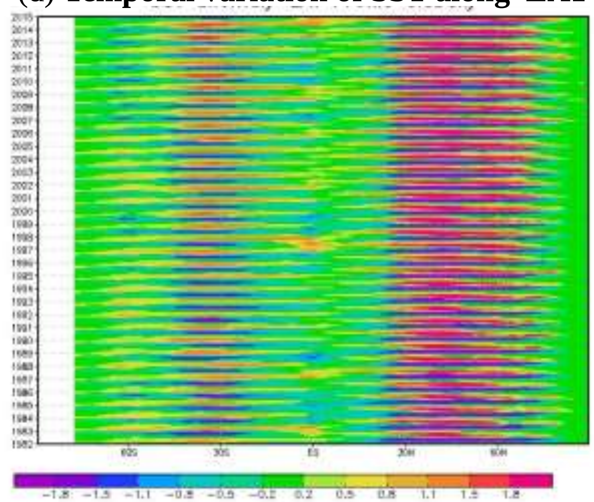
(b) Temporal variation of P along LAT



(c) Temporal variation of SST along LON

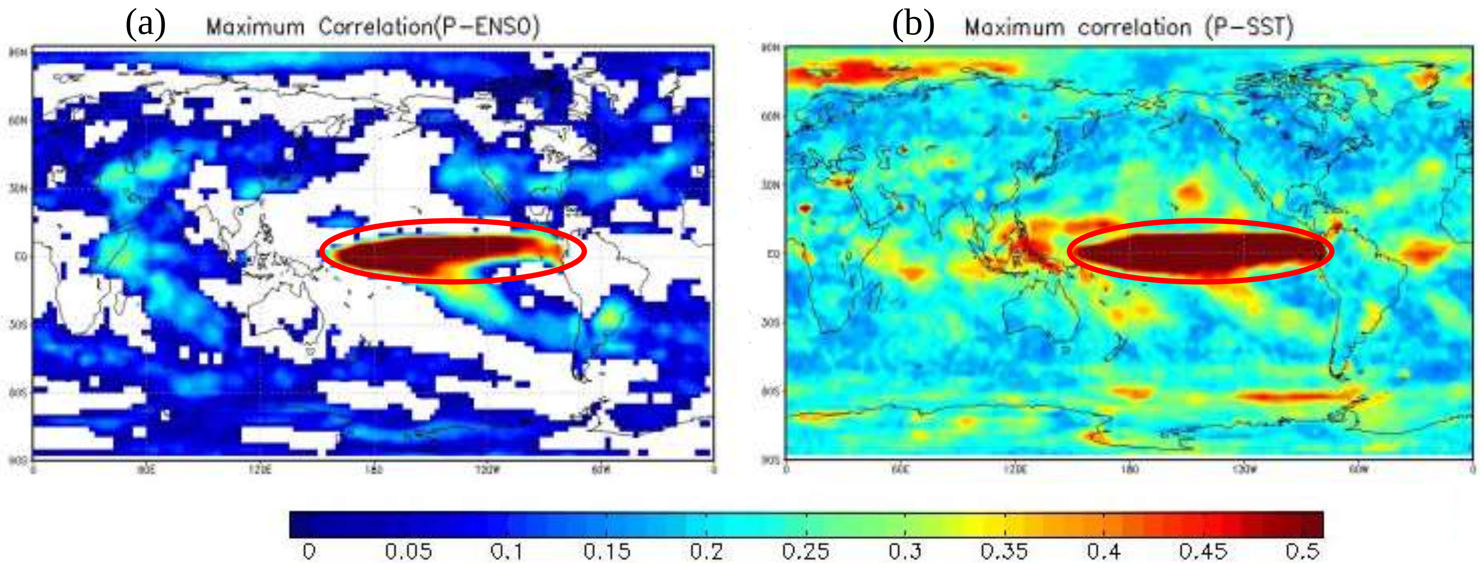


(d) Temporal variation of SST along LAT



Results

- ❑ Possible mechanism of predictability of P by SST



Teleconnection relationship between P~SST is similar with P~ENSO

CONTENT

- Introduction
- Literature Review
- Methodology and Data
- Preliminary Results
- **Conclusions**
- Future Work

Conclusions

- A **maximum Lead-time** of 6 month

- Correlation relationship between P and **SST** is better than other variables, and most relationships show **ENSO-related** features.

- Seasonal Forecast by single-variable **SST** is better than by other 8 single variables and the multiple-variable forecast.

- Predictability of precipitation **in some regions** is possible.

Thank you for your attention!

Q&A SESSION