Multi-decadal trend and decadal variability of the regional sea level over the Indian Ocean since the 1960s: roles of climate modes and external forcing

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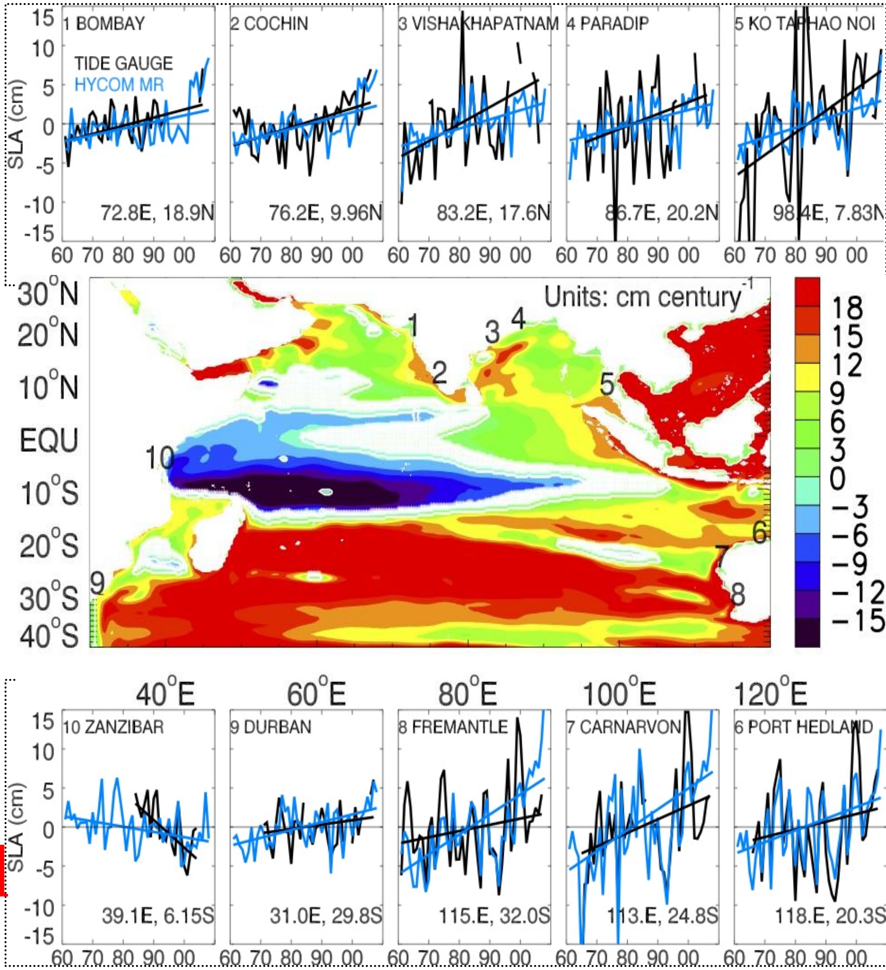
1. Background & goal

Previous studies: distinct pattern of SL trend; Indian Ocean warming (partly anthropogenic) has contributed; this effect however, has never been quantified

Goal

Quantify the effects of internal climate variability (modes) vs external forcing on the observed sea level trend pattern and decadal variability



Sea level trend 1961-2001

2. Approach

- **Observed and reanalysis data**

  (detect sea level variability)

- **Climate model large ensemble: Max-Planck Institute of Meteorology (MPI; 100 members) & NCAR CESM1 (40 members)**

  (assess external forcing vs natural variability)

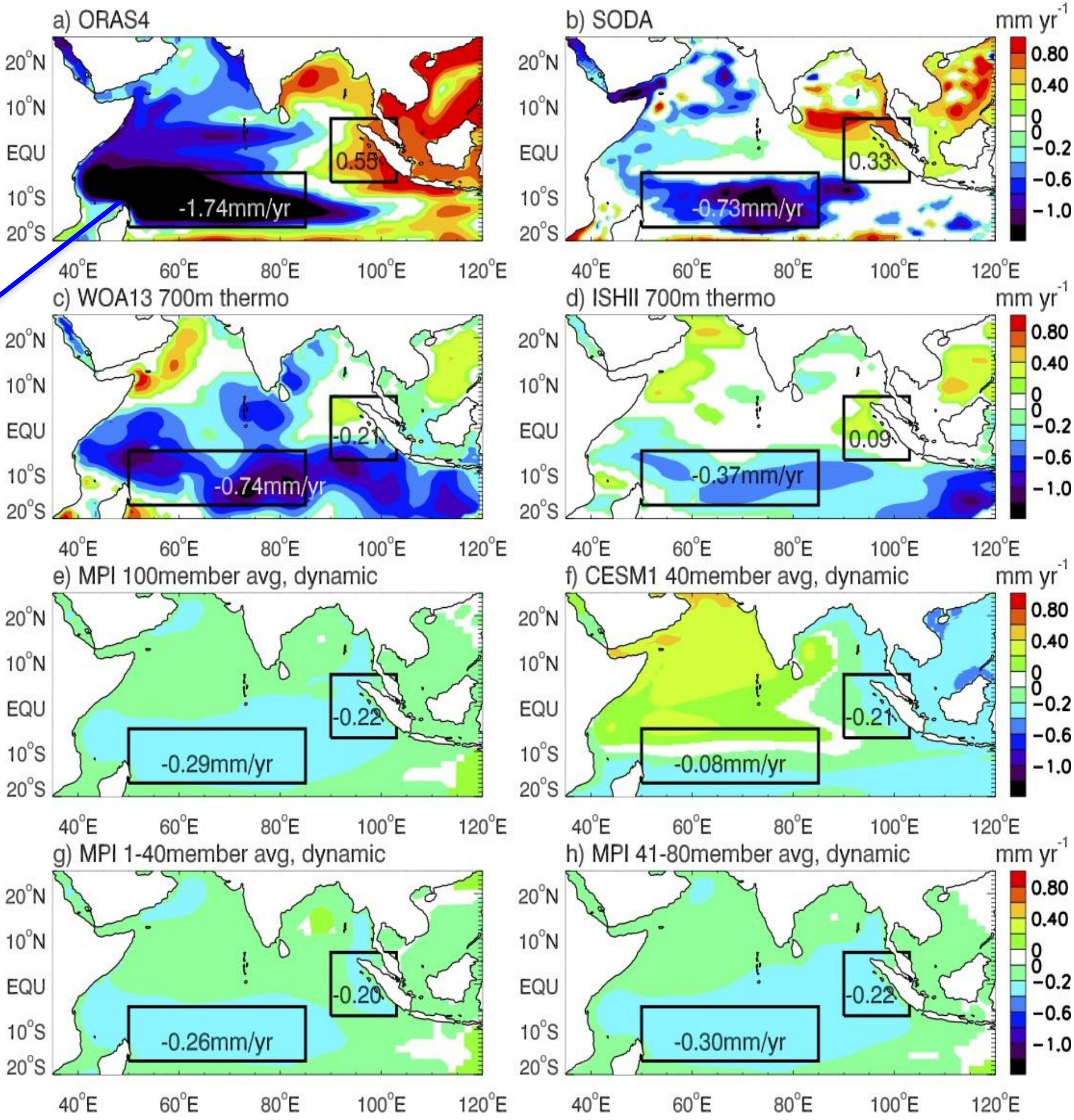
- **Bayesian dynamical linear model (DLM)**

  (extract the impacts of climate modes:

  ENSO, Indian Ocean Dipole (IOD) & monsoon)

3. Results

Linear trend:1958–2005
(global mean removed)



Seychelles sea level fall:

Internal variability:
81%

External forcing:
19% ± 2.4%

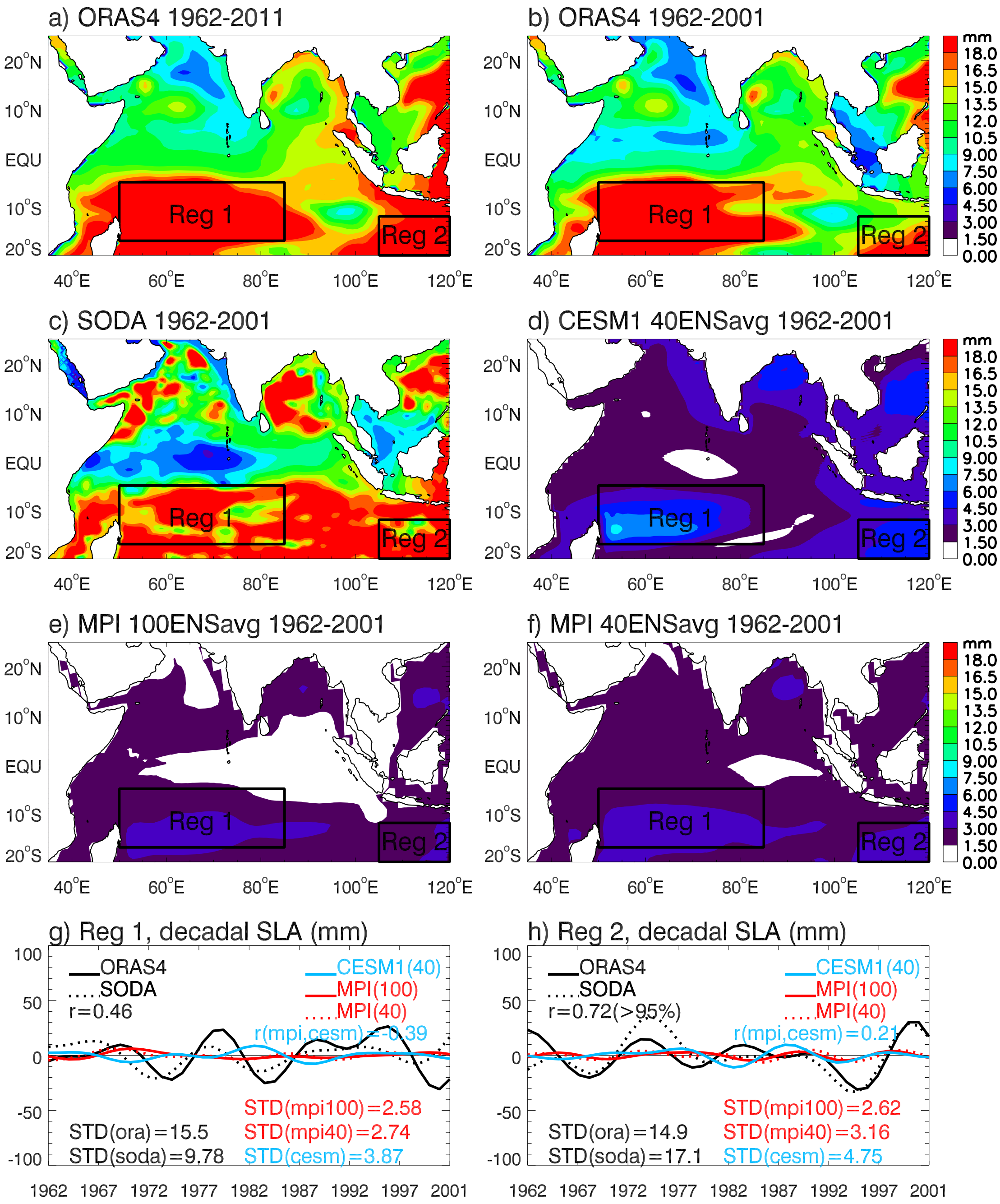
Obs: ORAS4+SODA avg
Model:MPI+CESM (140)

Decadal sea level anomaly (SLA) 1962-2011 (2001): Standard deviation (STD) (detrended&8yr low passed)

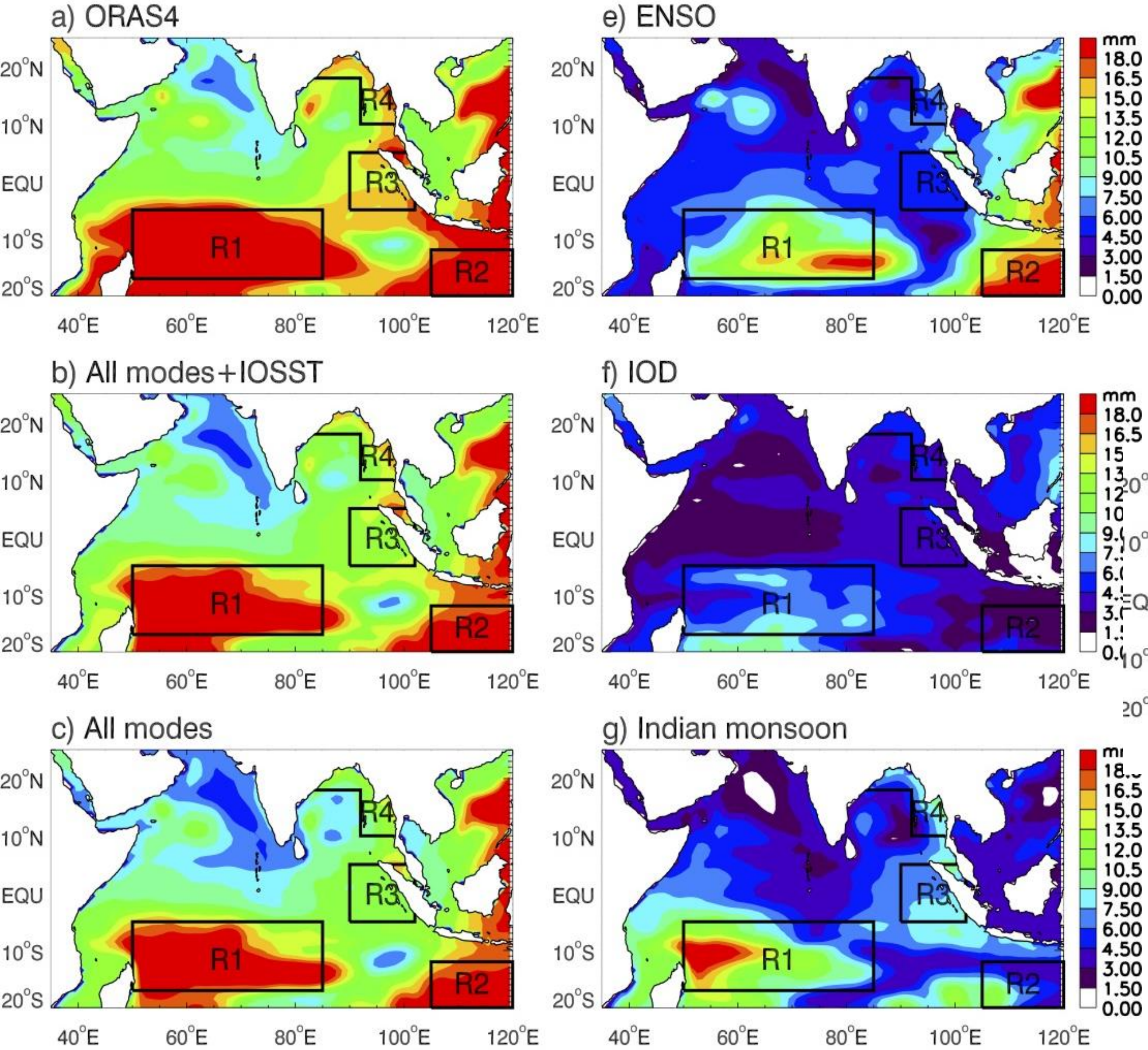
Internal variability is the predominant cause:
STD ratio: forced/observed:
18% ± 17% in Reg 1 (Seychelles);

17% ± 11% in Reg 2 (Indonesian Throughflow)

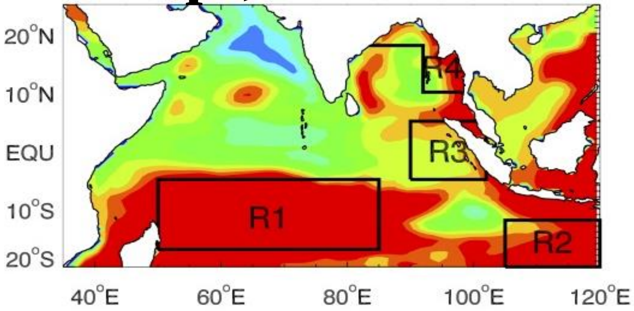
STD map for decadal SLA (mm): 1962-2001



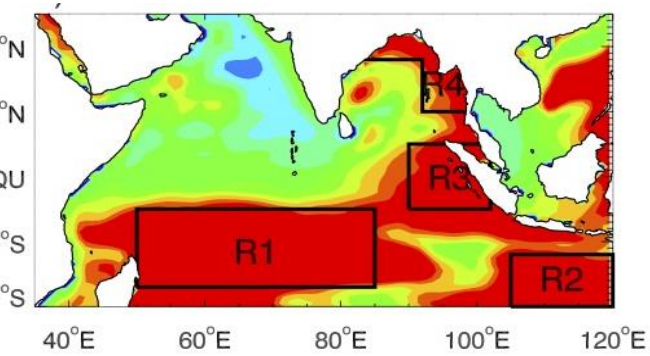
STD of decadal SLA (cm), yrmean data 1962-2011



Nov-Apr, ORAS4



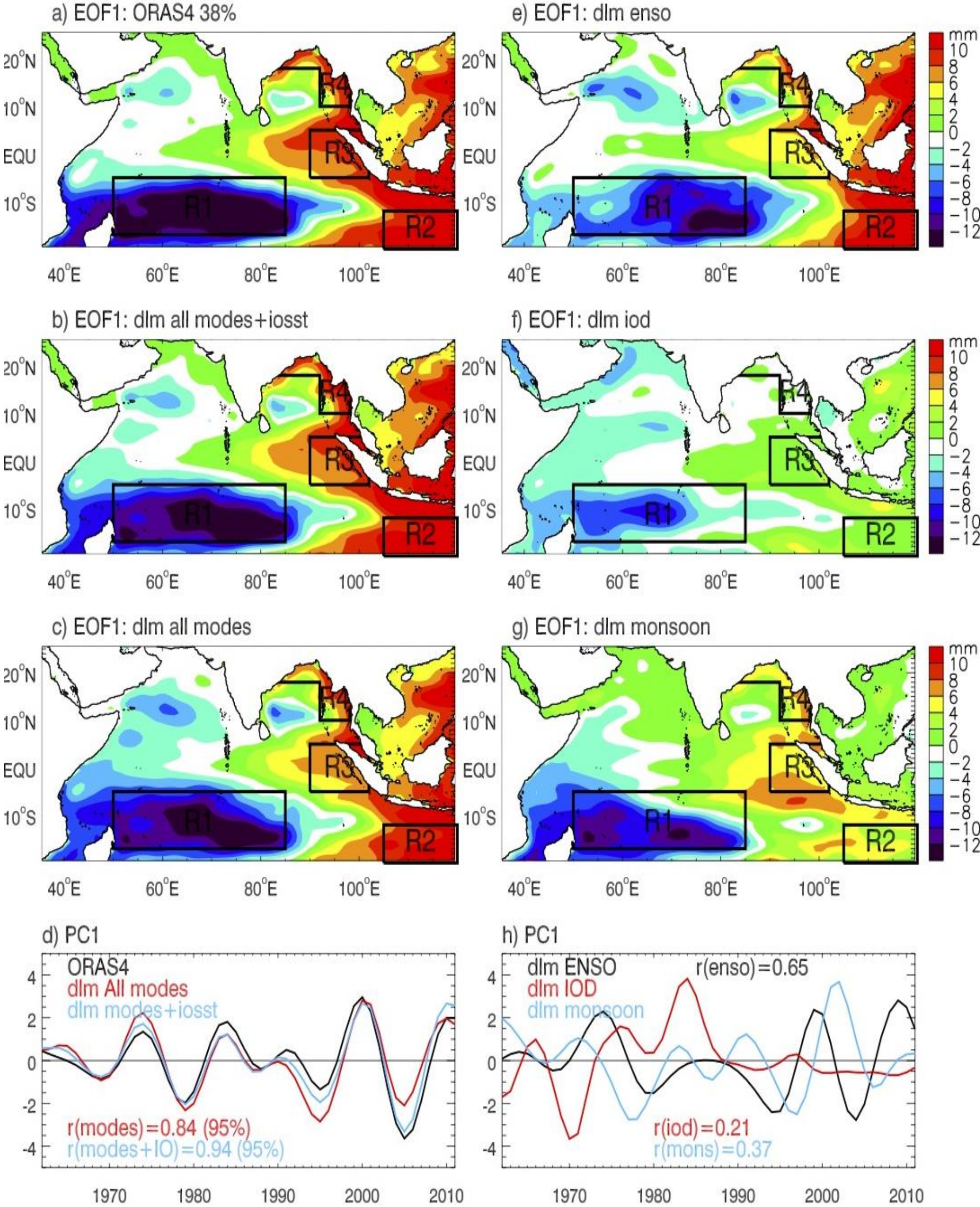
May-Oct, ORAS4



SLA EOF1: Winter season

(1) Climate modes explain most observed SLA

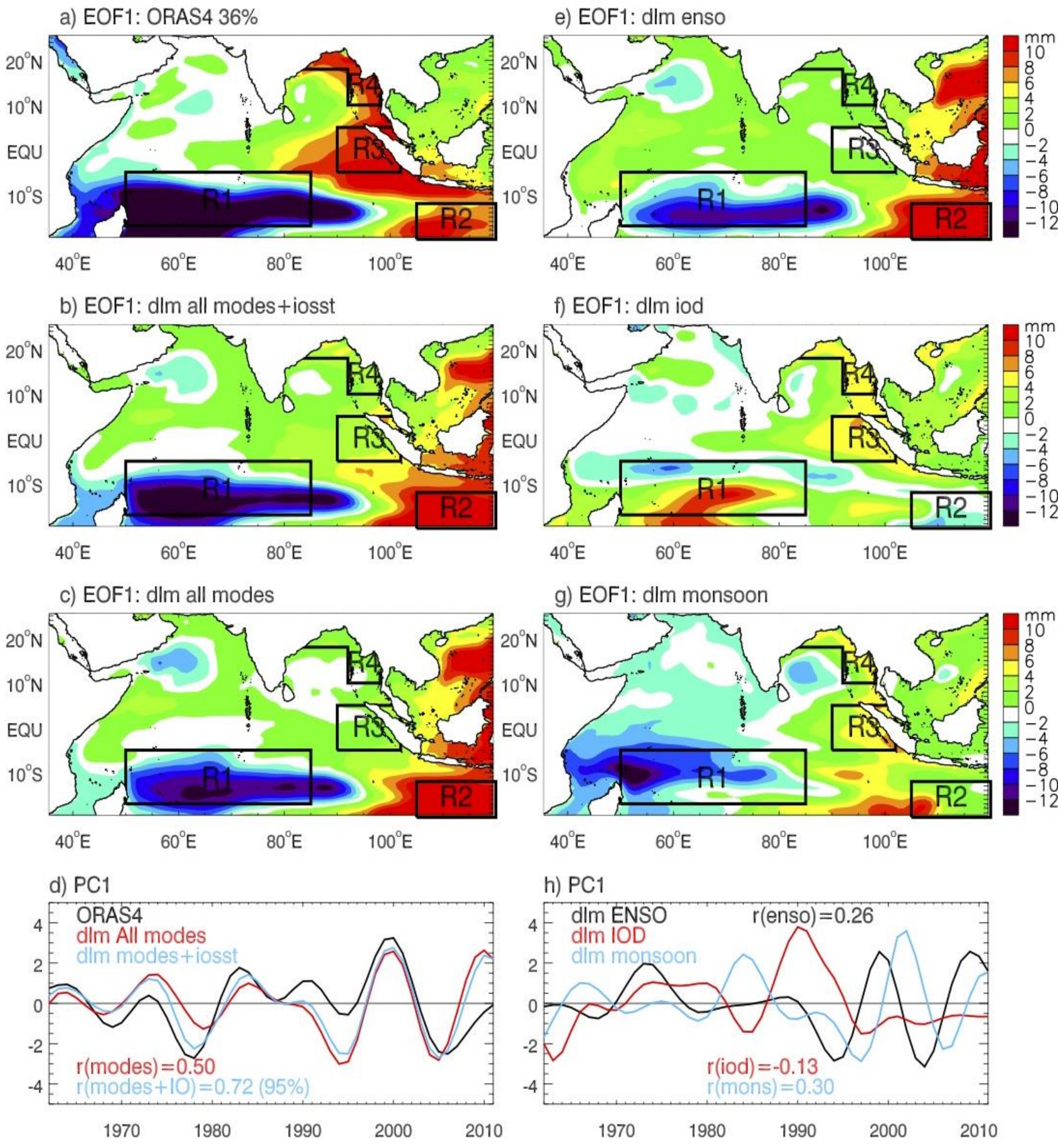
(2) ENSO dominant role; Monsoon also important; IOD – Seychelles region



SLA EOF1: Summer season

(1) ENSO dominates South IO SLAs;

(2) IOD & monsoon dominate East IO Coastal SLAs

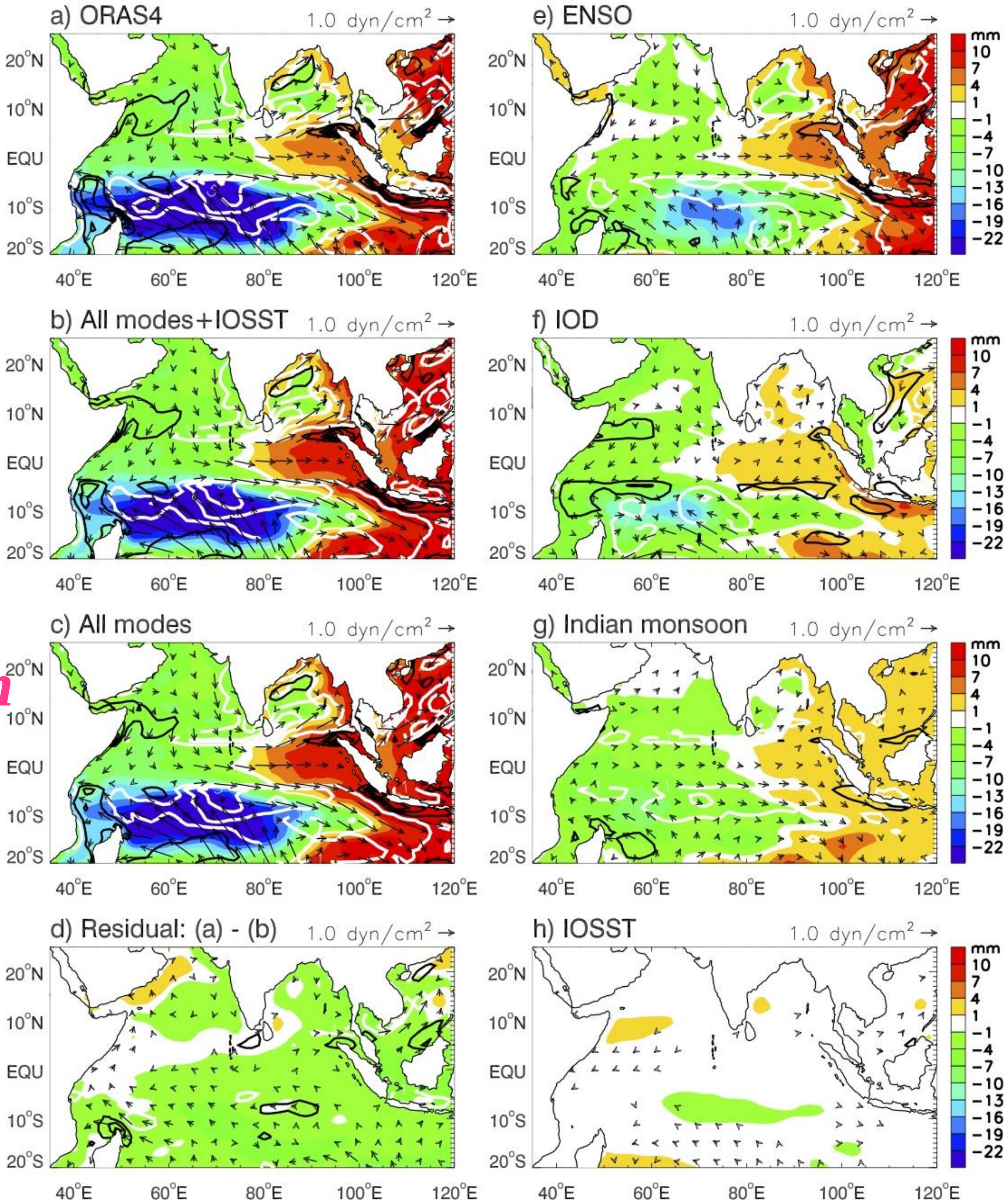


Processes:
Winter season:

Composite based on SLAs in Reg 1 (Seychelles)

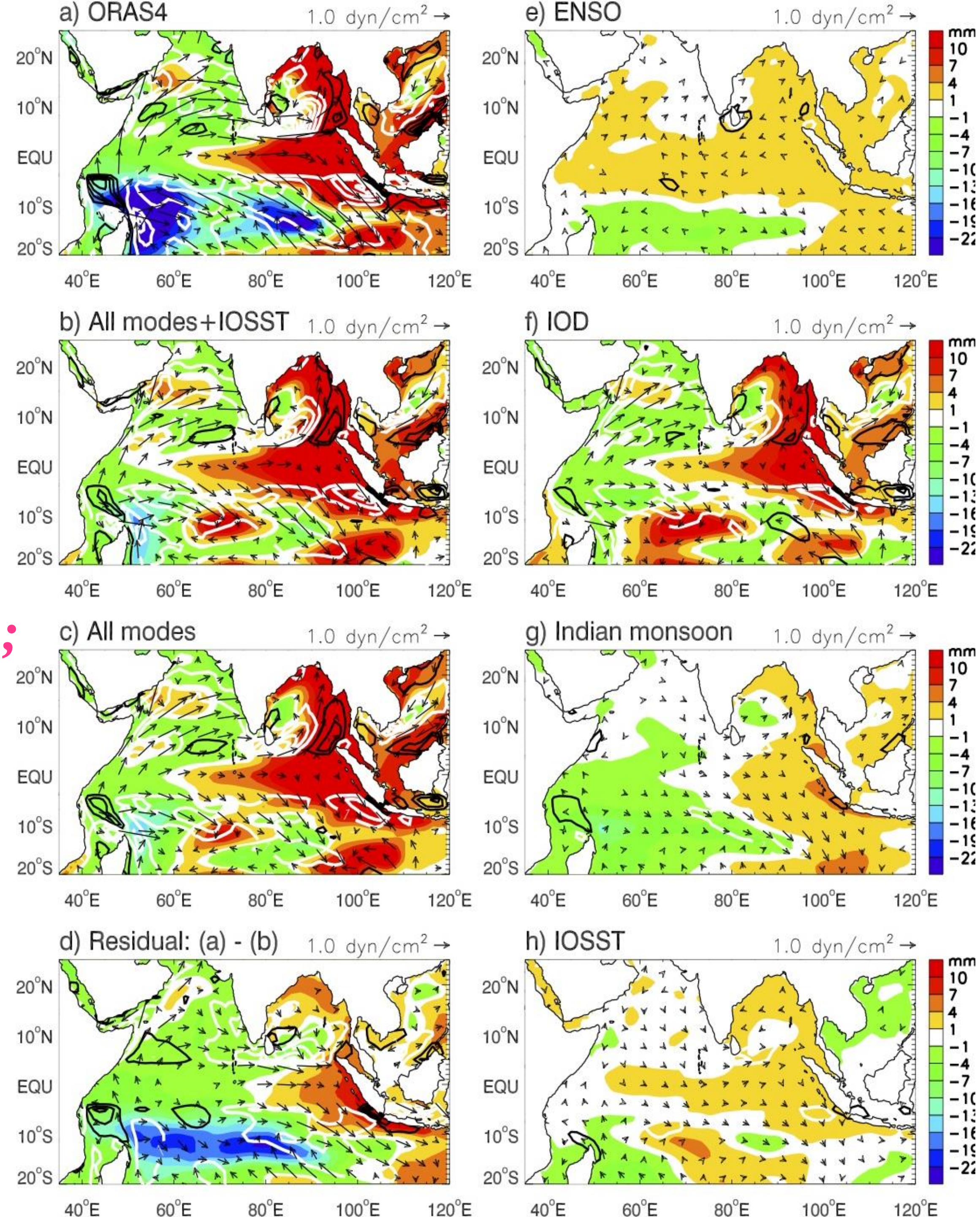
(1) Ekman pumping velocity – open ocean SLAs;

(2) EQ wind forcing: eastern boundary SLAs



Summary season: Composite based on SLA along Bay of Bengal coasts

EQ winds associated With IOD & monsoon dominate coastal SLAs; Local Ekman pumping velocity & longshore wind also contribute



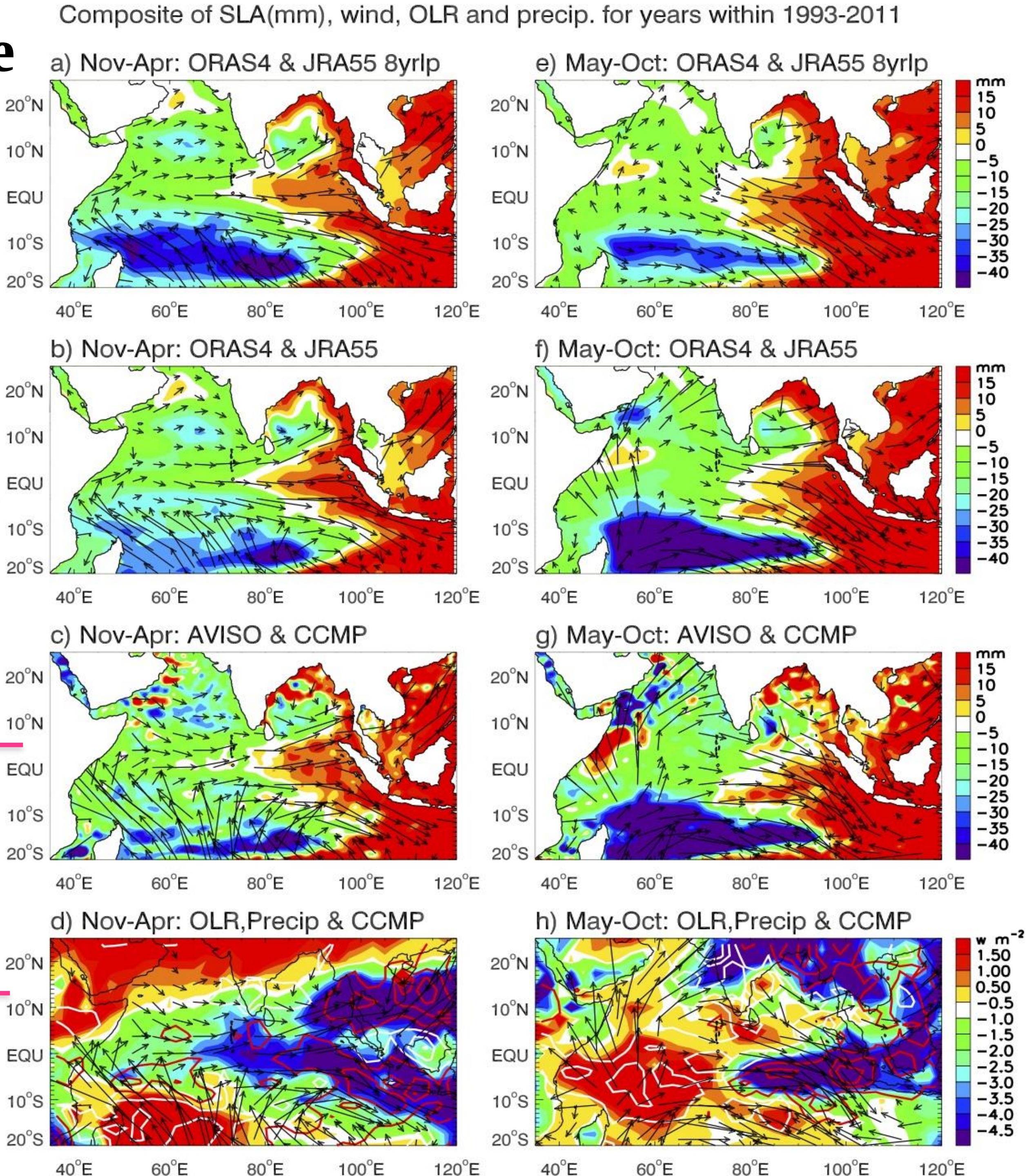
1993-2011 composite

8yr filtered:
SLA&wind
Reanalysis

Unfiltered SLA & wind
Reanalysis

Unfiltered SLA & wind
Satellite

Unfiltered wind, OLRA
& Precipitation



Composite of SLA(mm), wind, OLR and precip. for years within 1993-2011

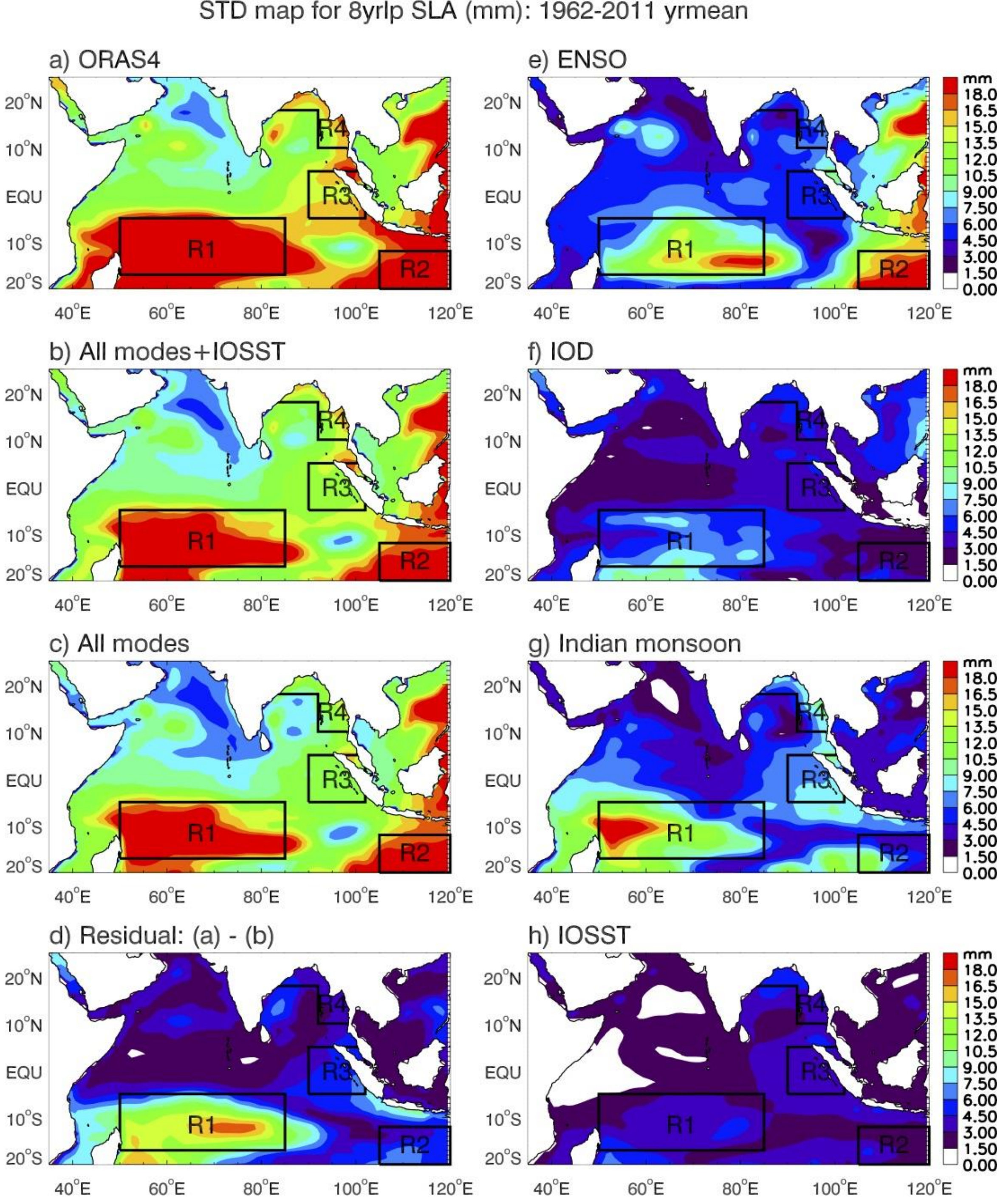
4. Summary and conclusions

(1) For both multi-decadal SL trend pattern and decadal variability (global SLR removed), internal variability dominates external forcing; natural variability (external forcing) accounts for ~81% (19% ± 2.4%) of observed falling trend and 18% ± 17% of the STD of decadal SLA over the Seychelles Island region;

(2) Climate modes (ENSO+IOD+monsoon) explain a large fraction of the observed decadal SLAs for both winter and summer seasons;

(3) During northern winter, variations of off-equatorial wind stress curl & equatorial winds associated with ENSO are the dominant cause for the basin-wide decadal SLA patterns; During summer, winds associated with IOD and monsoon are the major cause for SLAs along the east coasts of equatorial and North Indian Ocean, whereas ENSO still dominate SLAs over the South Indian Ocean.

Thank you!


STD map for 8yrlp SLA (mm): 1962-2011 yrmean
a) ORAS4
b) All modes+IOSST
c) All modes
d) Residual: (a) - (b)
e) ENSO
f) IOD
g) Indian monsoon
h) IOSST
R1
R2
R3
R4
20°N
10°N
EQU
10°S
20°S
40°E
60°E
80°E
100°E
120°E
mm
18.0
16.5
15.0
13.5
12.0
10.5
9.00
7.50
6.00
4.50
3.00
1.50
0.00

(b). Bayesian dlm

Observation equation:

$$Y(t) = b_0(t)+b_1(t)X_1(t)+ \ldots + b_M(t)X_M(t) + \varepsilon(t), \quad \varepsilon(t) \sim N(0,V(t)) \quad (1)$$

Using Kalman filtering and smoothing, Bayesian dlm allows b_i vary with time: measure **changing relation between** ***predictors*** X_i and ***response variable*** Y ("non-static" or "dynamical");

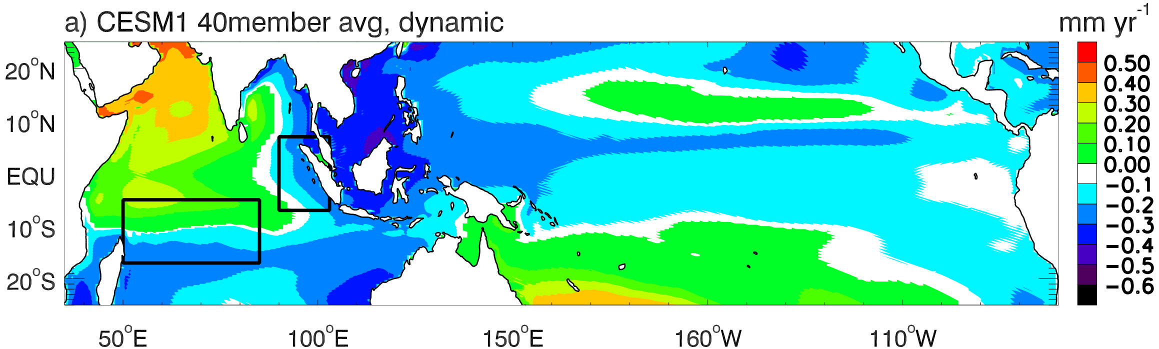
Climate Indices: IPO, etc. ***SLA***

State equation:

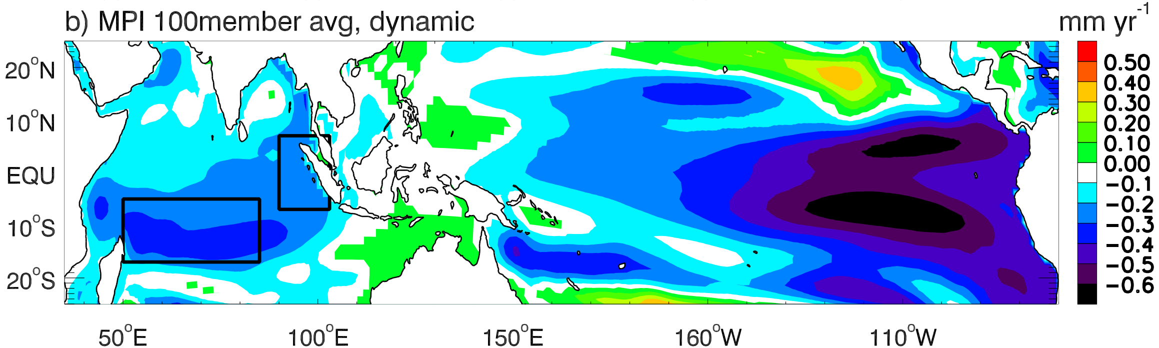
$$b_i(t)= b_i(t-1)+w(t), \qquad w(t) \sim N(0,W(t)). \qquad (2)$$

Posterior **predictive distribution of** b_i **at each time step** t **is updated based on its previous step** $t-1$ **distribution (i.e.,** ***prior*****) and the probability of** Y **conditional on** b_i **at time** t **(i.e.,** ***likelihood*****) using Bayes theorem** *(Petris et al. 2009)*

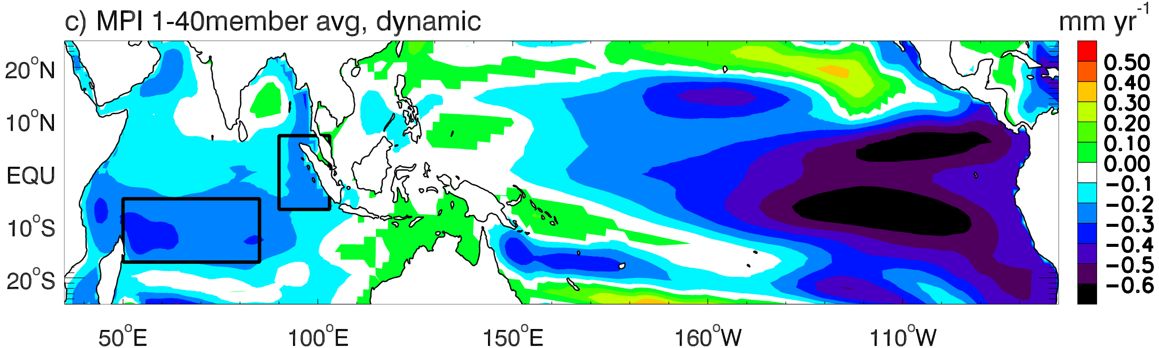
a) CESM1 40member avg, dynamic



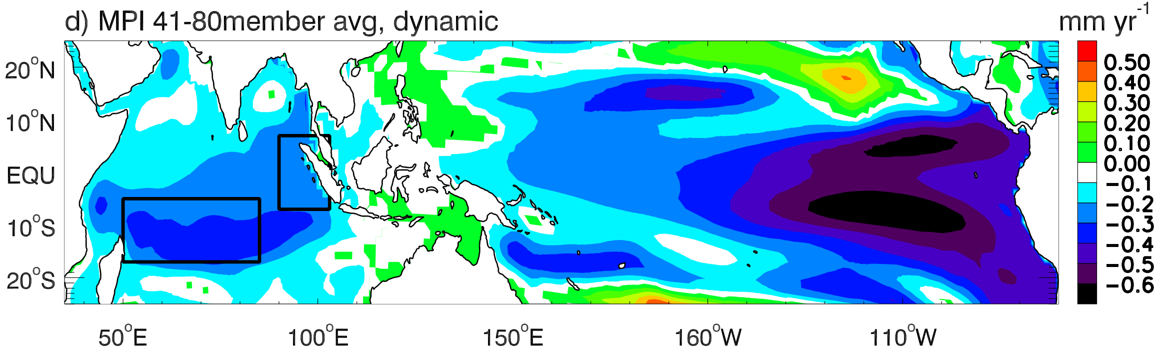
b) MPI 100member avg, dynamic

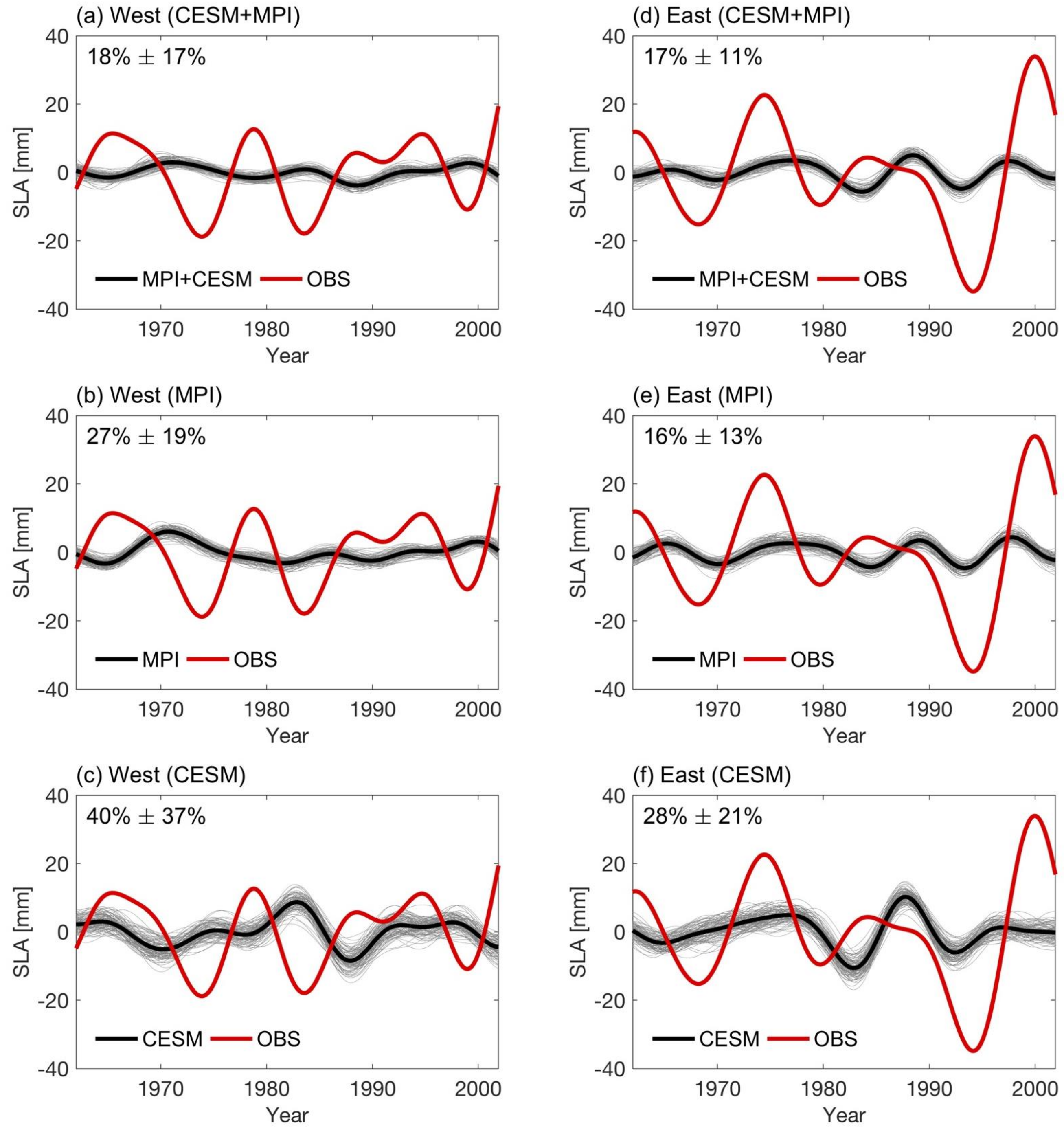


c) MPI 1-40member avg, dynamic



d) MPI 41-80member avg, dynamic




(a) West (CESM+MPI)
18% ± 17%
MPI+CESM
OBS
(b) West (MPI)
27% ± 19%
MPI
OBS
(c) West (CESM)
40% ± 37%
CESM
OBS
(d) East (CESM+MPI)
17% ± 11%
MPI+CESM
OBS
(e) East (MPI)
16% ± 13%
MPI
OBS
(f) East (CESM)
28% ± 21%
CESM
OBS
SLA [mm]
Year
40
20
0
-20
-40
1970
1980
1990
2000