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Information Synergy of ENSO and IOD on the Indian Summer Monsoon Rainfall in Observations and Climate Simulations

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1 Introduction

- The El Niño–Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) are two well-known temporal oscillations in sea surface temperature (SST), which are both thought to influence the interannual variability of Indian summer monsoon rainfall (ISMR).
- This study explores the information exchange from two source variables (ENSO and IOD) to one target (ISMR) using novel estimators such as partial information decomposition (PID).
- First, we demonstrate the concept of two-source IE with results from a simple idealized linear and nonlinear dynamical models for better understanding of Methodology.

4 Results and discussion



- Thereafter, the two-source IE concept is applied on observations and reanalysis datasets to quantify the information exchange from ENSO and IOD to IMSR.
- Finally, we apply the IE methods on three different global climate model (GCM) simulations from the fifth phase of the Coupled Model Intercomparison Project (CMIP5), and on dynamical downscaled regional climate model (RCM) to investigate if information exchange dynamics of ENSO and IOD to ISMR interannual variability are replicated in these climate models.

2 Method Overview

• <u>Shannon</u> (1948) introduced the concept of information entropy, which quantifies the average uncertainty of a given random variable X as,

$$H(X) = -\sum_{x} p(x) \log p(x),$$

• Mutual information (MI) quantifies the reduction in the uncertainty of one random variable given knowledge of another variable (<u>Cover and Thomas</u>, <u>1991</u>) and is defined by

$$I(X;Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)},$$

where p(x, y) is the joint distribution of variables X and Y, and p(x) and p(y) are the marginal distributions of X and Y, respectively.

The information I(X; Y, Z) that the two sources share with the target should decompose according to partial information decomposition by <u>Williams and Beer</u> (2010) into four parts as I(X;Y,Z)



Figure 1: Information exchange from two sources, Y and Z, to the target X decomposed according to PID as unique information (U), redundant information (R), and synergistic information (S).

3 Climate Models and Setup

- We focus on the South Asian summer monsoon seasons (June–July–August–September: JJAS); thus, monthly datasets for the time period 1951–2005 from observations and model simulations are used.
- Various observational reanalysis datasets and model simulations used to quantify twosource IE from the ENSO and IOD to ISMR interannual variability are listed in Table <u>1</u> and are also described here.

Acronym Ensemble Atm. resolution member

Figure2: Information exchange from I(PREC; IOD), I(PREC; ENSO), two-source information exchange I(PREC; ENSO, IOD), and net synergy $\times 10^{-2}$ nats for the observational datasets (a) GPCC, APHRODITE. (b) Global Climate Models (c) Regional Climate Model Simulations. Only significant values at 95 % confidence intervals are plotted

5 Conclusions

- The results from the observations and reanalysis data suggest that both IOD and ENSO influence the interannual variability of ISMR over the Indian subcontinent. We found that IOD and ENSO exhibit positive net synergy over the monsoon core region, and net redundant information over the southern part of India.
- The IE patterns in the three GCM simulations differ from those in the observations. However, the GCM Nor-ESM-M better captured the precipitation anomalies from ENSO and partly from IOD than the other two GCMs.

GCM modeling center

Max Planck Institute for Meteorology	MPI-ESM-LR	r1i1p1	$1.875^{\circ} \times 1.875^{\circ}$
Norwegian Climate Centre	Nor-ESM-M	rlilpl	$2.5^{\circ} \times 1.9^{\circ}$
SMHI, Sweden	EC-EARTH	r12i1p1	$1.125^{\circ} \times 1.125^{\circ}$
RCM modeling center			
CLMCom-ETH	COSMO-crCLIM		$0.22^{\circ} \times 0.22^{\circ}$
Observations and reanalysis datasets			
APHRODITE	_	_	$0.25^{\circ} \times 0.25^{\circ}$
GPCC	_	_	$0.5^{\circ} imes 0.5^{\circ}$
HadISST	_	_	$1^{\circ} \times 1^{\circ}$
NCEP reanalysis	_	_	$1.875^{\circ} \times 1.875^{\circ}$
ERA-Interim reanalysis	_	_	$0.5^{\circ} imes 0.5^{\circ}$
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 Table 1. CMIP5 GCMs, RCMs, and observation descriptions used in the current study.

- Downscaling the Nor-ESM-M simulation with the RCM COSMO-crCLM better replicated the observed IE patterns than downscaling the MPI-ESM-LR and EC-EARTH simulations.
- Downscaling MPI-ESM-LR and EC-EARTH did not compensate for errors in the large-scale driving simulations. These results highlight the importance of the choice of GCM simulations when performing dynamical downscaling for high-resolution regional climate projections.

6 References

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