

Process-Oriented Dynamical Models Evaluation for Seasonal Prediction through the Lens of Causal Network

Nachiketa Acharya

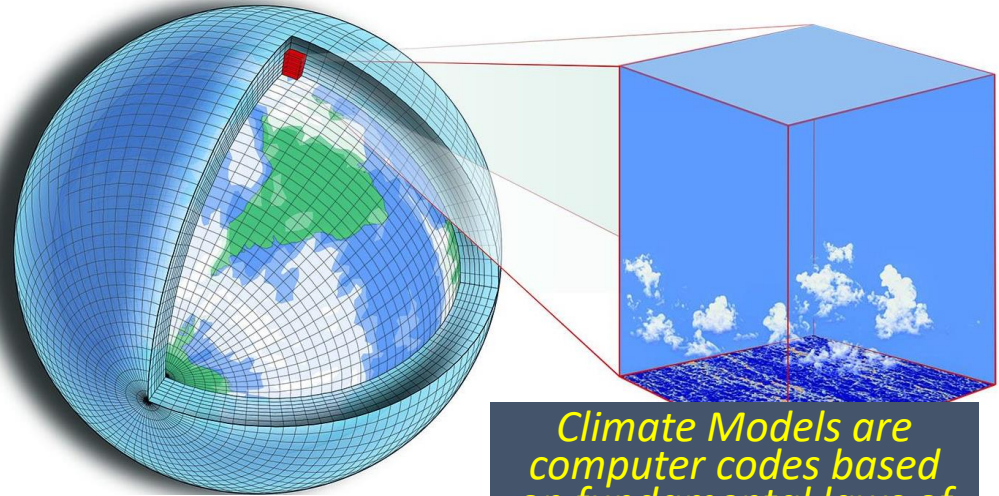
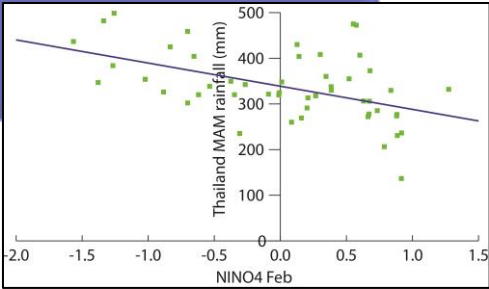
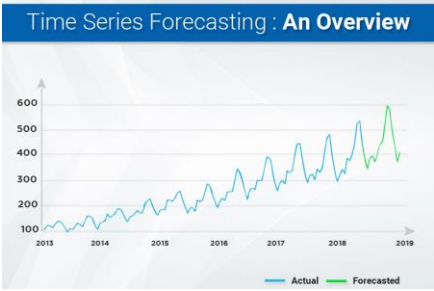
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Tools for Climate Forecast

Seasonal Prediction

Statistical Model

Dynamical Model
(Form physics)



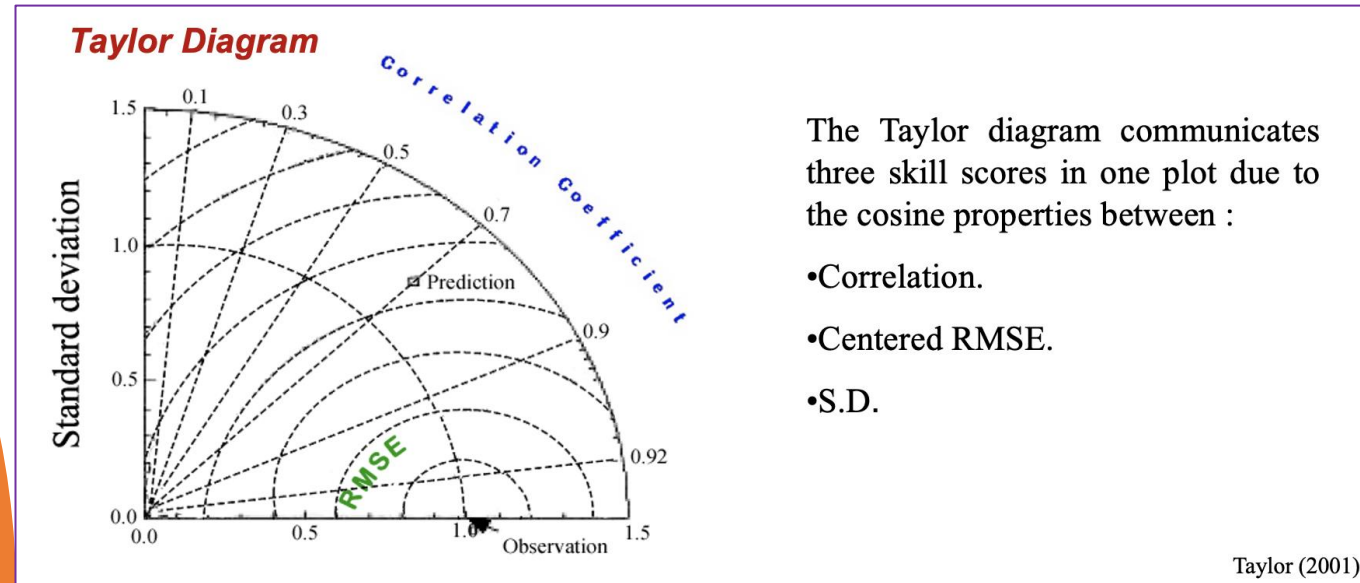
Climate Models are computer codes based on fundamental laws of physics

Limitations

- The autocorrelation of rainfall is very poor.
- The relation between rainfall and predictors go on changing .

Observed rainfall vs Model forecasted rainfall (mostly descriptive statistics)

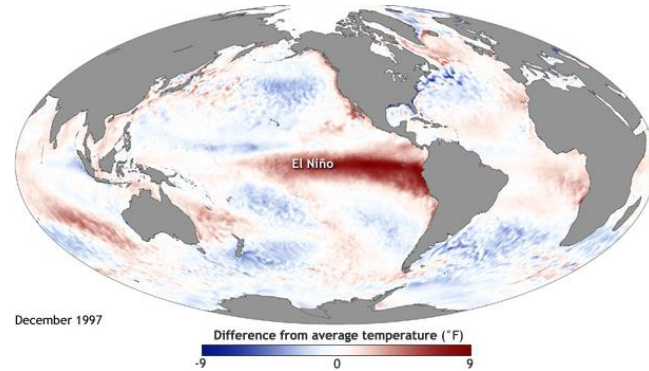
Standard Evaluation process of Dynamical Model



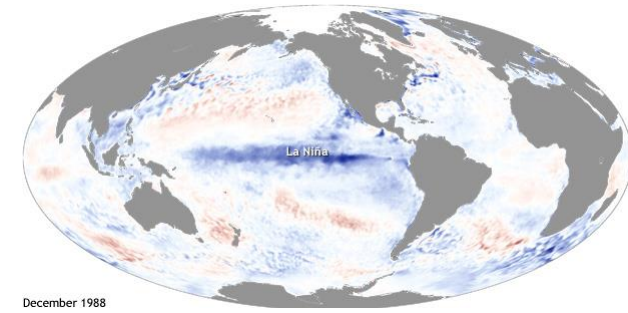
Limitation: Dose not provide “Why” part which will help dynamical modeling community to improve model physics, teleconnection or others factors.

Major Predictability of Seasonal Forecast time scale: ENSO

El Niño

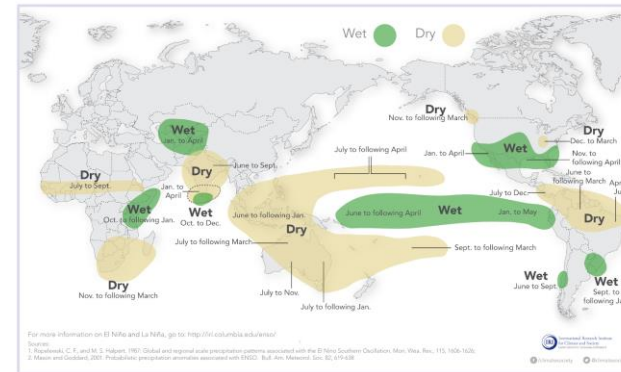


La Niña



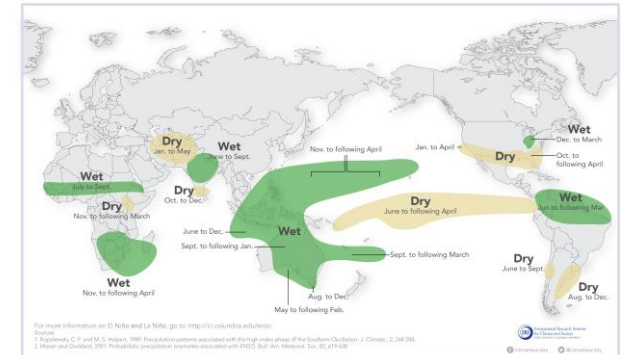
El Niño and Rainfall

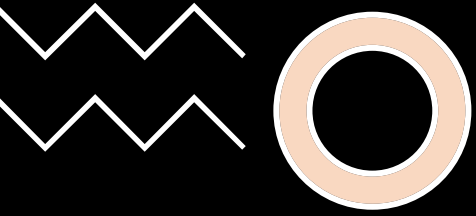
El Niño conditions in the tropical Pacific are known to shift rainfall patterns in many different parts of the world. Although they vary somewhat from one El Niño to the next, the strongest shifts remain fairly consistent in the regions and seasons shown on the map below.



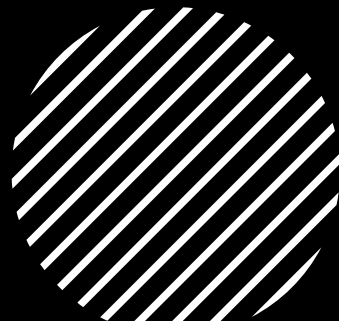
La Niña and Rainfall

La Niña conditions in the tropical Pacific are known to shift rainfall patterns in many different parts of the world. Although they vary somewhat from one La Niña to the next, the strongest shifts remain fairly consistent in the regions and seasons shown on the map below.





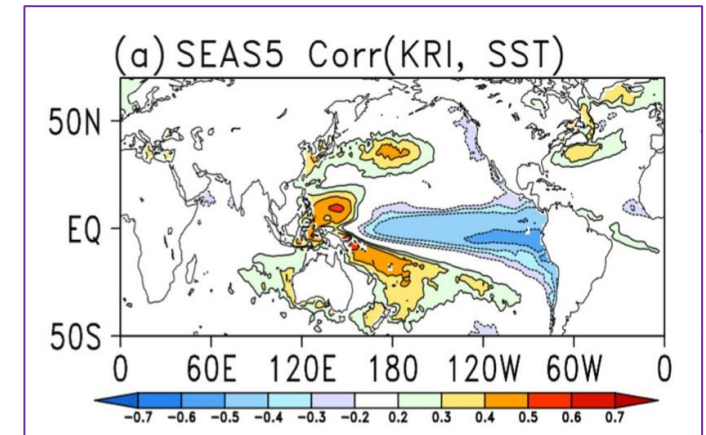
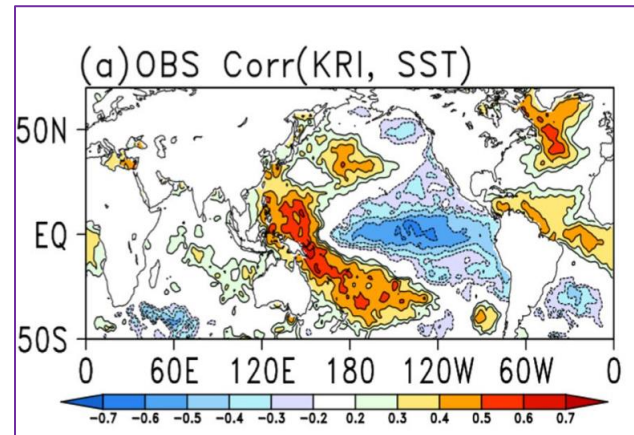
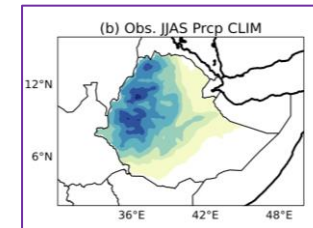
Process-oriented Evaluation based on Teleconnection



Observed teleconnection (rainfall-ENSO) vs Model forecasted teleconnection (rainfall-ENSO)

Common tool: Pearson's Correlation Coefficient

Example: Ethiopian "Kiremt" season, Acharya et al.2022, Ehsan et al 2021



Causal Pathways for Teleconnection

BAMS
Article

Quantifying Causal Pathways of Teleconnections

Marlene Kretschmer, Samantha V. Adams, Alberto Arribas, Rachel Prudden, Niall Robinson, Elena Saggioro, and Theodore G. Shepherd

ABSTRACT: Teleconnections are sources of predictability for regional weather and climate, but the relative contributions of different teleconnections to regional anomalies are usually not understood. While physical knowledge about the involved mechanisms is often available, how to quantify a particular causal pathway from data are usually unclear. Here, we argue for adopting a causal inference-based framework in the statistical analysis of teleconnections to overcome this challenge. A causal approach requires explicitly including expert knowledge in the statistical analysis, which allows one to draw quantitative conclusions. We illustrate some of the key concepts of this theory with concrete examples of well-known atmospheric teleconnections. We further discuss the particular challenges and advantages these imply for climate science and argue that a systematic causal approach to statistical inference should become standard practice in the study of teleconnections.

KEYWORDS: Atmospheric circulation; Teleconnections; Statistical techniques; Time series; Interannual variability; Regional effects


<https://doi.org/10.1175/BAMS-D-20-0117.1>

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In final form 27 April 2021

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AMERICAN METEOROLOGICAL SOCIETY

BAMS

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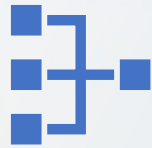
- “...the relative contributions of different teleconnections to regional anomalies are usually not understood. While physical knowledge about the involved mechanisms is often available, how to quantify a particular causal pathway from data are usually unclear”.
- However, they used “Partial Correlation”, “Multiple Linear Regression” and “Conditional Probability” to quantifying the Causal Pathways using five examples.
- Examples: Common drivers, Mediating pathways, Direct and indirect pathways, Blocking the correct paths in the network, Measuring nonlinear dependencies.



Goal of this study



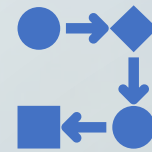
Causal discovery algorithms go beyond correlation-based measures by systematically excluding common driver effects and indirect links.



Here, we explore a causal network for model evaluation as a type of process-oriented framework.



Based on data-driven causal fingerprints, the causal network can understand differences between models and observations based on the physical process which potentially influences model biases in simulating climate variables.



This process based evaluation and informed model development community, to improve the teleconnection within model world.

3 Traps of Statistics (3S')

Symmetry

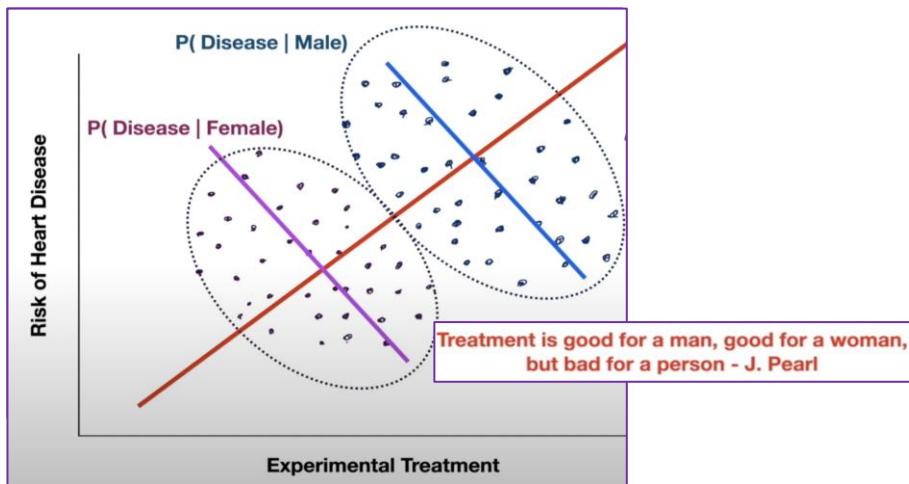
$Y = mX + b$

$\Rightarrow X = (Y - b)/m$

Symptoms cause disease??

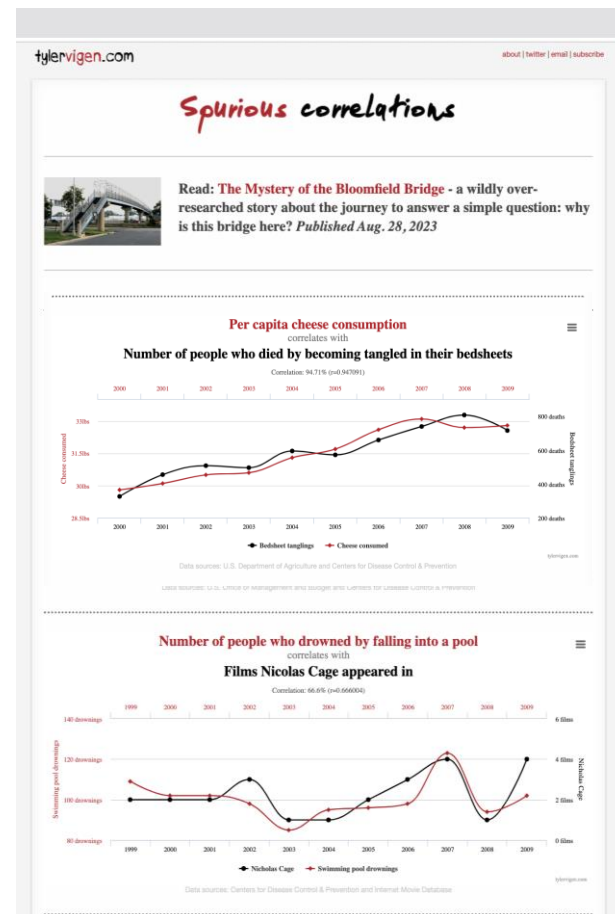
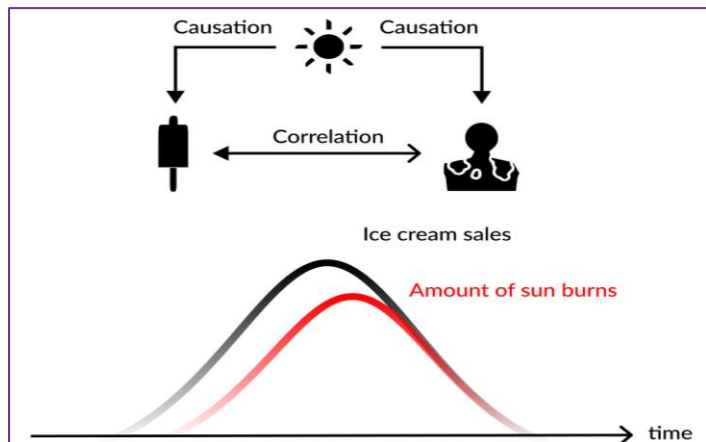
Labels: Symptom severity (pointing to Y), Disease severity (pointing to Y), All other factors (pointing to b)

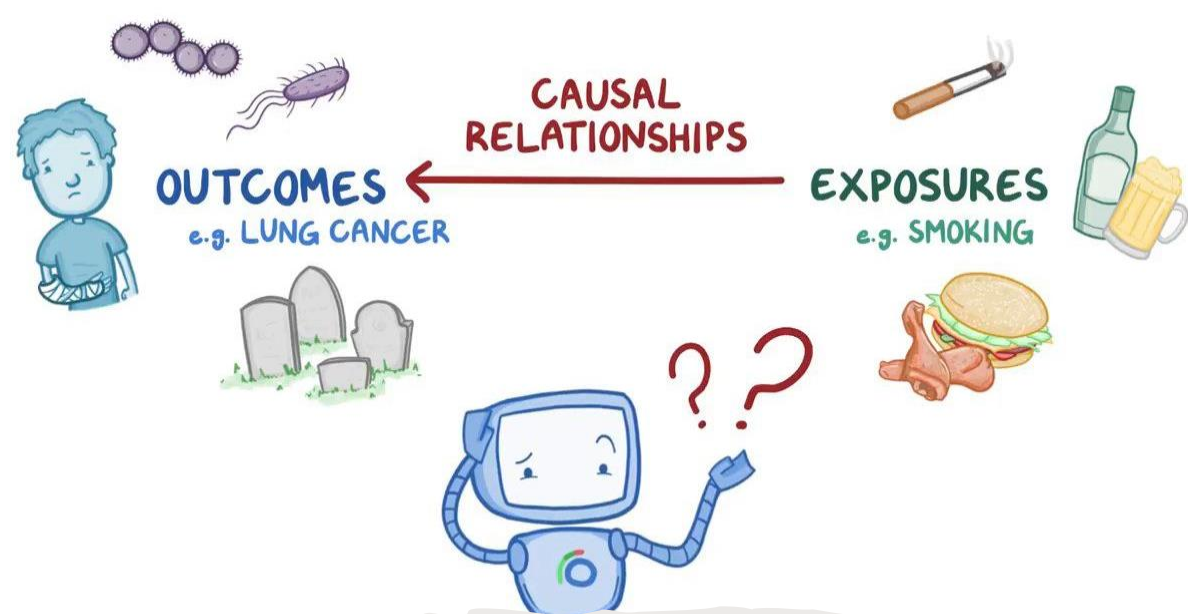
Simpson's Paradox



Spurious Correlation

Correlation \neq Causation



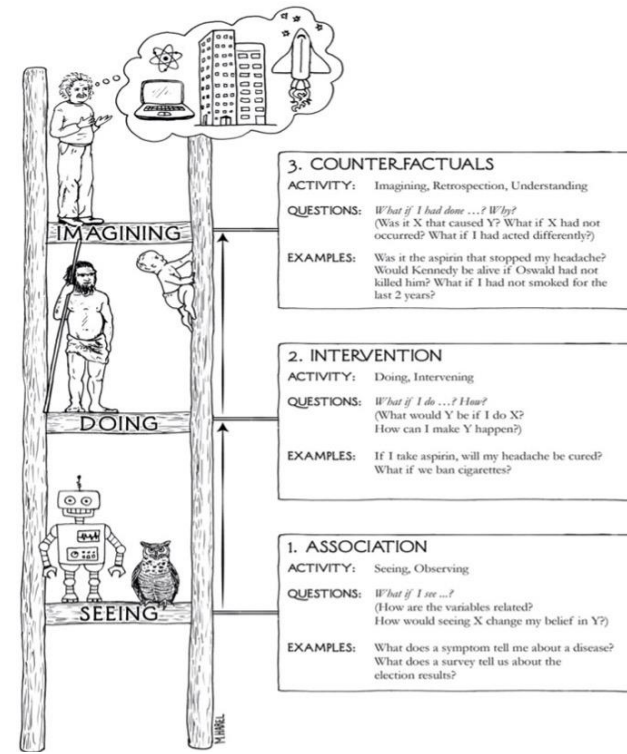
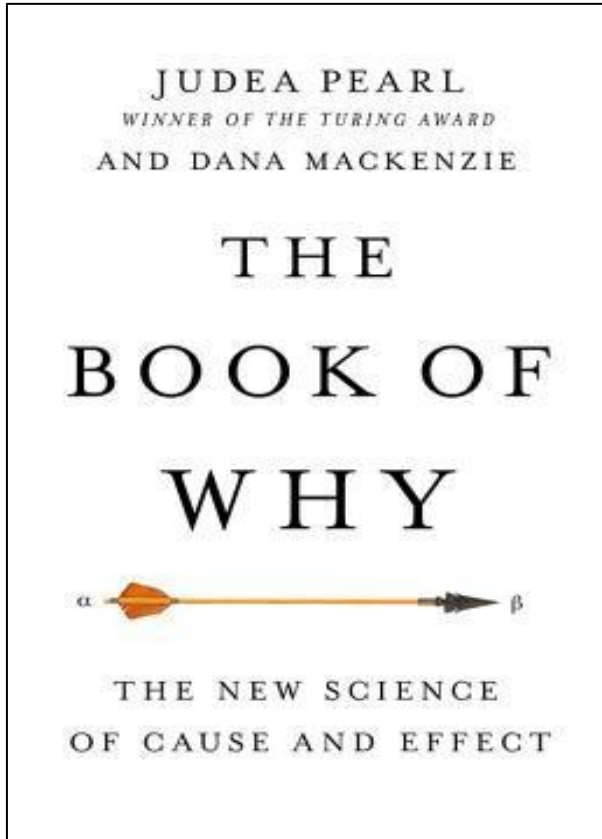


Causality

- Causality is the science of understanding the “cause – and- effect” relationships in the world around us.
- X (new drug) caused Y (patient’s health) if when all confounders (age, severity of illness etc.) are adjusted, an intervention in X results in a change in Y, but intervention in Y does not change X.

Pearl's Ladder of Causation

Causality



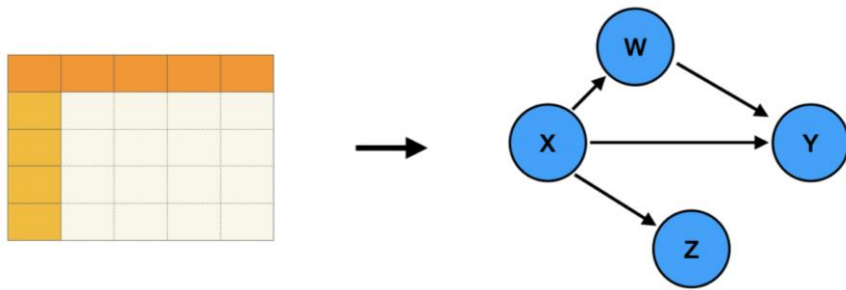
The Three Layer Causal Hierarchy

Level (Symbol)	Typical Activity	Typical Questions	Examples
1. Association $P(y x)$	Seeing	What is? How would seeing X change my belief in Y?	What does a symptom tell me about a disease? What does a survey tell us about the election results?
2. Intervention $P(y do(x), z)$	Doing Intervening	What if? What if I do X?	What if I take aspirin, will my headache be cured? What if we ban cigarettes?
3. Counterfactuals $P(y_x x', y')$	Imagining, Retrospection	Why? Was it X that caused Y? What if I had acted differently?	Was it the aspirin that stopped my headache? Would Kennedy be alive had Oswald not shot him? What if I had not been smoking the past 2 years?

Causal Modeling

Causal Discovery

Learn the graph/structure from the data

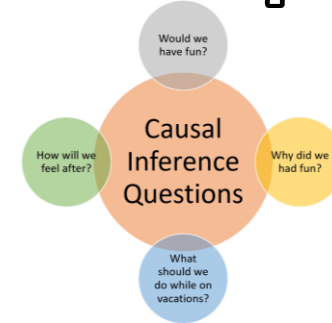


Build a graphical representation (often a **Directed Acyclic Graph** or DAG) that captures the causal relationships among variables.

“**Causal discovery** is the process of **building the causal model from data** when the model is unknown, while **causal inference** is the process of using the causal model (whether discovered or assumed) to **make meaningful causal statements and predictions.**”

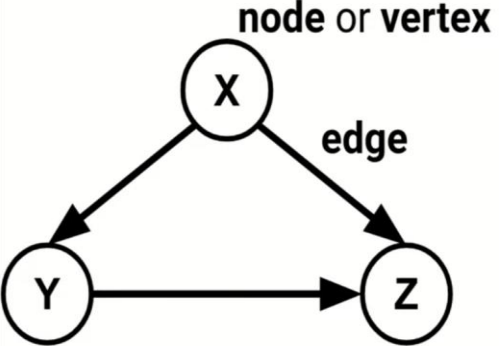
Causal Inference

Inferring/answering conditional questions from causal graph



It is about drawing meaningful and well-supported causal conclusions within a known causal framework.

Basics of Causal Graphs



Adjacent nodes: X and Y, Y and Z

Non-adjacent nodes:
X and Z

X is **parent** of Y

Y is **parent** of Z

Y is **child** of X

Z is **child** of Y

X is **ancestor**
of Y and Z

Y is **ancestor**
of Z

Y is **descendant**
of X

Z is **descendant**
of Y and X

Causal Graphs are Directed Acyclic Graphs (DAGs)

A DAG is a graph that provides a visual representation of causal relationships among a set of variables.

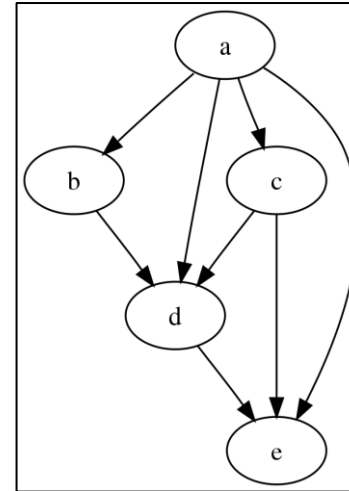
D = directed (all arrows point in only a single direction).

The direction of the arrow is the direction of causation:
 $A \rightarrow B$ means A causes B.

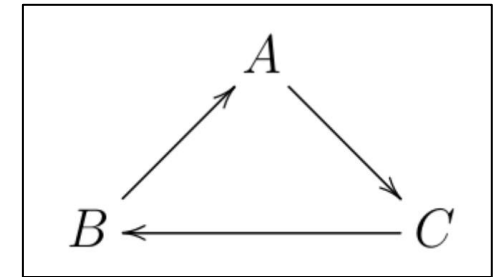
A = acyclic (no sequence of arrows forms a closed loop, which would be backwards causation). Causal Graph should be acyclic.

Several Methods available to find out DAG for Causal Discovery.

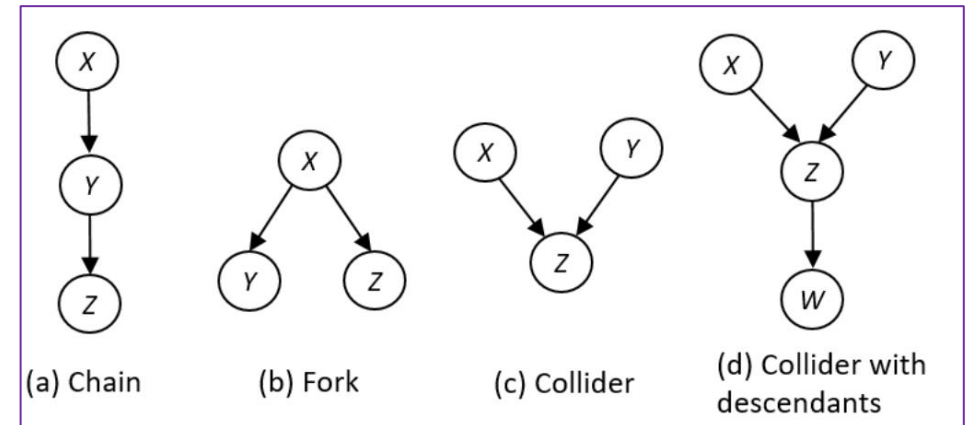
DAG



Not a DAG, Correlation

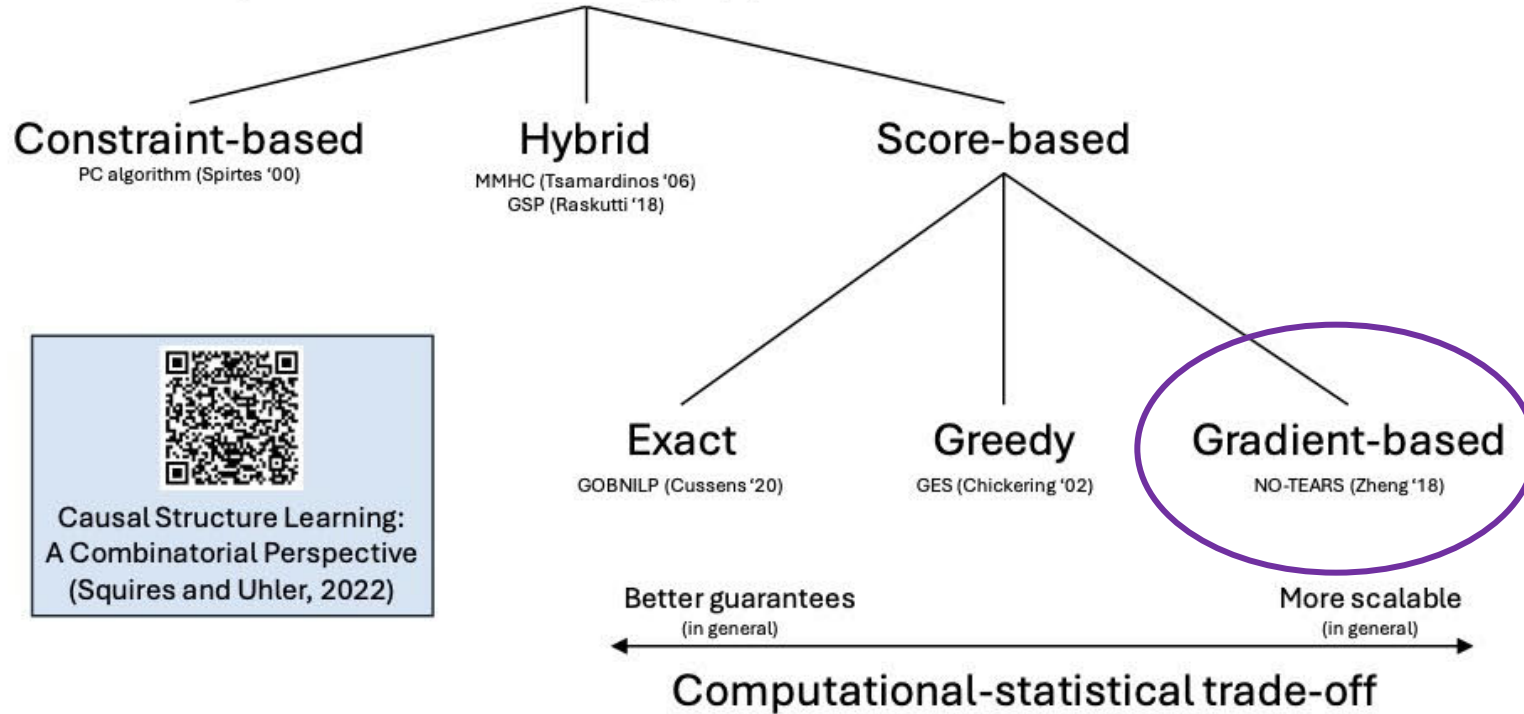


Types



Methods for Causal Discovery

Causal structure learning (aka causal discovery) approaches



Causal Structure Learning:
A Combinatorial Perspective
(Squires and Uhler, 2022)

A Survey on Causal Discovery Methods for Temporal and Non-Temporal Data

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Abstract

Causal Discovery (CD) is the process of identifying the cause-effect relationships among the variables of a system from data. Over the years, several methods have been developed primarily based on the statistical properties of data to uncover the underlying causal mechanism. In this study, we present an extensive discussion on the methods designed to perform causal discovery from both independent and identically distributed (i.i.d.) data and time series data. For this purpose, we first introduce the common terminologies in causal discovery, and then provide a comprehensive discussion of the algorithms designed to identify the causal edges in different settings. We further discuss some of the benchmark datasets available for evaluating the performance of the causal discovery methods, available tools or software packages to perform causal discovery readily, and the common metrics used to evaluate these methods. We also test some common causal discovery algorithms on different benchmark datasets, and compare their performances. Finally, we conclude by presenting the common challenges involved in causal discovery, and also, discuss the applications of causal discovery in multiple areas of interest.


1 Introduction

The identification of the cause-effect relationships among the variables of a system from the corresponding data is called Causal Discovery (CD). A major part of causal analysis involves unfolding the *cause and effect relationships* among the entities in complex systems that can help us build better solutions in health care, earth science, politics, business, education, and many other diverse areas (Peyrot (1996), Nogueira et al. (2021)). The *causal explanations* precisely the causal factors obtained from a causal analysis play an important role in decision-making and policy formulation as well as to foresee the consequences of interventions without actually doing them. Causal discovery algorithms enable the *discovery of the underlying causal structure* given a set of observations. The underlying causal structure also known as a causal graph (CG) is a representation of the cause-effect relationships between the variables in the data (Pearl (2009)). Causal graphs represent the causal relationships with directed arrows from the cause to the effect. Discovering the

arXiv:2303.15027v2 [cs.AI] 5 Apr 2023

“PCMCI” de facto model Earth Science

- Peter-Clark (PC)+Momentary Conditional Independence (MCI)
- After the paper by Runge (2019) PCMCI become “THE METHOD” for Causal Structure Learning in Earth Science.
- Part of it because of the “tigermite” package by Runge et al.



PERSPECTIVE
<https://doi.org/10.1038/s41467-019-10105-3> **OPEN**

Inferring causation from time series in Earth system sciences

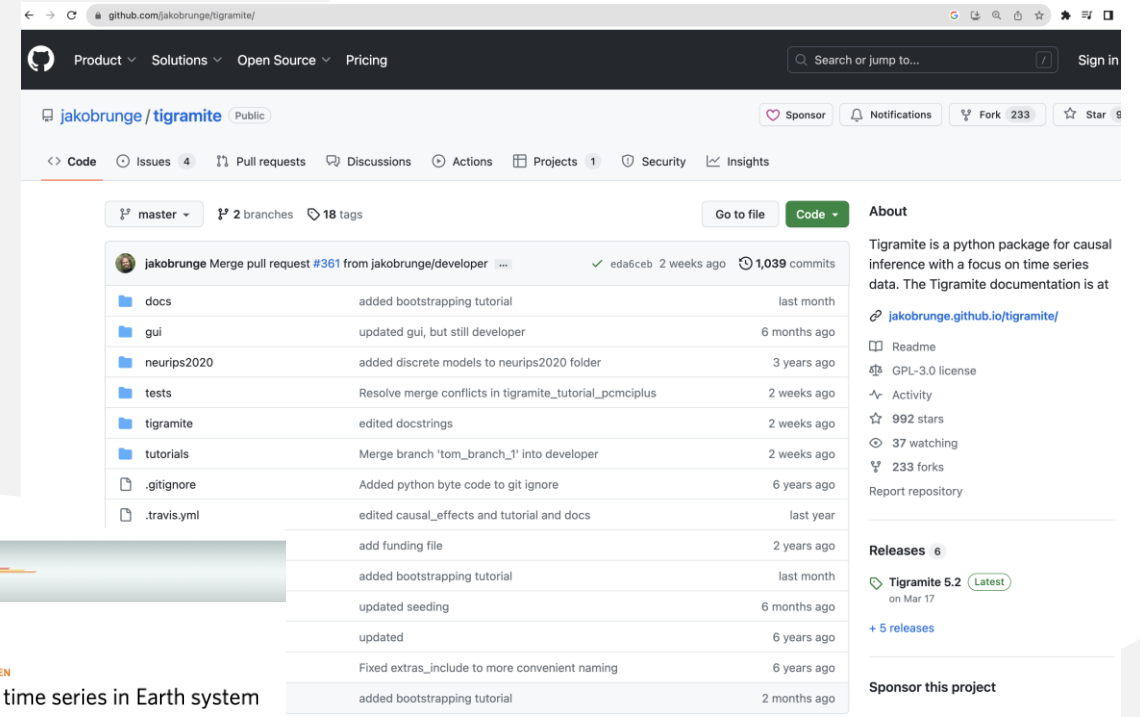
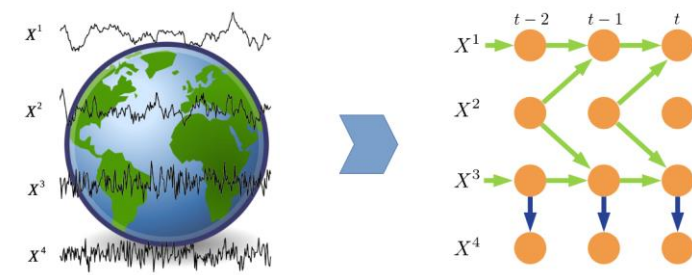
Jakob Runge^{1,2}, Sebastian Bathiany^{3,4}, Erik Bollt⁵, Gustau Camps-Valls⁶, Dim Coumou^{7,8}, Ethan Deyle⁹, Clark Glymour¹⁰, Marlene Kretschmer⁹, Miguel D. Mahecha¹¹, Jordi Muñoz-Marr⁹, Egbert H. van Nes⁴, Jonas Peters¹², Rick Quax^{13,14}, Markus Reichstein¹⁵, Marten Scheffer⁴, Bernhard Schölkopf¹⁶, Peter Spirtes¹⁷, George Sugihara⁹, Jie Sun^{9,18}, Kun Zhang¹⁹ & Jakob Zscheischler^{17,18,19}

The heart of the scientific enterprise is a rational effort to understand the causes behind the phenomena we observe. In large-scale complex dynamical systems such as the Earth system, real experiments are rarely feasible. However, a rapidly increasing amount of observational and simulated data opens up the use of novel data-driven causal methods beyond the commonly adopted correlation techniques. Here, we give an overview of causal inference frameworks and identify promising generic application cases common in Earth system sciences and beyond. We discuss challenges and initiate the benchmark platform causeme.net to close the gap between method users and developers.

Since Galileo Galilei, insight into the causes behind the phenomena we observe has come from two strands of modern science: observational discoveries and carefully designed experiments that intervene in the system of interest under well-controlled conditions. In one of Galilei's early experiments—albeit a thought experiment!—, the law of falling bodies is discovered by dropping two cannonballs of different masses from the tower of Pisa and measuring the effect of mass on the rate of fall to the ground. Discovering physical laws this way is a challenging problem when studying large-scale complex dynamical systems such as the Earth

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NATURE COMMUNICATIONS | (2019)10:2553 | <https://doi.org/10.1038/s41467-019-10105-3> | www.nature.com/naturecommunications

Particularities:

- Variables are resolved in time
- Autocorrelation

Additional assumption:

- Stationary causal structure

Why we choose DAG with No tears over PCMCI?

PCMCI is tailored for time series data, considering the **the temporal ordering and seeks to identify the time lag between cause and effect.** It infers causal relationships based on partial correlation estimation at different time points.

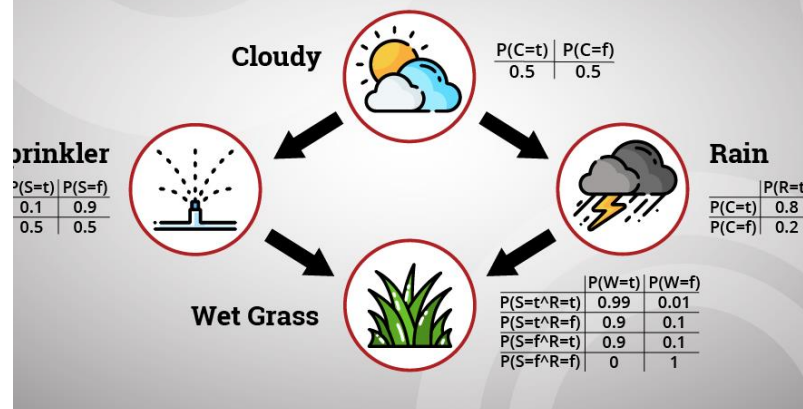
DAG with NO TEARS is designed for general observational data and focuses on **inferring causal relationships without assuming a specific temporal order.** It estimates partial correlations and optimizes the DAG structure to capture the most significant direct associations between variables.

Probabilities of wet grass can be changed based on the information on the cloud, rain, and sprinkler condition

“DAGs with NO TEARS (Nonlinear Optimization of Temporal Relationships in Systems) ”

- It is a novel method for Bayesian Network (BN) structure learning based on continuous optimization. BN is probabilistic graphical model consist of two parts: a structure and parameters.
- The structure is a directed acyclic graph (DAG) that expresses conditional independencies and dependencies among random variables associated with nodes. The parameters consist of conditional probability distributions associated with each node.
- Estimating the structure of DAGs, is a challenging problem since the search space of DAGs is combinatorial and scales superexponentially with the number of nodes.
- "DAGs with NO TEARS" introduced a fundamentally different strategy: formulate the structure learning problem as a purely continuous optimization problem over real matrices that avoids this combinatorial constraint entirely (Zheng et al.,2018)

Causal Bayesian Networks

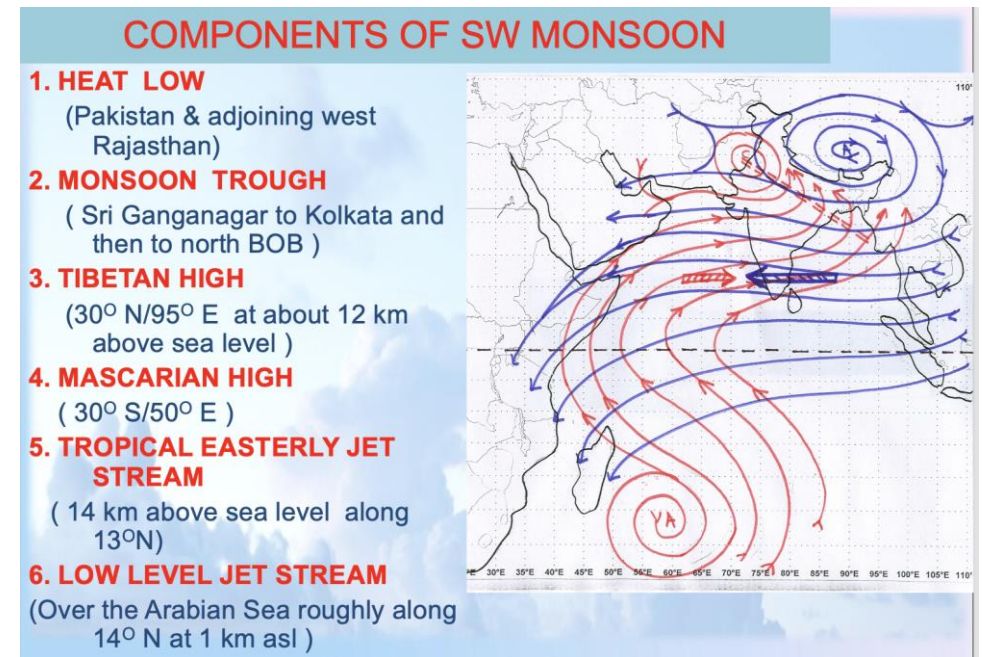
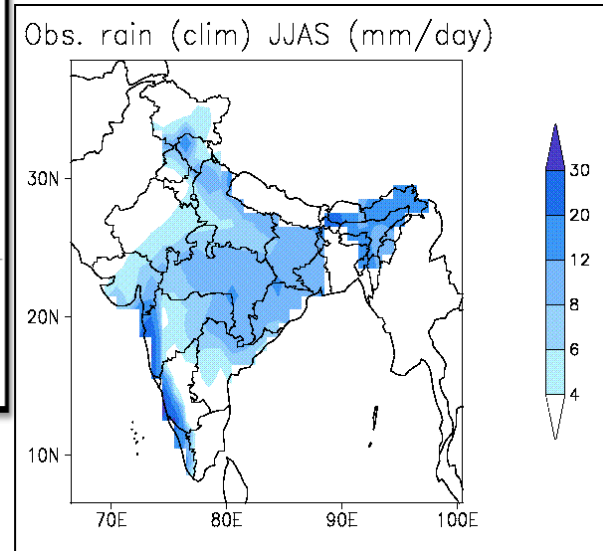
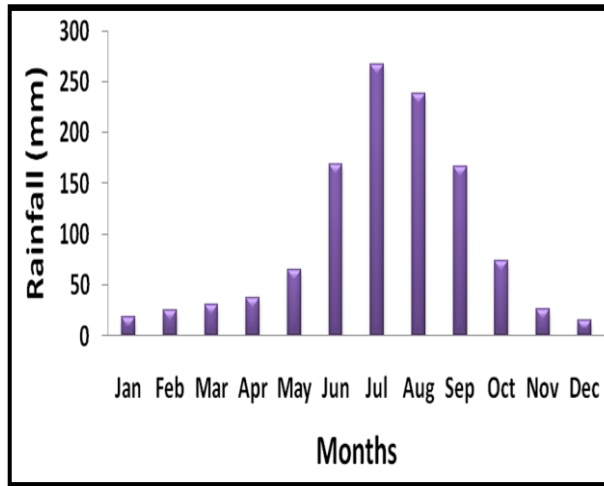




Steps for DAGs with NO TEARS

- **Estimating Partial Correlations:**
 - Calculate the partial correlations between pairs of variables while controlling for the effects of other variables.
 - Estimate the strength of the direct associations between variables.
- **Score Function and Optimization:**
 - Define a score function to evaluate the goodness of fit between the observed partial correlations and the hypothetical set of partial correlations in the DAG.
 - Employ an optimization algorithm to search for the DAG structure that maximizes the score function.
 - Iteratively explore different DAG structures by adjusting the presence or absence of edges between variables.
- **Sparsity Control:**
 - Apply a threshold or criteria to determine the significance of the estimated partial correlations.
 - Remove weaker or less significant edges to create a sparse DAG that focuses on the most important causal relationships.
- **Edge Orientation:**
 - Utilize additional techniques, such as constraint-based methods or local search algorithms, to orient the edges in the DAG and determine the direction of influence between variables.
- **Plotting the DAG:**
 - Visualize the resulting DAG, representing the estimated causal relationships among variables.
 - Use arrows to indicate the direction of influence between variables.

Case study: All India Summer Monsoon (Jun-Jul-Aug-Sep)



Monsoon is characterized by seasonal wind reversal in tropics

How good is CFSv2 to predict AISMR?

Predictability of AISMR: Process

What about last year (El Niño)?

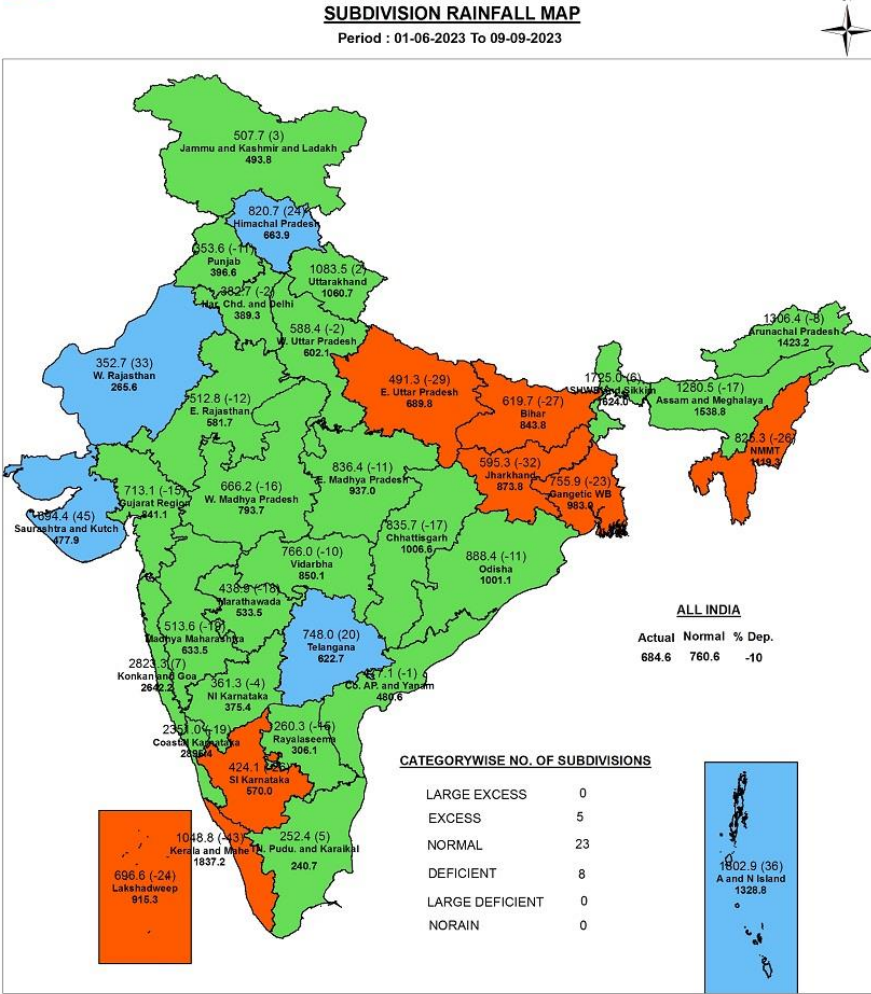
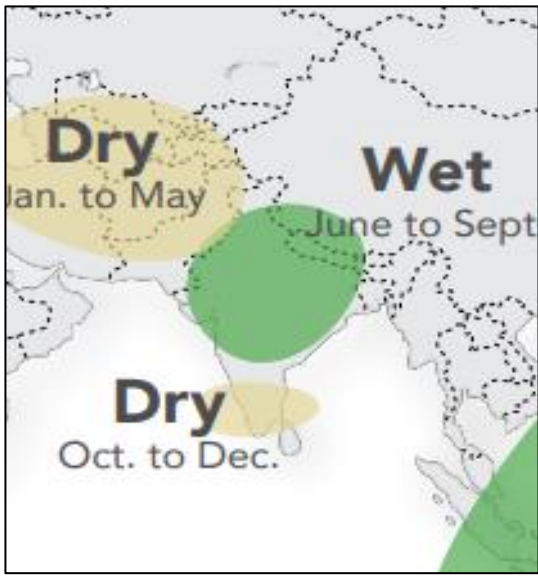
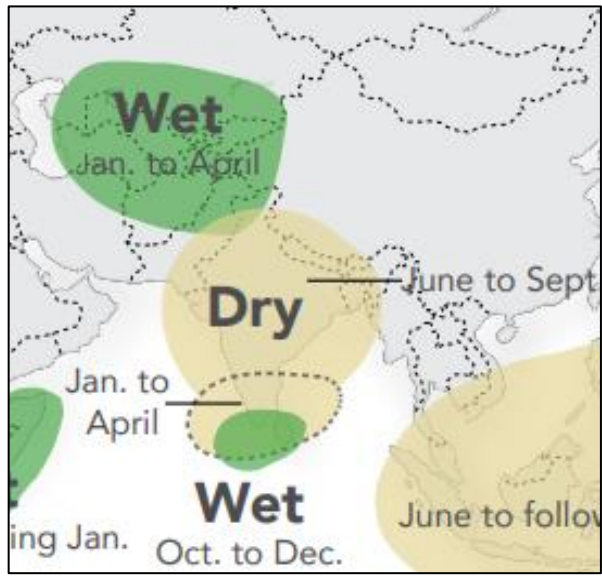


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INDIA METEOROLOGICAL DEPARTMENT

जल मौसम विज्ञान प्रभाग, नई दिल्ली
HYDROMET DIVISION, NEW DELHI

El Niño and Rainfall

La Niña and Rainfall



Legend
 Large Excess [60% or more] Excess [20% to 59%] Normal [-19% to 19%] Deficient [-59% to -20%] Large Deficient [-99% to -60%] No Rain [-100%] No Data

NOTES :
 a) Rainfall figures are based on operation data.
 b) Small figures indicate actual rainfall (mm), while bold figures indicate Normal rainfall (mm).
 c) Percentage Departures of rainfall are shown in brackets.

Predictability of AISMR: Process

by a neighboring diboron unit to form an sp-hybridized boron atom. However, there is no B-Li bond in this molecule. See (16).

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Earth Syst. Dynam., 11, 903–923, 2020
<https://doi.org/10.5194/esd-11-903-2020>
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Earth System Dynamics
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GEOPHYSICAL RESEARCH LETTERS, VOL. 47, 1030–1038, 2020

Impact of the Indian Ocean Dipole between the Indian Monsoon Rainfall

Karumuri Ashok¹, Zhaoyong Guan² and Toshio Yanagimachi¹

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Abstract. The influence of the recently discovered Indian Ocean Dipole (IOD) on the interannual variability of Indian summer monsoon rainfall (ISMR) has been investigated for the period 1958–1997. The IOD and El Niño/Southern Oscillation (ENSO) have complementarily affected the ISMR during the last four decades. Whenever ENSO-ISMR correlation is low (high), the IOD-ISMR correlation is high (low). The IOD plays an important role as a modulator of the Indian monsoon rainfall, and influences the correlation between the ISMR and ENSO. We have discovered that the ENSO-induced anomalous circulation over the Indian region is either countered or supported by IOD-induced anomalous meridional circulation depending upon the phase and amplitude of the two tropical phenomena in the Indo-Pacific sector.

Unraveling Monsoon

K. Krishna Kumar,¹ Balaji

The 132-year historical rain accompanied by El Niño events show that El Niño events with equatorial Pacific are more with the warmest 55% in the established using atmospheric Pacific warmings. These find

Climate is the decisiveness and subsistence of growing population measured by its agricultural even modest harvest failures economic and societal consequences are propelled by the successes of the summer monsoon rains (1). As a result, conditions are achieving new settings into motion timely preparedness and mitigation actions themselves can be actual verified monsoon rain Zimbabwe during 1997 wet tions led to curtailment of

1. Introduction

The Indian summer monsoon rainfall (ISMR) occurs during June–September plays a crucial role on both agriculture and economy of the Indian subcontinent. Of many phenomena that excite the ISMR variability (Krishna Kumar *et al.*, 1995; Slingo, 1999), the most important large scale forcing was the El Niño/Southern Oscillation (ENSO) till two decades back. The interannual variations of ENSO have motivated studies of the ENSO since the turn of twentieth century [Walker, 1923; Barnett, 1984]. It is well known that there was a negative correlation between anomalies of the ISMR and NINO3 SST (area-averaged surface temperatures over 5°N–5°S, 150°W–90°W) anomaly. However, the relationship between the ISMR and ENSO is susceptible to decadal changes; it is now weakening [Krishna Kumar *et al.*, 1999]. We witnessed two major ENSO events in the last decade of twentieth century. But the ISMR always normal or above normal during this period (as per the Indian Meteorological Department; the IS

The synergistic summer monsoon simulation

Praveen Kumar

¹Institute for Atmospheric

²Department

Correspondence

Revised: 10 Sep

Abstract. The El Niño–Southern oscillations in sea surface of Indian summer monsoon information exchange (IE) from two source variables (quantification of two-source systems). Our results show on a target is greater than the linear and nonlinear system (timers) for robustness. Neoreanalysis, three global climate regional climate model (R and (2) applies IE in the evolution of IOD contribute to ISMR into of the Indian subcontinent, synergistic predictors in the southern part of the Indian patterns derived from observations corresponding GCM simulation and moisture transport during the choice of GCM in driving that helps in better understanding

1 Introduction

The South Asian monsoon is considered as a key climate system. It is characterized by its strong seasonal contrast and high interannual variability. The monsoon is driven by the differential heating between the land and the ocean, and its variability is influenced by a variety of factors, including internal climate variability and external forcing. Understanding the monsoon system is crucial for predicting its future behavior and its impact on the environment and society.

16

by formaldehyde to form a three-membered ring structure consisting of B, C, and O atoms. See (20).

26. V. M. Dembitsky, H. Abu Ali, M. Srebnik, *Adv. Organomet. Chem.* **51**, 193 (2004).

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Indian Summer Monsoon Variability
 El-Niño Teleconnections and Beyond

2021, Pages 157–182

Chapter 8 - Indian Ocean Dipole influence on Indian summer monsoon and ENSO: A review

Annalisa Cherchi^a, Pascal Terray^b, Satyaban B. Ratna^c, Syam Sankar^d, K P Sooraj^e, Swadhin Behera^f

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Abstract

The Indian Ocean Dipole (IOD) is one of the dominant modes of variability of the tropical Indian Ocean and it has been suggested to have a crucial role in the teleconnection between the Indian summer monsoon and El Niño Southern Oscillation (ENSO). The main ideas at the base of the influence of the IOD on the ENSO-monsoon teleconnection include the possibility that it may strengthen summer rainfall over India, as well as the opposite, and also that it may produce a remote forcing on ENSO itself. In the future, the IOD is projected to increase in frequency and amplitude with mean conditions mimicking the characteristics of its positive phase. Still, state-of-the-art global climate models have large biases in representing the mean state and variability of both IOD and ISMR, with potential consequences for their future projections. However, the characteristics of the IOD and ENSO are likely to continue in a future warmer world, with persistence of their linkage.

Role of ENSO and IOD in the Indian Summer Monsoon Variability: A Review

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 Berhampur University, Berhampur-760007, Odisha
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ABSTRACT

The Indian Summer Monsoon Rainfall (ISMR) has contributed almost 75.3% to the annual rainfall during 1901–2020 and is considered as the lifeline of India for a sustainable agriculture and economy. ISMR exhibits significant spatial and temporal variability in the form intra-seasonal, seasonal, interannual and biennial oscillations. In the present study, we have used gridded Indian Meteorological Department (IMD) rainfall data from 1901 to 2020 with 0.250x0.250 resolution and have focused on ISMR variability due to coupled ocean atmosphere processes in the Indian and Pacific oceans. As proxies of these coupled ocean atmosphere processes, we consider the role of ENSO and IOD on ISMR. Although several studies were carried out on these aspects during the last two and half decades, the present study is different from other and aims to examine the ISMR variability during 1901–2020 over All India (AI) and different homogeneous zones (NEI, NWI, CI and SPI) under El Niño, La Niña, +ve and -ve IOD (without any co-occurrence) and with co-occurrence of El Niño with +ve IOD and La Niña with -ve IOD. Considering the changing relationship of ISMR with ENSO and IOD, this study also focuses on regional ISMR variability due to various ENSO-IOD conditions.

Keywords: ISMR, ENSO, IOD, Homogeneous zones and Precipitation concentration index.

1. Introduction

Agricultural practices in India and in many other south Asian countries are intricately linked to the performance of the monsoon, particularly ISMR (Parthasarathy *et al.*, 1988). Considering significant spatial-temporal variabilities of ISMR forced from both internal and external forcing, understanding ISMR variability and its prediction is extremely important. Since the internal forcing, mainly intra-seasonal oscillations set a limit to the predictability, major focus is on understanding external forcing including the coupled ocean-atmosphere interaction, SST, snow cover etc. to improve prediction of ISMR. Besides other external forcing, the El Niño Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) are widely considered as the two major climate drivers of ISMR (Ashok *et al.*, 2001; Behera & Ratnam, 2018; Cherchi *et al.*, 2021; Hrudya *et al.*, 2020; Krishnaswamy *et al.*, 2014; Rajeevan & Pai, 2007; Saji *et al.*, 1999; Varikoden *et al.*, 2020; Webster *et al.*, 1999). Past studies have elucidated on the relationship of ISMR with ENSO and IOD. However, weakening relationship between ENSO and ISMR after 1970s was revealed by studies conducted during the last two decades (Ashok *et al.*, 2019; Kawamura *et al.*, 2005; Kumar *et al.*, 1999), which lead to study the impacts of IOD on ENSO-ISMR relationship (Ashok *et al.*, 2001). The weakening relationship was attributed to shift in the spatial correlation pattern over the Indian subcontinent from northwest to north east. The study revealed that when the ENSO-ISMR correlation is low (high), the IOD-ISMR correlation is high (low). Many other studies (Anil *et al.*, 2016; Ashok *et al.*, 2004; Gadgil *et al.*, 2004; Webster *et al.*, 1999) also indicated that frequent emergence of the IOD have weakened the otherwise robust relationship between ENSO and ISMR. Thus, it was made apparent that IOD, which moderates the meridional circulation by inducing anomalous convergence (divergence) pattern over Bay of Bengal during positive (negative) IOD events, leads to excessive (deficit) monsoon rainfall over the monsoon trough region (Ashok *et al.*, 2003). This feature was evident in the typical IOD year of 1994 (Behera *et al.*, 1999) and positive IOD year 1997. Studies indicated the influences of ENSO and IOD on the ISMR as opposite to one another (Ashok *et al.*, 2004; Ashok & Saji, 2007). Years with co-occurrence of +ve IOD with El Niño (1961, 1963, 1967, 1972, 1977, 1982, 1983, 1994 and 1997) have positive anomalies of rainfall along the monsoon trough area, the west coast and northwest India while in years with pure +ve IOD events

In summary...

- Weakening relationship between ENSO and ISMR after 1970s was revealed by studies conducted during the last two decades.
- There is impacts of IOD on ENSO-ISMIR relationship.
- Frequent emergence of the IOD have weakened the otherwise robust relationship between ENSO and ISMR.
- Years with co-occurrence of +ve IOD with El Nino (1961, 1963, 1967, 1972, 1977, 1982, 1983, 1994 and 1997) have positive anomalies of rainfall along the monsoon trough area, the west coast and northwest India.

Current IOD/DMI index

IOD index (degC) from INCOIS-GODAS

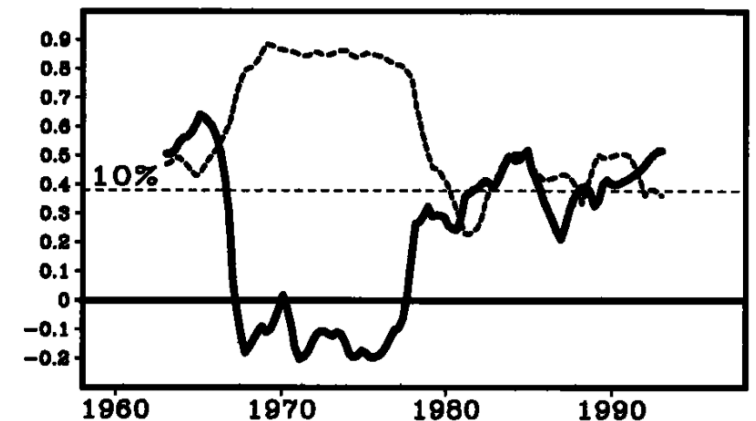
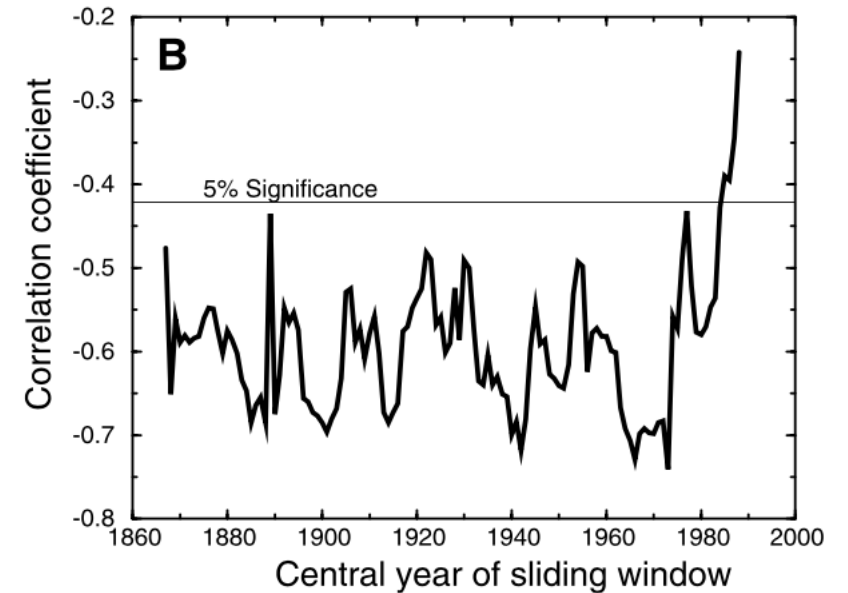
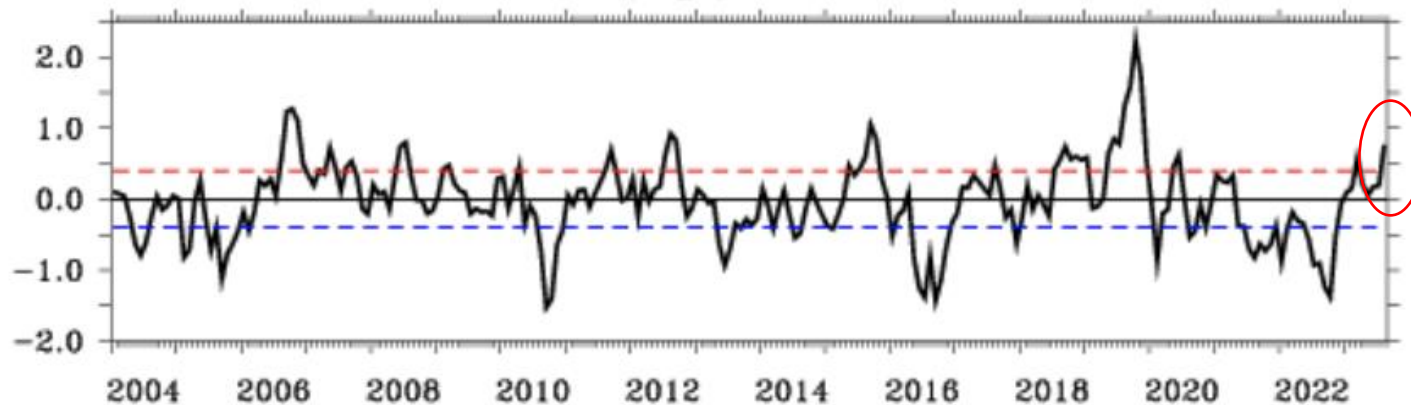
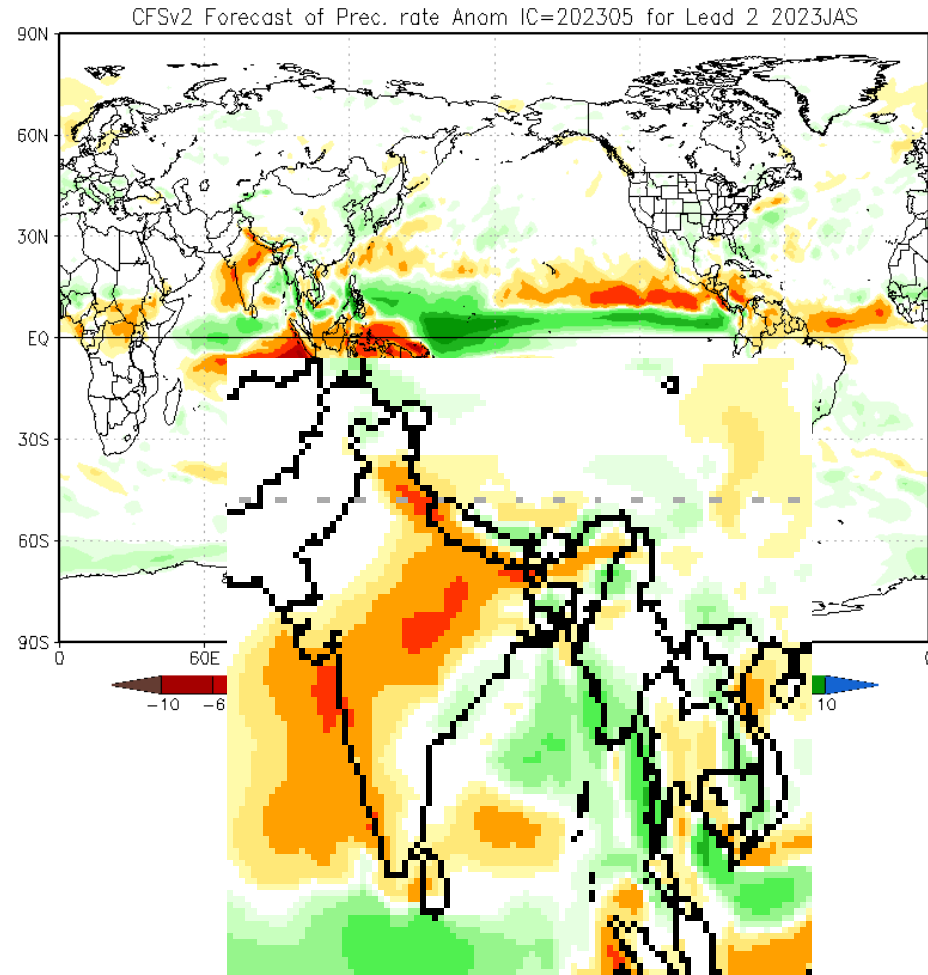
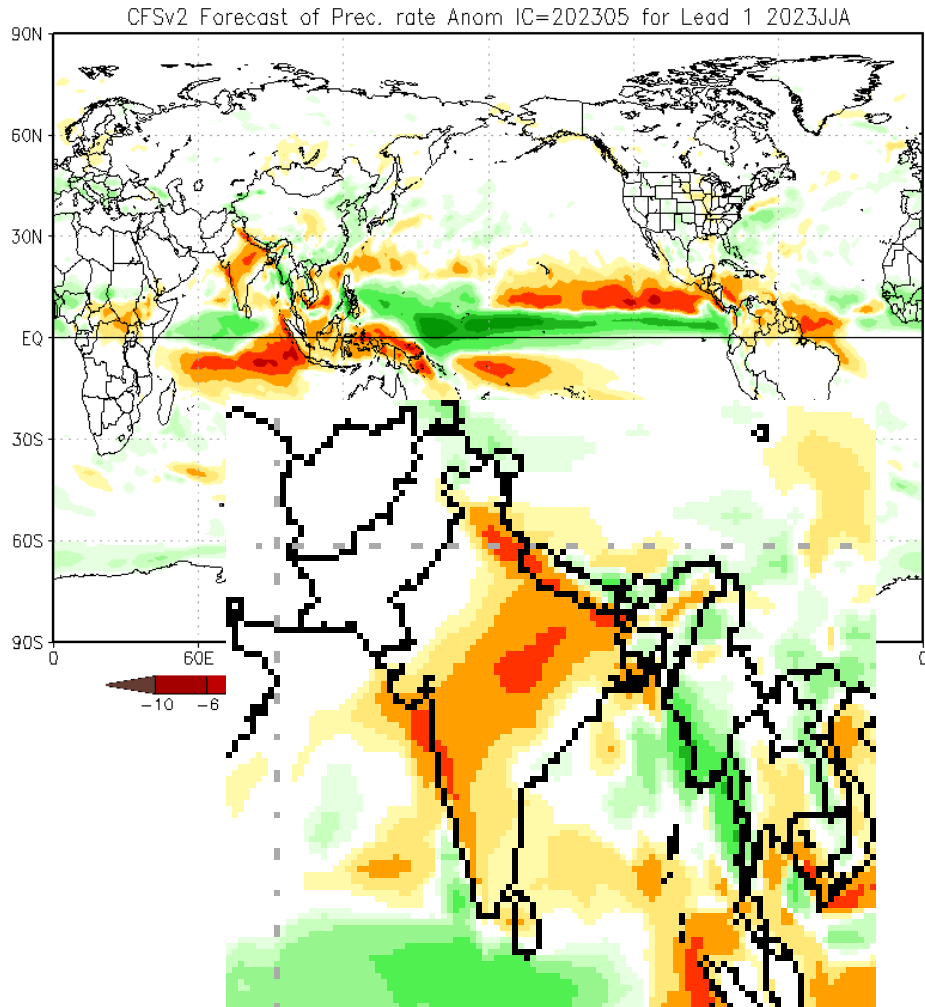


Figure 1. The 41-month sliding correlation coefficients between ISMR and IODMI (solid), and those between monthly ISMR and NINO3 SST (dashed; to be multiplied by -1) during 1958-1997. The significant correlation value at 90% confidence level is 0.38 (verified by 1,000 randomized time series, using the Monte-Carlo simulations)

How good is CFSv2 to predict AISMR?



CFSv2 forecast for 2023 monsoon

How good is CFSv2 to predict AISMR?

Observational References:

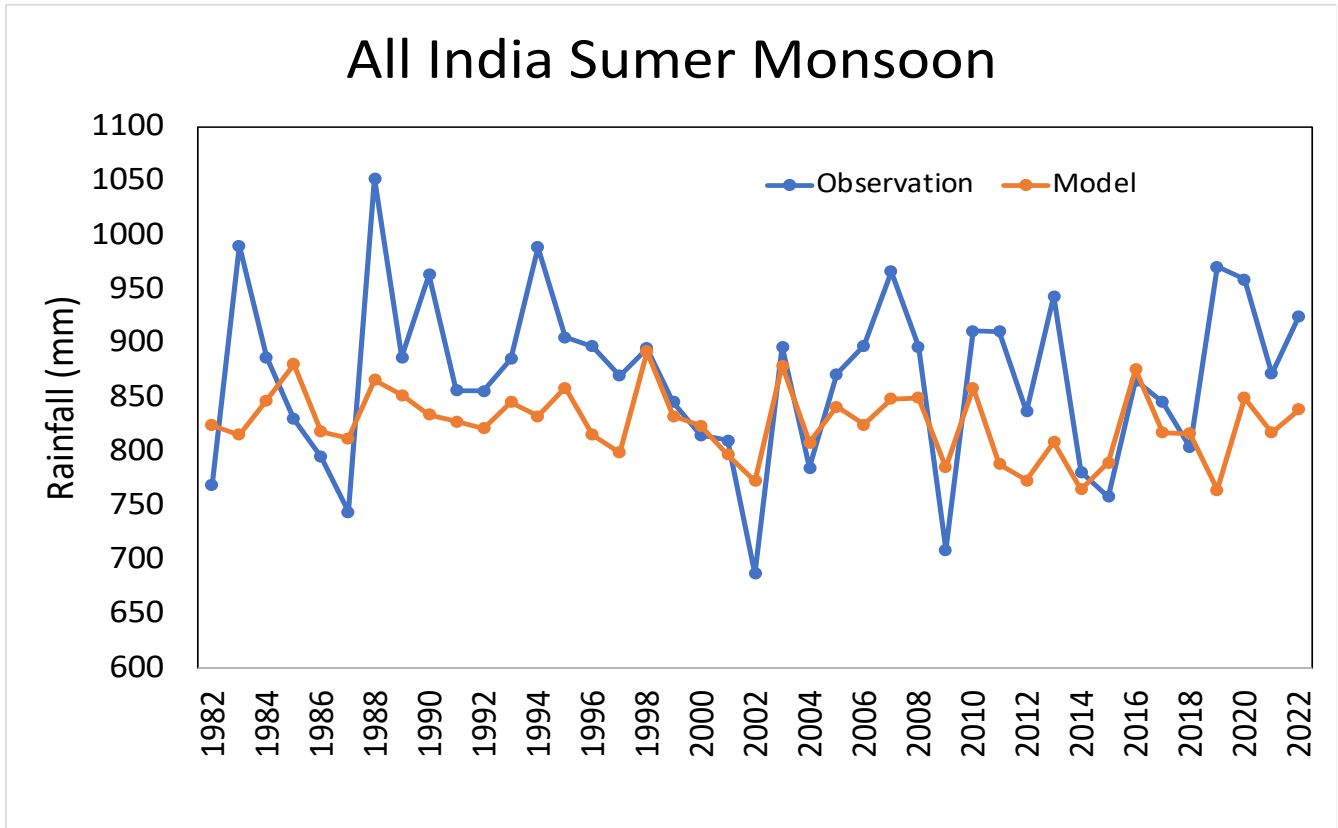
Rainfall data from India Met. Dept.

Niño 3.4 and DMI SST Indices from NOAA's PSL webpage.

Obs_{JJAS} = [O_k], k=1982-2022

Seasonal Climate Model: Climate Forecast system v2 from NCEP-Long (lead -1 hindcast from 1982-2022). Niño3.4 and DMI SST Indices calculated from SST.

Model_{Jun→JJAS} = [M_k], k=1982-2022



Kling-Gupta Efficiency=0.167

Kling-Gupta Efficiency (KGE)

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2}$$

• where r = correlation coefficient

$$\beta = \text{bias ratio} = \frac{\mu_e}{\mu_o}$$

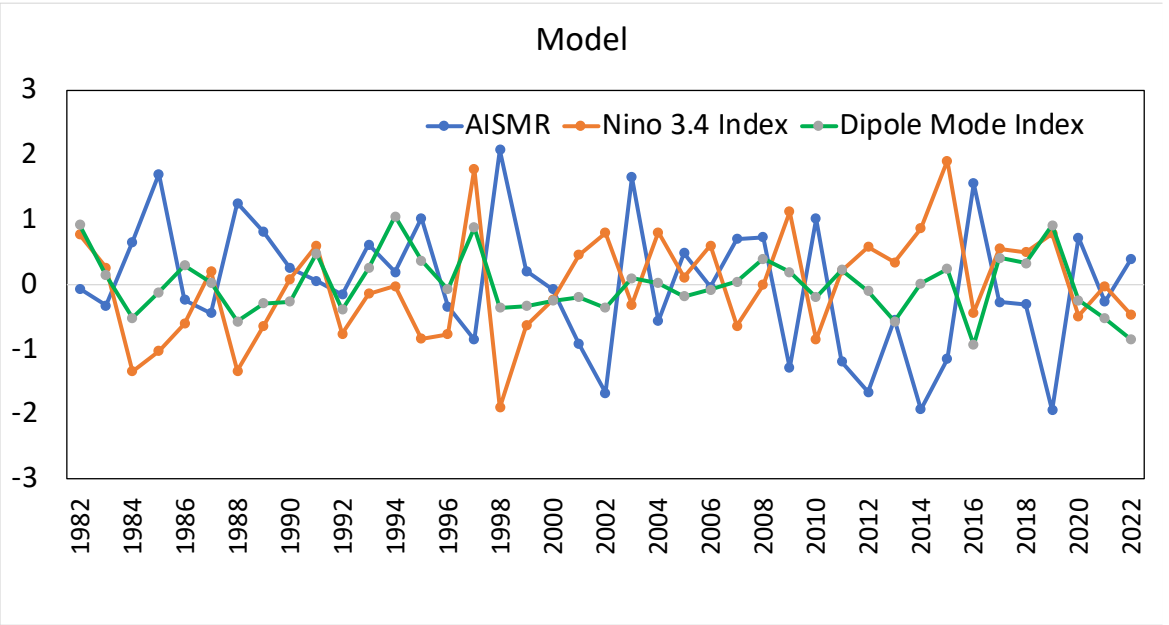
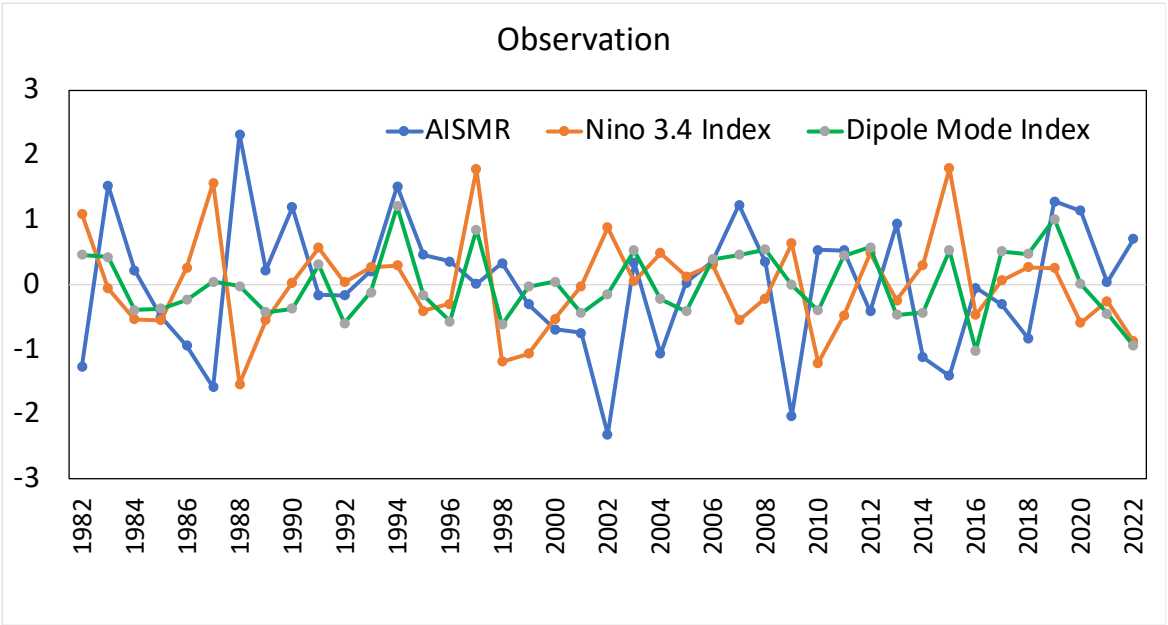
$$\gamma = \text{variability ratio} = \frac{CV_e}{CV_o} = \frac{\sigma_e / \mu_e}{\sigma_o / \mu_o}$$

• and CV = coefficient of variation

μ = mean

σ = standard deviation

Process-oriented dynamical Model evaluation: Traditionally

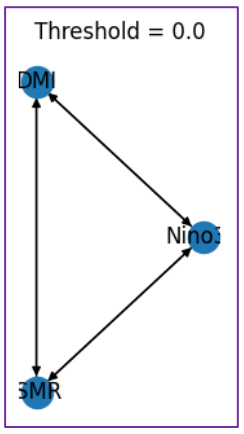


	AISMR	Nino 3.4 Index	Dipole Mode Index
AISMR	1	-0.57	0.11
Nino 3.4 Index		1	0.44
Dipole Mode Index			1

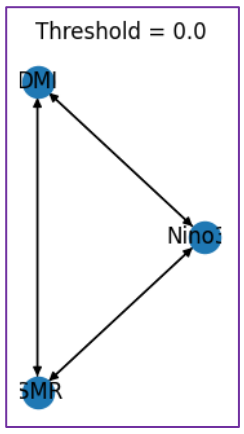
	AISMR	Nino 3.4 Index	Dipole Mode Index
AISMR	1	-0.75	-0.31
Nino 3.4 Index		1	0.48
Dipole Mode Index			1

Process-oriented dynamical Model evaluation: Causal Structure learning

Observation



CFSv2



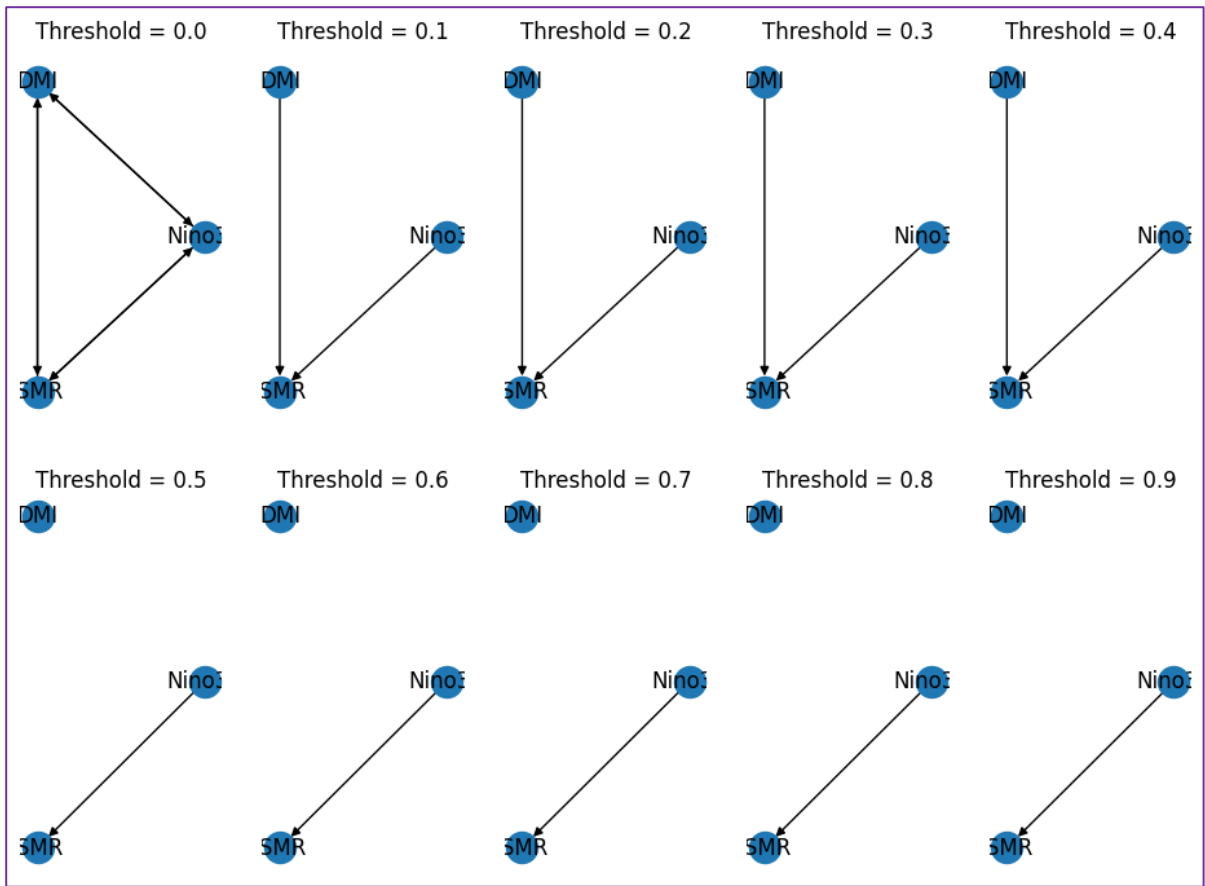
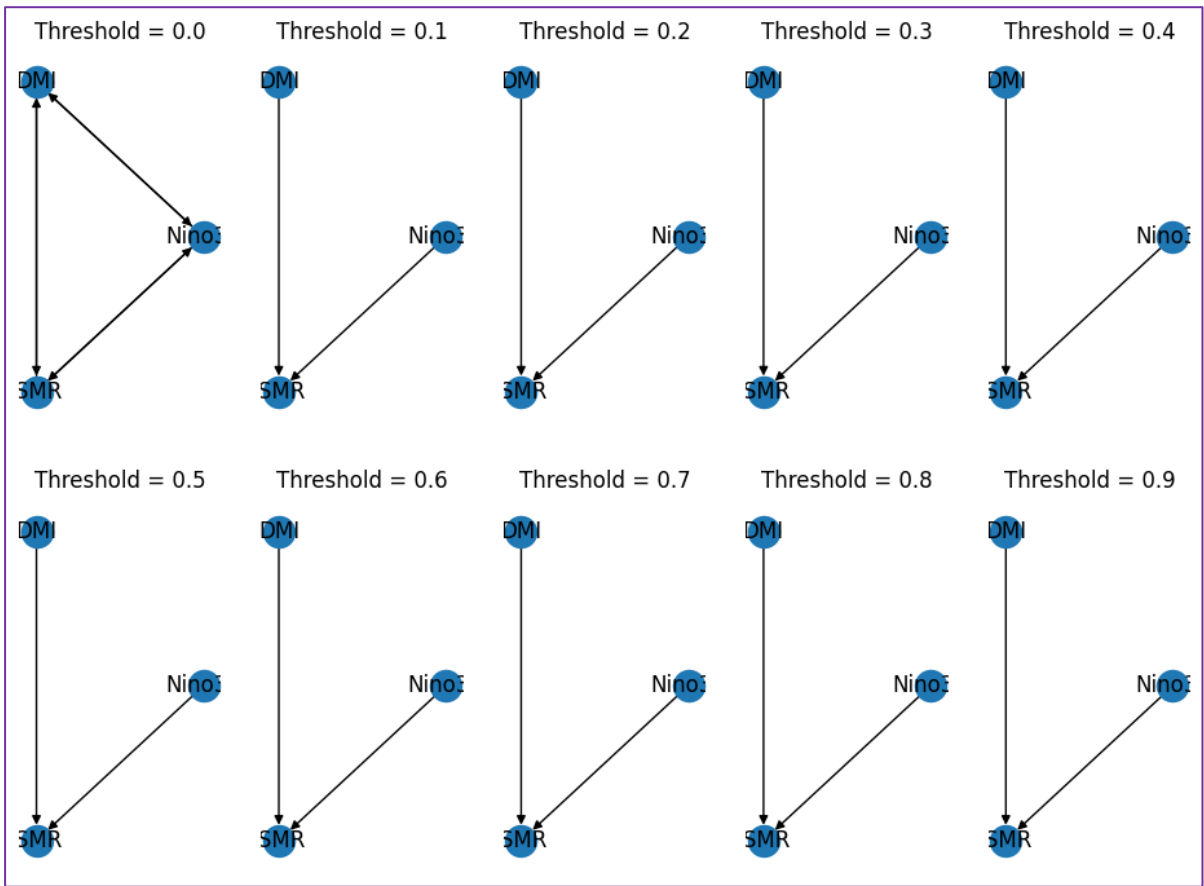
DAG between AISMR, Nino3.4 and DMI

Threshold: Partial Correlation value

Process-oriented dynamical Model evaluation: Causal Structure learning

Observation

CFSv2



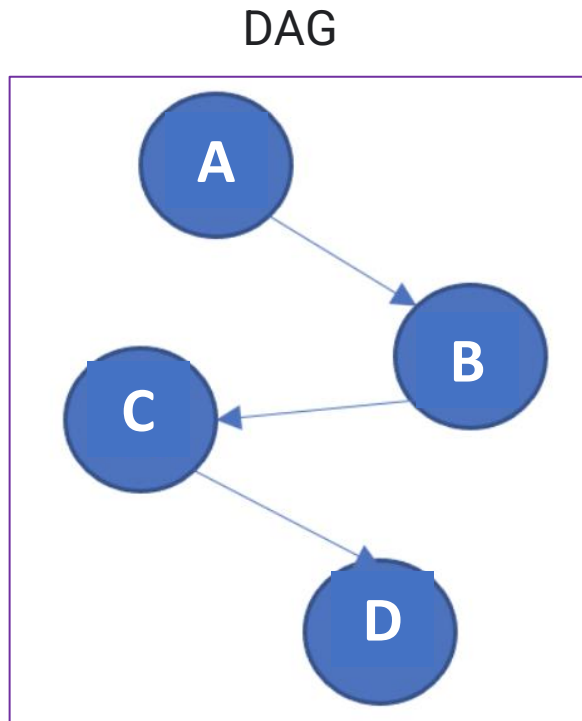
DAG between AISMR, Nino3.4 and DMI

Threshold: Partial Correlation value

How to Quantify the Similarity between Model and observational DAG?

- **Step 1: Convert DAG in Adjacency Matrix for both Obs. and Model.**
- **Step 2: Estimate Confusion Matrix from two Adjacency Matrix.**
- **Step 3: Calculate a score (F1?).**

➤ Step 1

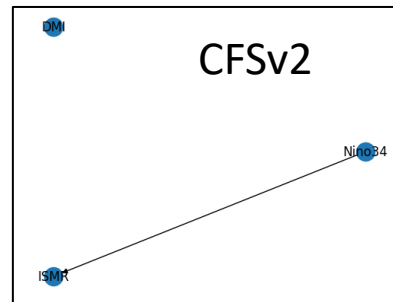
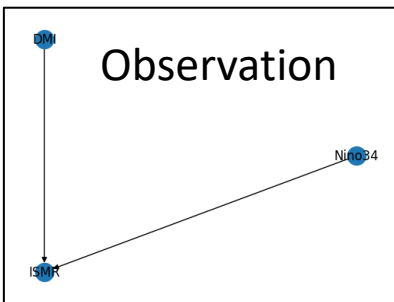


Adjacency Matrix

	A	B	C	D
A	0	1	0	0
B	0	0	1	0
C	0	0	0	1
D	0	0	0	0

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge from } j \text{ to } i \\ 0 & \text{otherwise} \end{cases}$$

Quantify the Similarity between Model and observational DAG



Adjacency Matrix

	Nino3.4 Index	Dipole Mode Index	AISMR
Nino3.4 Index	0	0	1
Dipole Mode Index	0	0	1
AISMR	0	0	0

	Nino3.4 Index	Dipole Mode Index	AISMR
Nino3.4 Index	0	0	1
Dipole Mode Index	0	0	0
AISMR	0	0	0

Confusion Matrix

	Positive	Negative
Positive	1 (TP)	0 (FP)
Negative	1 (FN)	7 (TN)

TP: True Positives
 TN: True Negatives.
 FP: False Positives.
 FN: False Negatives.

F1 Score: 0.67
 MCC Score: 0.67

$$F1 \text{ score} = \frac{2TP}{2TP + FN + FP}$$

$$MCC = \frac{TN \times TP - FP \times FN}{\sqrt{(TN + FN)(FP + TP)(TN + FP)(FN + TP)}}$$

Chico and Juman *BMC Genomics* (2020) 21:6
<https://doi.org/10.1186/s12864-019-6413-7>

BMC Genomics

RESEARCH ARTICLE Open Access

The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation

Davide Chicco^{2*} and Giuseppe Juman¹

Abstract: To evaluate binary classifications and their confusion matrices, scientific researches can employ several statistical rates, accordingly to the goal of the experiment they are investigating. Despite being a crucial issue in machine learning, no widespread consensus has been reached on a unified effective chosen measure yet. Accuracy and F1 score computed on confusion matrices have been (and still are) among the most popular adopted metrics in binary classification tasks. However, these statistical measures can dangerously show overoptimistic inflated results, especially on imbalanced datasets.

Results: The Matthews correlation coefficient (MCC), instead, is a more reliable statistical rate which produces a high score only if the prediction obtained good results in all of the four confusion matrix categories (true positives, false negatives, true negatives, and false positives), proportionally both to the size of positive elements and the size of negative elements in the dataset.

Conclusions: In this article, we show how MCC produces a more informative and truthful score in evaluating binary classifications than accuracy and F1 score, by first explaining the mathematical properties, and then the use of MCC in six synthetic use cases and in a real genomics scenario. We believe that the Matthews correlation coefficient should be preferred to accuracy and F1 score in evaluating binary classification tasks by all scientific communities.

Keywords: Matthews correlation coefficient, Binary classification, F1 score, Confusion matrices, Machine learning, Biostatistics, Accuracy, Dataset imbalance, Genomics

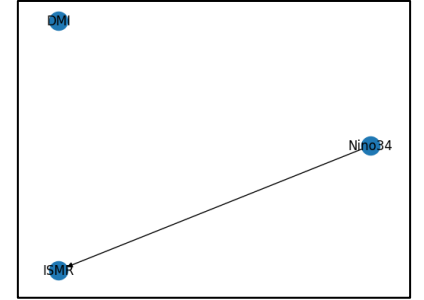
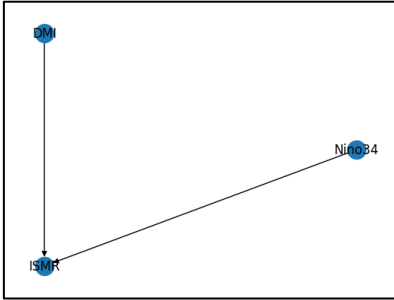
Background: Given a clinical feature dataset of patients with cancer traits [1, 2], which patients will develop the tumor, and which will not? Considering the gene expression of neuroblastoma patients [3], can we identify which patients are going to survive, and which will not? Evaluating the metagenomic profiles of patients [4], is it possible to discriminate different phenotypes of a complex disease? Answering these questions is the aim of machine learning and computational statistics, nowadays pervasive in analysis of biological and health care datasets, and many other scientific fields. In particular, these binary classification tasks can be efficiently addressed by supervised machine learning techniques, such as artificial neural networks [5], k-nearest neighbors [6], support vector machines [7], random forest [8], gradient boosting [9], or other methods. Here the word *binary* means that the data element statuses and prediction outcomes (class labels) can be twofold: in the example of patients, it can mean healthy/tumor, or low/high grade tumor. Usually scientists indicate the two classes as the negative and the positive class. The term *classification* means that the goal of the process is to attribute the correct label to each data instance (sample); the process itself is known as the classifier, or classification algorithm.

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BMC

Quantify the Similarity between Model and observational DAG



Adjacency Matrix

	Nino3.4 Index	Dipole Mode Index	AISMR
Nino3.4 Index	0	0	1
Dipole Mode Index	0	0	1
AISMR	0	0	0

	Nino3.4 Index	Dipole Mode Index	AISMR
Nino3.4 Index	0	0	1
Dipole Mode Index	0	0	0
AISMR	0	0	0

Confusion Matrix

	Positive	Negative
Positive	1 (TP)	0 (FP)
Negative	1 (FN)	2 (TN)

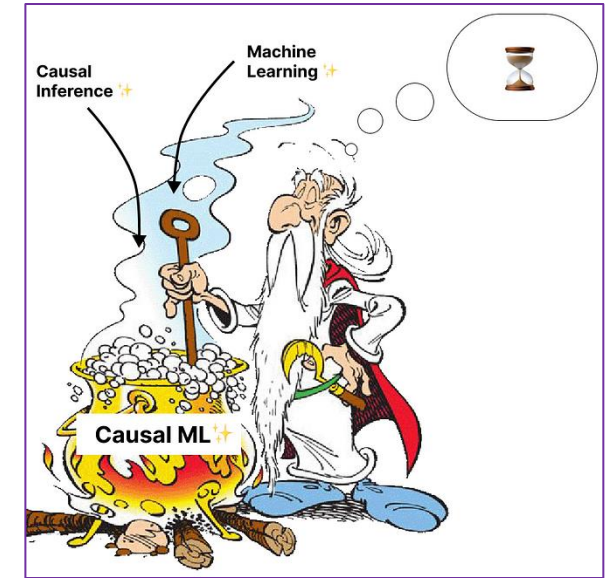
*Remove all irrelevant TN

F1 Score: 0.67
MCC Score: 0.57

F1 ignores the True Negatives and thus is misleading for unbalanced classes

Concluding Remarks

- Teleconnection is the most important factor for the process-oriented model diagnostic for seasonal forecast.
- Linear Correlation is de facto major for such practice.
- Proposing “Causal Structure Learning” for model evaluation as a type of process-oriented framework. Causality deals with understanding the cause and effect between different fields
- Causal discovery graphs from observation and dynamical model shows physical pathways of interaction.
- Quantification of similarity between causal discovery graphs of dynamical model and observations provides a causal-metric to assess the fidelity of dynamical models.



“CausalML combines techniques from machine learning and causal inference to understand and model causal relationships in data.”



Nachiketa Acharya

Senior Climate Data Scientist at Lynker



Thank you!

dr.nachiketaacharya@gmail.com
