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# Alternating mutual influence of El-Niño/Southern Oscillation and Indian monsoon

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# Background

- Analysing the interdependence between ENSO and Indian monsoon
- Mutual Granger Causality Estimation (both linear and nonlinear) is being used to detect directional coupling characteristics
- Different versions of the Niño-3 and Niño-3.4 index are used to check robustness
- Climate processes in the Asia-Pacific region are mainly driven by ENSO and Indian monsoons phenomena
- Significant parts of the world population live in monsoon-related areas



# El-Niño/Southern Oscillation

- Driven by the so-called Walker circulation
- Trade winds across equatorial Pacific blow from east to west
- These winds ascend in western Pacific, flowing back at hight altitudes
- Descend in easter Pacific
- Southern Oscillation causes upwelling of cooler ocean water
- The weaker the winds, the weaker the upwelling





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#### **ENSO** causes

- ENSO can be described as a positive feedback loop between the atmosphere and the ocean
- El Niño: Decreases trade winds lessen difference in SST across the Pacific The change further lessens the strength of the trade winds
- La Niña: Increased trade winds strengthen the difference in SST across the Pacific. The gradient in temperatures increases the strength of the trade winds



![](_page_3_Picture_5.jpeg)

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#### Indian Monsoon

- Primarily affects the Indian subcontinent
- Monsoon is a periodic seasonal wind
- Occurring every year from June to September
- Wind blows from sea to land in one season and reverses back in the next season
- Monsoon is derived from Arabic, which means season

![](_page_4_Picture_6.jpeg)

![](_page_4_Picture_7.jpeg)

![](_page_4_Picture_8.jpeg)

Figure 4

Figure 5

4

# Method

![](_page_5_Picture_1.jpeg)

- Monthly values of the ENSO and Indian monsoon indices for the period 1871-2006 were being analysed
- In this paper, Granger causality is being used
- Limitation: GC not necessarily true causality
- Given two or more time series, can we predict one variable based on what happens to other variables?
- In other words, is there an increase in R<sup>2</sup> (explained variance) when using a bivariate autoregressive model compared to a univariate AR?

![](_page_5_Figure_7.jpeg)

![](_page_5_Figure_8.jpeg)

# **Granger Causality**

![](_page_6_Picture_1.jpeg)

- Let  $x_1$  be denoted as the monsoon index, and the ENSO index  $x_2$
- Granger causality intents to reveal whether a process x<sub>1</sub> influences x<sub>2</sub> and vice versa
- A univariate model looks as follows:  $x_k(t) = f_k(x_k(t-1), \dots, x_k(t-d_k)) + \xi_k(t)$
- Where  $k = 1, 2, d_k$  is a model dimension  $\xi_k(t)$  Gaussian white noise, and  $f_k$  some function,  $f_k$  can be linear or not, authors use algebraic polynomials  $L_k$
- Coefficients of  $f_k$  are determined via the least-squares method (one stepahead), denoted  $\sigma_k^2$
- A bivariate model looks as follows:

$$x_{k}(t) = f_{k|j}(x_{k}(t-1), \dots, x_{k}(t-d_{k}), x_{j}(t-1), \dots, x_{j}(t-d_{k|j})) + \eta_{k}(t)$$

• Namely  $d_{j \rightarrow k}$  is the number of  $x_j$  values directly influecing  $x_k$ 

# **Granger Causality Results**

![](_page_7_Picture_1.jpeg)

- The so-called prediction improvement  $PI_{j \to k} = \sigma_k^2 \sigma_{k|j}^2$  measures the causality  $j \to k$ , later it's normalized values are plotted  $PI_{j \to k}/\sigma_k^2$
- In addition, an F-test is used to validate statistical significances about  $PI_{j \rightarrow k}$
- Only values p < 0.05 are considered
- Bivariate models for monsoon index:  $d_1 = 1$ ,  $d_{2\rightarrow 1} = 1$  and  $L_1 = 3$ Bivariate models for ENSO index:  $d_2 = 5$ ,  $L_2 = 1$  and  $d_{1\rightarrow 2} = 3$

![](_page_7_Figure_6.jpeg)

### **Granger Causality Results**

Optimal bivariate monsoon index model:

$$x_{1}(t) = a_{1,1}x_{1}(t-1) + b_{1,1}x_{2}(t-1) + c_{1,2}x_{2}^{3}(t-1) + \eta_{1}(t) + c_{1,1}x_{1}^{2}(t-1)x_{2}(t-1) + c_{1,2}x_{2}^{3}(t-1) + \eta_{1}(t)$$
where  $\sigma^{2}_{t} = 5.86 \pm 10^{2} \text{ mm}^{2}_{t}$  coefficients and standard

where  $\sigma_{\eta 1}^2 = 5.86 \cdot 10^2 \text{ mm}^2$ , coefficients and standard deviations of their estimates [Seber, 1977]  $a_{1,1} = 0.071 \pm 0.037$ ,  $b_{1,1} = -4.65 \pm 1.11 \text{ mm} \cdot \text{K}^{-1}$ ,  $c_{1,1} = (-35.3 \pm 7.59) \cdot 10^{-4} \text{ mm}^{-1} \cdot \text{K}^{-1}$ , and  $c_{1,2} = 1.53 \pm 0.38 \text{ mm} \cdot \text{K}^{-3}$ 

#### Optimal bivariate ENSO index model: $x_2(t) = a_{2,1}x_2(t-1) + a_{2,5}x_2(t-5) + b_{2,1}x_1(t-1)$ $+ b_{2,2}x_1(t-2) + b_{2,3}x_1(t-3) + \eta_2(t)$ where $\sigma_{\eta_2}^2 = 0.11 \text{ K}^2$ , $a_{2,1} = 0.92 \pm 0.025$ , $a_{2,5} = -0.083 \pm$ 0.025, $b_{2,1} = (-1.44 \pm 0.34) \cdot 10^{-3} \text{ mm}^{-1} \text{ K}$ , $b_{2,2} = (-1.04 \pm$ $0.34) \cdot 10^{-3} \text{ mm}^{-1} \text{ K}$ , and $b_{2,3} = (-1.01 \pm 0.35) \cdot 10^{-3} \text{ mm}^{-1} \text{ K}$

**Table 1.** Characteristics of Optimal AR-Models for the Entire

 Period 1871–2006 and Different Versions of the Niño-3 Index

| Data    | $d_2$ | $\frac{\hat{\sigma}_2^2}{\operatorname{var}[\mathbf{x}_2]}$ | $d_{1\rightarrow 2}$ | $L_2$ | $\frac{PI_{1\rightarrow 2}}{\hat{\sigma}_{2}^{2}}$ | $d_{2 \rightarrow 1}$ | $L_1$ | $\frac{PI_{2\rightarrow 1}}{\hat{\sigma}_{1}^{2}}$ |
|---------|-------|---|----------------------|-------|--|-----------------------|-------|--|
| GISST   | 5     | 0.18  | 3                    | 1     | 0.023  | 1                     | 3     | 0.028  |
| Kaplan  | 5     | 0.12  | 2                    | 1     | 0.021  | 1                     | 3     | 0.023  |
| HADISST | 6     | 0.15  | 2                    | 1     | 0.022  | 2                     | 3     | 0.030  |
| ERSST   | 5     | 0.10  | 2                    | 1     | 0.016  | 1                     | 3     | 0.022  |

![](_page_8_Figure_7.jpeg)

![](_page_8_Picture_8.jpeg)

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# Moving Window Coupling Analysis

- Moving window W = 30 to trace variations in coupling over time with intervals [T W, T]
- Bonferroni correction applied

 $p_c = \frac{0.05}{\frac{N}{W}}$  (dashed line)

- Different colours represent different Niño-3 indices
- Observed fluctuations of Granger causality are statistically significant at p < 0.05</li>

![](_page_9_Figure_6.jpeg)

Figure 9

![](_page_9_Picture_7.jpeg)

### Conclusions

- Results complement previously known results about ENSO and Indian monsoon anti-correlation
- The ENSO-to-monsoon influence is inertialless and nonlinear
- ENSO-to-monsoon influence is inertialless and nonlinear
- Moving window analysis shows alternation in the coupling
- ENSO-to-monsoon influence strongest 1890-1920 and 1950-1980
- ENSO-to-monsoon influence not present in 1920-1950 and after 1980
- Possible geophysical interpretation: Monsoon system can influence trade winds an therefore affect ENSO

![](_page_10_Picture_8.jpeg)

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#### Citations

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![](_page_11_Picture_8.jpeg)

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