Spatio-Temporal Climate Data Causality Analytics – An Analysis of ENSO’s Global Impacts

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1. Motivation

- El Niño and the Southern Oscillation (ENSO) is one of the most dominating climate factors that impacts remote weather/climate through atmospheric “teleconnection”.
- Most previous studies use the conventional correlation-based methods to study the impacts of ENSO on climate variables. These methods cannot identify cause-and-effect of such linkage.
- Granger causality (GC) approach is suitable to determine the causality relations with high memory data.
- We aim to find the causality relations between ENSO and climate variables by applying the GC approach to observation data.
- We also use the climate model simulation to further support the causality relations between ENSO and climate variables from the observation-based analyses.

2. Methods, Data and Model

2.1 Methods

- **Granger causality calculation via Vector Autoregressive model (VAR):**
  Using VAR(p) to denote an autoregression model of the lag order p, then VAR(p) on two time series *X* and *Y* is defined as:

$$\begin{pmatrix} X(t) \\ Y(t) \end{pmatrix} = \begin{pmatrix} d_1 \\ d_2 \end{pmatrix} + \begin{pmatrix} d_{11}^1 & d_{12}^1 \\ d_{21}^1 & d_{22}^1 \end{pmatrix} \times \begin{pmatrix} X(t-1) \\ Y(t-1) \end{pmatrix} + \cdots + \begin{pmatrix} d_{11}^p & d_{12}^p \\ d_{21}^p & d_{22}^p \end{pmatrix} \times \begin{pmatrix} X(t-p) \\ Y(t-p) \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix}$$

  The VAR can be applied to test the Granger causality of *X* and *Y*: if at least one of the elements $d_{21}^i, i = 1 \cdots p$ are nonzero, then *Y* is Granger caused by *X*.
- **The maximum lag correlation:** $Lag_{corr[\tau]} \doteq \frac{1}{n-\tau} \sum_{k=1}^{n-\tau} \left[\frac{x(k)-\bar{x}}{\sigma_x} \times \frac{y(k+\tau)-\bar{y}}{\sigma_y} \right]$

2.2 Data

- **The Hadley Centre Sea Ice and Sea Surface Temperature data (HadiSST):**
  1870-Present, 1˚x 1˚ Lat-Lon resolution, monthly mean
- **The Global Precipitation Climate Project Precipitation (GPCP) version 2.3:**
  1979-Present, 2.5˚ x 2.5˚ Lat-Lon resolution, monthly mean
- **The NCEP/NCAR reanalysis I surface air temperature:**
  1948-Present, 2.5˚ x 2.5˚ Lat-Lon resolution, monthly mean

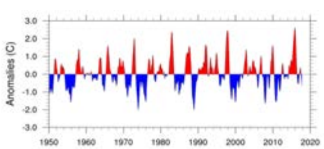

Figure 1. Time series of ENSO index: the running 3-month mean SST anomaly for the Niño 3.4 region (5⁰S-5⁰N, 170⁰W-120⁰W) from 1950 to 2017 with the 1950-2000 as the base period. Unit of SST anomaly is ⁰C.

2.3 Climate Model Simulations

- **The Community Atmospheric Model (version 5.3, CAM5.3):**
  1.9˚ Lat × 2.5˚ Lon resolution with 30 vertical levels and 30-min time step.

36-mon runs:
- **CAM5.3-Control**: forced by climatological SST
- **CAM5.3-p2K:** forced by climatological SST + 2 ˚K at the Nino3.4 region
- **CAM5.3-n2K:** forced by climatological SST - 2 ˚K at the Nino3.4 region

3. Impacts of ENSO on Surface Air Temperature and Surface Precipitation

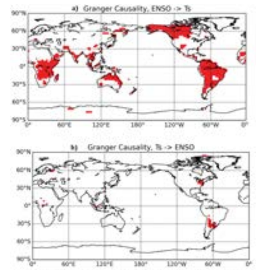

Fig 2. a) Regions where surface air temperature is granger caused by ENSO index (red shaded); b) Regions where surface air temperature causes ENSO (red shaded).

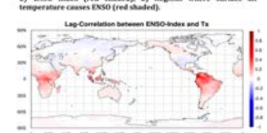

Fig 3. Maximum lag correlation between ENSO index and surface air temperature over land.

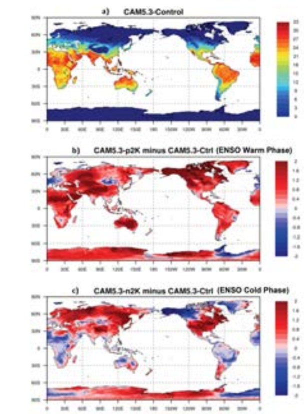

Fig 4. a) Land surface air temperature in the CAM5 control run; b) Anomalies of surface temperature in the CAM5+2K run (mimic ENSO warm phase) with respect to the control run; c) Anomalies of surface temperature in the CAM5-2K run (mimic ENSO cold phase) with respect to the control run. Unit of temperature is °C.

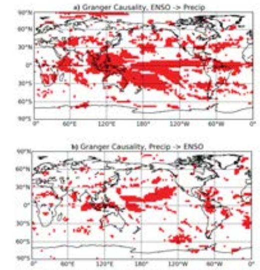

Fig 5. a) Regions where surface precipitation is granger caused by ENSO index (red shaded); b) Regions where surface precipitation causes ENSO (red shaded).

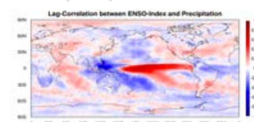

Fig 6. Maximum lag correlation between ENSO index and precipitation

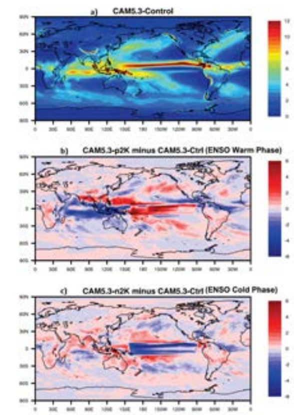

Fig 7. a) Surface precipitation in the CAM5 control run; b) Anomalies of precipitation in the CAM5+2K run (mimic ENSO warm phase) with respect to the control run; c) Anomalies of precipitation in the CAM5-2K run (mimic ENSO cold phase) with respect to the control run. Unit of precipitation is mm/day.

- Figure 2 indicates that ENSO is a driver of surface temperature anomalies in remote regions such as South America, northwest North America, equatorial South Africa, and northern Australia; while ENSO variation is not caused by surface temperature over land.
- ENSO has strong positive relationship with surface temperature in South America and equatorial South Africa, which indicates that El Niño events are most likely accompanied with higher surface temperature over these lands (Figure 3).
- Results of the climate model sensitivity simulations (Figure 4) are consistent with the observational-based analyses. Surface temperature over South America, northwest North America and south Africa show opposite anomalies for the ENSO warm and cold phases.

- ENSO is leading the changes in surface precipitation anomalies in many regions such as tropical Ocean and tropical land, with significant granger causality correlation over broad area in Figure 5(a), but not vice versa in Figure 5(b).
- ENSO has strong negative relationship with surface precipitation in Tropical Western Pacific and tropical South American (Figure 6).
- Model simulations (Figure 7) indicate that in the ENSO warm-phase events, there are positive anomalies (floods) in surface precipitation over Tropical Central and Eastern Pacific, and negative anomalies (droughts) in surface precipitation over Tropical Western Pacific.

4. Conclusions

- We analyzed observational data, reanalysis data and model data to comprehensively investigate the global impacts of ENSO using statistical methods (VAR GC method and maximum lag correlation) and global climate model simulations.
- Results show that the VAR method is able to clearly show ENSO as a cause instead of an effect to influence the remote climate variables and thus cause extreme weather events such as flooding, drought, extreme heat and cold, etc.
- Our model simulations using the CAM5.3 also successfully simulated ENSO’s remote impacts on surface temperature and precipitation, consistent to the findings from our observation-based statistical analysis.

Reference and Acknowledgement

- H. Song, J. Wang, J. Tian, J. Huang, Z. Zhang, “Spatio-Temporal Climate Data Causality Analytics – An Analysis of ENSO’s Global Impacts”, in Proceedings of the *8th International Workshop on Climate Informatics (CI 2018)*, 2018.
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