Unraveling the time-scale teleconnections between soil moisture and vegetation

EGU General Assembly 2020

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Image Signal Processing - ISP

Spatio-temporal Earth data analysis

- Multi-scale spatio-temporal representation:

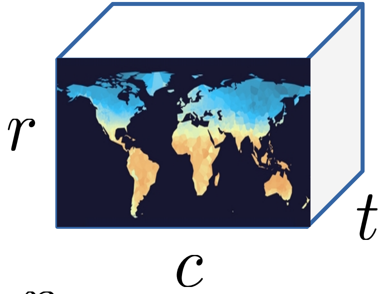
  Dimensional reduction methods

  ROCK-PCA: Rotated Complex Kernel - PCA

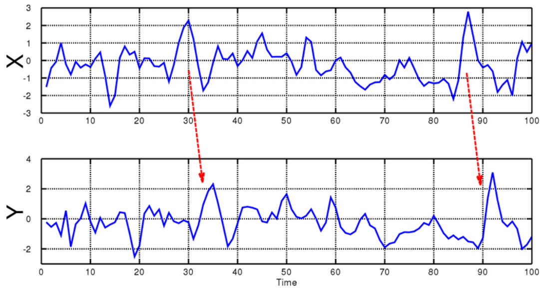
- Unravel Causal structure of data:

  Granger Causality methods

  XKGC: Cross-Kernel Granger Causality



$$t\ \overset{n}{\boxed{\mathbf{X}}} = \underset{t\times p}{\boxed{\Phi}} \cdot \underset{p\times n}{\boxed{\Psi}}^{T}$$



[1]“Nonlinear PCA for Spatio-Temporal Analysis of Earth Observation Data”
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[2]"Cross-Information Kernel Causality: Revisiting global teleconnections of ENSO over soil moisture and vegetation"
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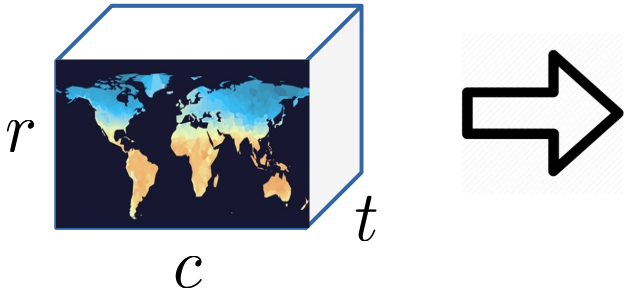
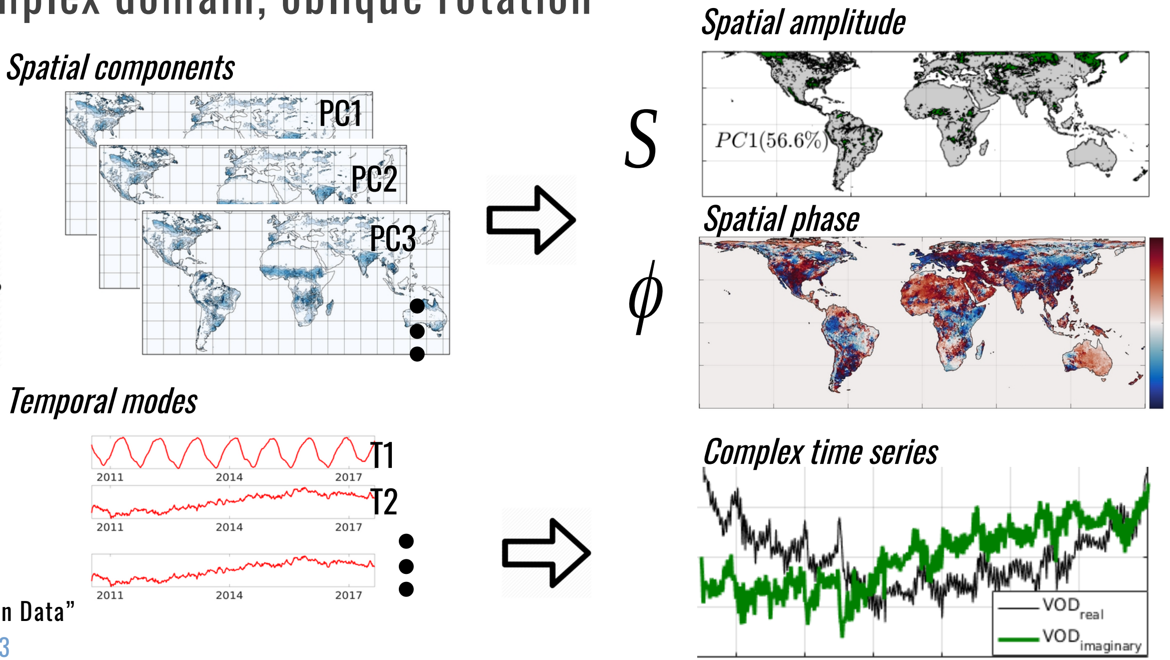
Learning spatio-temporal Earth data representations

- PCA/EOF is popular, yet cannot cope with nonlinear spatio-temporal relations
- ROCK-PCA: nonlinear, complex domain, oblique rotation





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Learning Causal structure of data

Granger Causality 1. The cause occurs before the effect

2.The cause contains information about the effect that is unique and is in no other variable.

a) $$y_{t+1} = \sum_{k=0}^{p} a_k y_{t-k} + \varepsilon_t^{y}$$

b) $$y_{t+1} = \sum_{k=1}^{p} a_k y_{t-k} + \sum_{l=1}^{q} b_l x_{t-l} + \varepsilon_t^{y|x}$$

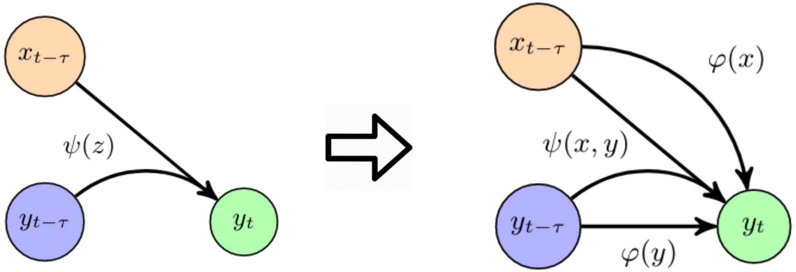
Causality index: $\delta_{x \to y} = \log(\mathbb{V}[\varepsilon_t^{y}]^2 / \mathbb{V}[\varepsilon_t^{y|x}]^2)$

XKGC: Cross-Kernel Granger Causality

$$\boldsymbol{\psi}(\mathbf{x}_t, \mathbf{y}_t) = [\phi_1(\mathbf{y}_t), \phi_2(\mathbf{x}_t), \phi_3(\mathbf{y}_t) + \phi_3(\mathbf{x}_t)]$$

$$\boldsymbol{K}(\mathbf{x}_t, \mathbf{y}_t) = \boldsymbol{K}_{\boldsymbol{xx}} + \boldsymbol{K}_{\boldsymbol{yy}} + \boldsymbol{K}_{\boldsymbol{xy}} + \boldsymbol{K}_{\boldsymbol{yx}}$$

- Generalizes GC for non-linear relations
- Take in account cross relations between variables
- Separate model for each relation



Kernel GC

XKGC

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Multi-scale Spatio-temporal representation

- SMOS Soil Moisture (SM)
- SMOS Vegetation Optical Depth (VOD)

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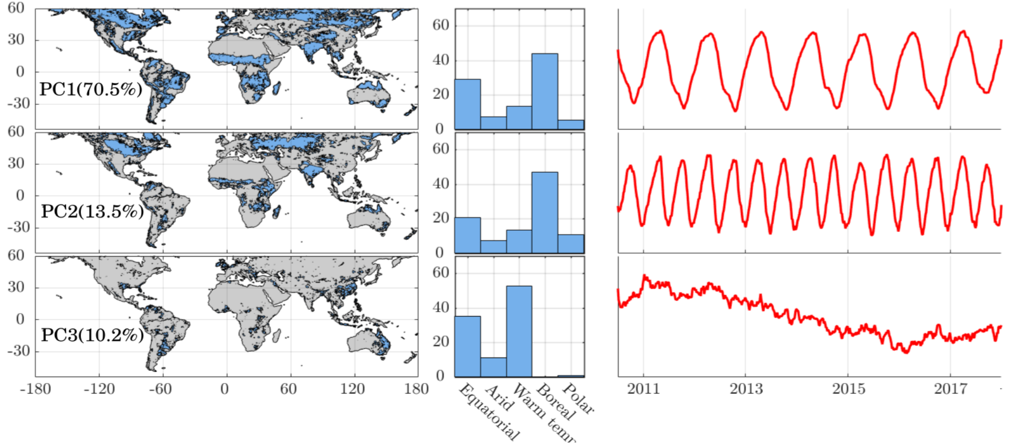
SM and VOD decomposition (ROCK-PCA)

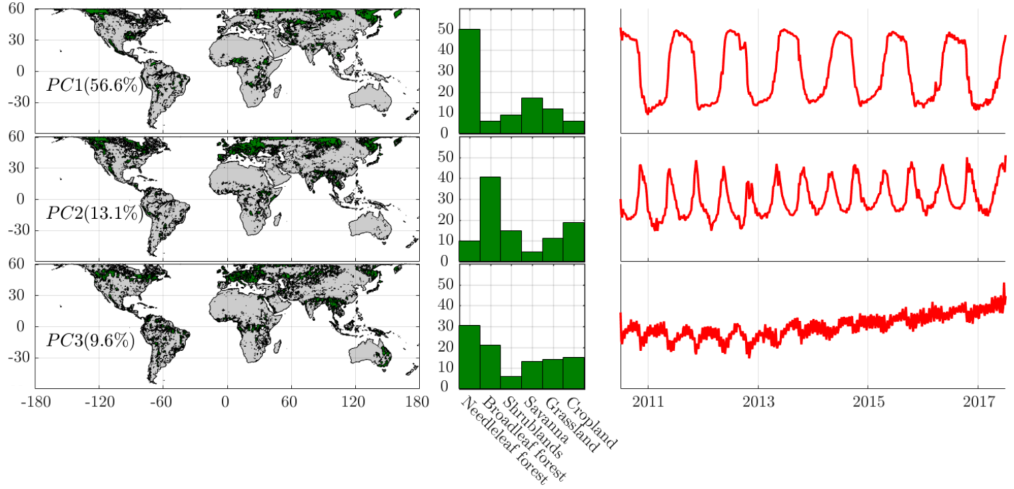
- SM: Soil Moisture
- VOD: Vegetation Optical Depth

- 1st: annual oscillation
- 2nd: seasonal oscillation
- 3rd: intrannual variability

Compressed description of the main variability modes

Spatio-temporal features for the three main time-scales.





SM: SMOS-BEC (Barcelona Expert Center)

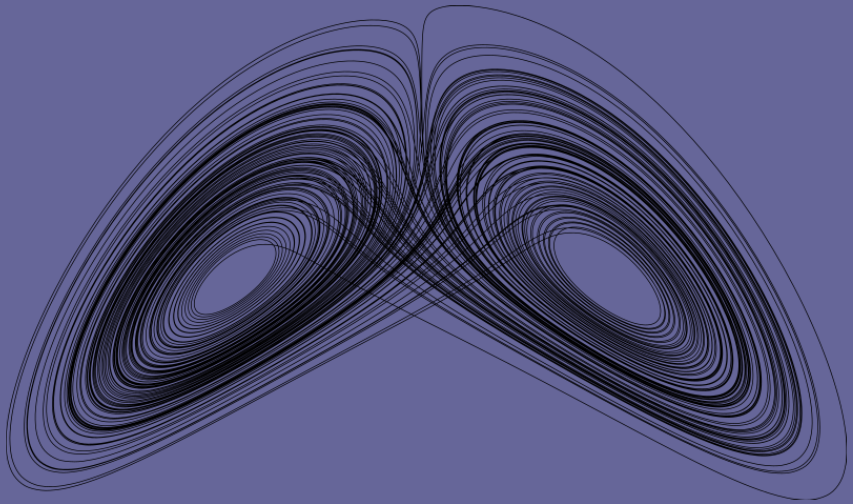
VOD: SMOS-IC (INRA-CESBIO)

June-2010 to June-2017

5-day temporal bin with asc/des orbits (with asc./desc avgd. orbits) + 25km res.

Spatio-temporal Causal structure analisys

- Time series to time series
- Spatialization



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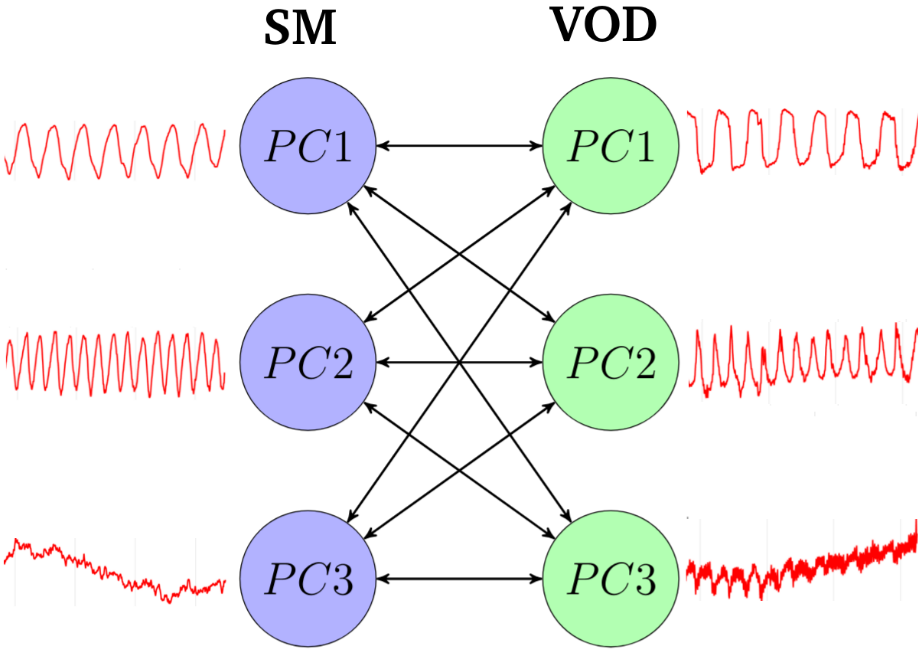
Relation of SM-VOD modes of variability

The regression models for each relation were trained to obtain the time embedding and the optimum kernel parameters: $\delta = \delta(\tau, \theta)$

- Models were cross-validated (Proof of stationarity)

- Threshold is estimated via surrogate time series

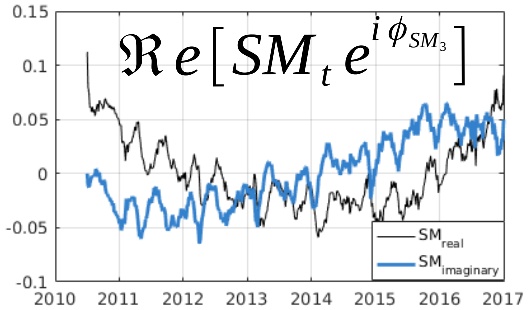
- Significance: $\delta > 0$ and $\delta > \delta_{threshold}$



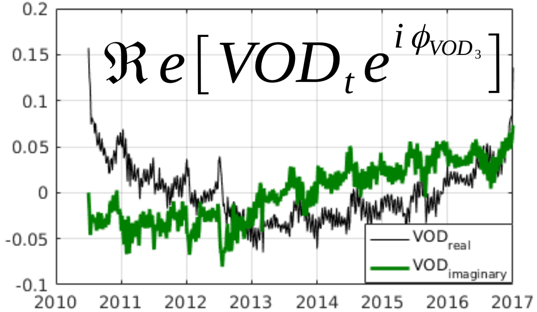
Relation of SM-VOD modes of variability

Significance $\delta > 0$

Example:

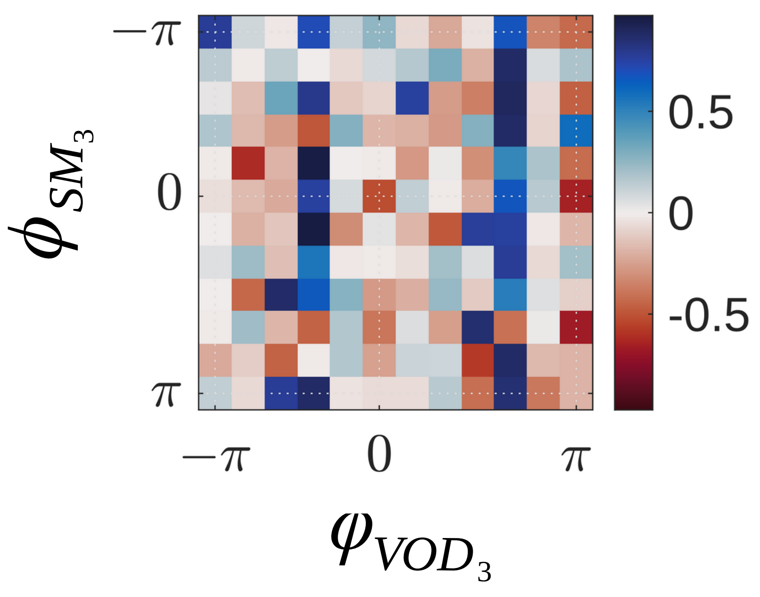


ϕ_{SM_3}



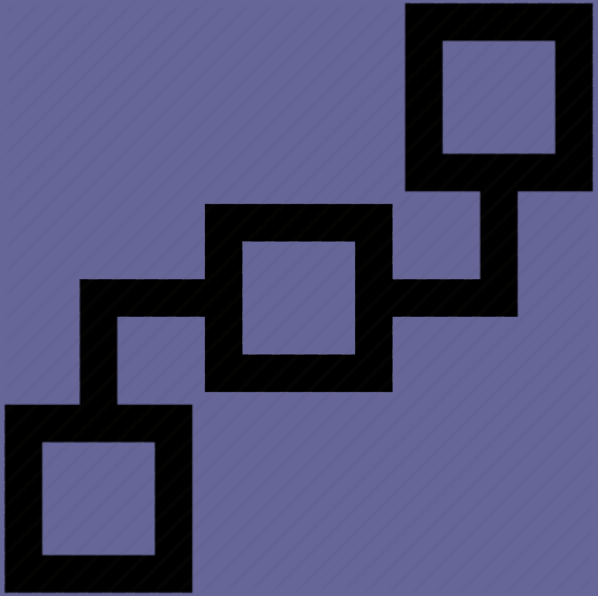
ϕ_{VOD_3}

$$\delta_{SM_3 \rightarrow VOD_3} = \delta(\phi_{SM_3}, \phi_{VOD_3})$$



Main results

- Phase to Phase relations
- Main causal relations
- Causality maps



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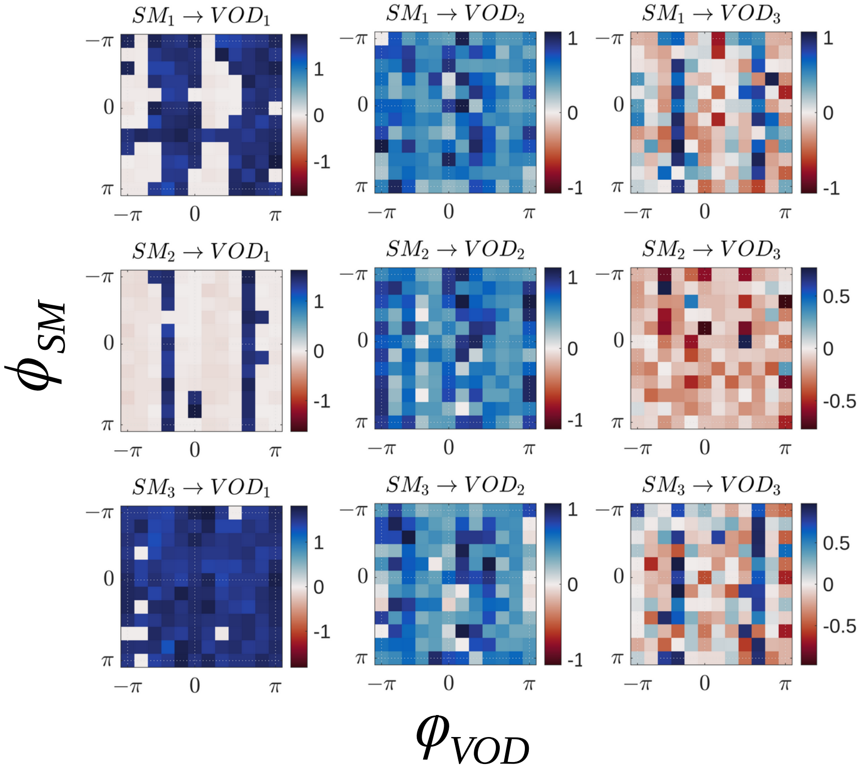
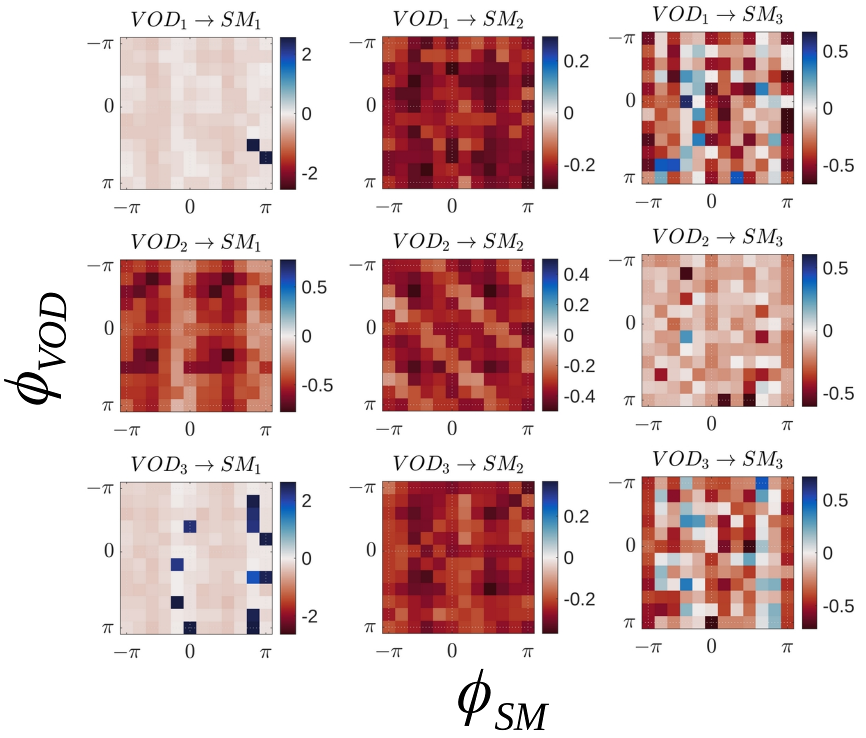
Phase to Phase relation of SM-VOD

In general SM → VOD and the interannual variability SM ←→ VOD

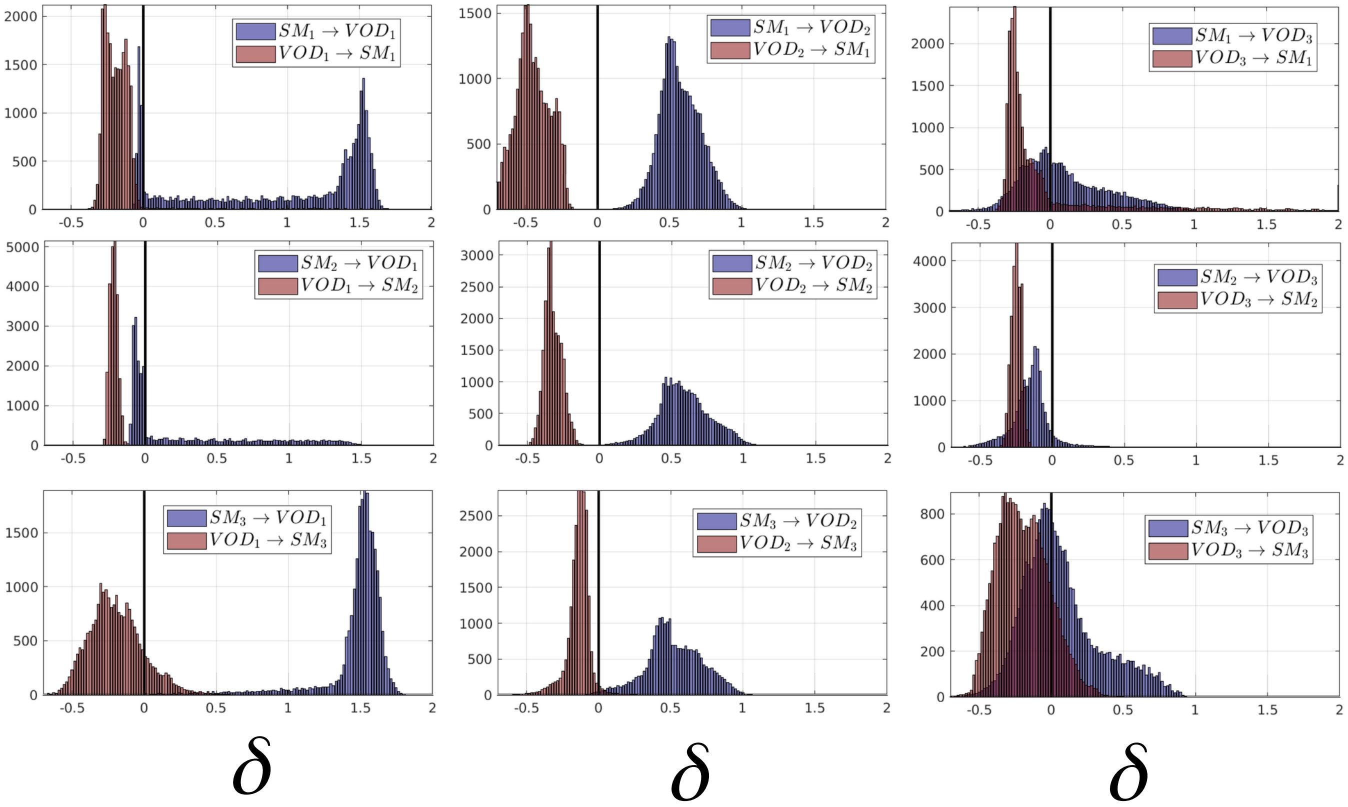


Significance $\delta > 0$



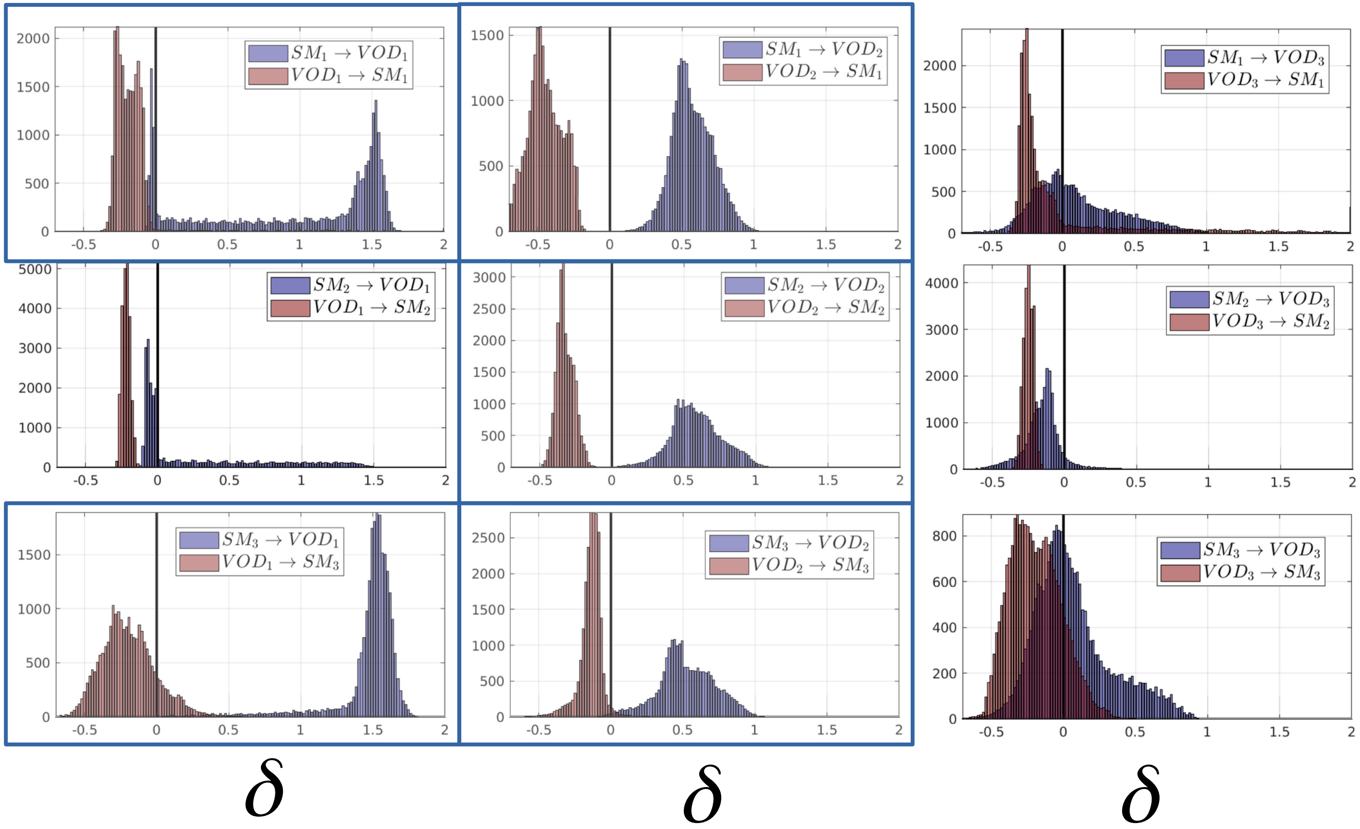
All SM-VOD relations

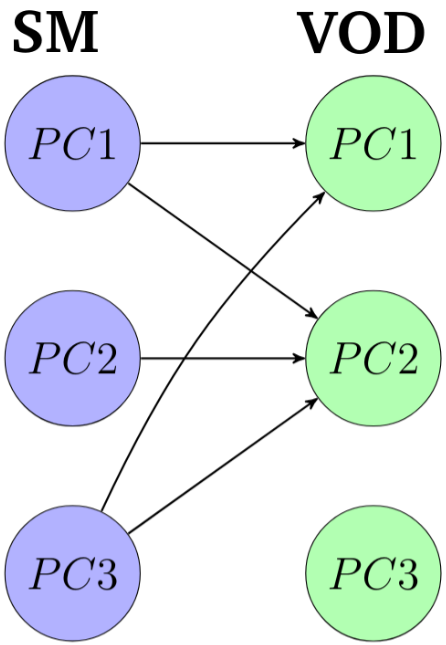
Significance $\delta > 0$



Main SM-VOD relations

Significance $\delta > 0$





Main SM-VOD relations

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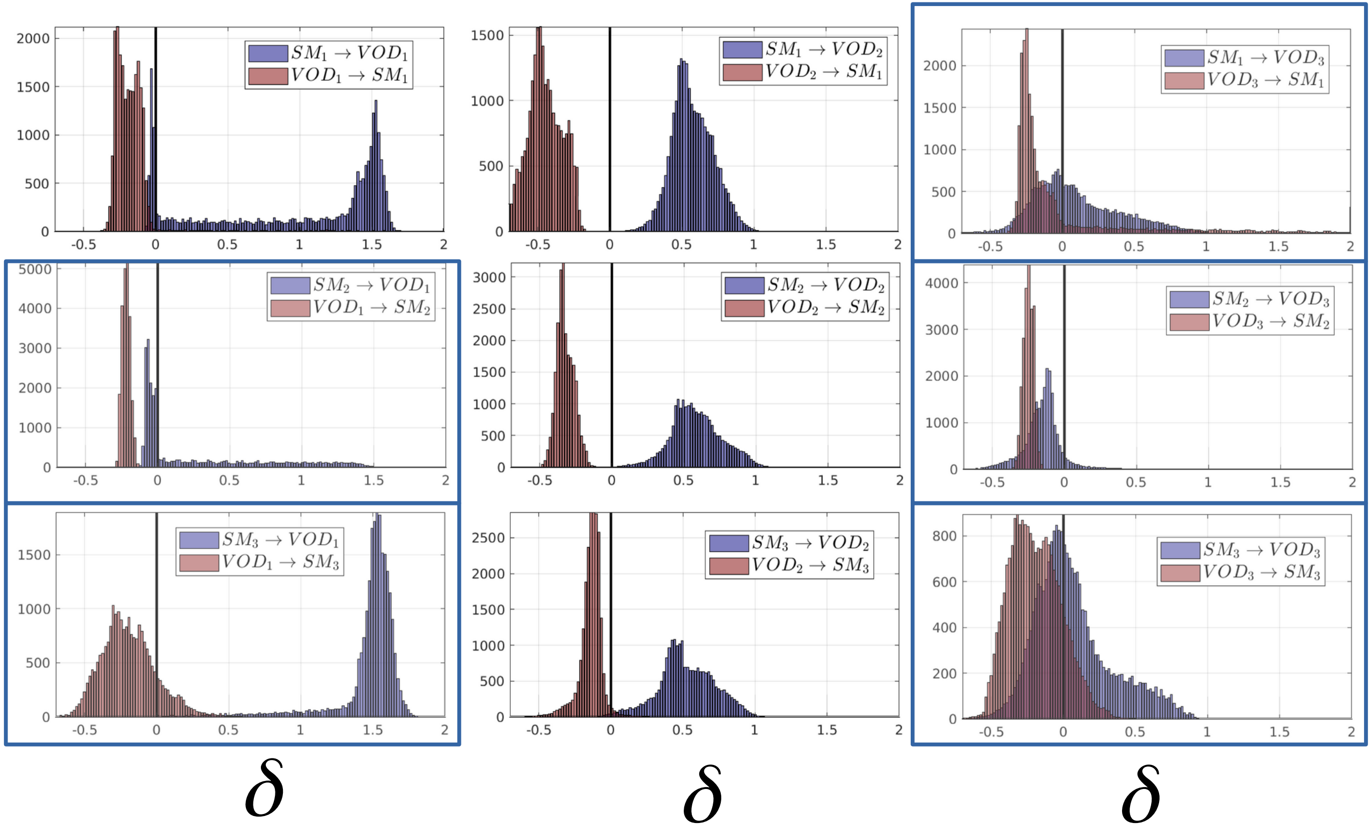
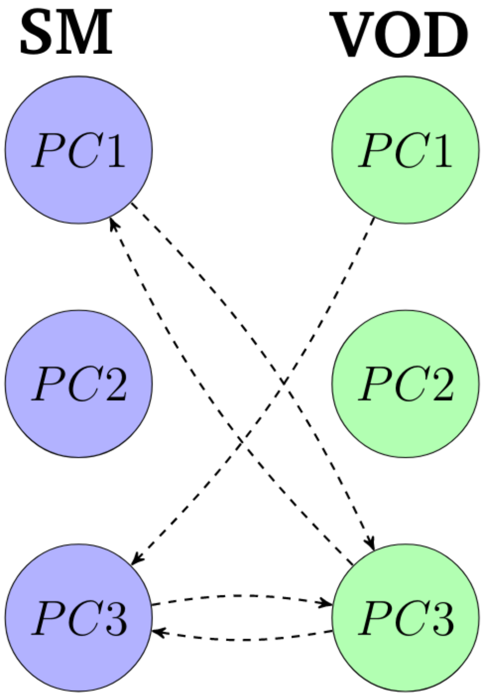
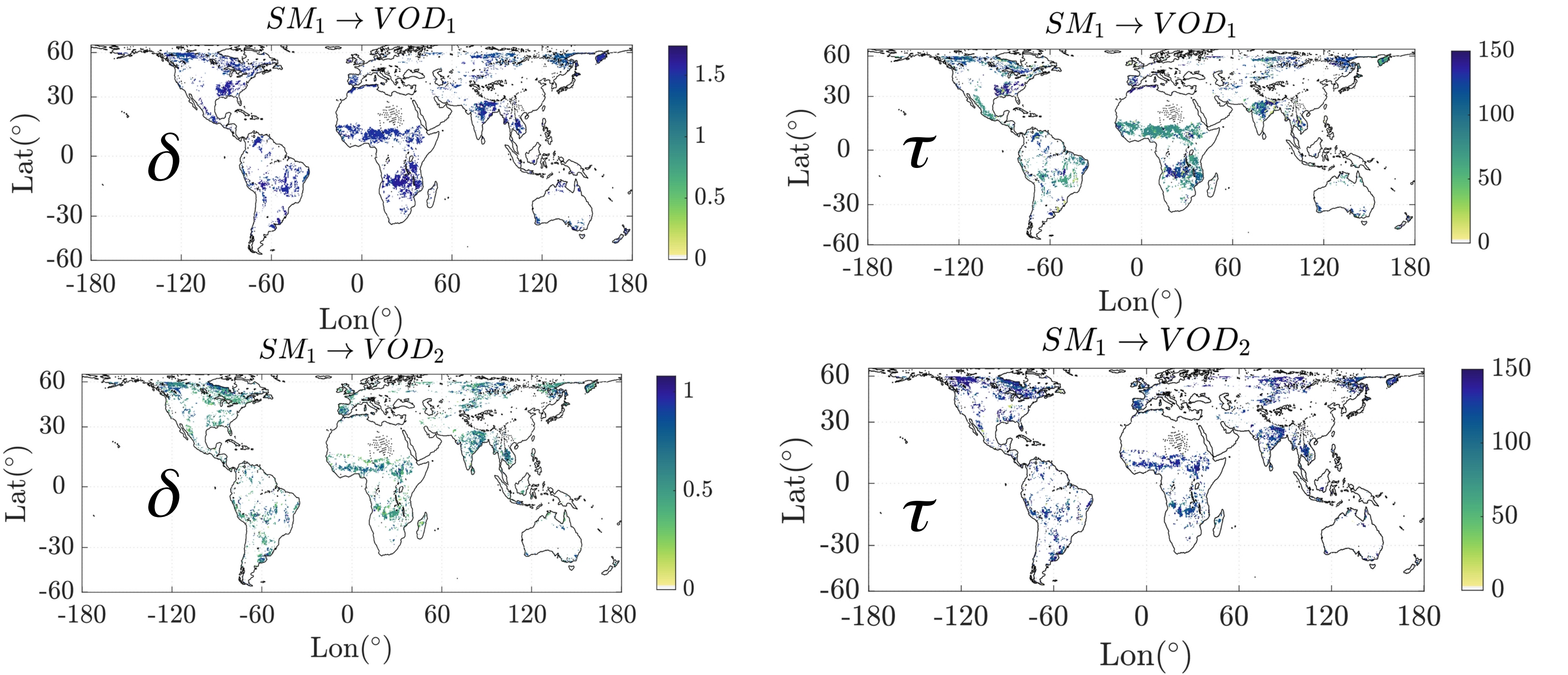




Maps of SM-VOD relation: SM1 → VOD1 & VOD2

SM1 → VOD1 mostly distributed over tropics. SM1 → VOD2 has a stronger representation over high latitudes



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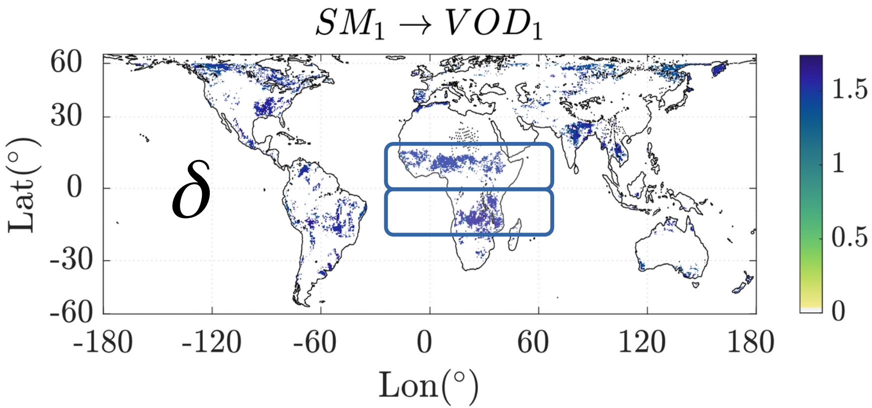
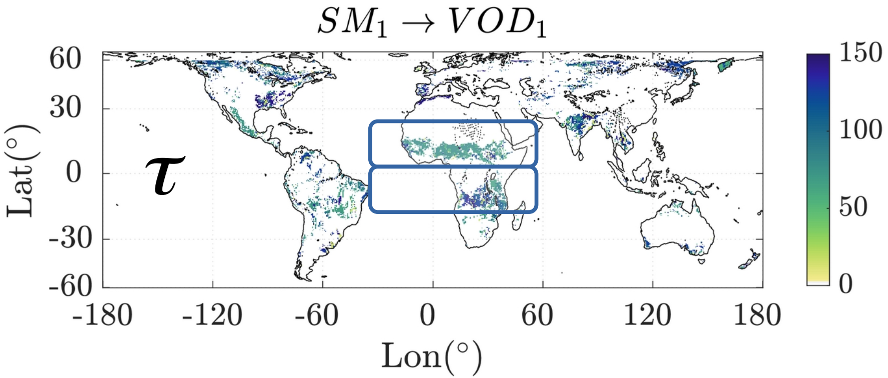
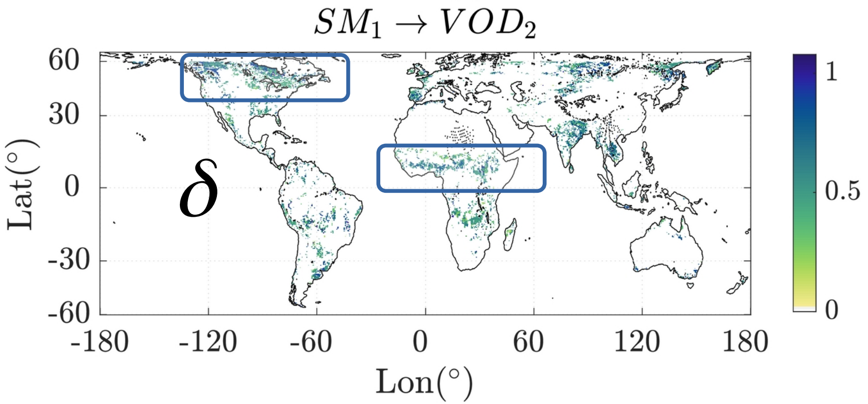
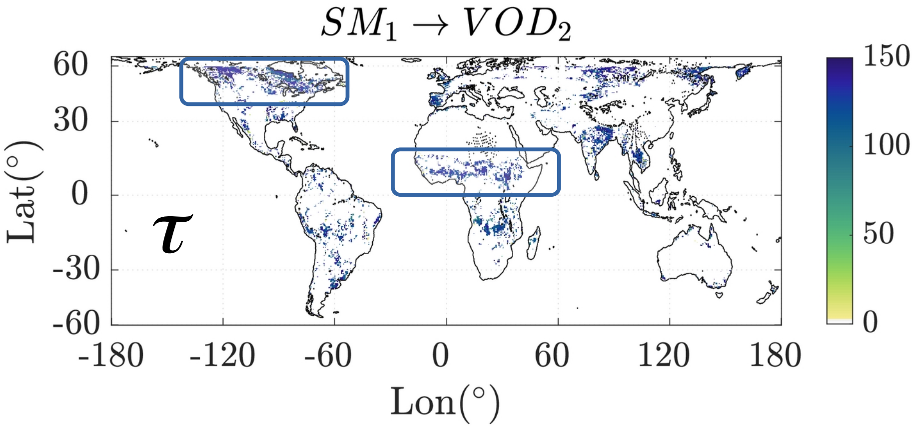


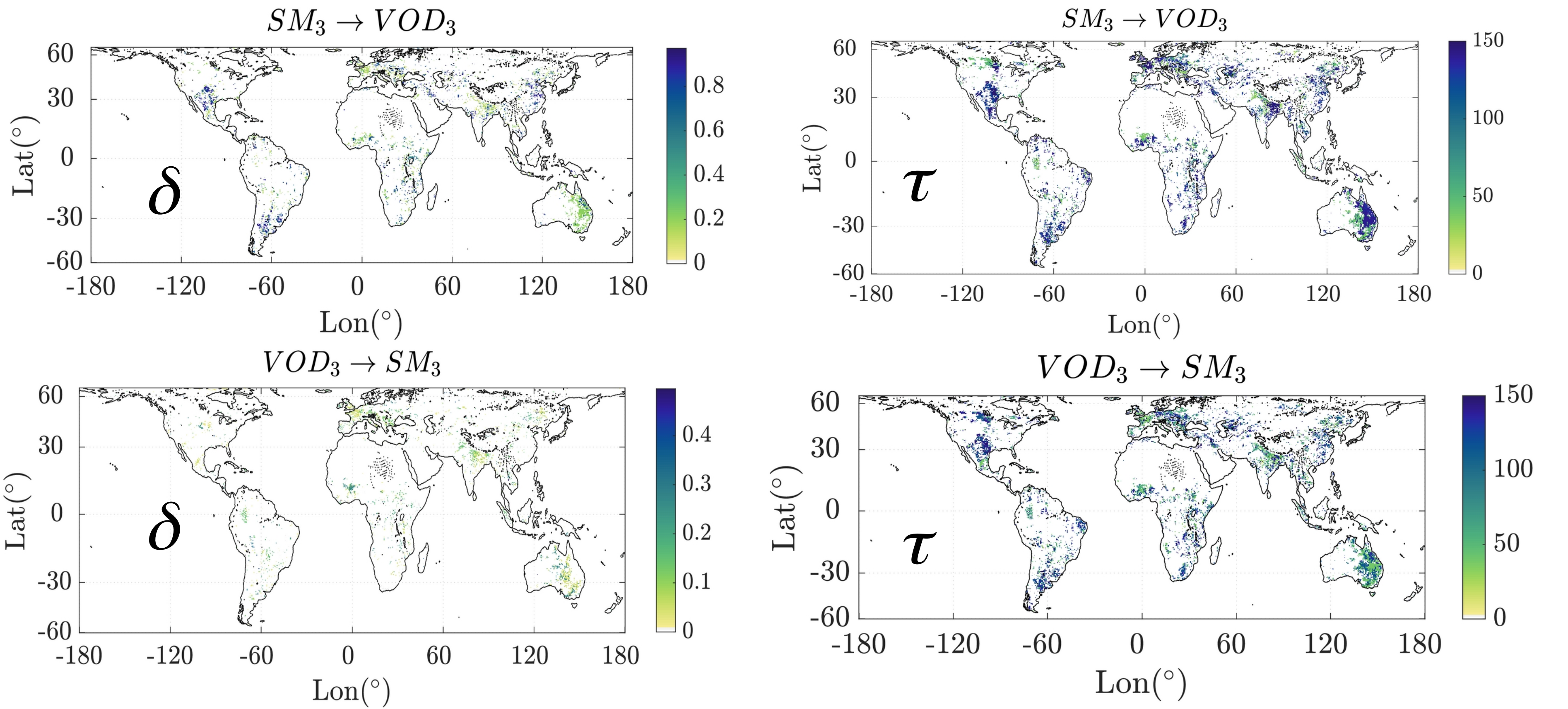






Maps of SM-VOD relation: SM3 ←→ VOD3

Asymmetric relation. Same spatial patterns with different time delay relations



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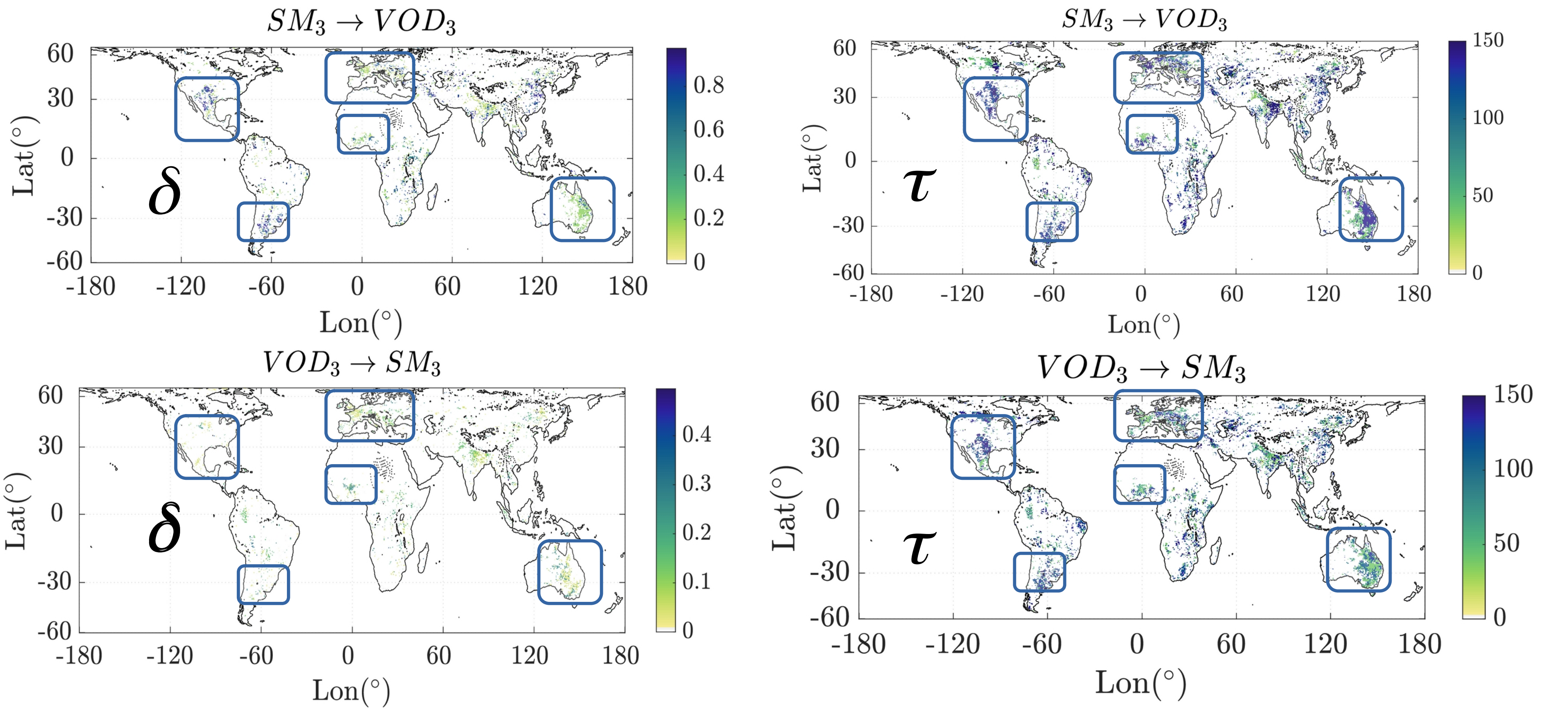
Asymmetric relation. Same spatial patterns with different time delay relations



Conclusions

Take-home messages

- Spatio-temporal Earth observation data representation
  - Nonlinear, multivariate, Multi-temporal scale
  - Complex approach allows a simple spatio-temporal analysis

- Dynamical analysis of main SM-VOD variability modes
  - SM drive the VOD inside the annual and seasonal changes
  - Low frequency changes of SM and VOD are interconnected with an asymmetric relation

Thanks!

References

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