Capturing the influence of ENSO on land surface variables for Tropical South America

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motivation (1/2)

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research question

Can the biospheric influence of ENSO be captured from land surface variables for Northern South America using dimensionality reduction analysis?

keywords

Isomap and Principal Component Analysis (PCA)

Gross primary productivity (GPP)

ENSO indices (MEI, ONI, El Niño-CP, etc)

Watersheds of Northern South America (SA)

Estupinan-Suarez et al. 2020. Capturing the influence of ENSO on land surface variables for Tropical South America. EGU2020-4187-Display. Section: CL4.20 – ENSO and Tropical Basins Interactions: Dynamics, Predictability and Modelling, EGU conference.

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motivation (2/2)

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background

- The response of tropical vegetation to El Niño Southern Oscillation (ENSO) is considered a main driver of atmospheric variations of CO_2 and CH_4 concentrations at interannual time scales (Zeng et al 2005, Pandey et al 2017).

- ENSO warm and cold phases, El Niño and La Niña respectively, cause contrasting climatic conditions along tropical South America. While some regions experience wetter conditions during El Niño, such as the Pacific coast, others regions such as the Amazon are exposed to warmer and drier climates (NOAA 2018).

- Besides this spatial variation, the biospheric response also differs between ENSO type and intensity, overruling of local conditions and ecosystems types (Zeng et al 2005, Wang et al 2015).

- Due to this complexity, there is a lack of understanding on what ecosystems and regions are systematically affected by ENSO and how biospheric variables respond,

methods (1/2)

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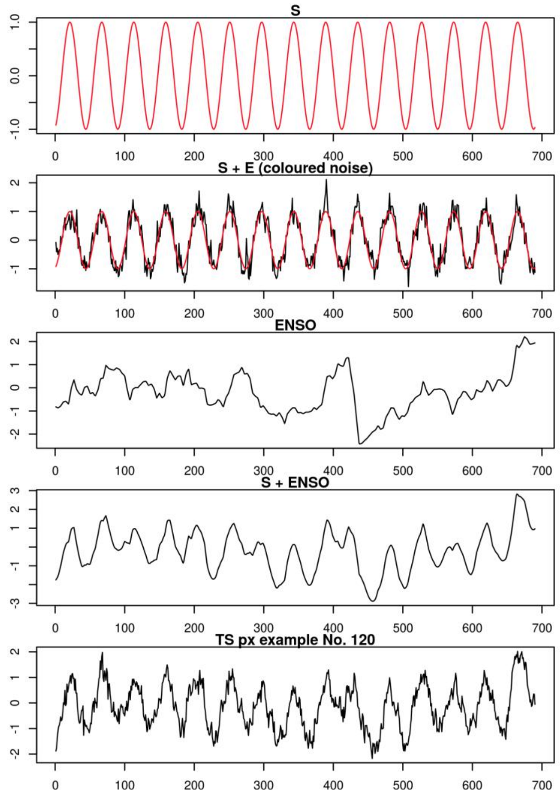
Concept

Dimmensionality reduction aims to find a few dimmesions (components) that explain the largest variance and reveal intrinsic features hidden in high dimensional data sets.

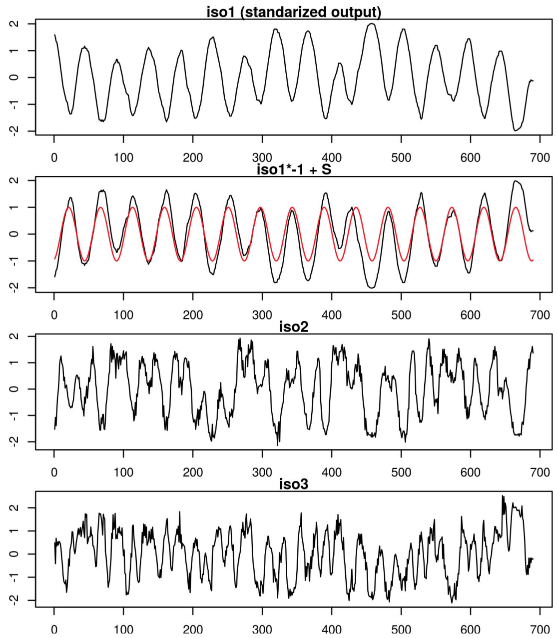
We applied PCA (linear) and Isomap (non-linear method) to reduce the space dimension.

Artificial time series

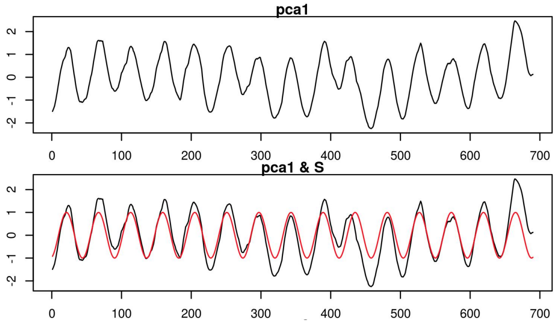


Isomap components

Tenenbaum et al (2000),
Gamez et al (2004)



PCA components



methods (2/2)

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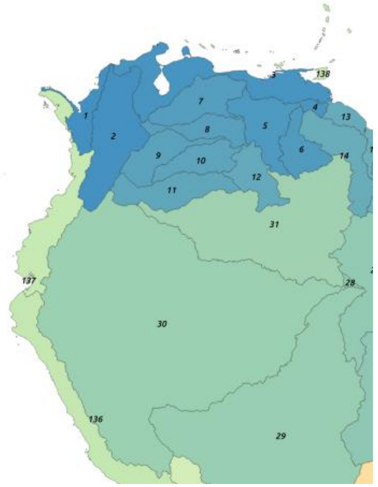
Study area: Northern SA



Latitude: 60° W to 83° W
Longitude: 14° S to 14° N

Data

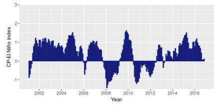
1km: GPP (BESS), EVI, NDVI, LST, LAI and FPAR (MODIS).

Watershed map: Source HydroBASINS - level 4

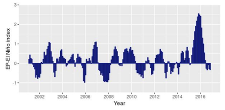
ENSO indices

Indices capturing long-term variability (Set1): MEI, ONI, OSI, CP-El Niño, EP-El Niño

Central Pacific (CP) El Niño Index



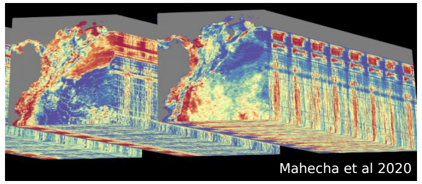
Eastern Pacific (EP) El Niño Index



Indices with strong seasonality (Set2): El Niño 1&2, El Niño 3, El Niño 3.4, El Niño 4

Data processing

Regional ESDL.
https://www.earthsystemdatalab.net/



(Estupinan-Suarez et al. in prep)

Workflow

Data gap filling

Split data by watershed

Multidimensional regression analysis

ENSO indices

Set 1

Set 2

FFT*

Long-term oscillation

Isomap

PCA

Calculate maximum lagged Pearson correlation between each component (1st to 6th) and ENSO indices

Find maximum correlation along components

* Fast Fourier Transformation

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methods (2/2)

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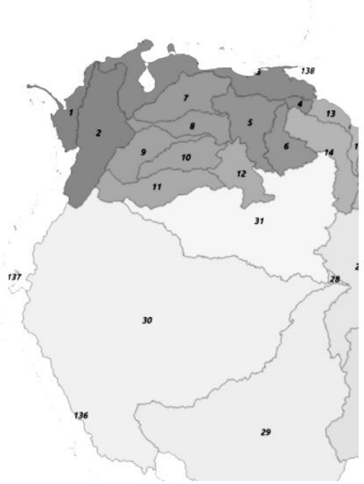
Study area

Latitude: 60° W to 83° W
Longitude: 14° S to 14° N



Data

1km: GPP (BESS), EVI, NDVI, LST, LAI and FPAR (MODIS).

Watershed map: Source HydroBASINS - level 4

ENSO indices

Indices capturing long-term variability (Set1): MEI, ONI, OSI, CP-El Niño, EP-El Niño

Indices with strong seasonality (Set2): El Niño 1&2, El Niño 3, El Niño 3.4, El Niño 4

Data processing

Regional ESDL.
https://www.earthsystemdatalab.net/

esa julia

(Estupinan-Suarez et al. in prep)

Workflow

Data gap filling

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Split data by watershed

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Multidimensional regression analysis

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Isomap | PCA

ENSO indices → Set 1 | Set 2 → FFT* → Long-term oscillation

Calculate maximum lagged[+] Pearson correlation between each component (1st to 6th) and ENSO indices

↓

Find maximum correlation along components

* Fast Fourier Transformation
[+] Assessed lags: 0, 1, 3 and 6 months

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results (1/3)
multidimensionality regression analysis: Isomap and PCA

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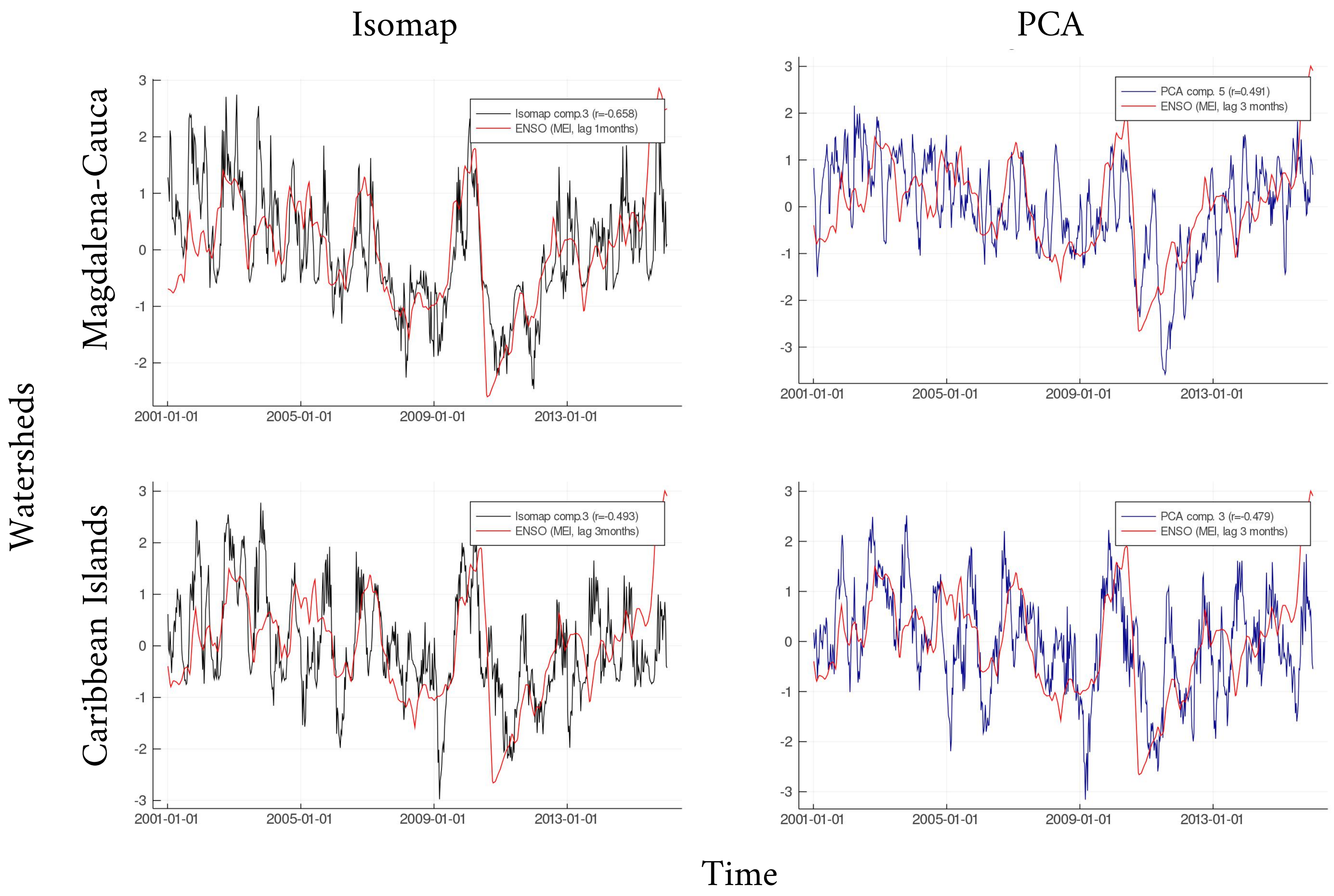

-> **Fig 1.** Correlation between GPP and ENSO using multidimensionality regression analysis. The Multivariate ENSO Index (MEI) has been standardized to $\mu=0$ and $\sigma=1$. Watersheds are in the rows whilst dimensionality reduction methods are in the columns.

- Magdalena-Cauca watershed shows the higher correlation between MEI and GPP using both methods. Nevertheless, there is not consistency in the lag time (Fig, 1).

- Isomap: Correlation > |0.5| are found in Magdalena-Cauca (-0.66) and the Caribbean (-0.65) basins, Colombian and Ecuadorean Pacific drainage (-0.59) and the Caribbean Islands (0.49)

- PCA components with the highest correlation are found in Magdalena-Cauca (0.49) and the Caribbean islands (-0.47).

results (2/3)
multidimensionality regression analysis: Isomap and PCA

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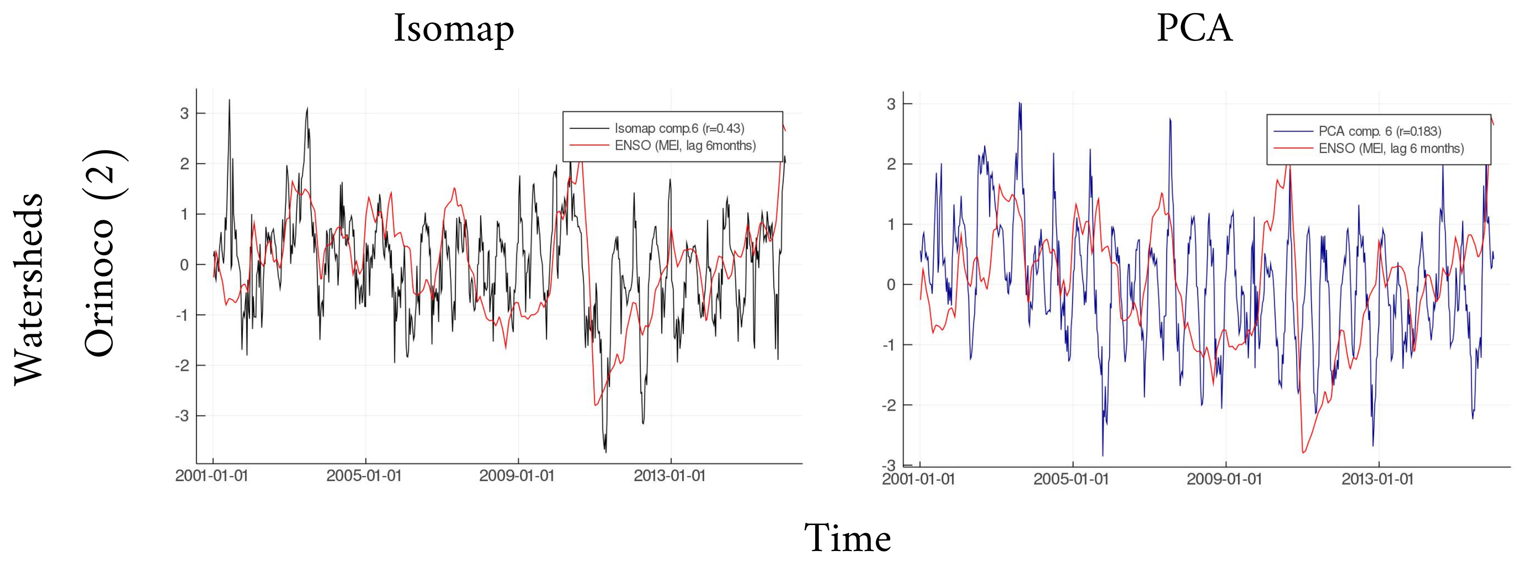

-> **Fig 2.** Correlation between GPP components and ENSO using multidimensionality regression analysis. The Multivariate ENSO Index (MEI) has been standardized to $\mu=0$ and $\sigma=1$. (from Fig1.),

- Isomap shows a higher capability of extracting GPP variability related to ENSO (Fig. 2, 3).

- Differences betweeen methods are clearly observed in watershed with lower impacts of ENSO such as Orinoco 2.

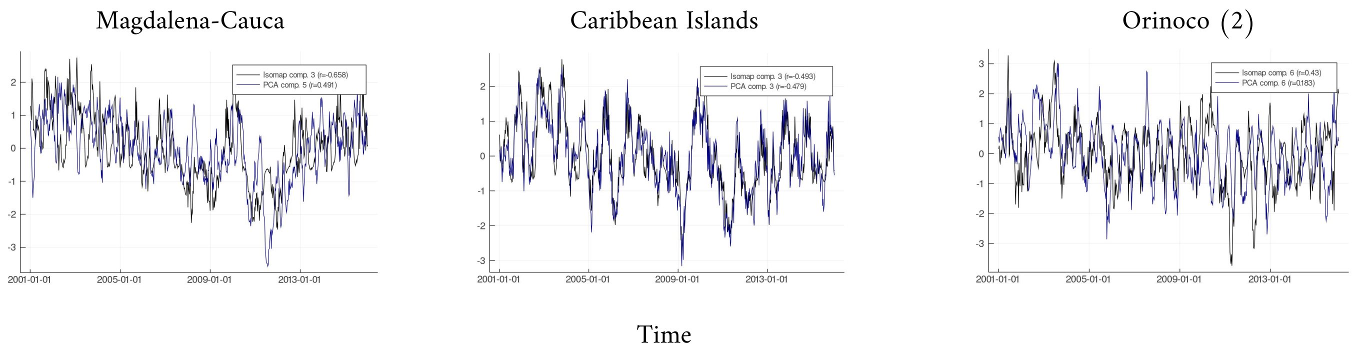

Fig 3. Time series of Isomap (black) and PCA (blue) components with the maximum lagged correlation to MEI in three different watersheds.

KEY MESSAGE

Isomap components are able to capture the biosphere variability related to ENSO in watersheds that have been historically affected such as Magdalena-Cauca valleys and the Caribbean region.

These results will be analyzed under the light of the regional climate anomalies.

results (3/3)
ENSO indices and its relation to GPP variability

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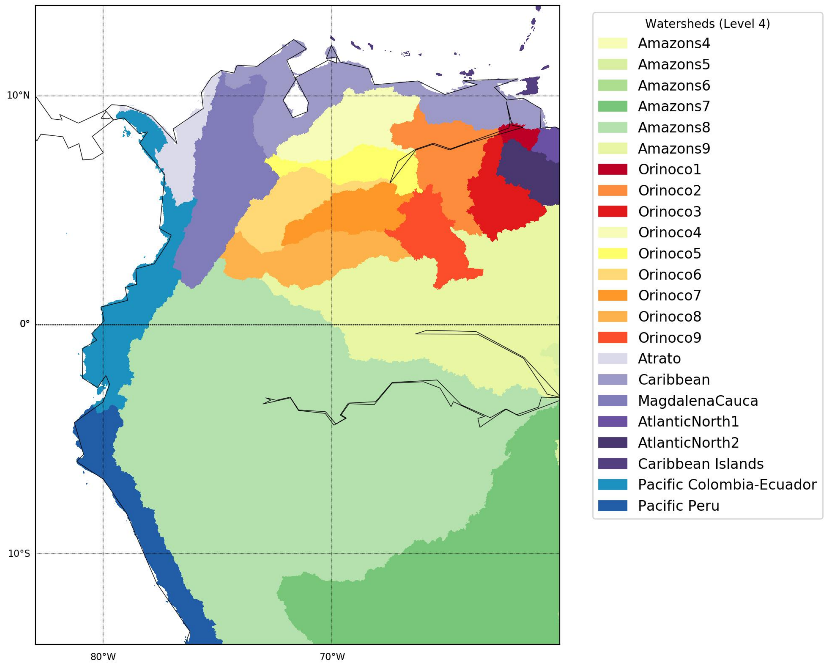
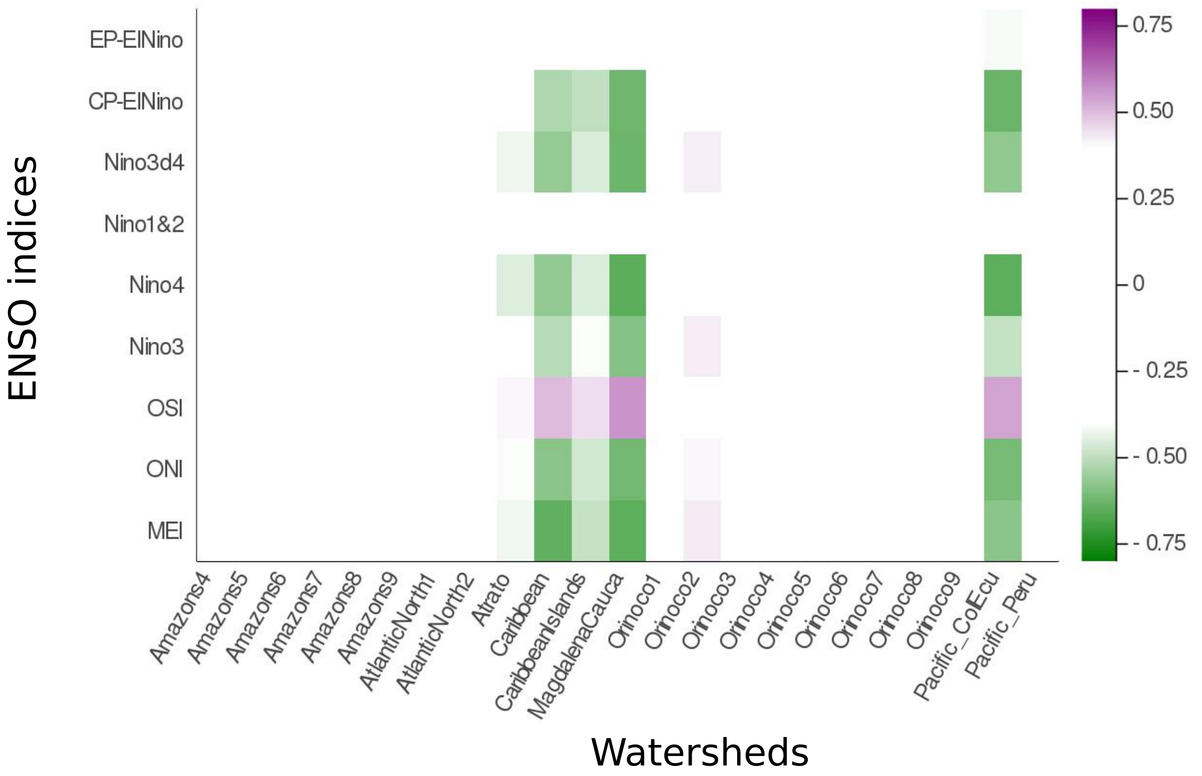


->Fig 4. Study area watersheds. Data source: HydroBASINS - Level 4



At watershed levels, GPP variability related to ENSO shows similar trends among indices except for El Niño 1&2 and EP-EL Niño.

Fig 5. Maximum lagged Pearson correlation between Isomap components by watersheds (x axis) and nine ENSO indices (y axis). Colormap shows values above |0,4|,

conclusion

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We found that isomap components are able to capture the biosphere variability related to ENSO in basins that have been historically affected such as Magdalena-Cauca valleys and the Caribbean region.

Implementation of non-linear methods increases our understanding of ENSO impacts spatially in regions where events intensity and frequency is increasing, and effective ecosystems management is urgent,

THANK YOU FOR READING!