BOTSWANA INTERNATIONAL UNIVERSITY OF SCIENCE & TECHNOLOGY

ABSTRACT

Abstract

Carbon sinks play an important role in absorbing almost half of the CO_2 emissions emanating from anthropogenic activities. However, regional contributions of atmospheric CO_2 are not well known in Southern Africa. This is partly attributed to shortage of in-situ data, data gaps and limitation in the theory in modeling atmospheric CO₂ dynamics. The shortage of in-situ observations and poor model skill have created a need for assimilation of observations into models in order to assess the variability of atmospheric levels in near real time globally. In this study, we investigated the variabilities of XCO₂ at multi-temporal scales based on reanalysis data from the carbon tracker (CT) assimilation model over Southern Africa from the year 2000 to 2016. The ensemble empirical mode decomposition (EEMD) statistical technique was used to decompose CO₂ time series into signals with different periodicities. The results demonstrate that the different component signals are driven by atmospheric, surface and oceanic forcings (e.g., rainfall, temperature, soil moisture and SST).

INTRODUCTION

Atmospheric CO₂ levels have increased since the start of the pre-industrial period from levels of 315ppm (Kirschbaum, 1999; Stocker, 2014; Allison, 2015; Morison & Lawlor, 1999) to present-day levels of more than 410 ppm (Earth System Research Laboratory 2019).

Regional trends of CO₂ and the factors that contribute to variation in atmospheric CO₂ levels are key in mitigating issues related to climate change (Lim et al., 2005). It is also necessary to study key drivers of CO₂ variability as well as their contributions to the CO₂-climatic responses because all they fall under complex and non linear climate systems.

This was achieved by breaking down these climate signals into single components then scrutinizing each component separately using the EEMD statistical method.

AIM AND OBJECTIVES

Aim

To assess the variability of CO₂ over different temporal scales in Southern Africa from 2000-2016

Objectives

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To find out the natural CO₂ flux distribution using the CT model 2017

To investigate the seasonal and inter-annual CO₂ variability and the relationship between different drivers.

To identify the timescale responsible for the regional natural CO₂ flux in Southern Africa.

Multi-scale CO₂ variabilities over Southern Africa Boipelo B Thande1, G. Mengistu Tsidu1 and A. Getachew Mengistu2 Department of Earth and Environmental Sciences, Botswana International University of Science and Technology, Palapye, Botswana

²Department of Physics, Addis Ababa University, Addis Ababa, Ethiopia

MATERIALS AND METHODS

Materials

- A column-averaged dry-air mole fraction of CO₂ (XCO₂) data from the CT2017 model from 2000 to 2016 at temporal resolution of an hour was used.
- Math-lab software package was used for analysis of XCO₂

Data acquisition

Climate drivers	Sources	Approach		
1. CO ₂	CT2017 https://www.esrl.noaa.gov/gmd/ccgg/carbontracker/	Ensemble Er Huang et al Intrisic Mode signal. Skillfully elin shown below		
2. Temperature	ECMWF-https://www.ecmwf.int/en/forecasts/datasets/ reanalysis-datasets/era-interim			
3. Rainfall	GPCC ftp://ftp-anon.dwd.de/pub/data/gpcc/html/download_gate.html			
4. Soil Moisture	Noah v3.3 from the Global Land Data Assimilation System Version 2.1 (GLDAS2.1)			
5. NDVI	EVI, MODIS			
Mathad and annroach				

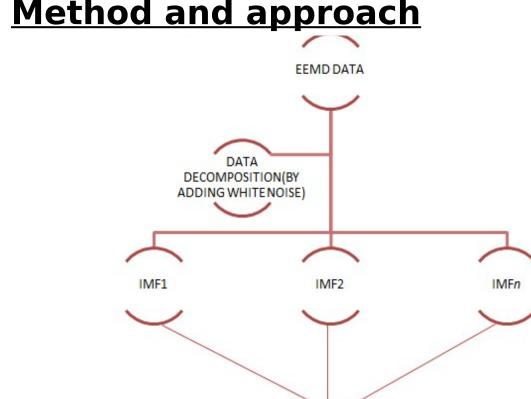


Fig 1: A summary of the how the EEMD data is decomposed into IMF's

IMF MEAN

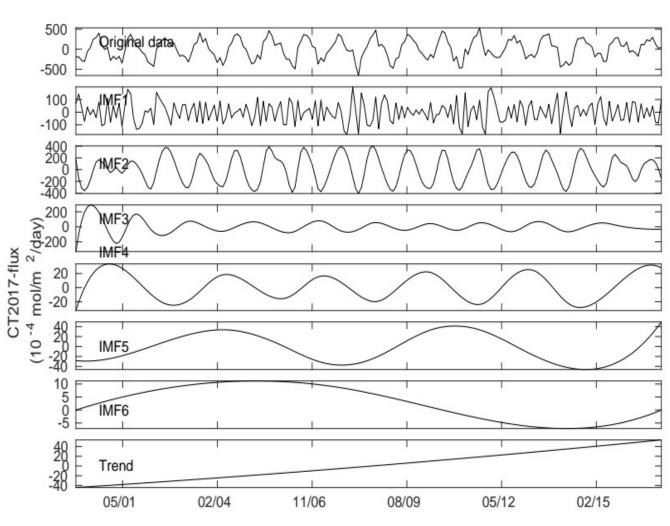


Fig 3: shows the time-series of the original CO₂ data (uppermost rows), IMF 1-6 (middle rows) and the residual (last row) which gives the overall trend averaged over southern Africa from year 2000-2016.

Table 1: A table showing the average months of each IMF(periodicity), as well as the contribution rate to the CO_2 flux, the trend component is the residual.

<u>IMF's</u>	<u>Mean</u> period(months)	<u>Contribution rate</u> (%)	<u>Correlation</u>
1	3.00	10.30	0.26
2	11.33	78.25	0.89
3	20.40	8.59	0.16
4	37.09	0.47	0.09
5	81.60	1.14	0.04
6	204.00	0.06	-0.03
trend		1.19	0.08

RESULTS AND DISCUSSIONS

Long Term average CO, natural flux over Southern Africa

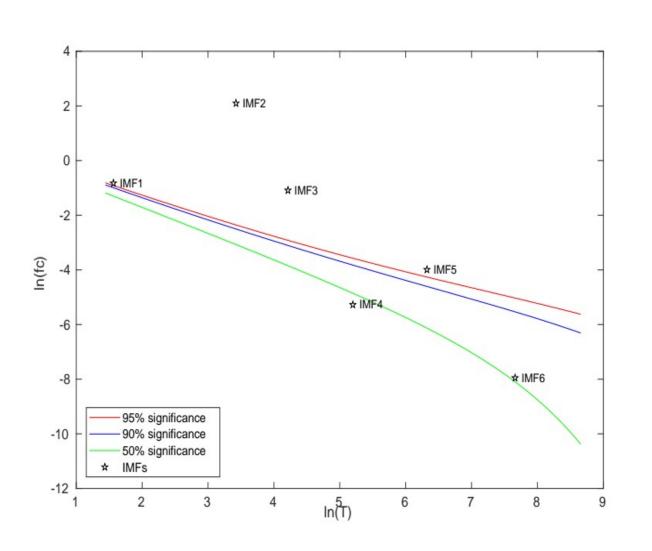


Fig 4: The averaged periodicity of CO₂ in Southern Africa (shown on the right side of the pane) and their significance of contribution (shown by left panels).

- EEMD CO₂ data was decomposed into 6 IMF's and 1 adaptive trend over a 16 year period shown by fig 3 above.
- Each IMF mirrors the qualities of change at various time scales from high recurrence to low recurrence, where IMF 1 is at 3 month scale, IMF2-biannual, IMF3-annual, IMF4-biennial, IMF5 3 to 4 year CO₂ cycles and IMF 6-decadal cycles.
- The overall adaptive trend depicted in figure 3 was positive and suggested that the sink for CO_2 in Southern Africa was increasing
- The Monte-Carlo confirmed that the significant IMF's of the CO2 flux were IMF 1,2,3 and 5 with a confidence interval of above 95%

I would like to enunciate my gratitude to my supervisor Prof G. Mengistu Tsidu, Anteneh Mengistu for his guidance and help throughout my thesis. My appreciation goes to my family, all my friends, members of academic and non-academic staff within and outside the Earth and BIUST | Driving Change Environmental science Department for the invaluable information. And NOAA Earth System Research Laboratory and others for their data products.

Empirical Mode Decomposition (EEMD) is a statistical approach proposed by al.,1998 that decomposes and isolates data into single componets called de Functions(IMF's). It does this through addition of white noise into the

liminate mode mixing through averaging a number of ensemble trials as

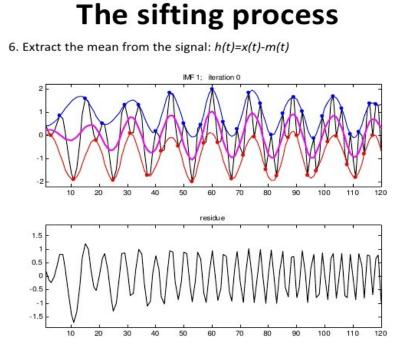


Fig 2: A sample figure illustrating the sifting process by extracting the mean from the signal.

The method was applied over Southern Africa to decompose the following data; Carbon dioxide(CO₂), NDVI, root zone soil moisture, temperature, precipitation and SST's data for a period of 16 years (2000-2016) at different temporal scales.

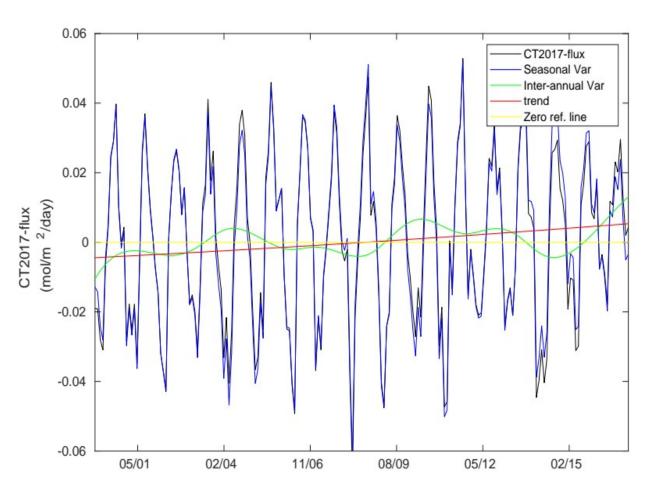


Fig 5: Reconstructed CO₂ fluxes showing temporal trends at seasonal scale (IMF 1 + IMF 2 + IMF 3 + trend component) and interannual scale (IMF4 + IMF5 + IMF6 + trend component)

- This means that results showed that CO₂ is linked to certain physical drivers which govern the natural atmospheric CO_2 flux. Whereas IMF 4 and 6 were uncertain confirmed by table 1.
- The reconstructed CO₂ flux differentiate the Seasonal and Inter-annual flux over the region where the extremas in the seasonal flux could suggest evidence of past events such as droughts, dry spells or relatively wet periods with a general slightly positive trend(fig 5).
- The results in fig 3 and 4 showed a relatively stable quasi-periodic variations in the average CO_2 flux over the region.

CONCLUSIONS & RECOMMENDATION

References

ACKNOWLEDGEMENTS

RESULTS AND DISCUSSIONS

Spatial distribution of CO₂ natural flux over Southern Africa

• A probability of 30-55% for a 3 to 4-month scale periodicity of the natural CO₂ flux in the southern part of Southern Africa depictedby IMF 1.

However as the timeframe increases (5 to 12 months) there is a shift in the periodicity of natural CO₂ flux distribution where a higher probability of 50-70% and mostly expressed in the northern part of the region.

• And most of these changes illustrate a normal seasonal transition of the CO₂ cycle.

The results displayed in fig7 are in agreement with table 1 above. The seasonal IMF's i.e. 1,2 and 3 showed a significantly higher probability of reoccurence as compared to IMF 4,5 and 6 contrary to Ahlstrom et al. 2015's claim that semi-arid ecosystems are largely influenced by IAV of CO.

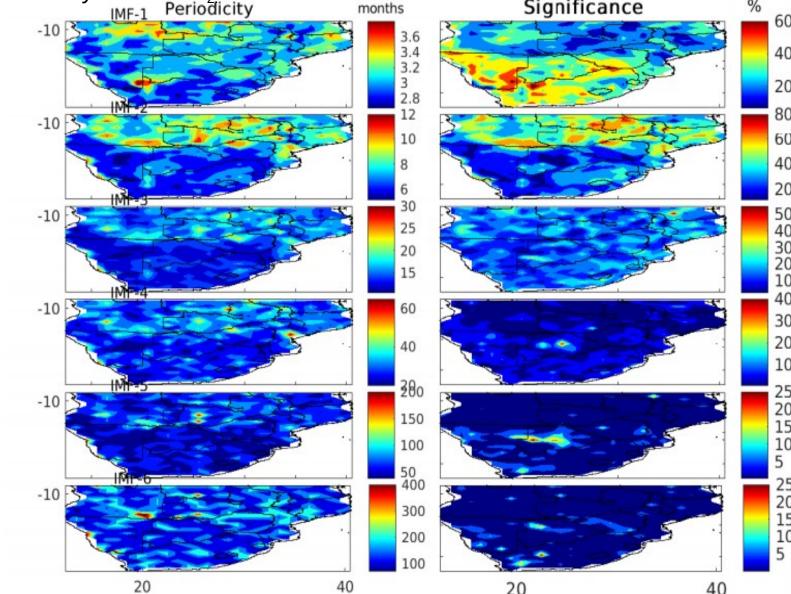


Fig 6: Multi-scale spatial distribution of CO₂ natural flux over Southern Africa. The figure shows the periodicity of each IMF and probability of reoccurence over the Southern Africa.

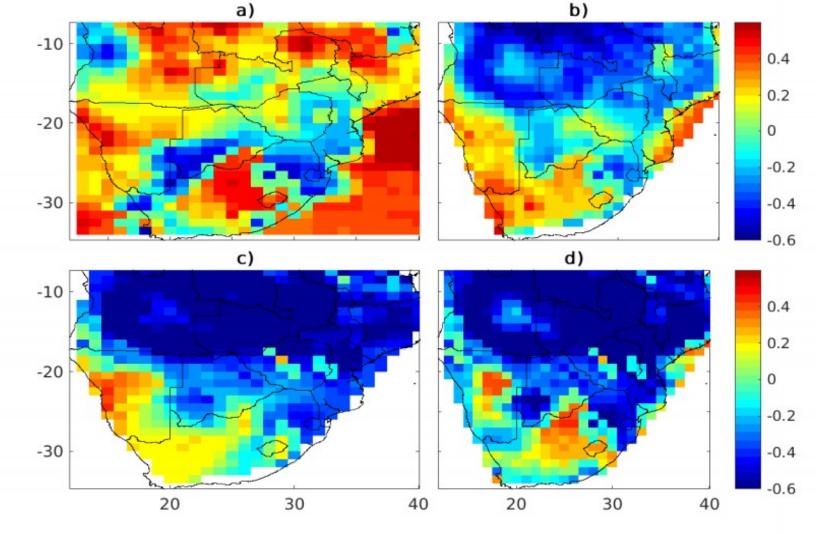


Fig 7: Seasonal correlation of CO₂ with other drivers. a)Temperature b)Precipitation c)Soil Moisture d)EVI, on the left ottom of the axis are lines of latitude and longitude. The far-right panel shows the correlation values with respect to the CO₂ natural-flux.

• Seasonal CO, correlation with other drivers

• a) Temperature showed a strong positive correlation of 0.5 to 0.6 to seasonal CO₂ flux across the region a few patches of negative correlations of ranges -0.2 to -0.6 in the south-central region and the northwestern part of Southern Africa.

• b) precipitation, c)Soil moisture and EVI show strong negative correlation values of -0.5 to -0.6 that are largely dominant in the northern part of Southern Africa as compared to the southwestern part of Southern Africa.

• The correlation of precipitation is generally poor across the region (-0.5 to -0.6) but the southwestern and southeastern coastal areas showed a positive good correlation of 0.4 that could be hypothetically be influenced by the atmospheric-land driven circulation of carbon fluxes. Therefore temperature remains a crucial driver that influences plant physiology through photosynthesis and respiration in in-situ studies (Wang et al., 2015) consequently affecting the regional CO₂ flux.

Seasonal changes in vegetation play a role in influencing the natural short-term flux of CO₂ and temerature has shown to be the dominant driver in the seasonal natural CO, flux distribution. Whereas the IAV have shown to add an insignificant amount to the overall regional flux. And in most cases, seasonal changes in CO₂ have a predictable quasi-periodic pattern. Nevertheless XCO₂ is a combination of several climatic components therefore the unexpected contributers to the feedback response might not be obvious, therefore can pose a challenge. Therefore this can be further investigated in the future.

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