Towards digital filter methods for CO_2 sink and source identification

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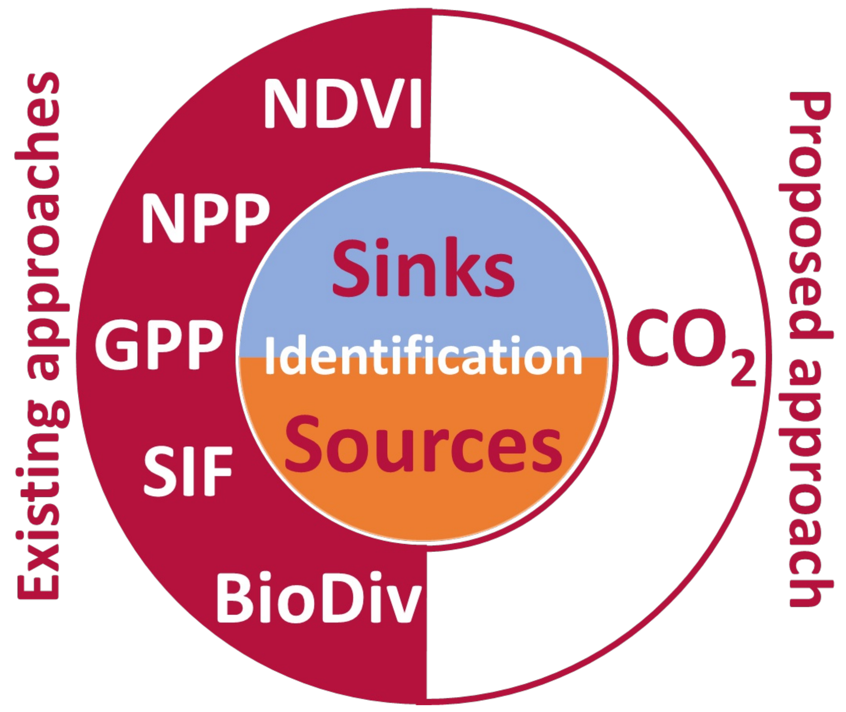
1 Introduction

The constant rise of atmospheric carbon dioxide (CO_2) concentrations has led to clearly detectable surface warming[1,2] that focuses our research on developing new methods of CO_2 reduction.
In recent studies, an ecosystem response to impacts is described by the different functional indices - NDVI[5], NPP, GPP[6,7], SIF[8], biodiversity[7], and their sets[9,10] with complex multi-data models. This makes them accurate but, also, resource-intensive, less straightforward and less sensitive to short-term changes.



High-level Carbon Balance model:

CB=EnvIn-EnvOut+∑IntSrck-∑IntSinkl

EnvIn – CO2 income to the area from the external environment;
EnvOut – CO2 gross output from the area to the external environment;
IntSrcs – internal CO2 sources;
IntSinks – internal CO2 sinks;
k – number of sources in the area;
l – number of sinks in the area.

Therefore, we propose using CO_2 concentrations (CDC) as an integral parameter, which can be directly measured in near real-time, for CO_2 source and sink areas identification.

3 Results

Sources test data

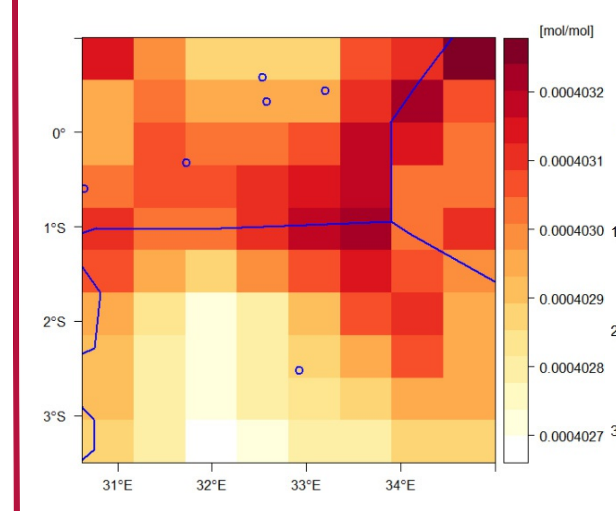


Fig.A. Source - CDCspatial

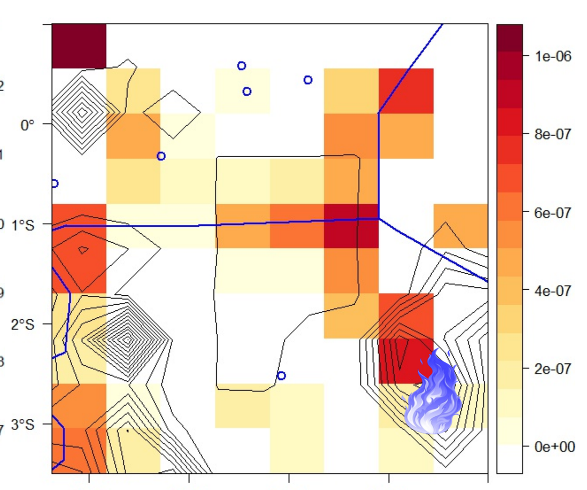


Fig.B. Filtered CDC spatial

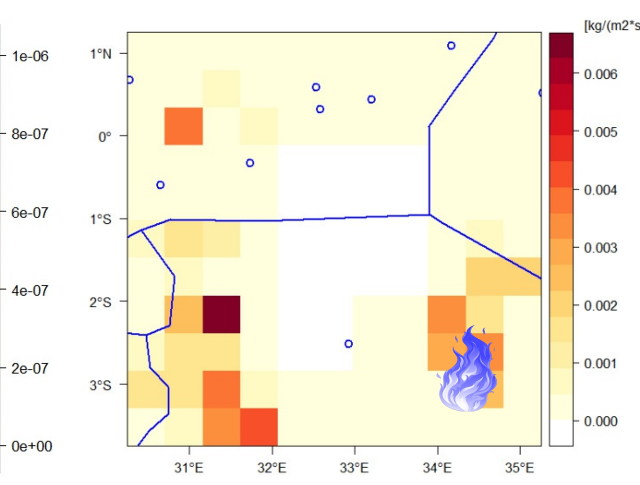


Fig.C. Test Fluxes data

For identification of the CO_2 sources areas, we chose a large fire event in the Serengeti National Park, Tanzania, which started on 22 July 2016 and lasted for 31 days. The CDC distribution for this date is shown in Fig.A, but the borders of the source area is not sharp.
In order to detect the fire area borders, we applied Laplacian filter, assuming that all the CDCs in the area were measured at the same time. The results are shown in Fig.B, where each cell has a certain shading, presenting a CDC intensity change within it. The cells with the dark shading are defined as CO_2 source areas. To verify the obtained results, we compare them with a CO_2 flux for the above-ground layer, taken from a ready CO_2 flux dataset[11]. The flux data are presented in Fig.C with isolines showing the rate of CDC

Sinks test data

For identification of the CO_2 sinks areas, we analysed the CDCs (Fig.D) for Alaska in June 2016[11], looking at land cover (LC) type, biomass, and growth phase (NDVI). First, we compared the filtered CDC data with the LC types in Alaska (Fig.E). A little spatial difference is detected in CO_2 fixation between the areas covered by shrubs and herbs (Fig.F), possibly due to the small amount of biomass in these ecosystems and the potential influence of the nearby ocean.
The filtered CDC is close to zero on the mountaintops due to the almost homogeneous CDCs in the barren land, ice and snow areas (the NDVI in Fig.F is also zero). In contrast, the central part of Alaska, an area independent of the external impacts with a large amount of evergreen biomass with high NDVI, is identified as a CO_2 sink area.

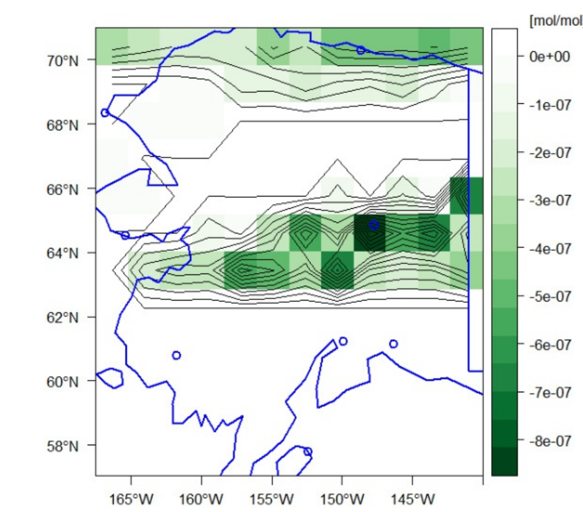


Fig.D. Filtered CDC spatial

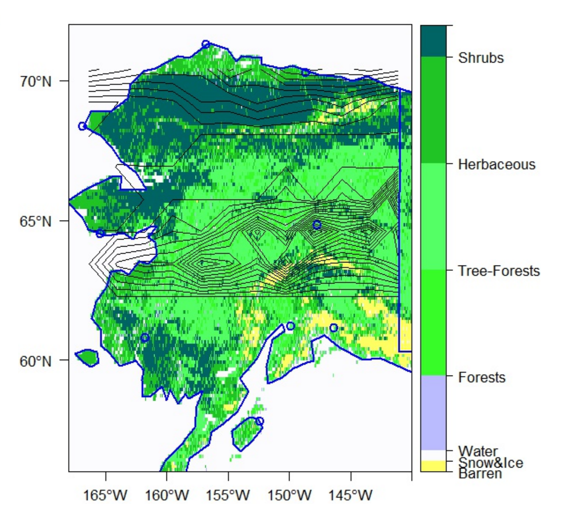


Fig.E. Filtered CDC and LC

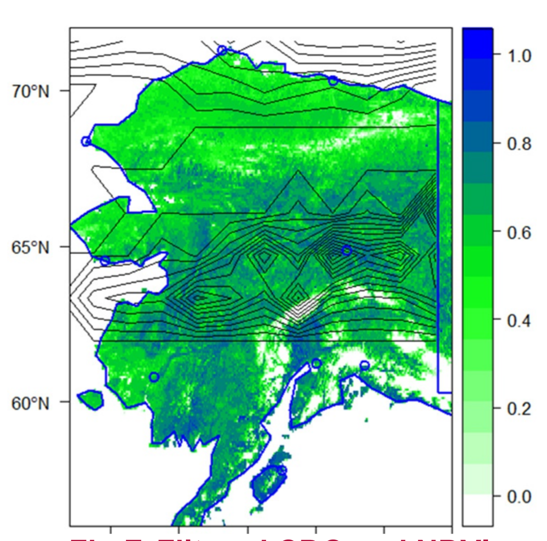
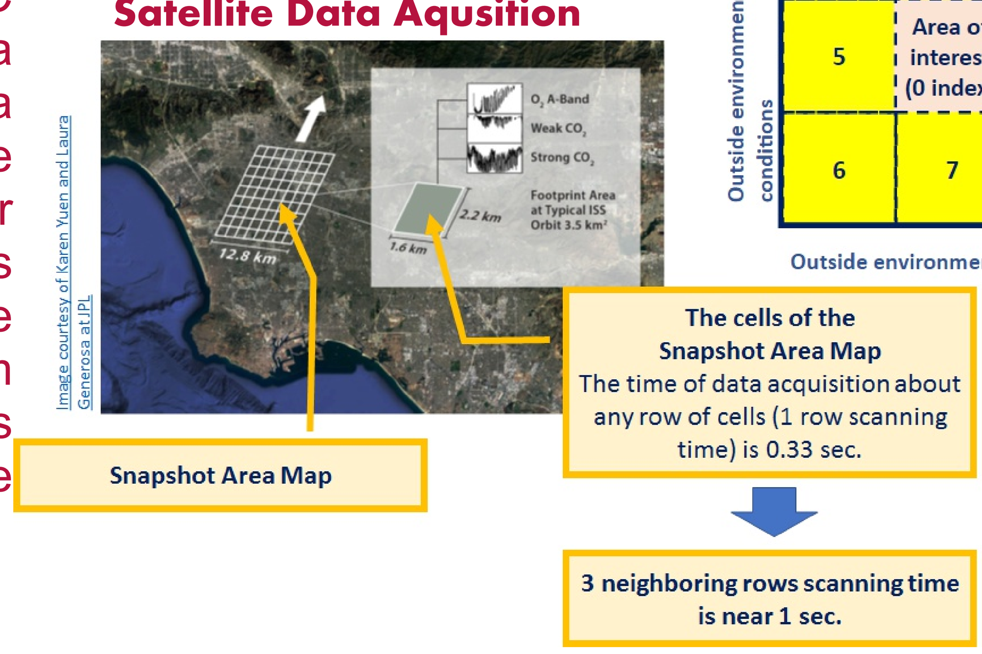


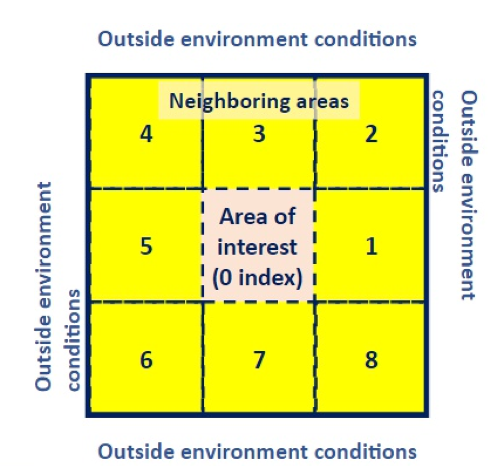
Fig.F. Filtered CDC and NDVI

2 Data & Methods

The proposed algorithm identifies and detects the borders of CO2 source and sinks area. We tested the proposed algorithm using two types of CO_2 data measured at the near-surface layer - CO_2 concentrations to apply digital filtration for sink and source areas identification and CO_2 flux data to verify the results[9].
In order to apply the Laplacian filter[10] to a CDC dataset formed by carbon balances, we performed a convolution operation, which mathematically means a combination of two matrices - in our case, one containing the CDCs and the other - the filter coefficients. The convolution operation, involves sliding the filter over the dataset, multiplying the CDCs by corresponding coefficients and adding them up. The result is a new dataset of the same size as the original, but calculated CDC differences can be positive, negative or zero.

Satellite Data Aqusition





Assumptions for the comparison:

- the data acquisition time is so short that it can be argued that the component values are constant.;
- the short acquisition time and the previous assumption allow us to interpret this process as a snapshot;
- the sizes of the areas are small, providing equal external impacts at all their parts;
- areas located so closely that external impact can be accounted as equal.

CB comparison for two areas:

CB1-CB2 = (EnvIn1 - EnvOut1 + ∑IntSrck1 - ∑IntSinkl1) - (EnvIn2 - EnvOut2 + ∑IntSrck2 - ∑IntSinkl2)

With equal external factors:

CB1 - CB2 = (∑IntSrck1 - ∑IntSinkl1) - (∑IntSrck2 - ∑IntSinkl2)

8 neighbouring area's CBs comparision:

$$F(CB) = \sum_{i=1}^{i=8} (CB_i - CB_0) \Rightarrow \nabla Lp(CB) = \begin{vmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{vmatrix}$$

A positive value after digital filtration means that the original CDC in the area of interest is greater than the average CDC in the neighbouring areas, and the area is identified as containing the CO_2 source. An area with a negative CDC after filtration is identified as containing a CO_2 sink. A zero value means that the CDCs in the area of interest and the neighbouring areas are equal - CO_2 homogeneous areas.

4 Outlook:

- to find a match between the different sizes of CO_2 sources and sinks and the required spatial resolution of the CO_2 datasets
- to do the digital filtration with other types of graphical filters and compare the obtained results
- to explore the dynamics of different CO_2 fixation properties in different parts of

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- R version 4.3.3 (2024-02-29 ucrt) -- "Angel Food Cake" Copyright (C) 2024 The R Foundation for Statistical Computing
- RStudio 2023.03.0+386 "Cherry Blossom"

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