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Earth Information System (EIS)

Monthly Highlights

April 2023

EIS supports release of OCO national carbon budgets

The OCO Science Team has worked to develop new techniques for estimating national scale carbon budget, with the goal of helping countries contribute to global stocktakes of emissions mandated by the Paris Accord.

Methods have been detailed in Byrne et al. [2023] and some components of the analysis are being ported to MAAP.

In this example, a Jupyter notebook allows users to reproduce derivation of national emissions from gridded estimates in support of policy applications.

Future work will expand the analysis done within the VEDA framework for increased transparency.

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Data_Description: National CO2 Budgets (2015-2020) inferred from atmospheric CO2 observations in support of the Global Stocktake
Data_sources: Net Carbon Exchange (NCE) version 10 of the Orbiting Carbon Observatory Model Intercomparison Project (OCO-2 MIP) [https://ocm.nasa.gov/oco/OCO2_MIP/]; Fossil Fuel and cement production emissions (FF) Open-source Data Inventory for Anthropogenic CO2 (ODIA) CI emission data product [Dole et al., 2018, https://doi.org/10.5194/essd-10-87-2018] with day-of-week and diurnal variations from Nassar et al. [2019, https://doi.org/10.5194/essd-10-87-2018]; Crop and Wood land fluxes (F wood trade + F crop trade); Disaggregated crop and wood trade data compiled by Food and Agriculture Organization of the United Nations (FAO) [http://www.fao.org/faostat/en/#data/RL]; River lateral fluxes (F rivers export); River fluxes based on the Global NEWS model.

Description: This is a pilot CO2 Budget for countries over 2015-2020. Estimates of

Plotting Gridded Data
Let's plot the net carbon exchange for LNL01 (LNL01 NCE) for 2016 and 2018. We can use xarray and matplotlib to do this. First, we will set some plotting parameters for our font sizes.

In [10]: SMALL_SIZE = 15
MEDIUM_SIZE = 20
BIGGER_SIZE = 22

plt.rc('font', size=MEDIUM_SIZE) # controls default text sizes
plt.rc('axes', labelsize=BIGGER_SIZE) # controls default text sizes
plt.rc('xtick', labelsize=SMALL_SIZE)
plt.rc('ytick', labelsize=SMALL_SIZE)
plt.rc('figure', figsize=(10, 10))

We'll plot LNL01
4-1000 pCO2 m

In [10]: fig, axs = plt.subplots(2, 1, sharex=True)
axs[0].set_title('LNL01 NCE')
axs[0].set_ylabel('pCO2 m')
axs[0].set_xlabel('Year')
axs[0].set_xlim(2015, 2020)
axs[0].set_ylim(-10, 10)

axs[1].set_title('LNL01 NCE')
axs[1].set_ylabel('pCO2 m')
axs[1].set_xlabel('Year')
axs[1].set_xlim(2015, 2020)
axs[1].set_ylim(-10, 10)

fig.tight_layout()

plt.show()

Let's use the Holoviews library to plot the net carbon exchange for South America, superimposed on a satellite imagery map. We will produce a DynamicMap of the latitude range [-60, 15] and the longitude range [-100, -10]. Notice that xarray makes it easy to grab these slices of the data.

In [12]: # base map
map_layer = hv.map(layer='satellite imagery',
name='base map layer',
opts={'label': 'Satellite Imagery',
value='Satellite Imagery',
button_label='Satellite Imagery',
background_color='black'})

def var_layer(name, year):
    data = ds.isel(year=year).latitude[0:15].longitude[-100:-10]
    image = data.hvplot(x='longitude', y='latitude')
    return image.opts(cmap='magma', toolbar='none')

def update_map(map):
    title = qm.get_if_exists('Open Street Map') else qm.get_if_exists('Satellite Imagery')
    return title.opts(label='Satellite Imagery')

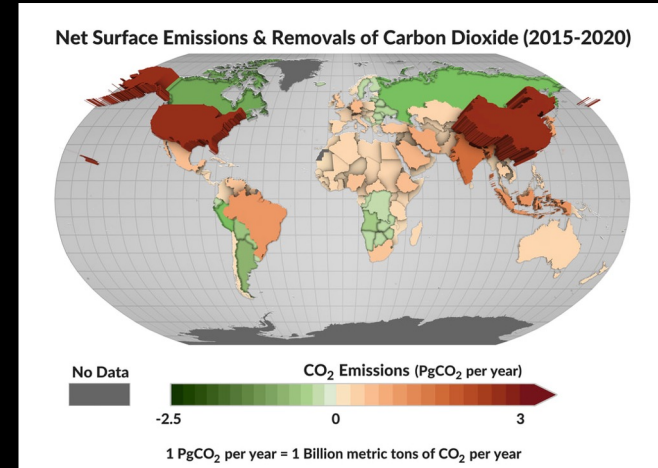
Stream_2015 = Stream.define('Stream_2015', name='LNL01_NCE', year='2015')
dmap_2015 = hv.DynamicMap(var_layer, streams=[Stream_2015])
Stream_2018 = Stream.define('Stream_2018', name='LNL01_NCE', year='2018')
dmap_2018 = hv.DynamicMap(var_layer, streams=[Stream_2018])
dfile = hv.DynamicMap(update_map, streams=[dmap_2015, dmap_2018, param.value])
pn.Column(dfile.rasterize(dmap_2015, aggregator=dask.dask.array.mean), dmap_2015)

Out[12]:
Move your cursor over the map to see information about each individual pixel. We will next plot the same thing for 2019.

In [13]: pn.Column(dfile.rasterize(dmap_2018, aggregator=dask.dask.array.mean), dmap_2018)

Out[13]:

```



Byrne, B., et al., Earth Syst. Sci. Data, 2023.
Right: Graphic by NASA SVS.

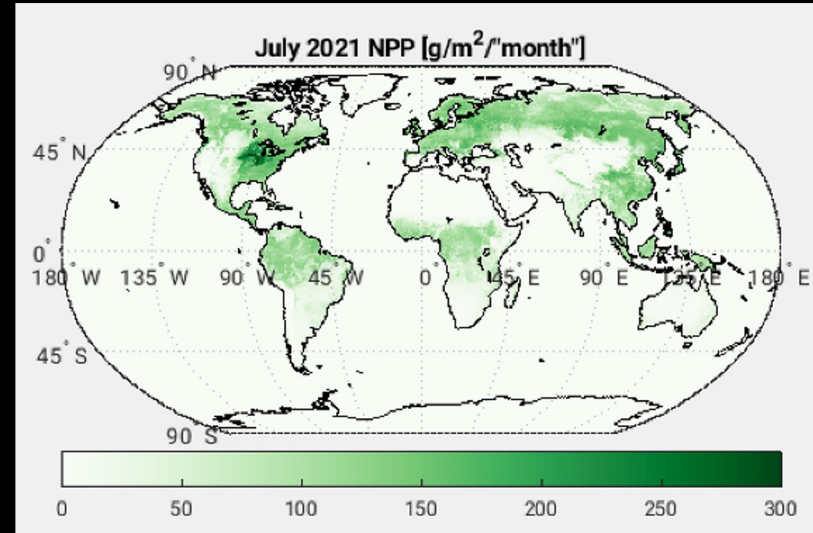
Quasi-operational processing of land-atmosphere CO₂ flux

Atmospheric models require gridded estimates of natural fluxes and human emissions as a starting point to infer refinements, but delivery of such estimates is often slow, delayed months or years behind real time.

Through EIS, we explored several options to expedite processing of the widely used CASA-GFED3 model.

The revised workflow leverages NASA HEC investments in large scale data analytics and will support a new release of the 20-year data product this summer.

New data will be produced at finer spatial and temporal scales than was possible with previous versions, with regular monthly updates.



EIS Engagements in April

Organization/ Meeting	Thematic Area	Outcome
NASEM Dissemination Meeting: U.S. Urban Greenhouse Gas Emissions Information Needs	GHG	Dialogue on urban stakeholder needs, coordination on information system tools.
GEWEX integrated product workshop	Freshwater	Coordination with the international groups on closing the global water budget
WMO state of the water report working group	Freshwater	Contributing to the upcoming state of the water report with EIS synthesis
USFS-NASA joint applications workshop: Addressing land and water monitoring needs using remote sensing data	Fire	Expanded engagement with USFS on active fire tracking (fire line containment) and fire severity assessments.
Brazil meetings on Fire Detection, Tracking, and Impacts (IBAMA-PrevFogo)	Fire	Alignment with EIS Phase 3 for expanded stakeholder engagement and impact.
Framework for Assessing Changes To Sea-level (FACTS)	Sea level	Rutgers Univ. researchers began implementing FACTS on EIS, in coordination with SMCE cyberinfrastructure experts