SY_01_A_Python_notebook_for_extracting_and_manipulating_Macrostra

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1 A Python notebook for extracting and manipulating Macrostrat data

1.1 Author

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1.2 Purpose

This Python Jupyter notebook is built as a demo to illustrate how to extract column data through the Macrostrat API and how to process and visualize them. It contains functions for data wrangling, tabulating, bootstrapping sampling, and visualization. By providing useful examples and Python scripts, this notebook could promote the Macrostrat database in the geology and paleontology communities.

1.3 Technical contributions

- building time series of spatial coverages of marine and non-marine sediments in Phanerozoic North America,
- building time series of spatial coverages of siliciclastic and carbonate lithologies throughout the Mesozoic North America
- bootstrapping samplings and visualizations of these time series

1.4 Methodology

NA

1.5 Results

This notebook provides some Python codes to retrieve and manipulate data from Macrostrat, especially to remove over-counted columns (due to their multiple environmental and/or lithological attributes within a single time step) when constructing the time series. There are no scientific results. Demo results are shown in the code section.

1.6 Funding

NA

1.7 Keywords

keywords=[“Macrostrat”, “time-series”, “stratigraphy”, “lithology”, “paleoenvironment”]

1.8 Citation

Shan Ye, 2021, A Python notebook for extracting and manipulating Macrostrat data.

1.9 Work In Progress - improvements

- todo 1; Retrieving and visualizing geological map data (waiting for the finalization of the new Macrostrat API routes)
- todo 2: Retrieve data from other geoscience databases (like the PBDB) and perform time series statistics (like Pearson’s r) between data from different sources

1.10 Suggested next steps

State suggested next steps, based on results obtained in this notebook. This section is optional.

1.11 Acknowledgements

The Macrostrat group at the University of Wisconsin-Madison, supervised by Dr. Shanan Peters.

2 Setup

2.1 Library import

Import all the required Python libraries.

The code cell below is an example.

[1]:
```
import json
import requests
import re
import builtins
import pandas as pd
import numpy as np
from random import choices
from collections import Counter
import matplotlib
import matplotlib.pyplot as plt
from IPython.display import clear_output
import geopandas as gpd
import plotly
```

3 Parameter definitions

NA

4 Data import

Data are retrieved from the Macrostrat database via its api (https://macrostrat.org/#api).

5 Data processing and analysis

The core of the notebook is here. Split this section into subsections as required, and explain processing and analysis steps.

5.0.1 Function 1: get data from the Macrostrat API and turn it into the json format

There are different levels of the lithological classification.

Regular expression is used to detect the level of lithology requested by the user.

This function returns 3 things in the following order:

- the json file
- the detected level of lithology
- the detected lithological name

These results will be used in the next function.

[2]:
```
def get_json(api):
    j = requests.get(api)
    l_level = "all"
    l_name = "any"

    if "lith_type" in api:
        x = re.search("(?<=lith_type=)[a-zA-Z]*", api)
        l_level = "lith_type"
        l_name = x.group()
    elif "lith=" in api:
        x = re.search("(?<=lith=)[a-zA-Z]*", api)
        l_level = "lith_name"
        l_name = x.group()
    elif "lith_class" in api:
        x = re.search("(?<=lith_class=)[a-zA-Z]*", api)
        l_level = "lith_class"
        l_name = x.group()
    return j.json(), l_level, l_name
```

5.0.2 Function 2: Process the returned json file and extract relevant column data

The Function 1 is embedded within this function, so users do not need to call the api twice.

This function returns a dataframe containing raw column data.

This dataframe will be used in the next function.

[3]:
```python
def col_json_proc(api):

    print("Reading api...")
    temp, l_level, l_name = get_json(api)
    df = pd.DataFrame()
    nrows = []

    for i in range(len(temp['success']['data'])):

        clear_output(wait = True)

        new_line = temp['success']['data'][i]['lith']
        nrow = len(temp['success']['data'][i]['lith'])
        df = df.append(pd.DataFrame(data = new_line))
        nrows.append(nrow)
        print('Extracting data from api...',np.round(i/
↪len(temp['success']['data'])*100,1),'%')

    all_unit_ids = []
    for i in range(len(temp['success']['data'])):
        all_unit_ids.append(temp['success']['data'][i]['unit_id'])

    s = np.array(all_unit_ids)
    df['unit_id'] = list(np.repeat(s, nrows, axis=0))
    df = df.sort_values('unit_id')

    clear_output(wait = True)
    print("Processing lithology...")
    l = []
    if l_level == "lith_type":
        for i in range(len(df)):
            if df["type"].iloc[i] == l_name:
                l.append(i)
    elif l_level == "lith_class":
        for i in range(len(df)):
            if df["class"].iloc[i] == l_name:
                l.append(i)
    elif l_level == "lith_name":
        for i in range(len(df)):
            if df["name"].iloc[i] == l_name:
                l.append(i)
    else:
        for i in range(len(df)):
            l.append(i)

    df_sub = df.iloc[l]
```

```
    clear_output(wait = True)
    print("Processing prop...")
    prop_pivot = list(df_sub.pivot_table( columns='unit_id', values='prop',␣
↪aggfunc='sum').iloc[0])
    for i in range(len(prop_pivot)):
        if prop_pivot[i] > 1:
            prop_pivot[i] = 1

    clear_output(wait = True)
    print("Assembling the data frame...")
    all_col_ids = []
    all_unit_ids = []
    all_t_age = []
    all_b_age = []
    all_max_thick = []
    all_min_thick = []
    all_pbdb_collections = []
    all_col_area = []
    for i in range(len(temp['success']['data'])):
        all_col_ids.append(temp['success']['data'][i]['col_id'])
        all_unit_ids.append(temp['success']['data'][i]['unit_id'])
        all_t_age.append(temp['success']['data'][i]['t_age'])
        all_b_age.append(temp['success']['data'][i]['b_age'])
        all_max_thick.append(temp['success']['data'][i]['max_thick'])
        all_min_thick.append(temp['success']['data'][i]['min_thick'])
        all_pbdb_collections.
↪append(temp['success']['data'][i]['pbdb_collections'])
        all_col_area.append(temp['success']['data'][i]['col_area'])

    df2 = pd.DataFrame()
    df2['col_id'] = all_col_ids
    df2['unit_id'] = all_unit_ids
    df2['t_age'] = all_t_age
    df2['b_age'] = all_b_age
    df2['max_thick'] = all_max_thick
    df2['min_thick '] = all_min_thick
    df2['pbdb_collections'] = all_pbdb_collections
    df2['col_area'] = all_col_area
    df2 = df2.sort_values('unit_id')
    df2['prop'] = prop_pivot

    return df2
```

5.0.3 Function 3: Converting the raw column data to the time series data, with bootstrapping sampling

This function will be directly used by the user.

It has 2 arguments: - the raw column data returned from the Function 2 - the number of iterations for the bootstrapping sampling

It will return a dataframe the following fields for each of the 1 million year time step from 540 Ma to the present: - the mean number of columns - the standard deviation of the number of columns - the mean number of stratigraphic units - the standard deviation of the number of stratigraphic - the mean column area - the standard deviation of column area

[4]:
```
def get_time_series(df2, bs):
    steps = list(range(3000))
    t = 540
    n = len(df2)
    sample = list(range(n))

    res = np.ndarray(shape=(bs,t,3), dtype=float)

    for b in range(bs):
        print("Processing boostrapping reps:", b+1, "out of", bs)
        if b > 1:
            sample = np.random.choice(list(range(n)), n, replace=True)
        packages = df2.iloc[sample]

        total_cols,total_packages,total_area = [],[],[]

        for i in range(t):
            cand = []
            for j in range(len(packages)):
                if packages['b_age'].iloc[j] >= steps[i]+1 and␣
↪packages['t_age'].iloc[j] < steps[i]+1:
                    cand.append(j)
            col_cand = packages['col_id'].iloc[cand]
            total_cols.append(len(set(col_cand)))
            total_packages.append(len(cand))

            if total_cols[i] > 1:
                freq = Counter(col_cand)
                df_col = pd.DataFrame(freq.keys(),columns=['col_id'])
                df_col['Freq'] =freq.values()
                df_col.rename(columns={'A':'col_id','B':'Freq'})
                df_col_cand = pd.DataFrame(col_cand)
                col_temp = df_col.merge(df_col_cand, left_on='col_id',␣
↪right_on='col_id')
                cols = col_temp['Freq']
            else:
                cols = [1] * len(cand)

            t_area = 0
            for j in range(len(packages['col_area'].iloc[cand])):
```

```
            if total_cols[i] > 1:
                t_area += (packages['col_area'].iloc[cand].iloc[j]/
↪col_temp['Freq'].iloc[j])
            else:
                t_area += (packages['col_area'].iloc[cand].iloc[j])

        total_area.append(t_area)

        clear_output(wait = True)
        print("boostrapping reps:", b+1,'...', np.round(i/t*100,1),'%')

    np1 = np.array(total_cols)
    np2 = np.array(total_packages)
    np3 = np.array(total_area)

    stack = np.stack((np1, np2, np3), axis=1)

    res[b] = stack

clear_output(wait = True)
print('calculating mean and std...')
mean_all = np.mean(res, axis=0)
std_all = np.std(res, axis=0)

clear_output(wait = True)
print('finalizing the result...')
col_mean, col_std, package_mean, package_std, area_mean, area_std =␣
↪[],[],[],[],[],[]
for i in range(len(mean_all)):
    col_mean.append(mean_all[i][0])
    package_mean.append(mean_all[i][1])
    area_mean.append(mean_all[i][2])
    col_std.append(std_all[i][0])
    package_std.append(std_all[i][1])
    area_std.append(std_all[i][2])

res_ts = pd.DataFrame()
res_ts['time'] = range(1,541)
res_ts['col_mean'] = col_mean
res_ts['col_std'] = col_std
res_ts['package_mean'] = package_mean
res_ts['package_std'] = package_std
res_ts['area_mean'] = area_mean
res_ts['area_std'] = area_std

clear_output(wait = True)
return res_ts
```

5.0.4 Function 4: Creating a map of a specific time step

This function is to plot a map showing the spatial coverage of the specific lithology or environment at the given time.

This function has 3 arguments: - The API route - The time (in Ma) - The color for columns with positive values (optional; the default is brown color)

[5]:
```
def plot_col(api, age, color = "brown"):
    df = col_json_proc(api)
    clear_output(wait = True)
    col = gpd.read_file('data/col.geojson')
    col['color'] = 0
    selected_col = []
    for row in df.iterrows():
        if row[1]['t_age'] < age and row[1]['b_age'] >= age:
            if int(row[1]['col_id']) not in selected_col:
                selected_col.append(int(row[1]['col_id']))
    for i in range(len(col)):
        if int(col.iloc[i,0]) in selected_col:
            col.iloc[i,4] = 1
    cmap = matplotlib.colors.ListedColormap(['#B3B3B3', color])
    boundaries = [-1,0,1]
    norm = matplotlib.colors.BoundaryNorm(boundaries, cmap.N, clip=True)
    print("Processing data...")
    clear_output(wait = True)
    f, ax = plt.subplots(1, figsize=(14, 10))
    ax = col.plot(column ='color',cmap = cmap ,ax=ax,linestyle='solid')
    plt.show()
    return
```

5.0.5 Examples

1. Processing and visualizing time series of marine and non-marine paleoenvironmental coverages in Cretaceous Macrostrat database is pretty big. Depending on your computer's capability and the specific variable you request in the API, the bootstrapping sampling could take several minutes.

[6]:
```
# Retriving the non-marine data via the Macrostrat API
api_non_marine = 'https://macrostrat.org/api/units?
 ↪environ_class=non-marine&project_id=1&response=long'
# Processing the API and get the raw column data
df_non_marine = col_json_proc(api_non_marine)
# Converting the raw column data into the time series data, with 5 iterations␣
 ↪for bootstrapping
ts_non_marine = get_time_series(df_non_marine, 5)
# Preview the time series data
ts_non_marine
```

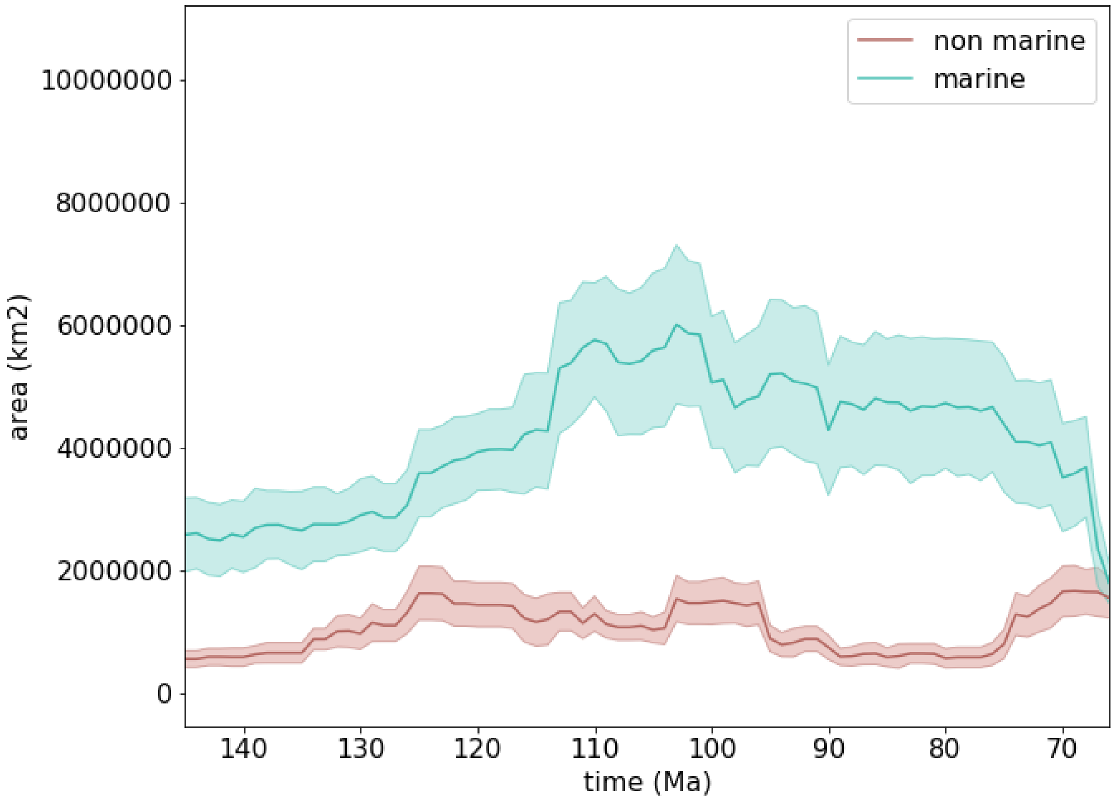
```
[6]:       time  col_mean     col_std  package_mean  package_std     area_mean  \
     0        1     358.2   76.056295         492.8    14.878172  8.882459e+06
     1        2     323.0   70.265212         439.6    12.092973  7.674419e+06
     2        3     115.0   25.628110         154.8     4.833218  2.416121e+06
     3        4     129.0   27.085051         169.4     6.621178  2.917438e+06
     4        5     113.2   24.350770         154.6     2.244994  2.637957e+06
     ..     …         …           …             …            …             …
     535    536       1.0    0.000000           1.0     0.000000  5.602354e+04
     536    537       1.0    0.000000           1.0     0.000000  5.602354e+04
     537    538       2.8    0.400000           3.0     0.632456  6.298714e+04
     538    539       2.8    0.400000           3.0     0.632456  6.298714e+04
     539    540       2.8    0.400000           3.0     0.632456  6.298714e+04

              area_std
     0    1.803264e+06
     1    1.531307e+06
     2    4.557400e+05
     3    5.916809e+05
     4    5.318767e+05
     ..            …
     535  7.275958e-12
     536  7.275958e-12
     537  1.192870e+03
     538  1.192870e+03
     539  1.192870e+03

     [540 rows x 7 columns]
```

```
[7]: # Retriving the marine data via the Macrostrat API
     api_marine = 'https://macrostrat.org/api/units?
      ↪environ_class=marine&project_id=1&response=long'
     # Processing the API and get the raw column data
     df_marine = col_json_proc(api_marine)
     # Converting the raw column data into the time series data, with 5 iterations␣
      ↪for bootstrapping
     ts_marine = get_time_series(df_marine, 5)
     # Preview the time series data
     ts_marine
```

```
[7]:       time  col_mean     col_std  package_mean  package_std     area_mean  \
     0        1      48.6   10.307279          67.8    10.283968  1.130064e+06
     1        2      63.4   14.374978          92.2     4.578209  1.362317e+06
     2        3      59.2   11.320777          81.0     7.563068  1.322042e+06
     3        4      75.4   15.304901         101.8     1.833030  1.252075e+06
     4        5      75.4   15.435025         102.8     3.187475  1.525152e+06
     ..     …         …           …             …            …             …
     535    536      87.0   19.728152         124.2     7.520638  1.425297e+06
```

```
536   537      85.0  19.005262        117.4     7.418895  1.459940e+06
537   538      79.4  17.012936        108.8     8.158431  1.331288e+06
538   539      79.0  17.435596        108.2     8.255907  1.332612e+06
539   540      79.0  17.435596        108.2     8.255907  1.332612e+06

          area_std
0    254376.816844
1    261564.652108
2    197619.251841
3    310537.476995
4    351468.708609
..             …
535  382183.050764
536  317133.730029
537  312878.295096
538  313907.811528
539  313907.811528

[540 rows x 7 columns]
```

[8]:
```python
# Plot the time series data for the spatial coverage of both marine and␣
↪non-marine environment
fig, ax = plt.subplots(figsize=(10, 8))
ax.plot(ts_non_marine['time'], ts_non_marine['area_mean'], label = 'non␣
↪marine',color='#b36660')
ax.plot(ts_marine['time'], ts_marine['area_mean'], label =␣
↪'marine',color='#40bdb0')
ax.fill_between(ts_non_marine['time'],␣
↪ts_non_marine['area_mean']-ts_non_marine['area_std'],␣
↪ts_non_marine['area_mean']+ts_non_marine['area_std'],
    alpha=0.5, edgecolor='#b36660', facecolor='#db9a95')
ax.fill_between(ts_marine['time'],␣
↪ts_marine['area_mean']-ts_marine['area_std'],␣
↪ts_marine['area_mean']+ts_marine['area_std'],
    alpha=0.5, edgecolor='#40bdb0', facecolor='#95dbd4')
ax.set_xlim(145,66)
ax.legend(fontsize = 16)
ax.set_xlabel("time (Ma)",fontsize = 16)
ax.set_ylabel("area (km2)",fontsize = 16)
ax.ticklabel_format(style='plain')
ax.tick_params( labelsize=16)
```



2. Processing and visualizing time series of siliciclastic and carbonate coverages in Phanerozoic Macrostrat database is pretty big. Depending on your computer's capability and the specific variable you request in the API, the bootstrapping sampling could take several minutes.

[9]:
```
# Retriving the siliciclastic data via the Macrostrat API
api_sil = 'https://macrostrat.org/api/units?
↪lith_type=siliciclastic&project_id=1&response=long'
# Processing the API and get the raw column data
df_sil = col_json_proc(api_sil)
# Converting the raw column data into the time series data, with 5 iterations␣
↪for bootstrapping
ts_sil = get_time_series(df_sil, 5)
# Preview the time series data
ts_sil
```

[9]:
```
   time  col_mean    col_std  package_mean  package_std     area_mean  \
0     1     384.0  80.152355         524.2     8.657944  9.095427e+06
1     2     363.8  74.547703         505.6     8.708616  8.151908e+06
2     3     149.4  29.247906         210.6    11.038116  3.165299e+06
3     4     167.6  41.156287         228.8    10.609430  3.454461e+06
4     5     157.2  37.461447         220.0     5.796551  3.503530e+06
```

```
..    …       …          …           …          …              …
535   536     63.0  14.113823        83.0     4.289522  1.080437e+06
536   537     60.6  14.263239        79.4     1.854724  1.024080e+06
537   538     57.8  14.133648        74.6     3.555278  9.564772e+05
538   539     57.4  13.573504        75.0     3.847077  9.445372e+05
539   540     57.4  13.573504        75.0     3.847077  9.445372e+05

         area_std
0    2.136334e+06
1    1.940202e+06
2    5.914352e+05
3    8.298879e+05
4    7.858647e+05
..            …
535  1.909944e+05
536  2.071629e+05
537  2.012853e+05
538  2.048563e+05
539  2.048563e+05

[540 rows x 7 columns]
```

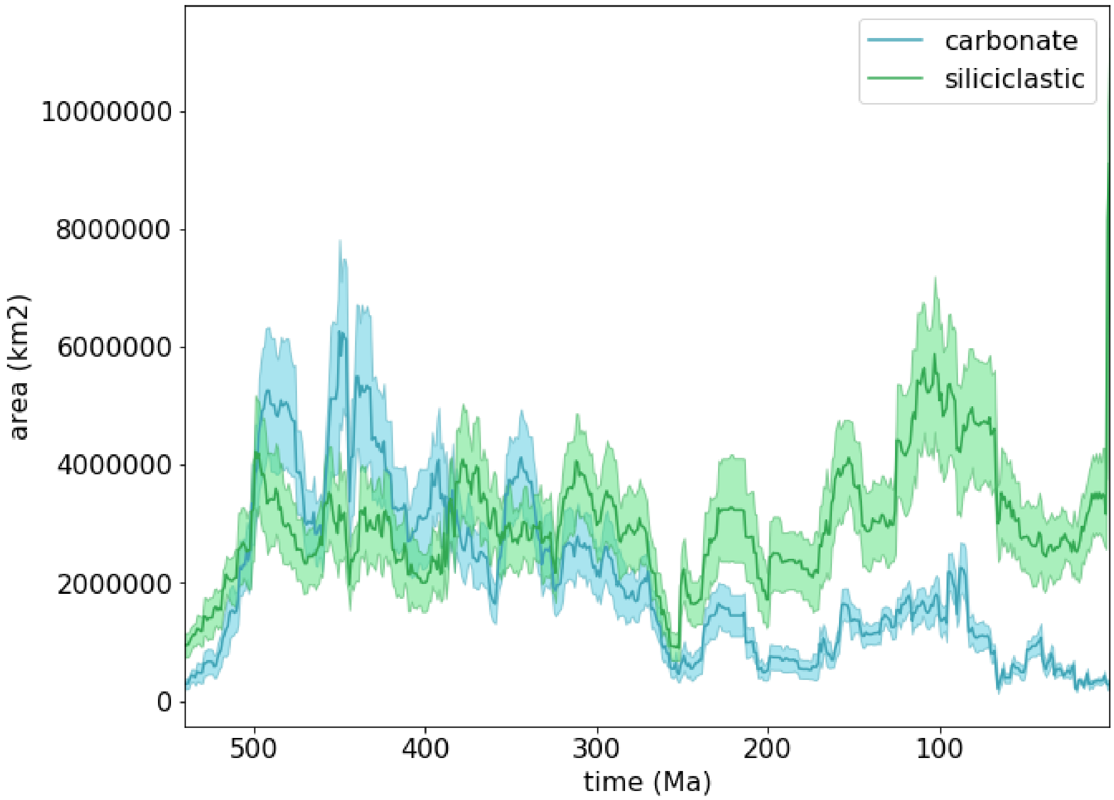
[10]:
```python
# Retriving the carbonate data via the Macrostrat API
api_carb = 'https://macrostrat.org/api/units?
 ↪lith_type=carbonate&project_id=1&response=long'
# Processing the API and get the raw column data
df_carb = col_json_proc(api_carb)
# Converting the raw column data into the time series data, with 5 iterations␣
 ↪for bootstrapping
ts_carb = get_time_series(df_carb, 5)
# Preview the time series data
ts_carb
```

[10]:
```
     time  col_mean   col_std  package_mean  package_std      area_mean  \
0       1       7.6  1.743560          11.2     2.925748  271114.154483
1       2       8.0  1.897367          10.4     2.059126  277146.095300
2       3       8.0  1.264911          11.0     2.756810  328480.098467
3       4      13.4  2.870540          16.4     2.576820  419778.921600
4       5       8.8  1.939072          10.8     2.638181  346358.566600
..    …       …         …           …          …              …
535   536      25.8  6.013319          32.8     1.939072  432269.435460
536   537      24.4  5.425864          31.2     0.979796  390636.512560
537   538      20.2  4.833218          25.0     3.286335  297372.025000
538   539      19.2  4.791659          23.8     3.059412  289184.514767
539   540      19.2  4.791659          23.8     3.059412  289184.514767

          area_std
```

```
0       64068.766828
1       92622.084946
2       28437.630626
3       91540.149909
4       40934.384384
..               …
535   109353.213644
536    96266.014024
537    88039.843198
538    87934.728921
539    87934.728921

[540 rows x 7 columns]
```

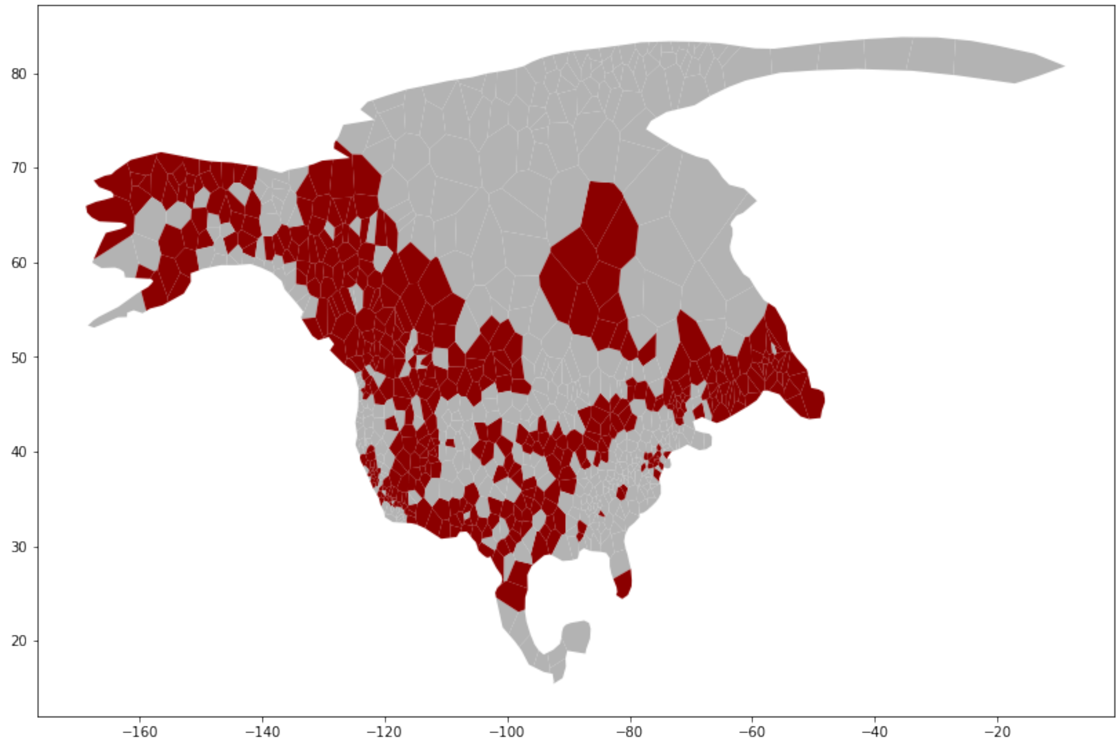
[11]:

```
# Plot the time series data for the spatial coverage of both siliciclastic and␣
↪carbonate
fig, ax = plt.subplots(figsize=(10, 8))
ax.plot(ts_carb['time'], ts_carb['area_mean'], label =␣
↪'carbonate',color='#3ea3b5')
ax.plot(ts_sil['time'], ts_sil['area_mean'], label =␣
↪'siliciclastic',color='#32a852')
ax.fill_between(ts_carb['time'], ts_carb['area_mean']-ts_carb['area_std'],␣
↪ts_carb['area_mean']+ts_carb['area_std'],
    alpha=0.5, edgecolor='#3ea3b5', facecolor='#55cbe0')
ax.fill_between(ts_sil['time'], ts_sil['area_mean']-ts_sil['area_std'],␣
↪ts_sil['area_mean']+ts_sil['area_std'],
    alpha=0.5, edgecolor='#32a852', facecolor='#55e07b')
ax.set_xlim(540,1)
ax.legend(fontsize = 16)
ax.set_xlabel("time (Ma)",fontsize = 16)
ax.set_ylabel("area (km2)",fontsize = 16)
ax.ticklabel_format(style='plain')
ax.tick_params( labelsize=16)
```



3. Mapping the spatial coverage of non-marine environment at 1 Ma

[13]:
```
api = 'https://macrostrat.org/api/units?
↪environ_class=non-marine&project_id=1&response=long'
age = 1
plot_col(api, age, "darkred")
```



6 References

The Macrostrat database: https://macrostrat.org/