An intro to working with geospatial data in Python

Including `rasterio` and `geopandas`.

Based loosely on:

- Capentries Incubator tutorial
- GeoPanas docs
- Rasterio docs

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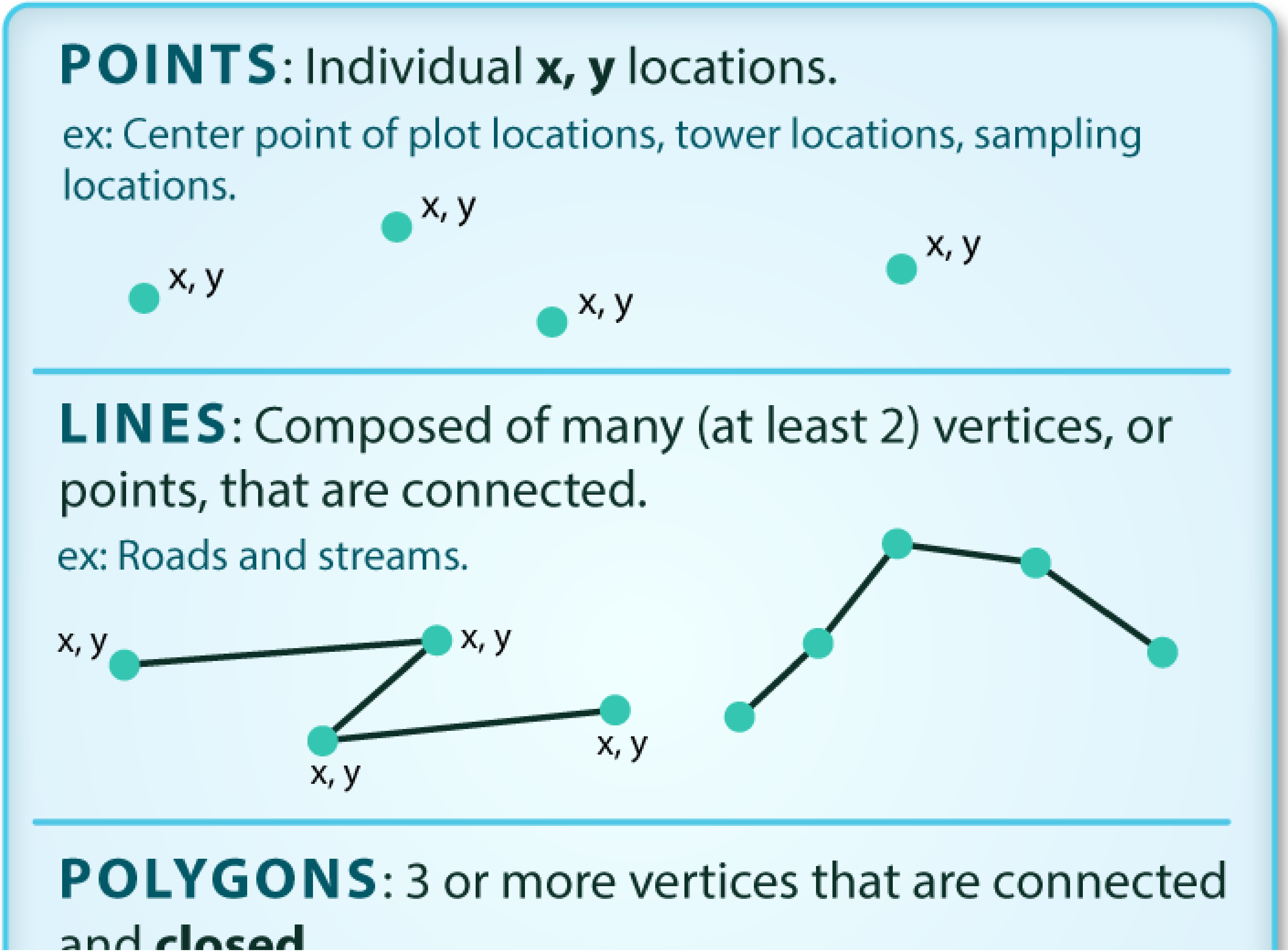
Overview

- What is a vector, raster and CRS?
- Using `geopandas` to work with vectors
- Using `rasterio` to work with rasters
- Linking `rasterio` to `xarray`
- Using `geopandas` and `rasterio` together

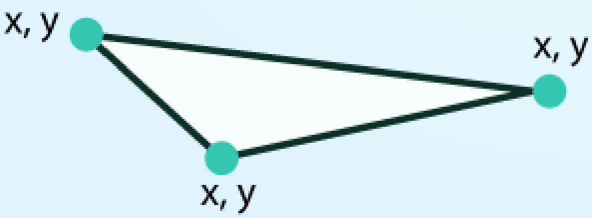
What are vectors?

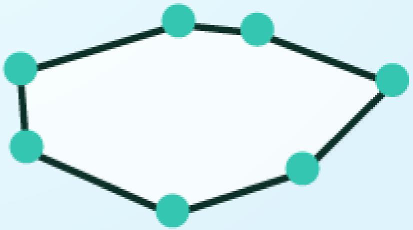
Vectors are **discrete geometric locations (vertices) that define the shape of a spatial object** on the Earth's surface.



and **closed**.

ex: Building boundaries and lakes.



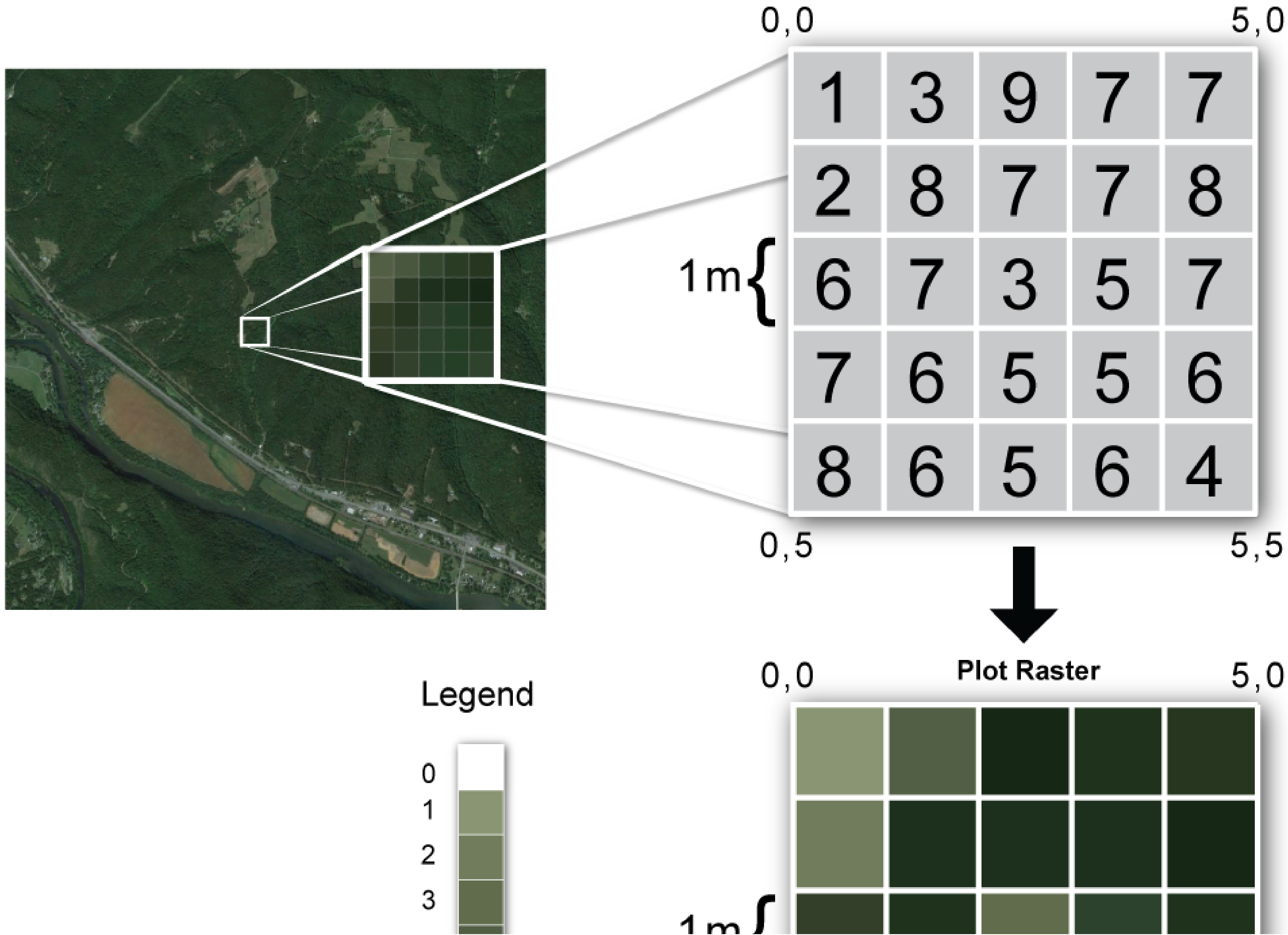


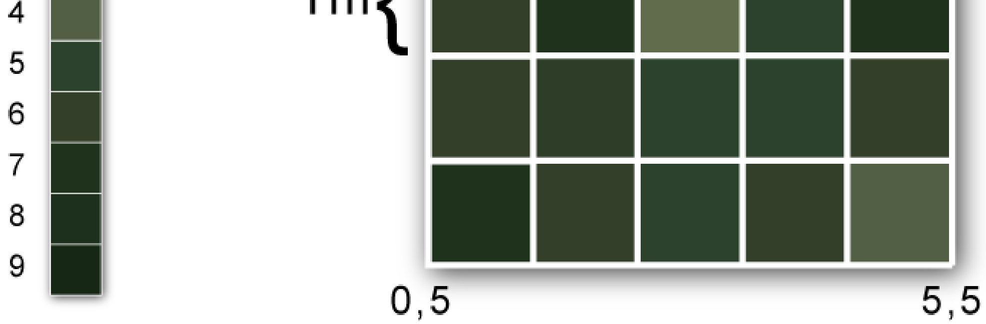
Vector data can be stored in lots of formats:

- Shapefiles: `.shp`
- GeoJSON: `.json`
- XYZ file: `.xyz`
- CSV file with lat/lon columns: `.csv`
- *etc...*

What a rasters?

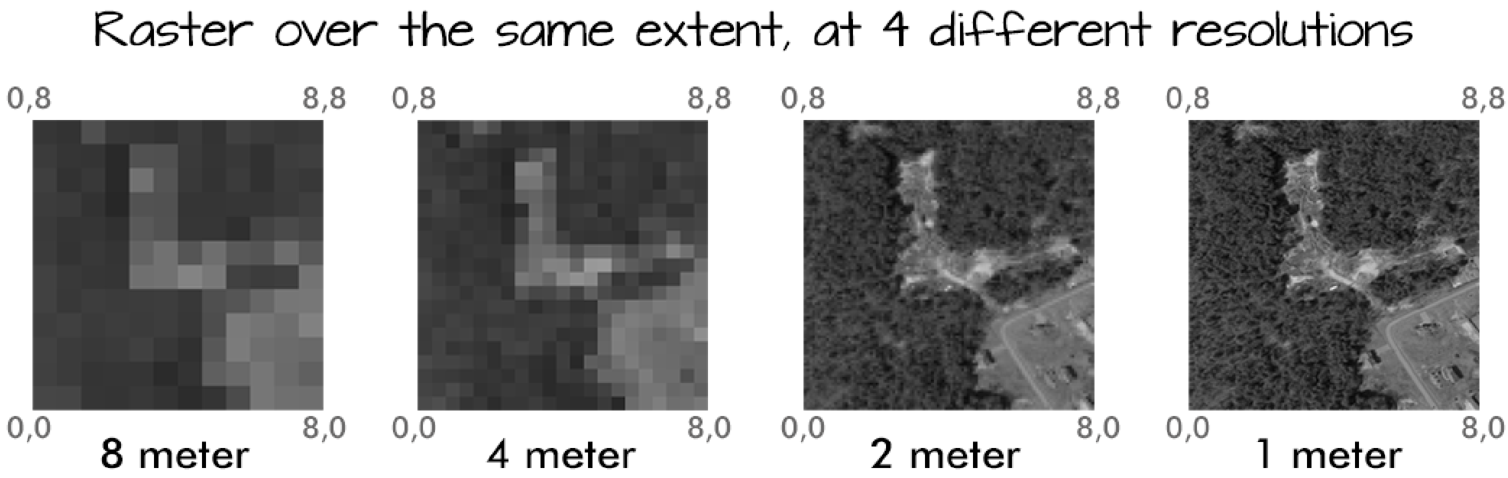
Rasters are **pixelated/gridded** data where each pixel is associated with a specific geographic location.



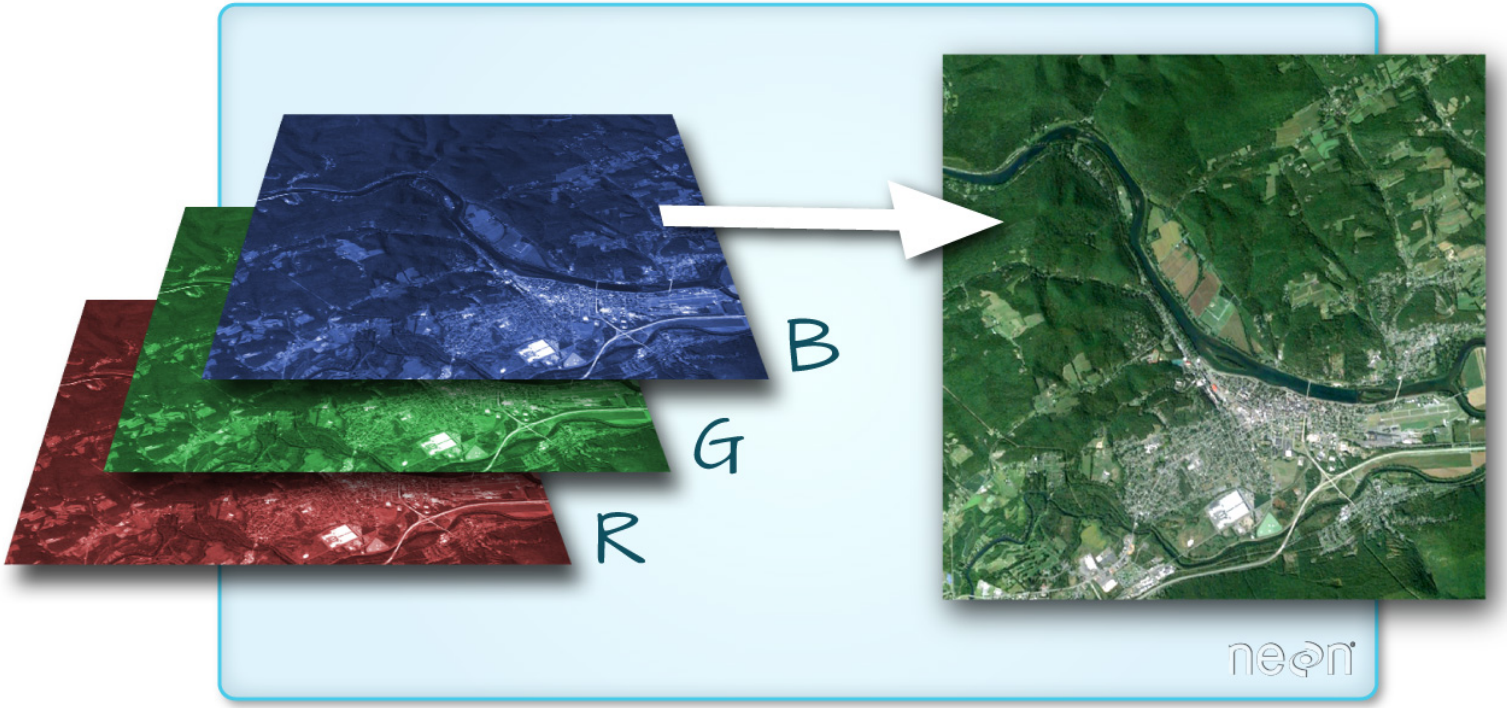


4
5
6
7
8
9
0,5
5,5

Rasters can have different resolutions, from metres to >kilometres:



Rasters can have one or more bands. Bands could represent colours in a colour image, or other dimensions of interest (e.g. time).



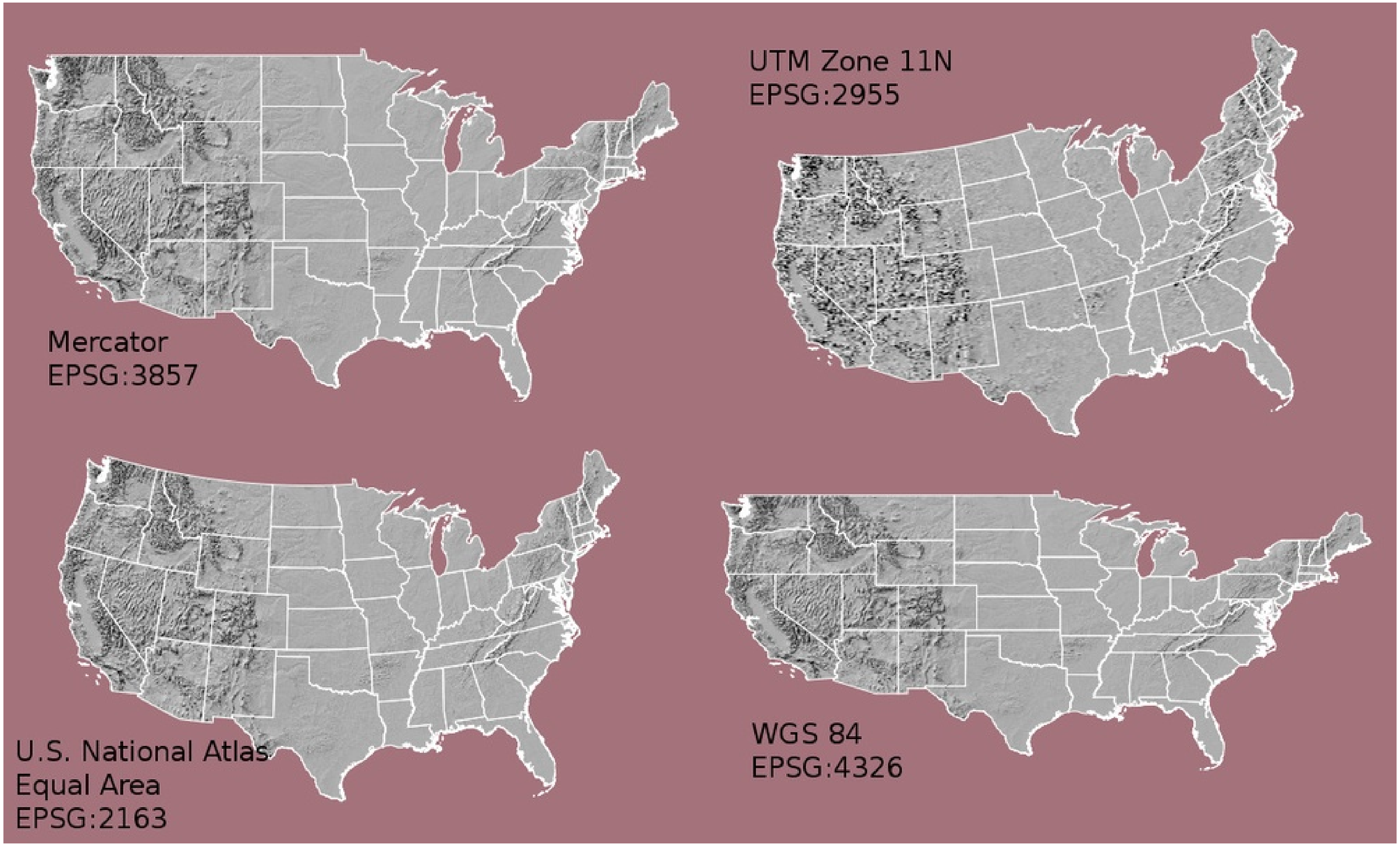
Rasters can be stored in lots of formats:

- GeoTIFF: `.tiff`
- ASCII/Esri grid: `.grd`
- NetCDF following CF Conventions: `.nc`
- JPEG2000: `.jpeg`

What is a CRS?

Coordinate Reference System

Data are only geospatial if they have a CRS. The CRS connects the data to the Earth's surface and detail how the 3D globe should be flatten onto a 2D image.


Mercator
EPSG:3857
UTM Zone 11N
EPSG:2955
U.S. National Atlas
Equal Area
EPSG:2163
WGS 84
EPSG:4326

CRSs can be *geopgrahic* or *projected*.

- *Geographic* CRSs use units of latitude and longitude (and sometimes height). Popular example: WGS 84. Geographic coordinate systems are generally best for working on large (global) scales.
- *Projected* CRSs project lat/lon values to a 2D plane (eastings and northings). Popular example: EPSG:3857, a spherical projection using by e.g. Google.

CRSs can be uniquely described by:

- EPSG codes: a database of CRS information maintained by the International Association of Oil and Gas Producers.
- Well-Known Text (WKT): Open Geospatial Consortium (OGC) standard. Nested listed of parameters describing CRS. Difficult to read, but can represent more complex geopgrahic information.
- PROJ string: Simpler than WKT, but now deprecated in favour of WKT.

British National Grid, `EPSG:27700`: https://epsg.io/27700.

Using `geopandas` to work with vectors

GeoPandas combines Pandas and Shapely to be able to manage vector data in a Pandas DataFrame.

See https://geopandas.org/. Recommended installation is via Conda: `conda install -c conda-forge geopandas`.

In [35]:

```
import geopandas as gpd

# This could be a path to e.g. a Shapefile, GeoJSON file etc.
# Here we're using a dataset provided with GeoPandas
file_path = gpd.datasets.get_path("naturalearth_lowres")
gdf = gpd.read_file(file_path)
gdf
```

Out[35]:

	pop_est	continent	name	iso_a3	gdp_md_est	geometry
0	920938	Oceania	Fiji	FJI	8374.0	MULTIPOLYGON (((180.00000 -16.06713, 180.00000...
1	53950935	Africa	Tanzania	TZA	150600.0	POLYGON ((33.90371 -0.95000, 34.07262 -1.05982...
2	603253	Africa	W. Sahara	ESH	906.5	POLYGON ((-8.66559 27.65643, -8.66512 27.58948...
3	35623680	North America	Canada	CAN	1674000.0	MULTIPOLYGON (((-122.84000 49.00000, -122.9742...
4	326625791	North America	United States of America	USA	18560000.0	MULTIPOLYGON (((-122.84000 49.00000, -120.0000...
...	...	...	...	...	...	...
172	7111024	Europe	Serbia	SRB	101800.0	POLYGON ((18.82982 45.90887, 18.82984 45.90888...
173	642550	Europe	Montenegro	MNE	10610.0	POLYGON ((20.07070 42.58863, 19.80161 42.50009...
174	1895250	Europe	Kosovo	-99	18490.0	POLYGON ((20.59025 41.85541, 20.52295 42.21787...
175	1218208	North America	Trinidad and Tobago	TTO	43570.0	POLYGON ((-61.68000 10.76000, -61.10500 10.890...
176	13026129	Africa	S. Sudan	SSD	20880.0	POLYGON ((30.83385 3.50917, 29.95350 4.17370, ...

177 rows × 6 columns

In [36]:

```python
gdf.crs
```

Out[36]:

```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World.
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

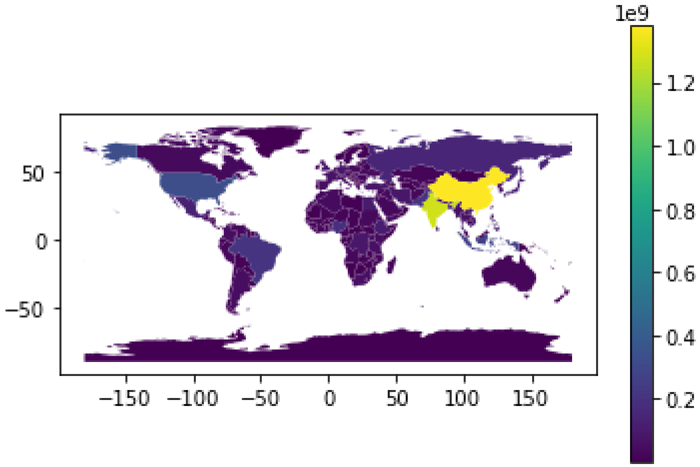
Plotting

In [37]:

```
gdf.plot("pop_est", legend=True)
```

Out[37]:

```
<AxesSubplot:>
```



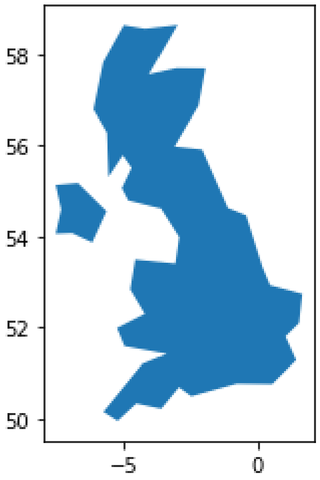
Pandas filtering

In [38]:

```
# Filter the dataset where column iso_a3 equals GBR and then plot
gdf[gdf['iso_a3'] == 'GBR'].plot()
```

Out[38]:

```
<AxesSubplot:>
```

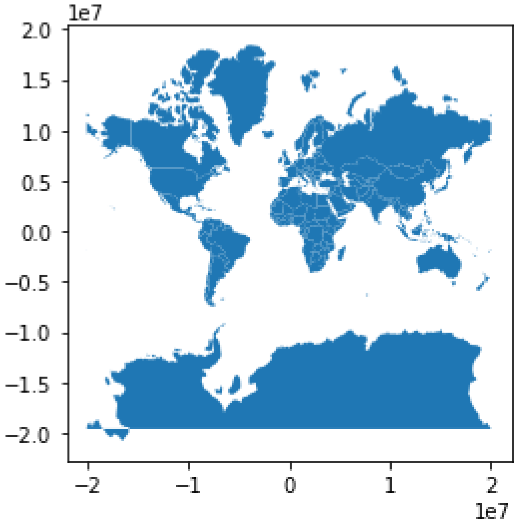


Changing the projection

In [39]:

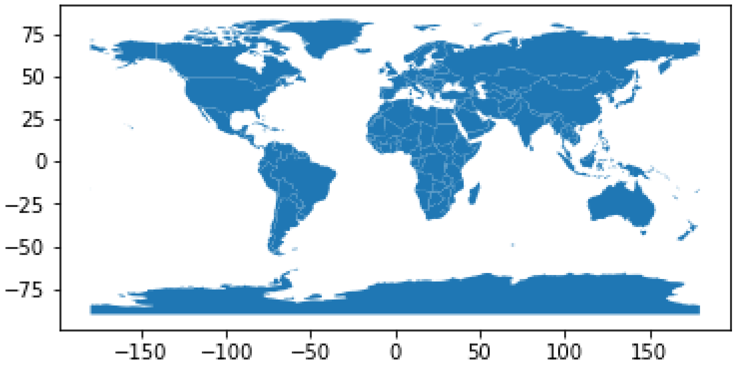
```
gdf_wm = gdf.to_crs('EPSG:3857')
gdf_wm.plot()
```

Out[39]: <AxesSubplot:>



In [40]:
```
gdf.plot()
```

Out[40]: <AxesSubplot:>



Areas, centroids and distances

We can easily measure the area of polygons:

In [41]:

```
# Create a new column 'area' that is the area of each geometry (country)
gdf_wm['area'] = gdf_wm.area
gdf_wm.sort_values('area', ascending=False)
```

Out[41]:

	pop_est	continent	name	iso_a3	gdp_md_est	geometry	area
18	142257519	Europe	Russia	RUS	3745000.00	MULTIPOLYGON (((19895609.388 11436139.118, 200...	8.304514e+13
3	35623680	North America	Canada	CAN	1674000.00	MULTIPOLYGON (((-13674486.249 6274861.394, -13...	5.216648e+13
22	57713	North America	Greenland	GRL	2173.00	POLYGON ((-5205721.290 17490757.185, -4831982....	3.628550e+13
4	326625791	North America	United States of America	USA	18560000.00	MULTIPOLYGON (((-13674486.249 6274861.394, -13...	2.186228e+13
139	1379302771	Asia	China	CHN	21140000.00	MULTIPOLYGON (((12186724.586 2060702.116, 1209...	1.497731e+13
...	...	...	...	...	...	...	...
175	1218208	North America	Trinidad and Tobago	TTO	43570.00	POLYGON ((-6866186.192 1204901.071, -6802177.4...	8.051555e+09
79	4543126	Asia	Palestine	PSE	21220.77	POLYGON ((3940438.428 3696430.498, 3888101.327...	7.015327e+09
128	594130	Europe	Luxembourg	LUX	58740.00	POLYGON ((672711.849 6468481.737, 694939.873 6...	5.785823e+09
160	265100	Asia	N. Cyprus	-99	3600.00	POLYGON ((3643685.108 4182926.430, 3651554.656...	5.686154e+09
159	4050	Antarctica	Antarctica	ATA	810.00	MULTIPOLYGON (((-5416874.996 -14393907.644, -5...	NaN

177 rows × 7 columns

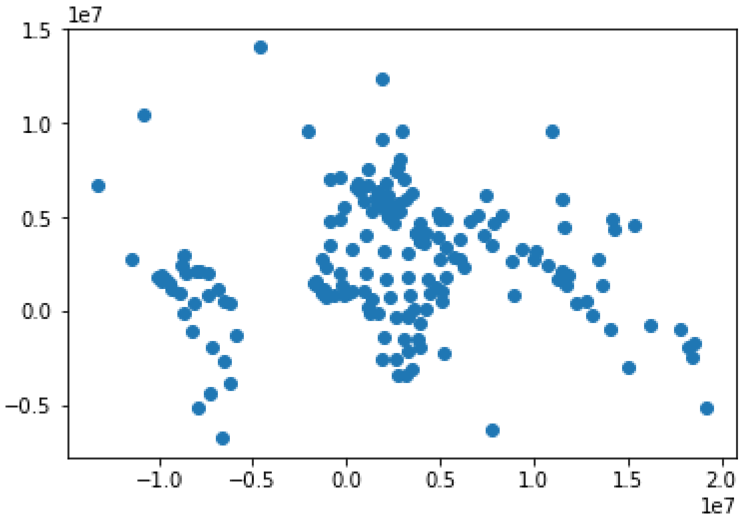
We can get the centre of the polygons:

In [42]:

```
# Create a new column that is the centroid of each geometry (country)
gdf_wm['centroid'] = gdf_wm.centroid
gdf_wm['centroid'].plot()
```

Out[42]:

```
<AxesSubplot:>
```



We can calculate distances between these centroids. E.g. say we want to calculate the distance from the UK:

In [43]:

```
# Get the row that is for the UK
uk_centroid = gdf_wm[gdf_wm['name'] == 'United Kingdom']['centroid'].iloc[0]
# Create a new column and use the distance() method to calculate the distance to the UK centroid
gdf_wm['distance_to_uk'] = gdf_wm['centroid'].distance(uk_centroid)
gdf_wm.sort_values('distance_to_uk', ascending=False)
```

Out[43]:

	pop_est	continent	name	iso_a3	gdp_md_est	geometry	area	centroid	distance_to_uk
136	4510327	Oceania	New Zealand	NZL	174800.0	MULTIPOLYGON (((19690839.812 -4875534.642, 196...	5.005072e+11	POINT (19211133.527 -5143927.928)	2.310196e+07
134	279070	Oceania	New Caledonia	NCL	10770.0	POLYGON ((18454544.055 -2401420.887, 18545826....	2.686859e+10	POINT (18427504.310 -2423487.891)	2.107120e+07
89	282814	Oceania	Vanuatu	VUT	723.0	MULTIPOLYGON (((18614489.182 -1792201.332, 186...	8.119409e+09	POINT (18598636.273 -1752068.573)	2.092808e+07
0	920938	Oceania	Fiji	FJI	8374.0	MULTIPOLYGON (((20037508.343 -1812498.413, 200...	2.128334e+10	POINT (18248781.791 -1958098.338)	2.070252e+07
135	647581	Oceania	Solomon Is.	SLB	1198.0	MULTIPOLYGON (((18047007.277 -1173496.191, 180...	2.549835e+10	POINT (17807849.653 -989994.877)	1.989061e+07
...	...	...	...	...	...	...	...	...	...
129	11491346	Europe	Belgium	BEL	508600.0	POLYGON ((685356.051 6586647.408, 672711.849 6...	7.485603e+10	POINT (509597.156 6561035.236)	1.043256e+06
130	17084719	Europe	Netherlands	NLD	870800.0	POLYGON ((768676.624 7072687.677, 789483.757 7...	1.067734e+11	POINT (614065.187 6856791.175)	9.944941e+05
133	5011102	Europe	Ireland	IRL	322000.0	POLYGON ((-689945.390 7145114.483, -671588.863...	1.626143e+11	POINT (-891472.831 7020537.812)	5.929234e+05
143	64769452	Europe	United Kingdom	GBR	2788000.0	MULTIPOLYGON (((-689945.390 7145114.483, -7740...	7.223808e+11	POINT (-323128.917 7189485.698)	0.000000e+00

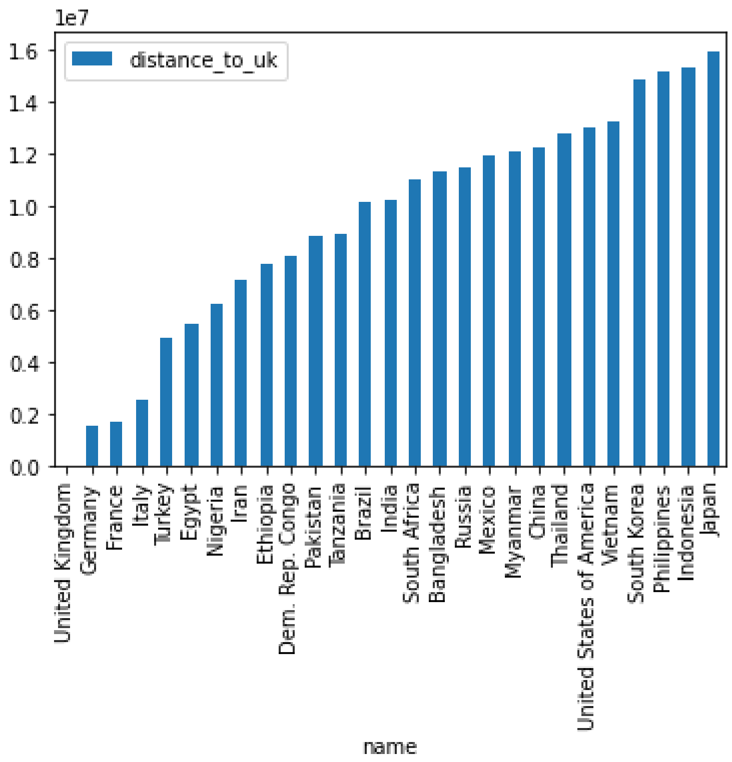
	pop_est	continent	name	iso_a3	gdp_md_est	geometry	area	centroid	distance_to_uk
159	4050	Antarctica	Antarctica	ATA	810.0	MULTIPOLYGON (((-5416874.996 -14393907.644, -5...	NaN	POINT EMPTY	NaN

177 rows × 9 columns

Remember this is just a Pandas DataFrame, so we can do all the usual Pandas stuff with the data.

In [44]:
```
# Get only countries with populations of >50 million and plot on a bar chart
gdf_big = gdf_wm[gdf_wm['pop_est'] > 50000000]
gdf_big = gdf_big.sort_values('distance_to_uk')
gdf_big.plot.bar(x='name', y='distance_to_uk')
```

Out[44]:
```
<AxesSubplot:xlabel='name'>
```



Writing to file

In [45]:
```
gdf_big[['name','geometry','distance_to_uk']].to_file('./data/big_countries.geojson',
                                                       driver='GeoJSON')
```


```
{ ⊟
  "type":"FeatureCollection",
  "crs":{ ⊟
    "type":"name",
    "properties":{ ⊟
      "name":"urn:ogc:def:crs:EPSG::3857"
    }
  },
  "features":[ ⊟
    { ⊟
      "type":"Feature",
      "properties":{ ⊟
        "name":"United Kingdom",
        "distance_to_uk":0.0
      },
      "geometry":{ ⊟
        "type":"MultiPolygon",
        "coordinates":[ ⊞ ]
      }
    },
    { ⊟
      "type":"Feature",
      "properties":{ ⊟
        "name":"Germany",
        "distance_to_uk":1560271.9499936707
```

Using `rasterio` to work with rasters

Rasterio is library that wraps around the ubiquitous GDAL library to give a user-friendly interface for dealing with raster data.

See https://rasterio.readthedocs.io/en/latest/. Recommended installation is via Conda: `conda install -c conda-forge rasterio`.

In [46]:

```
import rasterio as rio

rs = rio.open('./data/rainfall_5km_2017.tif')
rs.crs
```

Out[46]:

```
CRS.from_wkt('PROJCS["unnamed",GEOGCS["OSGB 1936",DATUM["OSGB_1936",SPHEROID["Air
y 1830",6377563.396,299.324964600004,AUTHORITY["EPSG","7001"]],AUTHORITY["EPS
G","6277"]],PRIMEM["Greenwich",0],UNIT["degree",0.0174532925199433,AUTHORITY["EPS
G","9122"]],AUTHORITY["EPSG","4277"]],PROJECTION["Transverse_Mercator"],PARAMETER
["latitude_of_origin",49],PARAMETER["central_meridian",-2],PARAMETER["scale_facto
r",0.9996012717],PARAMETER["false_easting",400000],PARAMETER["false_northing",-10
0000],UNIT["metre",1,AUTHORITY["EPSG","9001"]],AXIS["Easting",EAST],AXIS["Northin
g",NORTH]]')
```

In [47]:

```
rs.res
```

Out[47]:

```
(5000.0, 5000.0)
```

In [48]:

```
rs.bounds
```

Out[48]:

```
BoundingBox(left=0.0, bottom=0.0, right=700000.0, top=1250000.0)
```

In [49]:

```
rs.shape
```

Out[49]:

```
(250, 140)
```

In [50]:

```
rs.count
```

Out[50]:

```
366
```

Rasterio is really just adding some metadata to NumPy arrays:

In [51]:
```
arr = rs.read(300, masked=True)
arr
```

Out[51]:
```
masked_array(
  data=[[--, --, --, ..., --, --, --],
        [--, --, --, ..., --, --, --],
        [--, --, --, ..., --, --, --],
        ...,
        [--, --, --, ..., --, --, --],
        [--, --, --, ..., --, --, --],
        [--, --, --, ..., --, --, --]],
  mask=[[ True,  True,  True, ...,  True,  True,  True],
        [ True,  True,  True, ...,  True,  True,  True],
        [ True,  True,  True, ...,  True,  True,  True],
        ...,
        [ True,  True,  True, ...,  True,  True,  True],
        [ True,  True,  True, ...,  True,  True,  True],
        [ True,  True,  True, ...,  True,  True,  True]],
  fill_value=-3.4e+38,
  dtype=float32)
```

In [52]:

```python
print(rs.nodata)
arr = rs.read(300)
arr
```

```
-3.4e+38
```

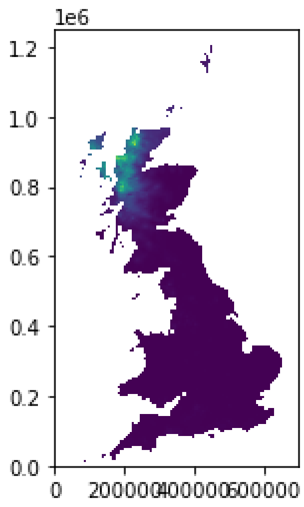
Out[52]:

```
array([[-3.4e+38, -3.4e+38, -3.4e+38, ..., -3.4e+38, -3.4e+38, -3.4e+38],
       [-3.4e+38, -3.4e+38, -3.4e+38, ..., -3.4e+38, -3.4e+38, -3.4e+38],
       [-3.4e+38, -3.4e+38, -3.4e+38, ..., -3.4e+38, -3.4e+38, -3.4e+38],
       ...,
       [-3.4e+38, -3.4e+38, -3.4e+38, ..., -3.4e+38, -3.4e+38, -3.4e+38],
       [-3.4e+38, -3.4e+38, -3.4e+38, ..., -3.4e+38, -3.4e+38, -3.4e+38],
       [-3.4e+38, -3.4e+38, -3.4e+38, ..., -3.4e+38, -3.4e+38, -3.4e+38]],
      dtype=float32)
```

Plotting

Rasterio has a convert `rasterio.plot.show()` function, which wraps around Matplotlib:

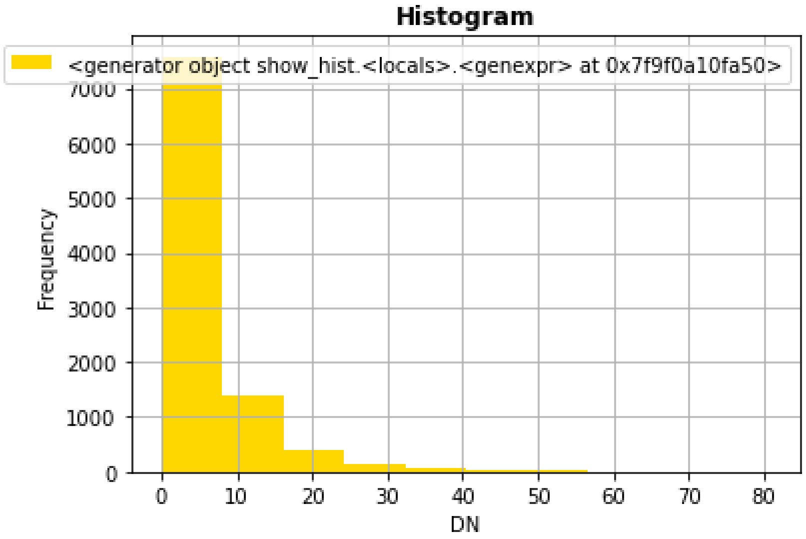
In [53]:
```
from rasterio.plot import show, show_hist

show(rs)
```



Out[53]: `<AxesSubplot:>`

In [54]:

```
show_hist(rs.read(300, masked=True))
```



Commond line interface

Rasterio has a fairly extensive CLI capable of performing common useful tasks:

```
$ rio --help
Usage: rio [OPTIONS] COMMAND [ARGS]...

  Rasterio command line interface.

Options:
  -v, --verbose           Increase verbosity.
  -q, --quiet             Decrease verbosity.
  --aws-profile TEXT      Select a profile from the AWS credentials file
  --aws-no-sign-requests  Make requests anonymously
  --aws-requester-pays    Requester pays data transfer costs
  --version               Show the version and exit.
  --gdal-version
  --help                  Show this message and exit.

Commands:
  blocks     Write dataset blocks as GeoJSON features.
  bounds     Write bounding boxes to stdout as GeoJSON.
  calc       Raster data calculator.
  clip       Clip a raster to given bounds.
  convert    Copy and convert raster dataset.
  edit-info  Edit dataset metadata.
  env        Print information about the Rasterio environment.
  gcps       Print ground control points as GeoJSON.
  info       Print information about a data file.
  insp       Open a data file and start an interpreter.
  mask       Mask in raster using features.
  merge      Merge a stack of raster datasets.
  overview   Construct overviews in an existing dataset.
  rasterize  Rasterize features.
  rm         Delete a dataset.
  sample     Sample a dataset.
  shapes     Write shapes extracted from bands or masks.
  stack      Stack a number of bands into a multiband dataset.
  transform  Transform coordinates.
  warp       Warp a raster dataset.
```

`rio insp` and `rio info` are particularly useful for having a quick look at files. For example, to quickly get metadata about a file:

```
$ rio info rainfall_5km_2015-300.tif --verbose
```


```
{"bounds": [0.0, 0.0, 700000.0, 1250000.0], "checksum": [8245], "colorinterp":
["gray"], "compress": "lzw", "count": 1, "crs": "PROJCS[\"unnamed\",GEOGCS[\"Airy
1830\",DATUM[\"unknown\",SPHEROID[\"airy\",6377563.396,299.3249753150345],TOWGS84[4
 "descriptions": [null], "driver": "GTiff", "dtype": "float32", "height": 250,
"indexes": [1], "interleave": "band", "lnglat": [-2.7933739244523172,
55.516181609501864], "mask_flags": [["nodata"]], "nodata": -3.4e+38, "res":
[5000.0, 5000.0], "shape": [250, 140], "stats": [{"max": 20.69357681274414, "mean":
3.7167322386771935, "min": 0.0}], "tiled": false, "transform": [5000.0, 0.0, 0.0,
0.0, -5000.0, 1250000.0, 0.0, 0.0, 1.0], "units": [null], "width": 140}
```


Quickly plotting a file:

```
$ rio insp rainfall_5km_2015-300.tif
Rasterio 1.0.25 Interactive Inspector (Python 3.7.3)
Type "src.meta", "src.read(1)", or "help(src)" for more information.
>>> rasterio.plot.show(src)
```

Quickly reprojecting (changing coordinate system) and resampling (changing resolution) is very easy with `rio warp`:

Change CRS to British National Grid:

```
$ rio warp input.tif output.tif --dst-crs EPSG:27700
```

Resample to 1x1 km grid using cubic interpolation:

```
$ rio warp input.tif output.tif --res 1000 --resampling cubic
```

Based on another raster:

```
$ rio warp input.tif output.tif --like template.tif
```

Linking `rasterio` with `xarray`

A neat little package called `rioxarray` lets you combine `rasterio`s functionality into `xarray`, as well as adding an easier-to-use interface to some function (e.g. reprojection, clipping).

`xarray`: Multidimensional labelled arrays. Introduces labels in the form of dimensions, coordinates and attributes on top of raw NumPy-like multidimensional arrays.

In [55]:

```python
import xarray
import rioxarray
import pandas as pd

xds = rioxarray.open_rasterio('./data/rainfall_5km_2017.tif', masked=True)
xds
```

Out[55]:

```
<xarray.DataArray (band: 366, y: 250, x: 140)>
[12810000 values with dtype=float64]
Coordinates:
  * band         (band) int64 1 2 3 4 5 6 7 8 ... 360 361 362 363 364 365 366
  * y            (y) float64 1.248e+06 1.242e+06 1.238e+06 ... 7.5e+03 2.5e+03
  * x            (x) float64 2.5e+03 7.5e+03 1.25e+04 ... 6.925e+05 6.975e+05
    spatial_ref  int64 0
Attributes:
    scale_factor:  1.0
    add_offset:    0.0
    grid_mapping:  spatial_ref
```

xarray.DataArray (**band**: 366, **y**: 250, **x**: 140)

[12810000 values with dtype=float64]

▾ Coordinates:

band

(band)

int64

1 2 3 4 5 6 ... 362 363 364 365 366

y

(y)

float64

1.248e+06 1.242e+06 ... 2.5e+03

x

(x)

float64

2.5e+03 7.5e+03 ... 6.975e+05

spatial_ref

()

int64

0

▾ **Attributes:**

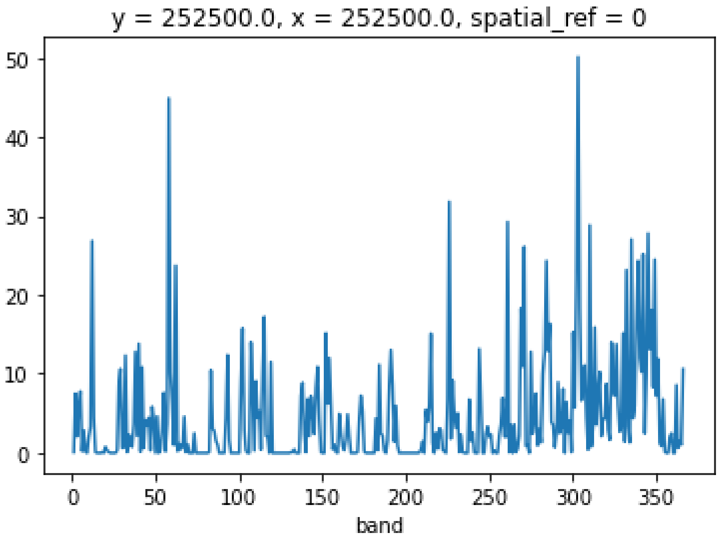
scale_factor :	1.0
add_offset :	0.0
grid_mappi...	spatial_ref

In [56]:

```python
xds.sel(x=250000, y=250000, method='nearest').plot()
```

Out[56]:

```
[<matplotlib.lines.Line2D at 0x7f9f0a029490>]
```



Clipping a raster with a vector

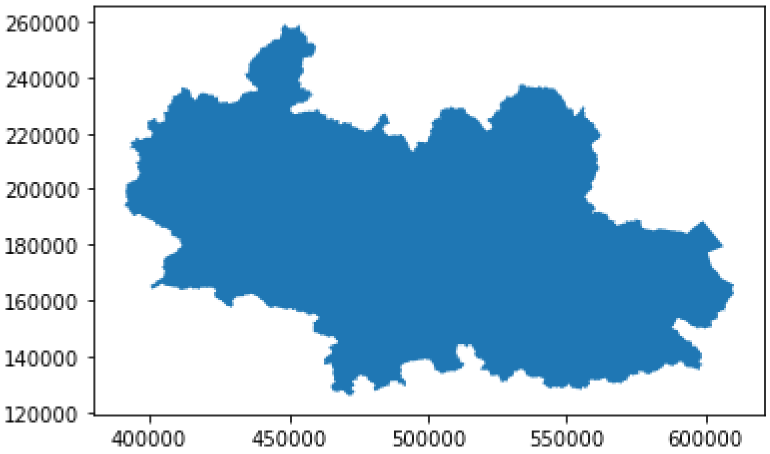
Say we want to clip data for the Thames catchment, for which we have a Shapefile (vector):

In [57]:

```
gdf_thames = gpd.read_file('./data/thames_catchment_osgb/thames_catchment_osgb.shp')
gdf_thames.plot()
```

Out[57]:

```
<AxesSubplot:>
```

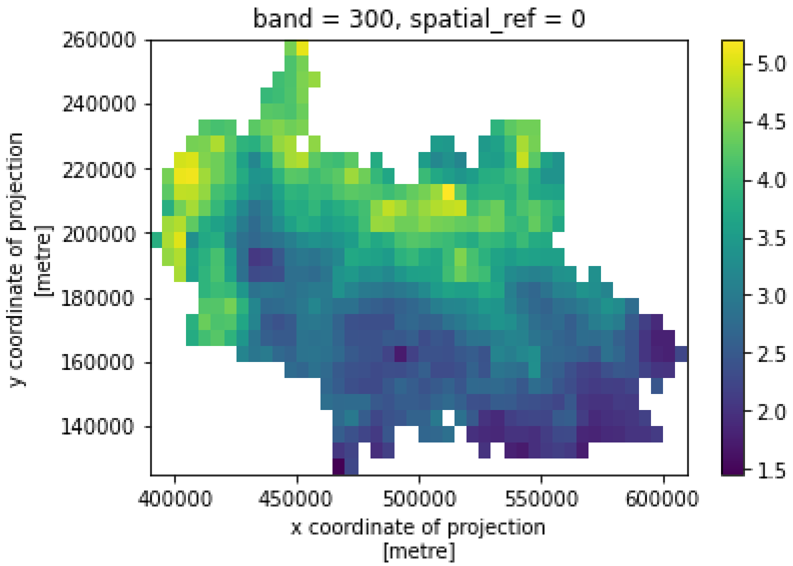


In [58]:

```
clipped = xds.rio.clip(gdf_thames.geometry, gdf_thames.crs)
clipped.sel(band=300).plot()
# Could also do: clipped[299,:,:].plot()
```

Out[58]:

```
<matplotlib.collections.QuadMesh at 0x7f9f09ff60d0>
```



In [59]:

```
clipped.rio.to_raster('./data/thames.tif')
```

Reprojecting and resampling a raster

Reprojecting a raster to a different CRS is simple with rioxarray. Say we want to reproject the previous raster to EPSG:3857 (used by e.g. Google Maps), and at the same time resample it from 5x5 km to 1x1 km using bilinear interpolation.

In [60]:

```
# Rasterio resampling methods available: nearest, bilinear, cubic,
# cubic_spline, lanczos, average, mode, max, min, med, q1, q3
from rasterio.warp import Resampling

clipped_wm = clipped.rio.reproject('EPSG:3857',
                                   resolution=(1000,1000),
                                   resampling=Resampling.bilinear)
clipped_wm.rio.crs
```

Out[60]:

```
CRS.from_epsg(3857)
```

In [61]:

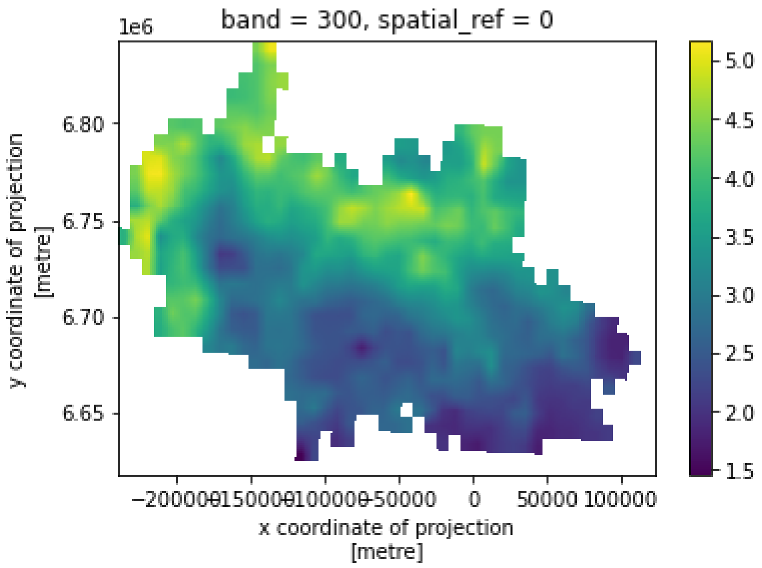
```
clipped_wm.rio.resolution()
```

Out[61]:

```
(1000.0, -1000.0)
```

In [62]:
```
clipped_wm.sel(band=300).plot()
```

Out[62]: <matplotlib.collections.QuadMesh at 0x7f9efba5c2e0>



Note the x-coordinate origin is now at the Prime Meridian in Greenwich.

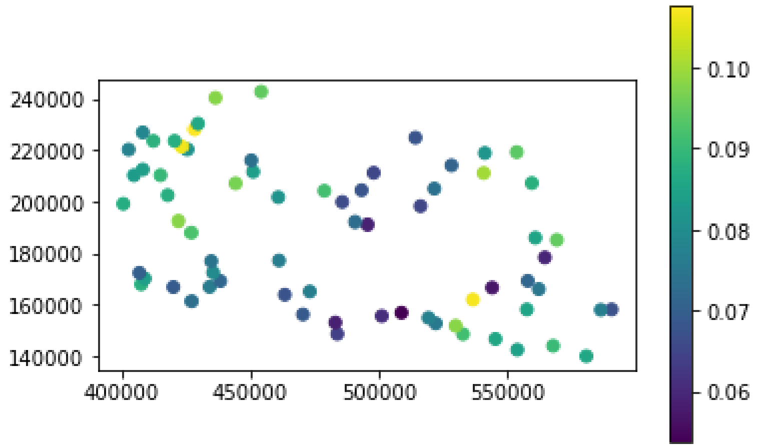
Bringing it all togther: Interpolating point data

Say we have some sampling data at various points around the country, and we want turn this into a raster by interpolating between the points. We can use `geopandas`, `rasterio` and `rioxarray` to do this.

Here I'm using some soil chemistry data from the Thames catchment. Our data looks like this:

In [63]:
```
gdf = gpd.read_file('./data/thames_k_att_shp/thames_k_att_osgb.shp')
gdf.plot('k_att', legend=True)
```

Out[63]: `<AxesSubplot:>`



Burn the shapefile into a raster

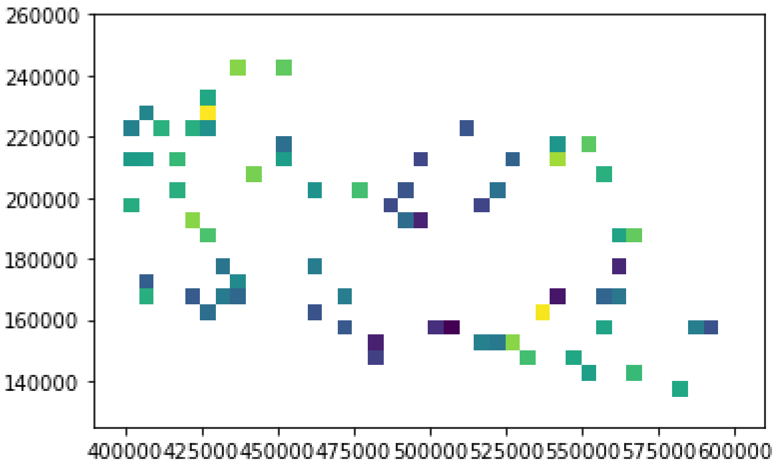
In [64]:

```
from rasterio import features

# Base our raster on a template raster (the Thames catchment in this case)
rs_thames = rio.open('./data/template.tif')
meta = rs_thames.meta.copy()

# Open a new file to write the burnt raster to
with rio.open('./data/rasterized.tif', 'w+', **meta) as out:
    out_arr = out.read(1)
    # Turn the Shapefile into geom, value tuples to pass to the rasterize function
    shapes = ((geom, value) for geom, value in zip(gdf.geometry, gdf.k_att))
    # Perform the burning using rasterio's rasterize
    rasterized = features.rasterize(shapes, out=out_arr, transform=out.transform)
    # Write the burnt raster to file
    out.write(rasterized, 1)
```

Having a look at our burnt raster:

In [65]:

```
with rio.open('./data/rasterized.tif') as src:
    show(src)
```



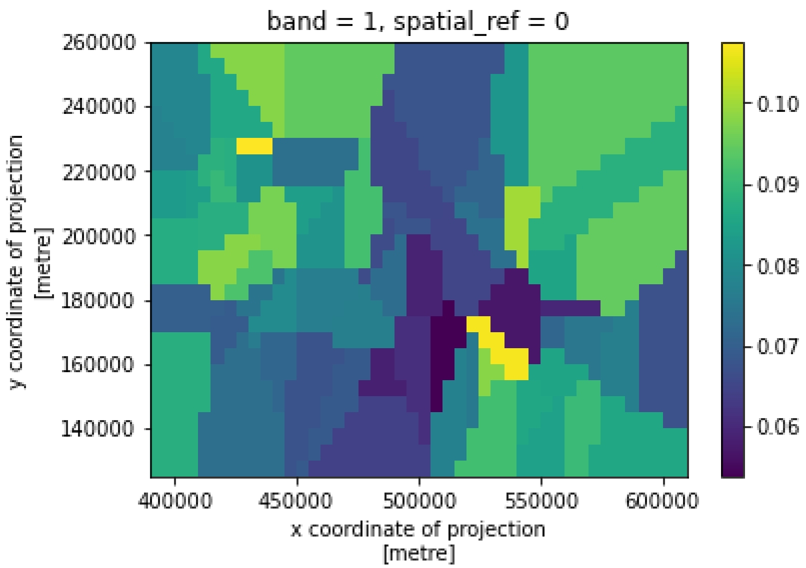
Using `interpolate_na` from `rioxarray`

This method uses `scipy.interpole.griddata` to interpolate missing data by nearest neighbour, linearly or cubically. See https://docs.scipy.org/doc/scipy/reference/generated/scipy.interpolate.griddata.html.

In [66]:

```
xds_int = rioxarray.open_rasterio('./data/rasterized.tif')
filled = xds_int.sel(band=1).rio.interpolate_na('nearest')
filled.plot()
```

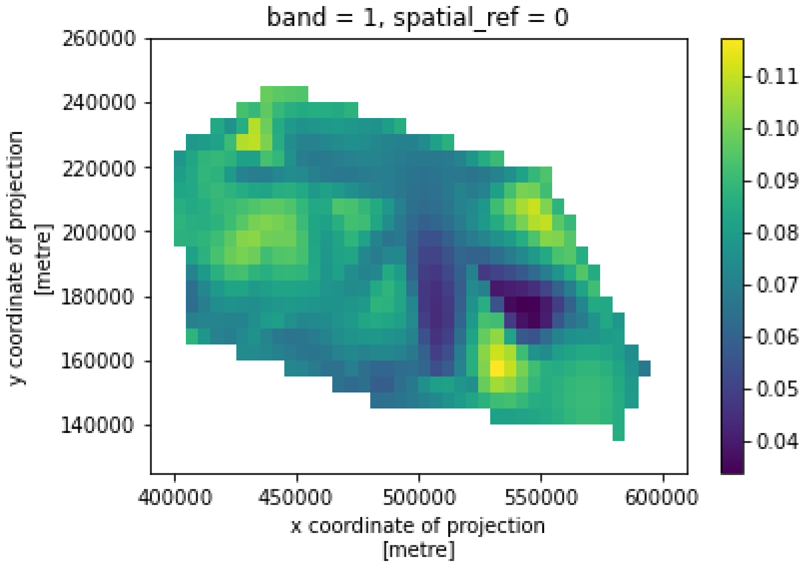
Out[66]: <matplotlib.collections.QuadMesh at 0x7f9efb8a76a0>



In [67]:

```
filled = xds_int.sel(band=1).rio.interpolate_na('cubic')
# Set nodata to NaN
filled = filled.where(filled != filled.rio.nodata)
filled.plot()
```

Out[67]: <matplotlib.collections.QuadMesh at 0x7f9efb7db130>



Further info:

- Very extensive course, mainly focussed on vector data (but with a bit of raster): https://automating-gis-processes.github.io/site/index.html
- Great intro to both raster and vector processing in Python: https://carpentries-incubator.github.io/geospatial-python/aio/index.html
- GeoPandas, Rasterio and rioxarray docs

Next talk: Any volunteers? Ideas for topics?

27 April 2021