

# Introduction to the dataset

WORKING WITH GEOSPATIAL DATA IN PYTHON



**Joris Van den Bossche**

Open source software developer and  
teacher, GeoPandas maintainer

# Artisanal mining site data from IPIS

IPIS: International Peace Information Service



Image: Connormah, [CC BY-SA 3.0](#), from Wikimedia Commons

# Artisanal mining site data from IPIS

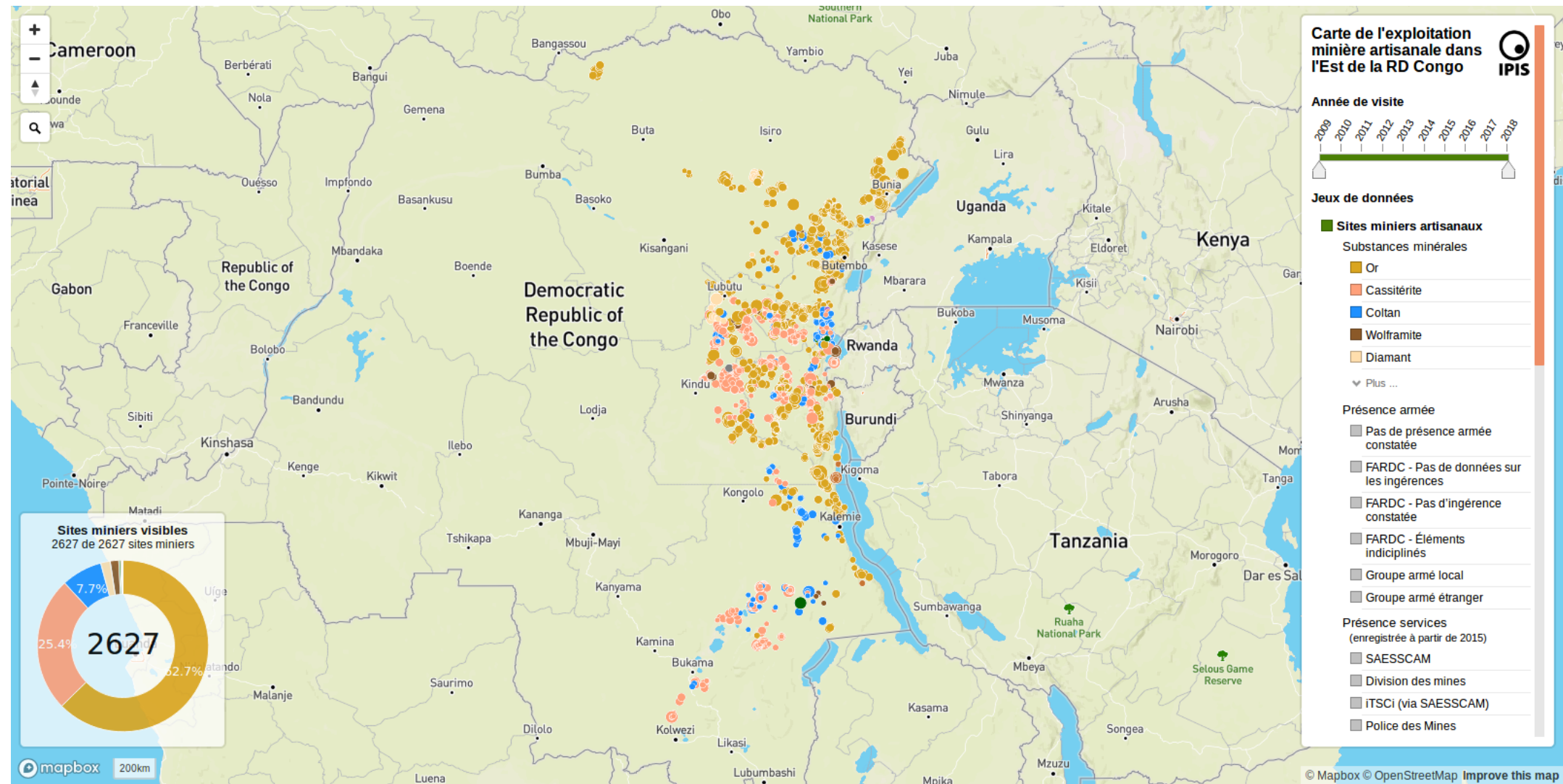
IPIS: International Peace Information Service



Source: GAO. | GAO-15-581

Image: G.A.O, public domain, from Wikimedia Commons

# Artisanal mining site data from IPIS



More analysis (re. social & security)

# Geospatial file formats

Reading files: `geopandas.read_file("path/to/file.geojson")`

Supported formats:

- ESRI Shapefile
  - One "file" consists of multiple files! ( `.shp` , `.dbf` , `.shx` , `.prj` , ...)
- GeoJSON
- GeoPackage ( `.gpkg` )
- ...

& PostGIS databases!



# Writing to geospatial file formats

Writing a GeoDataFrame to a file with the `to_file()` method:

```
# Writing a Shapefile file
geodataframe.to_file("mydata.shp", driver='ESRI Shapefile')

# Writing a GeoJSON file
geodataframe.to_file("mydata.geojson", driver='GeoJSON')

# Writing a GeoPackage file
geodataframe.to_file("mydata.gpkg", driver='GPKG')
```

# Let's practice!

WORKING WITH GEOSPATIAL DATA IN PYTHON

# Additional spatial operations

WORKING WITH GEOSPATIAL DATA IN PYTHON



**Joris Van den Bossche**

Open source software developer and  
teacher, GeoPandas maintainer



# Overview of spatial operations

## Spatial relationships:

- `intersects`
- `within`
- `contains`
- ...

## Join attributes based on spatial relation:

- `geopandas.sjoin`

## Geometry operations:

- `intersection`
- `union`
- `difference`
- ...

## Combine datasets based on geometry operation:

- `geopandas.overlay`

# Unary union

Convert a series of geometries to a single union geometry



africa

# Unary union

Convert a series of geometries to a single union geometry:



africa



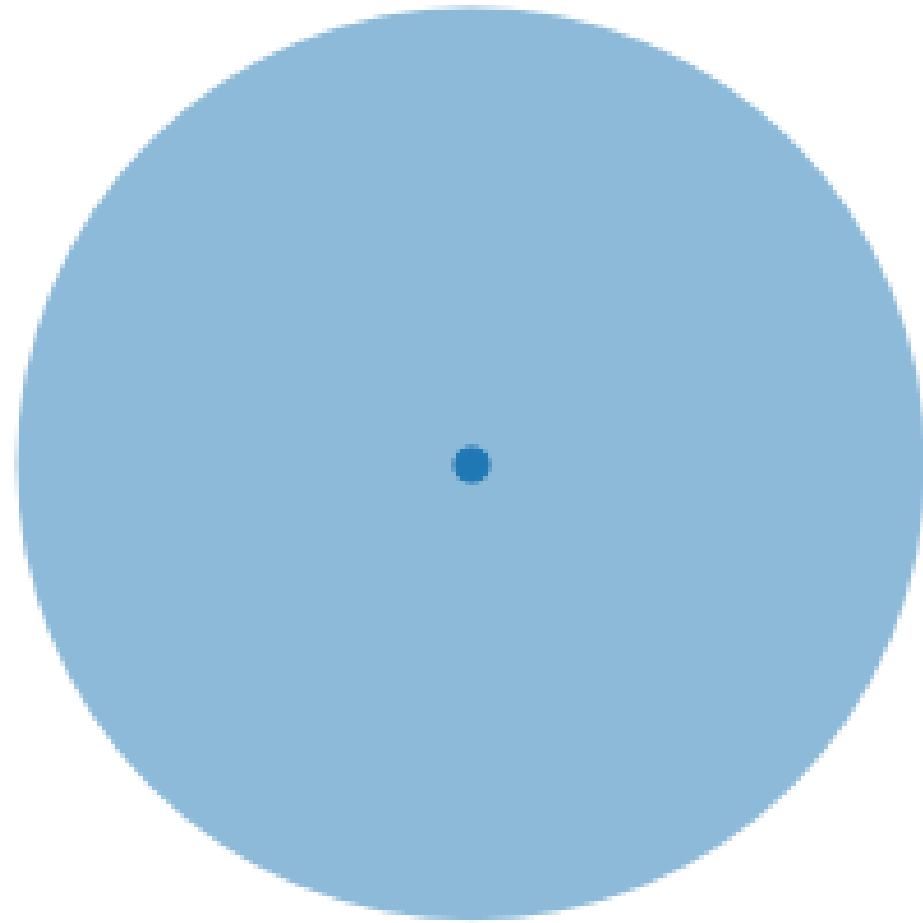
africa.unary\_union

# Buffer operation



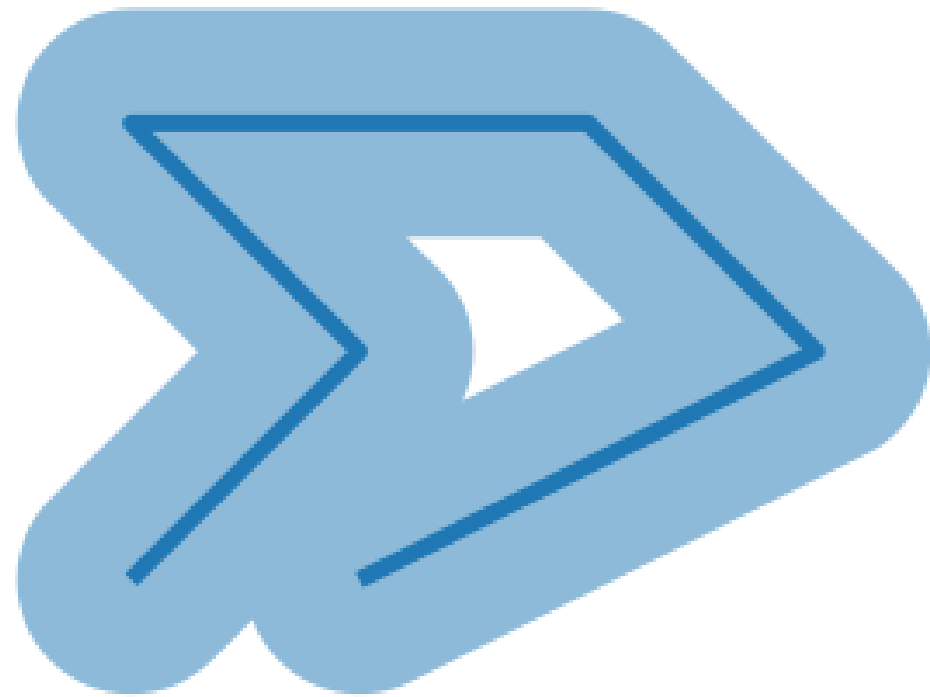
point

# Buffer operation

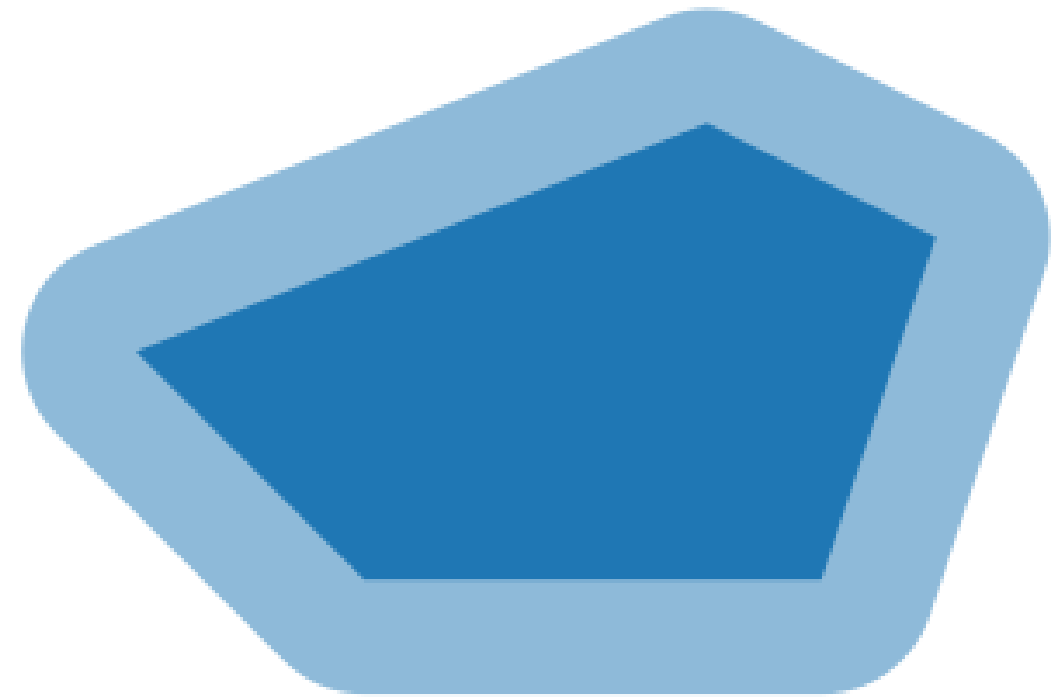


```
point.buffer(distance)
```

# Buffer operation



`line.buffer(distance)`



`polygon.buffer(distance)`



# Let's practice!

WORKING WITH GEOSPATIAL DATA IN PYTHON

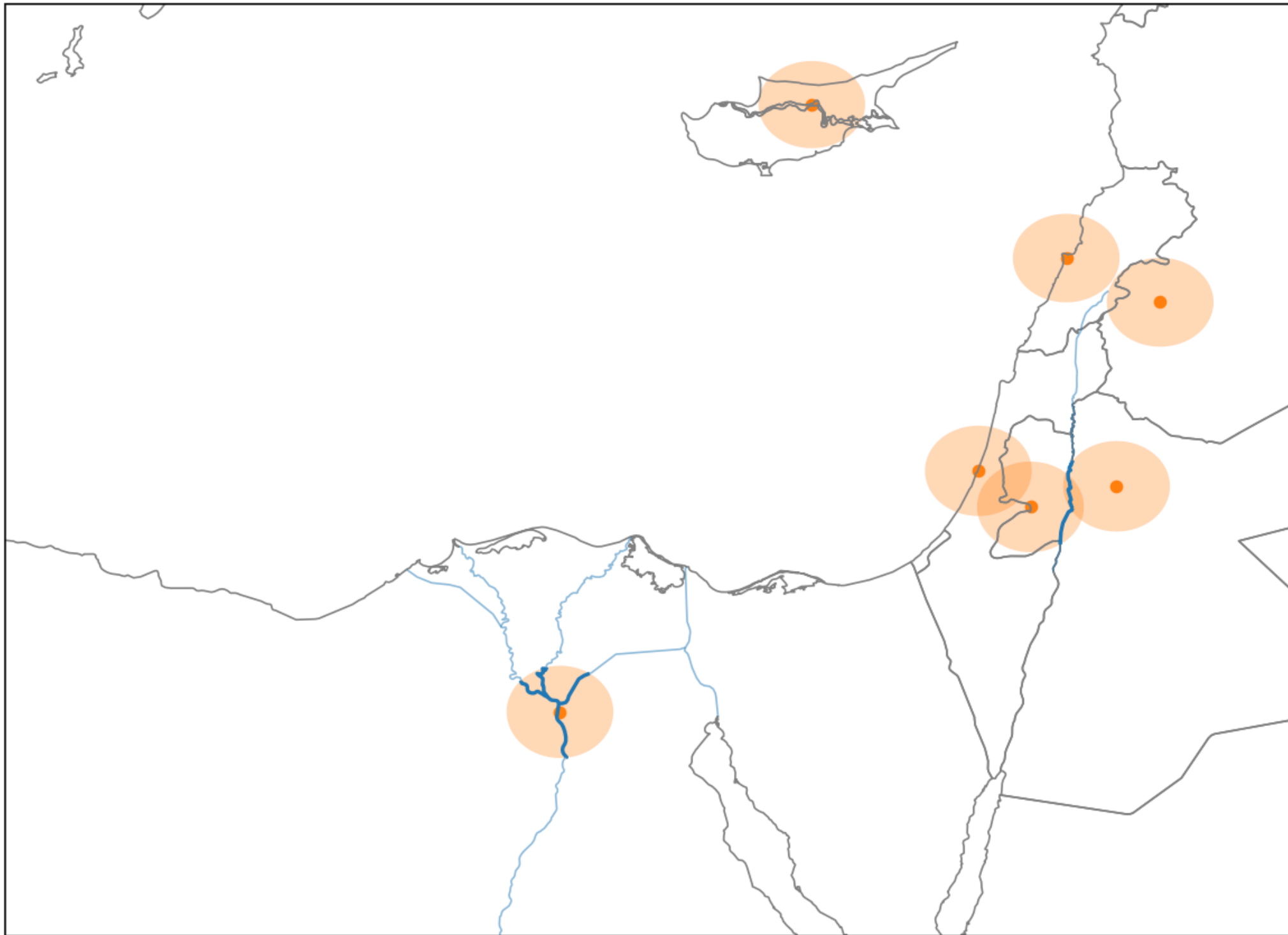
# Applying custom spatial operations

WORKING WITH GEOSPATIAL DATA IN PYTHON



**Joris Van den Bossche**

Open source software developer and  
teacher, GeoPandas maintainer



# Total river length within 50 km of each city?

For a single point ( `cairo` ):

```
area = cairo.buffer(50000)
rivers_within_area = rivers.intersection(area)
print(rivers_within_area.length.sum() / 1000)
```

```
186.397219642
```

# The apply() method

`Series.apply()` : call a function on each of the values of the Series

`Series.apply(function, **kwargs)`

- `function` : the function being called on each value; the value is passed as the first argument
- `**kwargs` : additional arguments passed to the function

For a `GeoSeries`, the function is called as `function(geom, **kwargs)` for each `geom` in the `GeoSeries`

# Applying a custom spatial operation

The function to apply:

```
def river_length(geom, rivers):  
    area = geom.buffer(50000)  
    rivers_within_area = rivers.intersection(area)  
    return rivers_within_area.length.sum() / 1000
```

Call function on the single geometry:

```
river_length(cairo, rivers=rivers)
```

```
186.3972196423455
```



# Applying a custom spatial operation

Applying on all cities:

```
cities.geometry.apply(river_length, rivers=rivers)
```

```
0      0.000000  
1      0.000000  
2    106.072198  
...
```

# Applying a custom spatial operation

Applying on all cities and assigning result to new column:

```
cities['river_length'] = cities.geometry.apply(river_length, rivers=rivers)
cities.head()
```

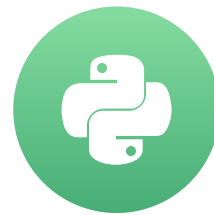
|    | name         | geometry                    | river_length |
|----|--------------|-----------------------------|--------------|
| 0  | Vatican City | POINT (1386304.6 5146502.5) | 0.000000     |
| 1  | San Marino   | POINT (1385011.5 5455558.1) | 0.000000     |
| 2  | Vaduz        | POINT (1059390.7 5963928.5) | 106.072198   |
| .. | ...          | ...                         | ...          |

# Let's practice!

WORKING WITH GEOSPATIAL DATA IN PYTHON

# Working with raster data

WORKING WITH GEOSPATIAL DATA IN PYTHON



**Joris Van den Bossche**

Open source software developer and  
teacher, GeoPandas maintainer

# Raster

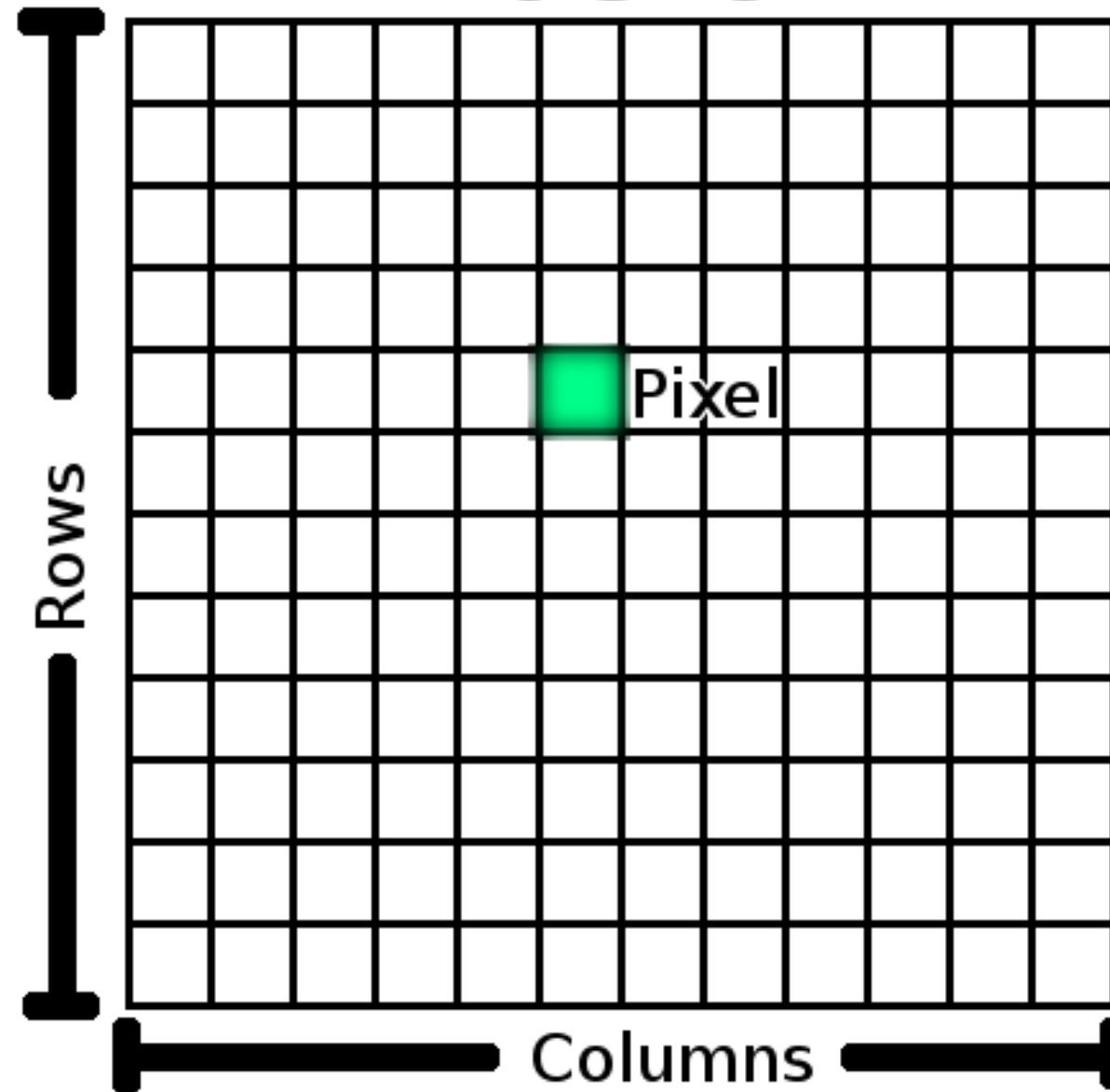
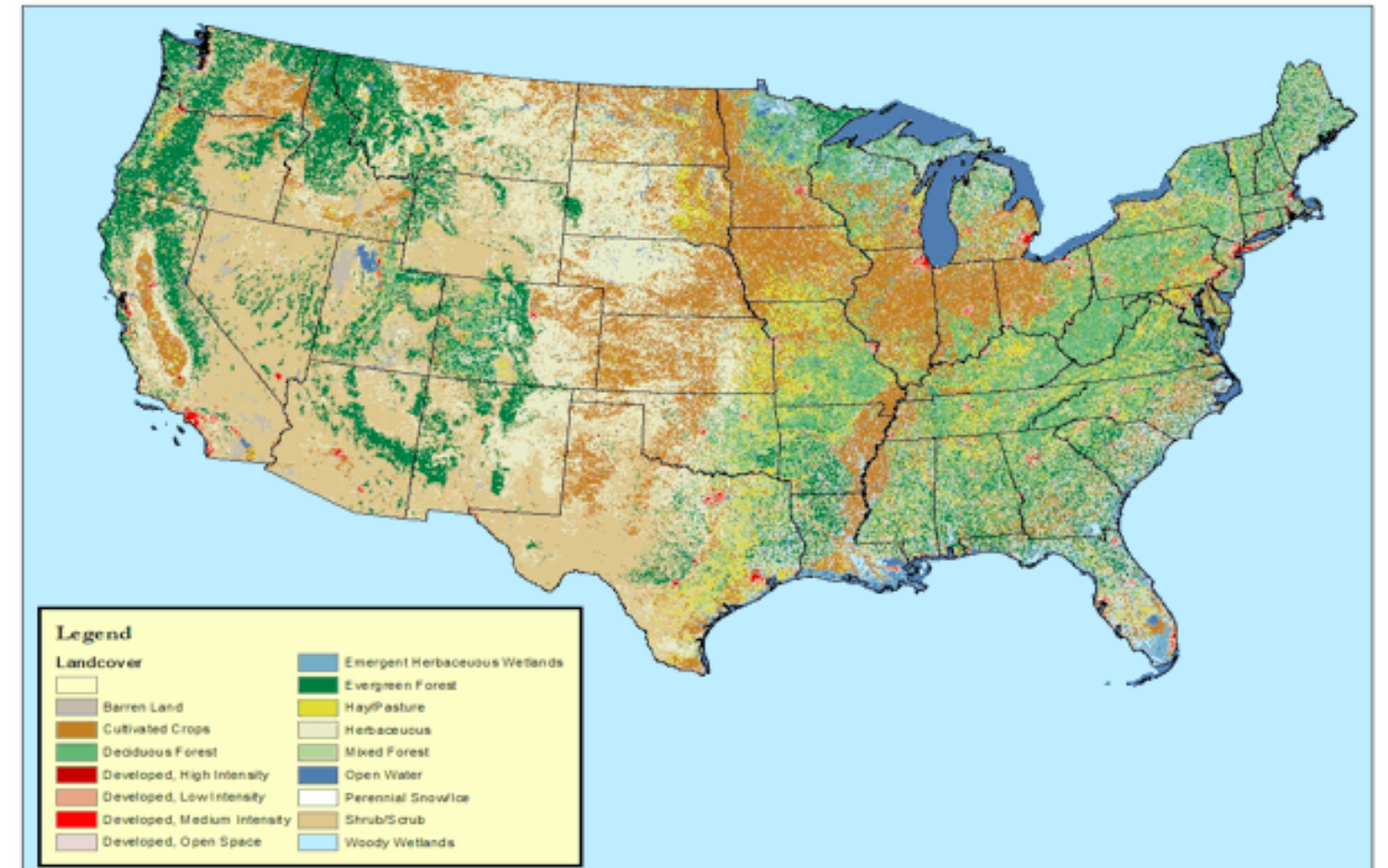
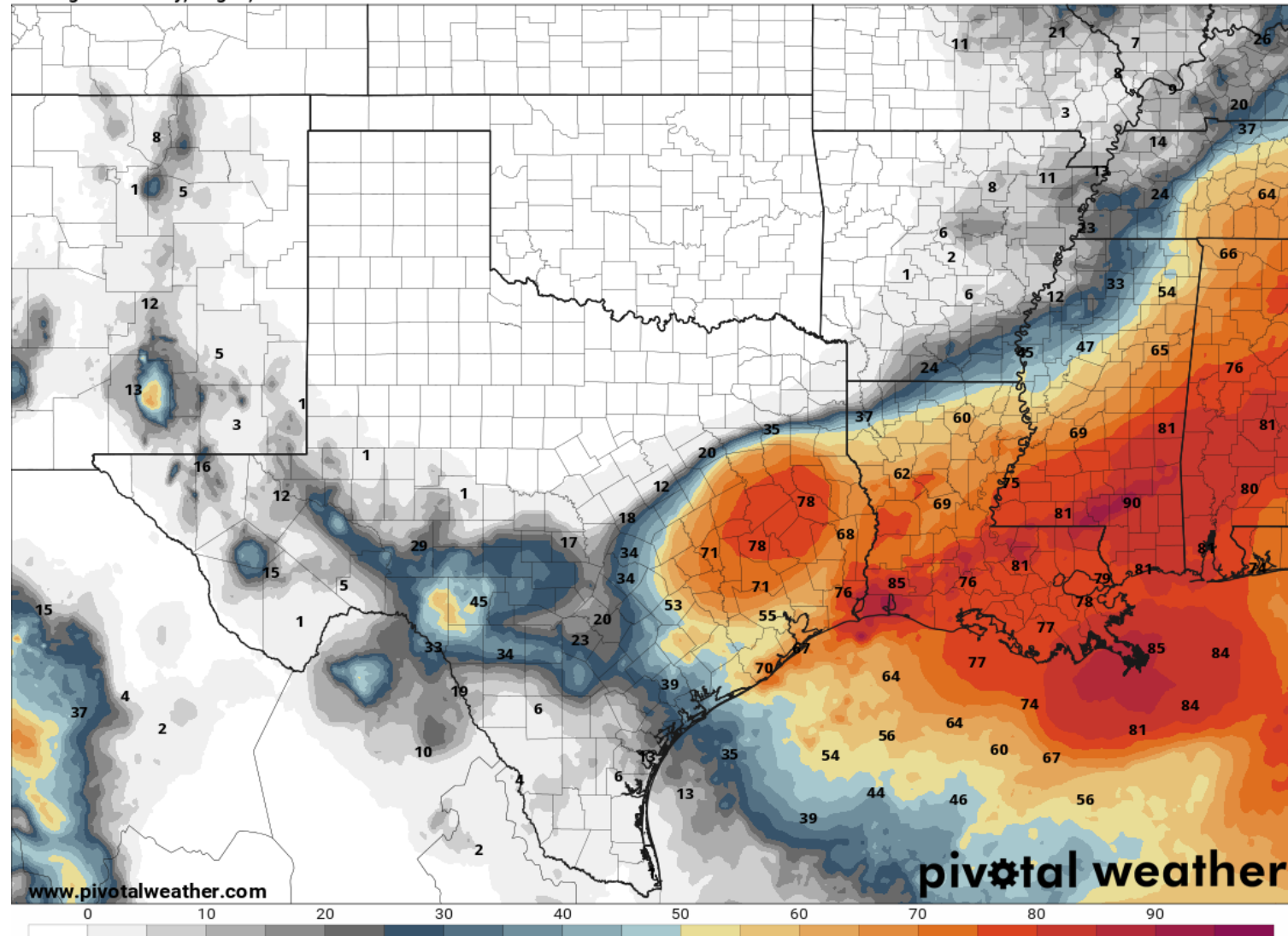


Image source: QGIS documentation

# Raster data

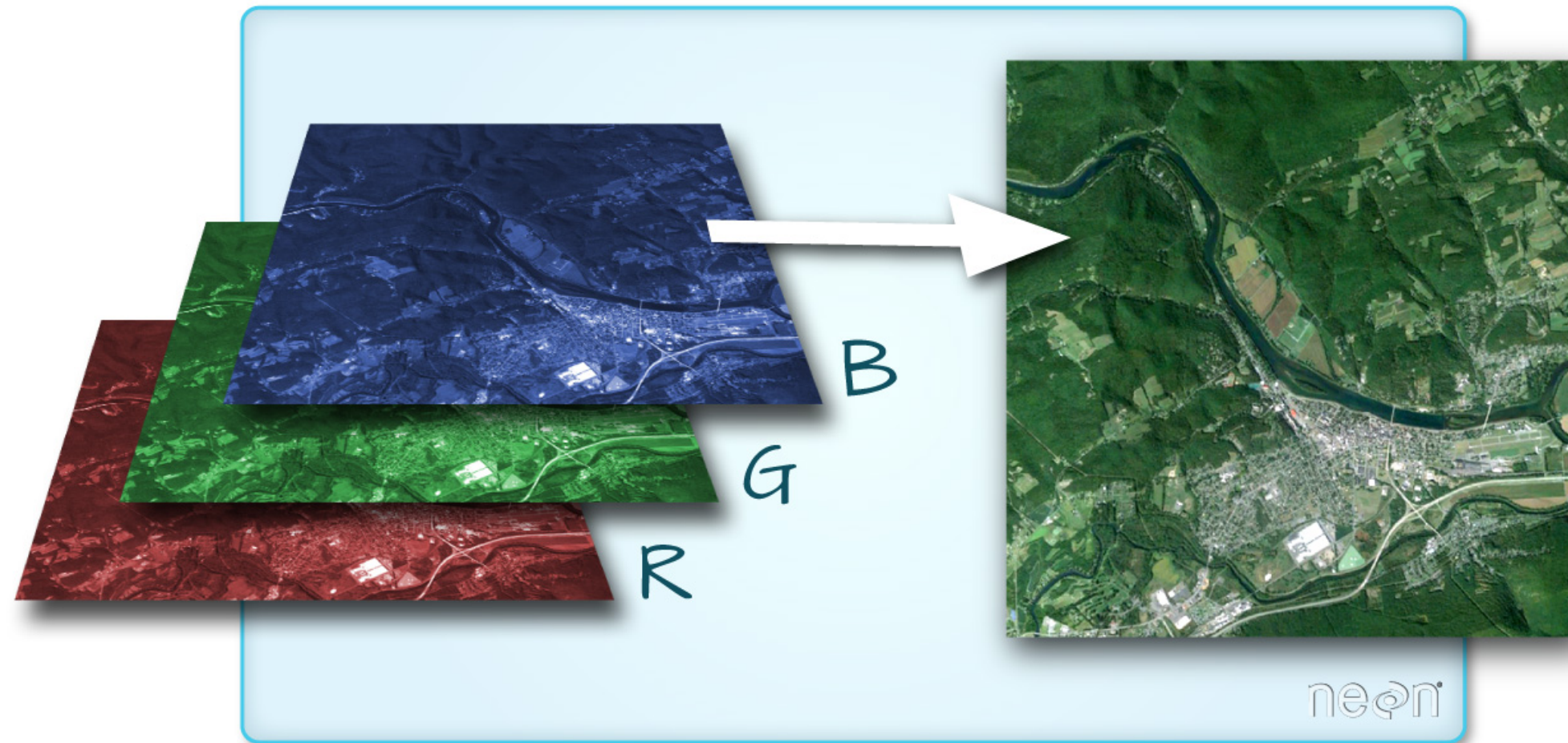
24-Hour Probability of Precipitation  $\geq 0.25$  Inches (percent)  
Ending Wednesday, Aug. 1, 2018 at 7 a.m. CDT

Init: Tue 2018-07-31 12z WPC





# Raster data with multiple bands



# The rasterio package

```
import rasterio
```

- "Pythonic" bindings to GDAL
- Reading and writing raster files
- Processing tools (masking, reprojection, resampling, ..)

<https://rasterio.readthedocs.io/en/latest/>

# Opening a raster file

```
import rasterio  
  
src = rasterio.open("DEM_world.tif")
```

Metadata:

```
src.count
```

```
1
```

```
src.width, src.height
```

```
(4320, 2160)
```

# Raster data = numpy array

```
array = src.read()
```

Standard `numpy` array:

```
array
```

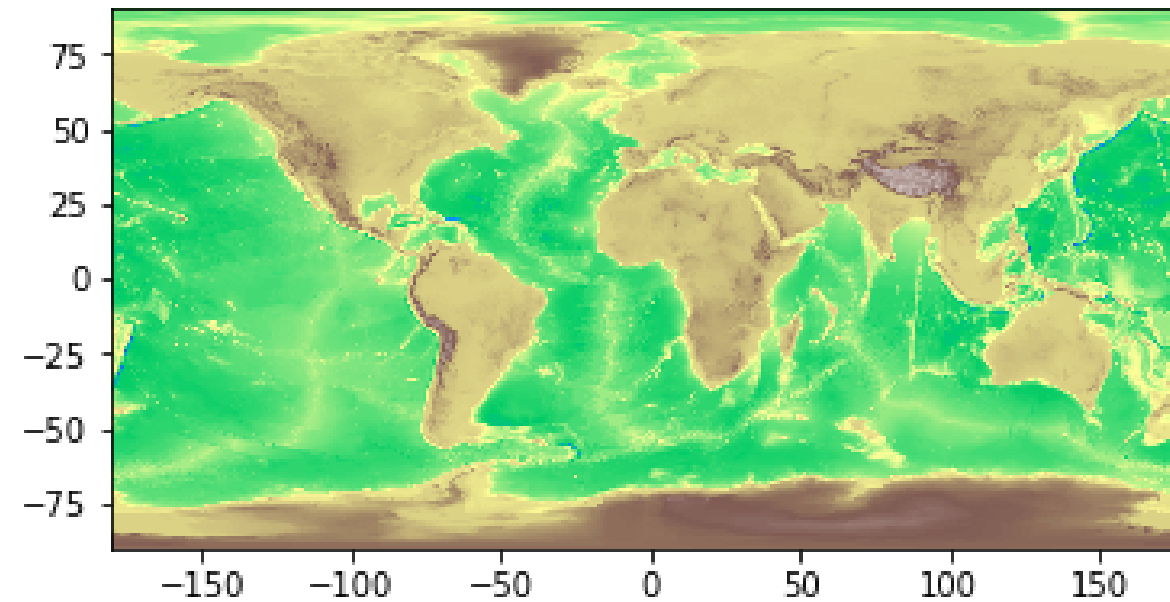
```
array([[[-4290, -4290, -4290, ..., -4290, -4290, -4290],
        [-4278, -4278, -4278, ..., -4278, -4278, -4278],
        [-4269, -4269, -4269, ..., -4269, -4269, -4269],
        ...,
        [ 2804,  2804,  2804, ...,  2804,  2804,  2804],
        [ 2804,  2804,  2804, ...,  2804,  2804,  2804],
        [ 2804,  2804,  2804, ...,  2804,  2804,  2804]]], dtype=int16)
```

# Plotting a raster dataset

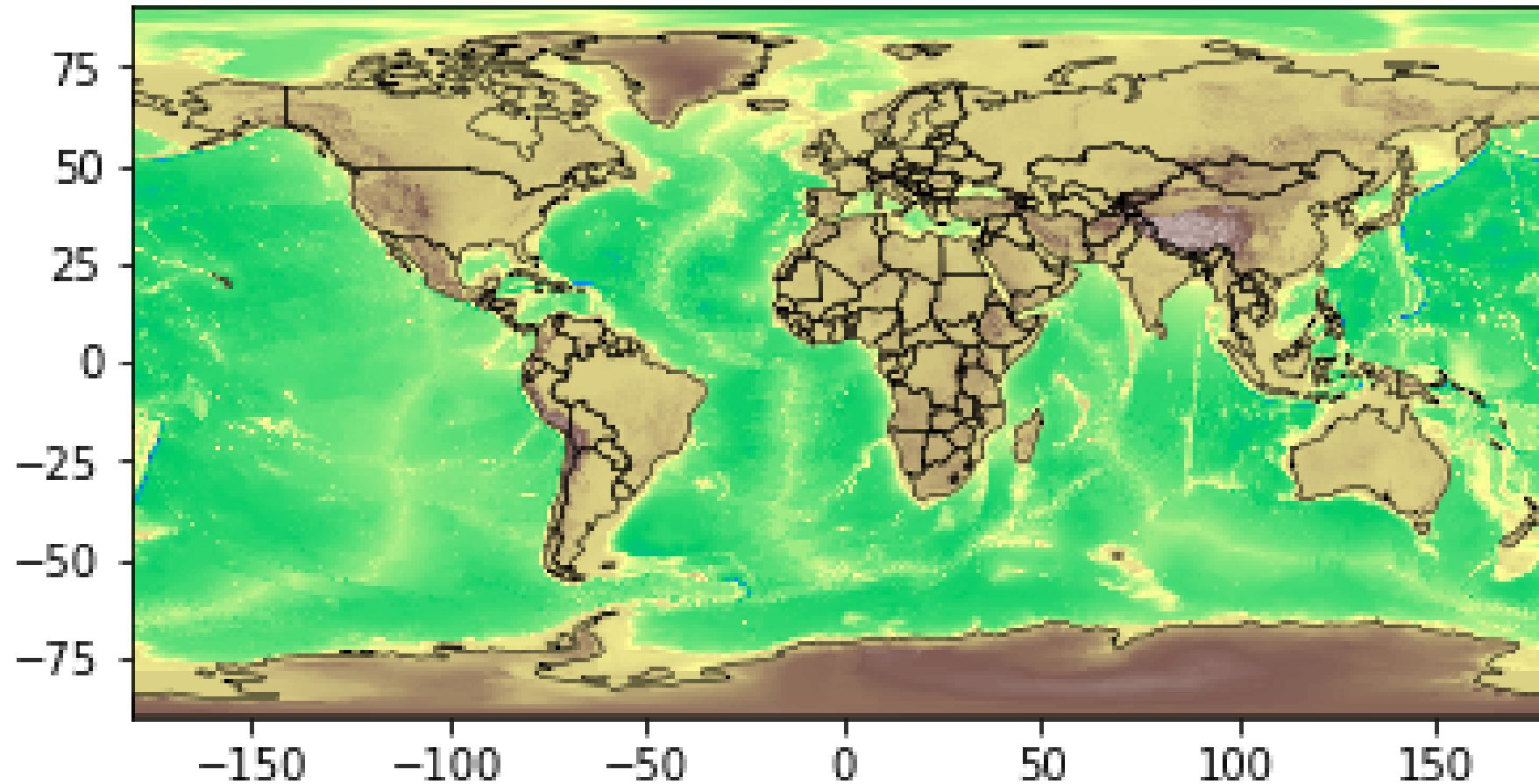
Using the `rasterio.plot.show()` method:

```
import rasterio.plot
```

```
rasterio.plot.show(src, cmap='terrain')
```



# Extracting information based on vector data



**rasterstats** : Summary statistics of geospatial raster datasets based on vector geometries  
(<https://github.com/perrygeo/python-rasterstats>)



# Extract raster values with rasterstats

- For point vectors:

```
rasterstats.point_query geometries, "path/to/raster",  
                           interpolation='nearest' | 'bilinear')
```

- For polygon vectors:

```
rasterstats.zonal_stats(geometries, "path/to/raster",  
                          stats=['min', 'mean', 'max'])
```

# Extract raster values with rasterstats

```
result = rasterstats.zonal_stats(countries.geometry, "DEM_gworld.tif",
                                stats=['mean'])

countries['mean_elevation'] = pd.DataFrame(result)

countries.sort_values('mean_elevation', ascending=False).head()
```

|     | name       | continent  | geometry                    | mean_elevation |
|-----|------------|------------|-----------------------------|----------------|
| 157 | Tajikistan | Asia       | POLYGON ((74.98 37.41, ...  | 3103.231105    |
| 85  | Kyrgyzstan | Asia       | POLYGON ((80.25 42.34, ...  | 2867.717142    |
| 24  | Bhutan     | Asia       | POLYGON ((91.69 27.77, ...  | 2573.559846    |
| 119 | Nepal      | Asia       | POLYGON ((81.11 30.18, ...  | 2408.907816    |
| 6   | Antarctica | Antarctica | (POLYGON ((-59.57 -80.04... | 2374.075028    |
| ..  | ...        | ...        | ...                         | ...            |

# Let's practice!

WORKING WITH GEOSPATIAL DATA IN PYTHON

# The end

WORKING WITH GEOSPATIAL DATA IN PYTHON



## Instructors

Joris Van den Bossche & Dani Arribas-Bel

# Taking the next steps ...

More on GeoPandas:

- GeoPandas docs and example gallery: <https://geopandas.readthedocs.io/>
- Other online sources, e.g.: <https://automating-gis-processes.github.io/2018/>

Looking for spatial statistics? Check [PySAL](#)

Working with multi-dimensional gridded data? Check [xarray](#)

Want to create interactive web maps? Check [folium](#), [ipyleaflet](#) or [geoviews](#)

Make matplotlib plots with projection support? Check [cartopy](#)

# Good luck!

WORKING WITH GEOSPATIAL DATA IN PYTHON