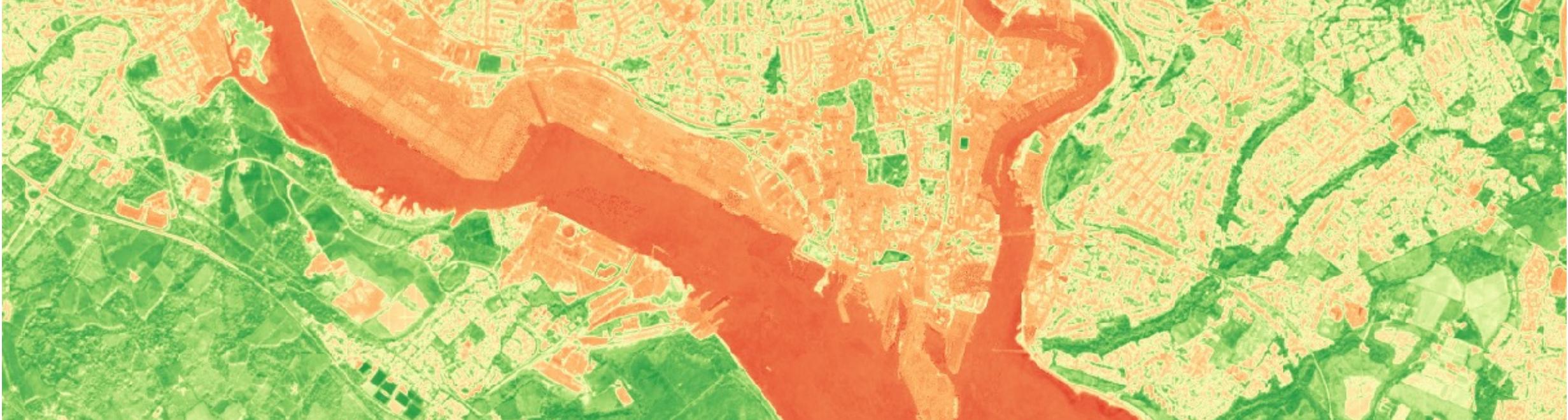


An introduction to geospatial data & processing

Dr Robin Wilson

www.rtwilson.com



What is geospatial data?

Schools in Oxfordshire

ID	Name	Type	Status	Phase	Gender	Pupils
123290	Headington School	Other Independent School	Open	Secondary	Girls	1046
122967	Bartlemas Nursery School	LA Nursery School	Open	Nursery	Mixed	63
122968	Headington Quarry Foundation Stage School	LA Nursery School	Open	Nursery	Mixed	81
122969	Grandpont Nursery School	LA Nursery School	Open	Nursery	Mixed	75
		Voluntary Controlled School				
123129	Dorchester St Birinus Church of England School	Voluntary Controlled School	Open	Primary	Mixed	78
		Voluntary Controlled School				
123130	Great Milton Church of England Primary School	Voluntary Controlled School	Open	Primary	Mixed	161
		Voluntary Controlled School				
123131	Marsh Baldon Church of England Controlled School	Voluntary Controlled School	Open	Primary	Mixed	70
		Voluntary Controlled School				
123132	Culham Parochial Church of England School	Voluntary Controlled School	Open	Primary	Mixed	51
		Voluntary Controlled School				
123133	Crowmarsh Gifford Church of England School	Voluntary Controlled School	Open	Primary	Mixed	204
		Voluntary Controlled School				
123134	Harpsden Parochial School	Voluntary Controlled School	Closed	Primary	Mixed	0

Data

Schools in Oxfordshire

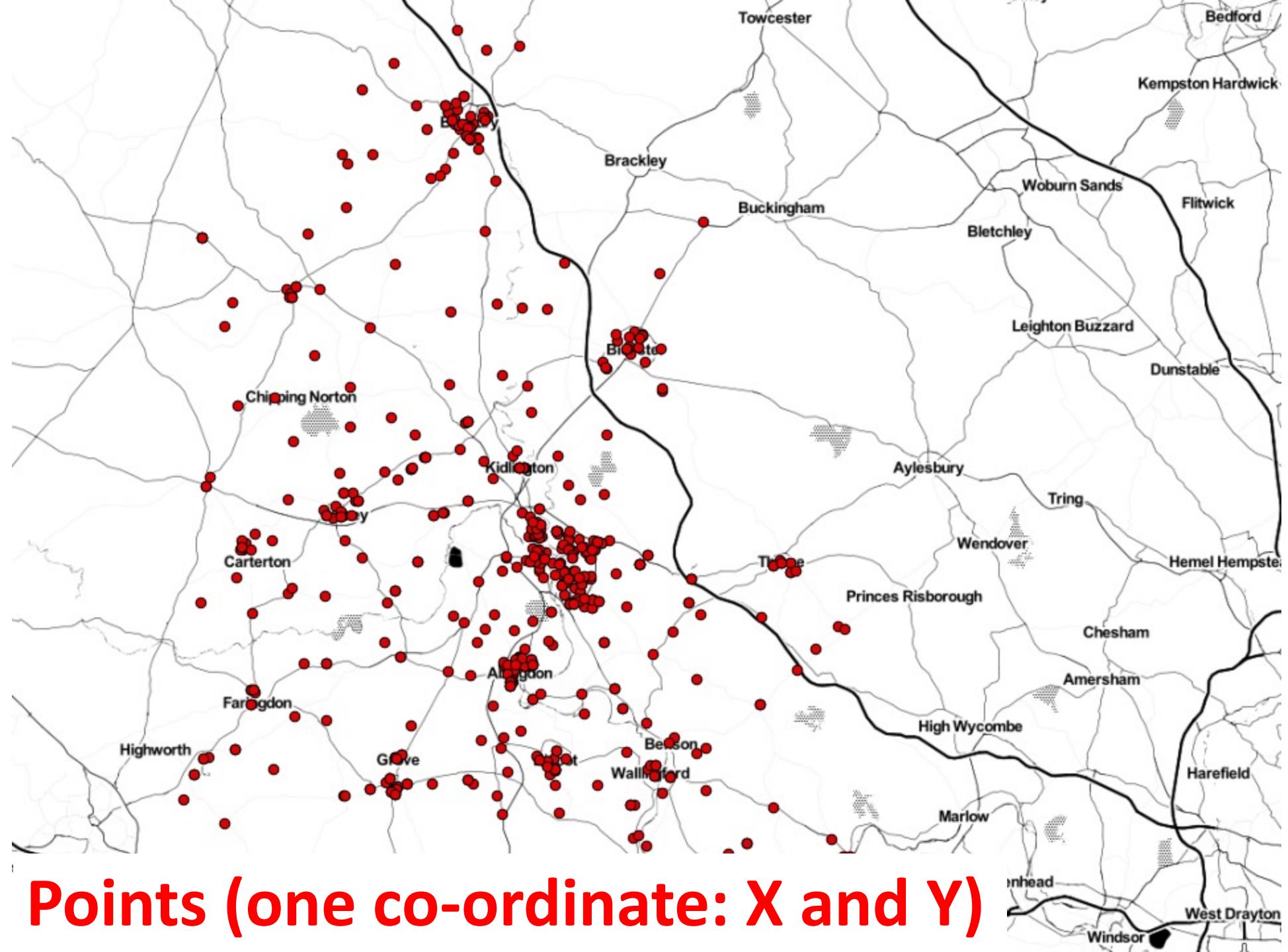
ID	Name	Type	Status	Phase	Gender	Pupils	X	Y
123290	Headington School	Other Independent School	Open	Secondary	Girls	1046	453825	206828
122967	Bartlemas Nursery School	LA Nursery School	Open	Nursery	Mixed	63	453107	205197
122968	Headington Quarry Foundation Stage School	LA Nursery School	Open	Nursery	Mixed	81	455495	206950
122969	Grandpont Nursery School	LA Nursery School	Open	Nursery	Mixed	75	451204	205180
123129	Dorchester St Birinus Church of England School	Voluntary Controlled School	Open	Primary	Mixed	78	457895	194371
123130	Great Milton Church of England Primary School	Voluntary Controlled School	Open	Primary	Mixed	161	462976	202879
123131	Marsh Baldon Church of England Controlled School	Voluntary Controlled School	Open	Primary	Mixed	70	456387	199612
123132	Culham Parochial Church of England School	Voluntary Controlled School	Open	Primary	Mixed	51	450766	195061
123133	Crowmarsh Gifford Church of England School	Voluntary Controlled School	Open	Primary	Mixed	204	461707	189029
123134	Harpsden Parochial School	Voluntary Controlled School	Closed	Primary	Mixed	0	475602	180862

Geographic Data ('Geodata')

Schools in Oxfordshire

Everything
happens
somewhere
Geographic Data ('Geodata')

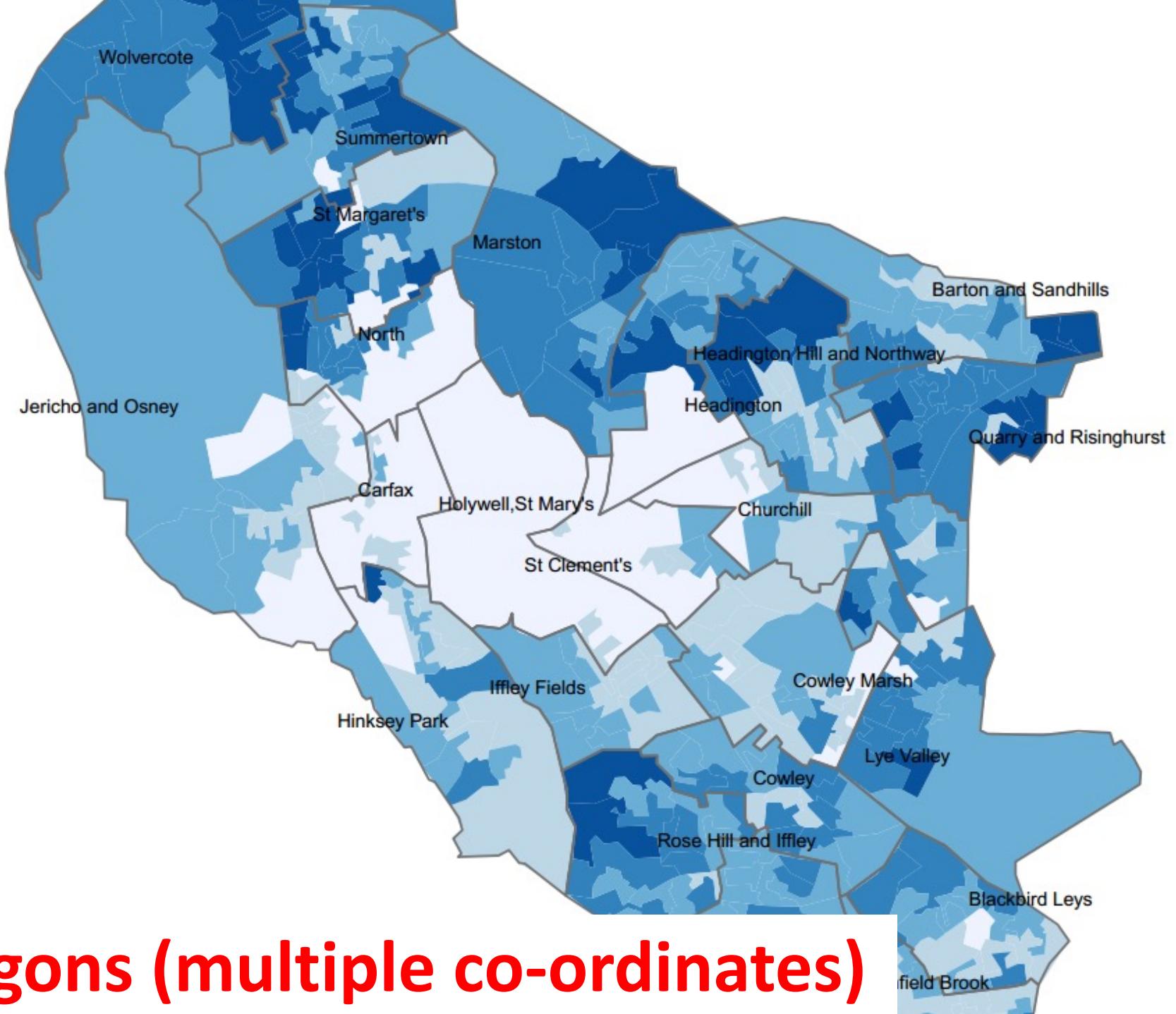
ID	Name	Type	Status	Gender	Y
123290	Headington School	Other Independent School	Open	Secondary	453825
122967	Bartlemas Nursery School	LA Nursery School	Open	Nursery	453107
	Headington Quarry Foundation Stage				
122968	School	LA Nursery School	Open	Nursery	455495
122969	Grandpont Nursery School	LA Nursery School	Open	Nursery	451204
	Dorchester St Birinus Church of England School	Voluntary Controlled School	Open	Primary	457895
123129				Mixed	194371
123130	Great Milton Church of England Primary School	Voluntary Controlled School	Open	Primary	462976
123131	Marsh Baldon Church of England Controlled School	Voluntary Controlled School	Open	Primary	456387
123132	Culham Parochial Church of England School	Voluntary Controlled School	Open	Primary	450766
123133	Crowmarsh Gifford Church of England School	Voluntary Controlled School	Open	Primary	461707
123134	Harston Parochial School	Voluntary Controlled School	Open	Primary	47102



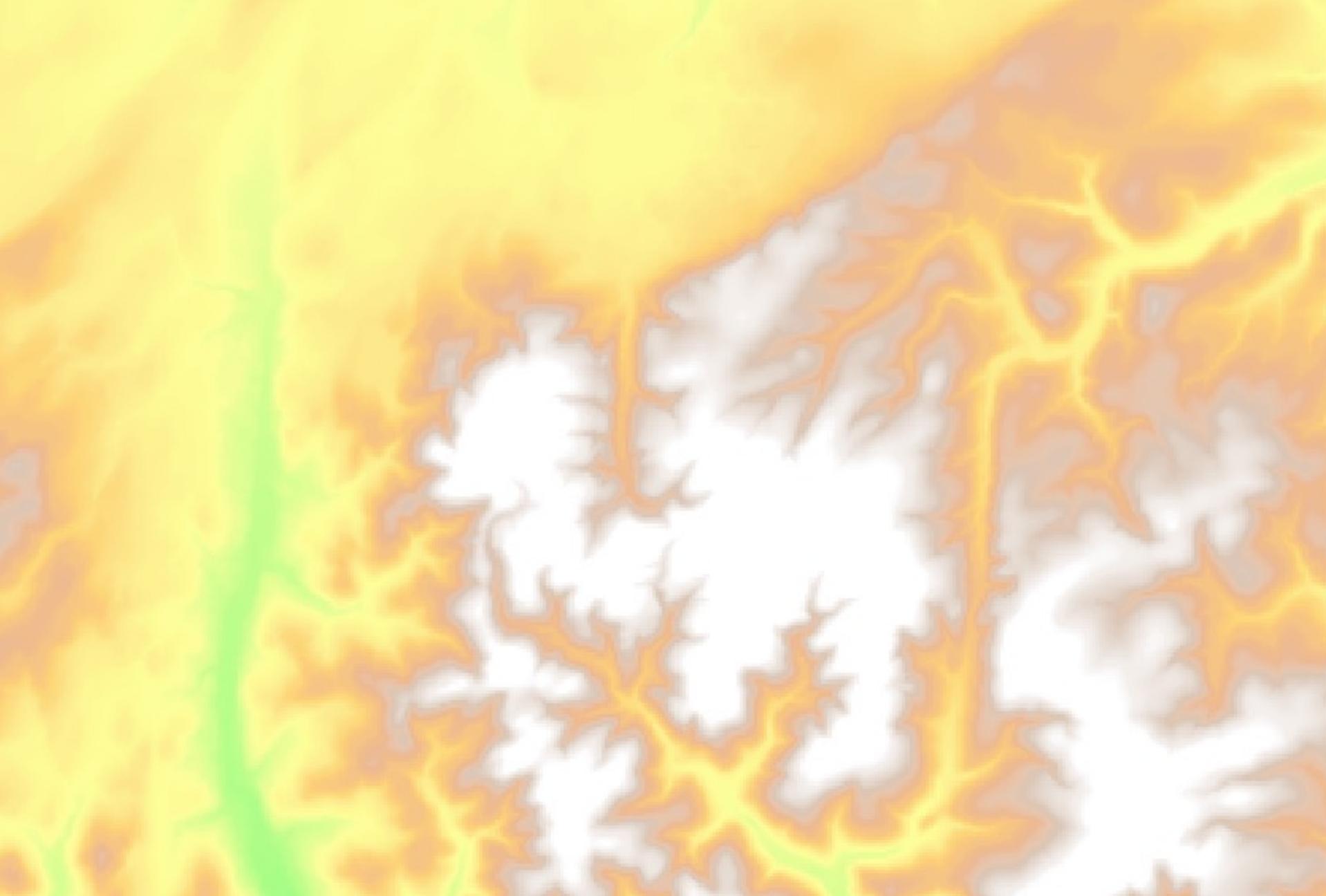
Points (one co-ordinate: X and Y)



Lines (multiple co-ordinates)



Polygons (multiple co-ordinates)



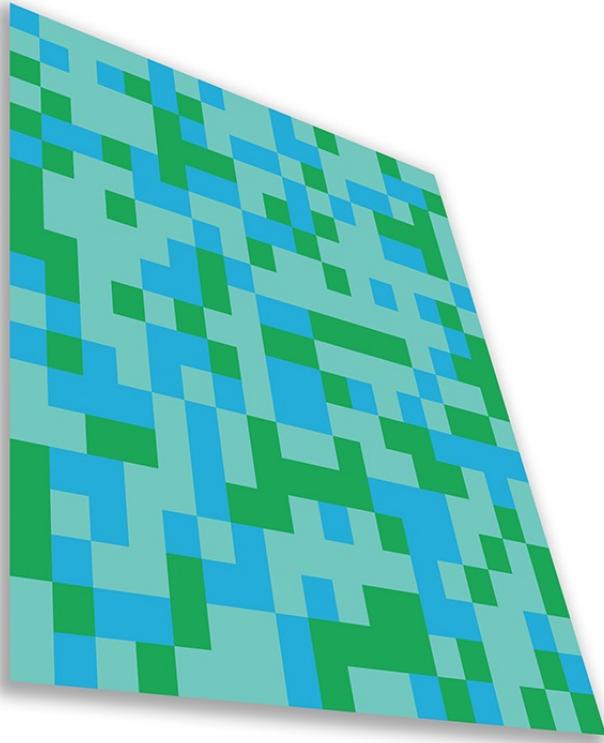
Raster (grid of values plus metadata)

10 11 13 17 20 23 ...

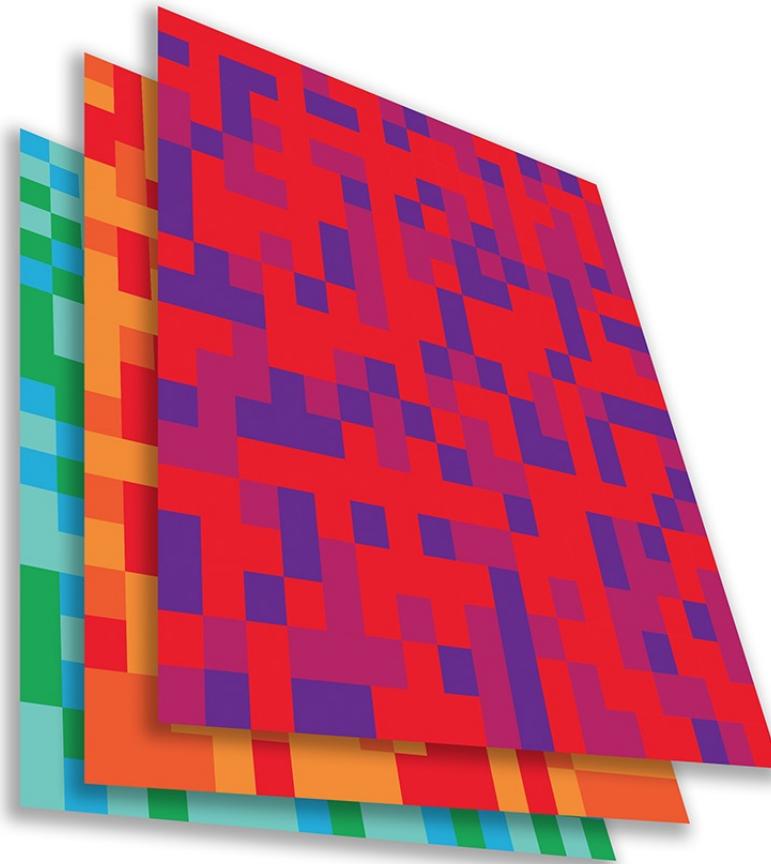
Pixel size



Raster (grid of values plus metadata)



Single Band Raster



Multi Band Raster

Raster (multiband)

Beware of projections and co-ordinate systems



Latitude, Longitude for the whole world in degrees (but which comes first?)
X, Y in projected co-ordinate systems for specific areas usually in metres



OSGB36 / British National Grid -- United Kingdom Ordnance Survey

[Transform](#)[Get position on a map](#)

Available transformations

to EPSG:4326 ▾

United Kingdom (UK) , accuracy 1.0 m, code 7710

(default) [grid]

United Kingdom (UK) , accuracy 2.0 m, code 1314 [7]

United Kingdom (UK) , accuracy 21.0 m, code 1195 [3]

United Kingdom (UK) - England onshore.,

accuracy 10.0 m, code 1196 [3]

United Kingdom (UK) , accuracy 21.0 m, code 1197 [3]

United Kingdom (UK) , accuracy 18.0 m, code 1198 [3]

United Kingdom (UK) - Wales onshore.,

accuracy 35.0 m, code 1199 [3]

United Kingdom (UK) , accuracy 3.0 m, code 5622 [3]

United Kingdom (UK) , accuracy 1.0 m, code 5339 [grid]

Selected transformation

Method: NTv2

Grid Files: OSTN15_NTv2_OSGBtoETRS.gsb

Remarks: Parameter values taken from OSGB36 to ETRS89 (2) (tfm code 7709) assuming that ETRS89 is coincident with WGS 84 within the accuracy of the tfm. Replaces OSGB36 to WGS 84 (7) (tfm code 5339).

Information source: EPSG

Revision date: 2021-08-19

Covered area powered by MapTiler



Center coordinates

305371.94 610575.38

Projected bounds:

-103976.3 -16703.87

652897.98 1199851.44

WGS84 bounds:

-9.0 49.75

2.01 61.01

United Kingdom (UK) - offshore to boundary of UKCS within 49°45'N to 61°N and 9°W to 2°E; onshore Great Britain (England, Wales and Scotland). Isle of Man onshore.

Attributes

Unit: metre

Scope: Engineering survey, topographic mapping.

Geodetic CRS: OSGB36

Area of use: United Kingdom (UK) - offshore to

boundary of UKCS within 49°45'N to 61°N and 9°W to 2°E; onshore Great Britain (England, Wales and Scotland). Isle of Man onshore.

Datum: Ordnance Survey of Great Britain 1936

Ellipsoid: Airy 1830

Coordinate system: Cartesian 2D CS. Axes: easting, northing (E,N). Orientations: east, north. UoM: m.

Prime meridian: Greenwich

Data source: EPSG

Information source: Ordnance Survey of Great Britain.

Where to get geospatial data?

- National mapping agencies (eg. Ordnance Survey)
- National statistical organisations (eg. Office for National Statistics)
- OpenStreetMap
- Satellite operators (eg. NASA, ESA, commercial operators)
- My FreeGISData site – www.freegisdata.rtwilson.com
- **Customers, Clients...**

This page contains a categorised list of links to over 500 sites providing freely available geographic datasets - all ready for loading into a Geographic Information System.

We have links to everything from arctic permafrost maps to gridded population data - simply scroll through the list, or use the dropdown menus above to jump to a specific section of interest. See the FAQ for more information on the what, who, how and why of the list.

Beware: The data linked to below may be inaccurate, incomplete, or just plain wrong. As always, critically examine the data you are using, look at what organisation produced it and what agenda they may have, and beware that there are disputes over some of the data (particularly country boundaries).

This list was last updated on 17 September 2023.

Physical Geography

General

- [Natural Earth - Vector](#): Includes coastline, land, oceans, islands, rivers, lakes, glaciated areas and bathymetry. Available at multiple levels of detail. A version of this data is also available in the Wagner VII projection, which has good equal area properties. [here](#).
- [Natural Earth - Raster](#): Includes various raster images, intended for use as backgrounds for other data, for example hypsometric tints, satellite derived land cover, shaded relief etc.
- [Global Map](#): A set of consistent GIS layers covering the whole globe at 1km resolution including: transportation, elevation, drainage, vegetation, administrative boundaries, land cover, land use and population centres. Produced by the International Steering Committee on Global Mapping.
- [DIVA-GIS Country Data](#): A collection of data collected from a number of the sources below - includes administrative areas, inland water, roads and railways, elevation, land cover, population and climate. Probably the easiest place to get a simple set of data for a specific country.
- [UNEP GEOdata](#): A wide range of data from the United Nations Environment Programme including Global Forest Cover, Global Potential Evapotranspiration, Global Average Monthly Temperatures, Dams, Watershed Boundaries and much more. To get data, choose Advanced Search and select Geospatial Data Sets from the top drop-down link
- [Koordinates](#): GIS data aggregation site including data in a number of categories such as elevation, environment, climate etc. Some global datasets, some based on continents, some for specific countries. Mostly vector, but some raster. [Registration required](#)
- [MapCruzin](#): GIS aggregation site including wide range of data for various areas of the world. Some datasets appear to be of low quality, but others are good.
- [GeoNetwork](#): GIS aggregation site including a wide range of data under various categories (both human and physical).
- [European Environment Agency](#): Maps and datasets from the European Environment Agency, covering a huge range of physical geography and environmental topics. Europe only.

Tools for processing geospatial data



Command-line tools

Translate formats
Reproject
Resample
Get information
Query

Formats

Raster	Vector
GeoTIFF / COG (.tif)	GeoJSON (.geojson)
ERDAS Imagine (.img)	GeoPackage (.gpkg)
JPEG2000 (.jp2)	GeoParquet (.parquet)
Grid (.grd or others)	Shapefile (.shp, .dbf, .shx etc)
	CSV (.csv)
	ESRI File GeoDatabase (.gdb)
	Database connections (PostGIS, Spatialite)

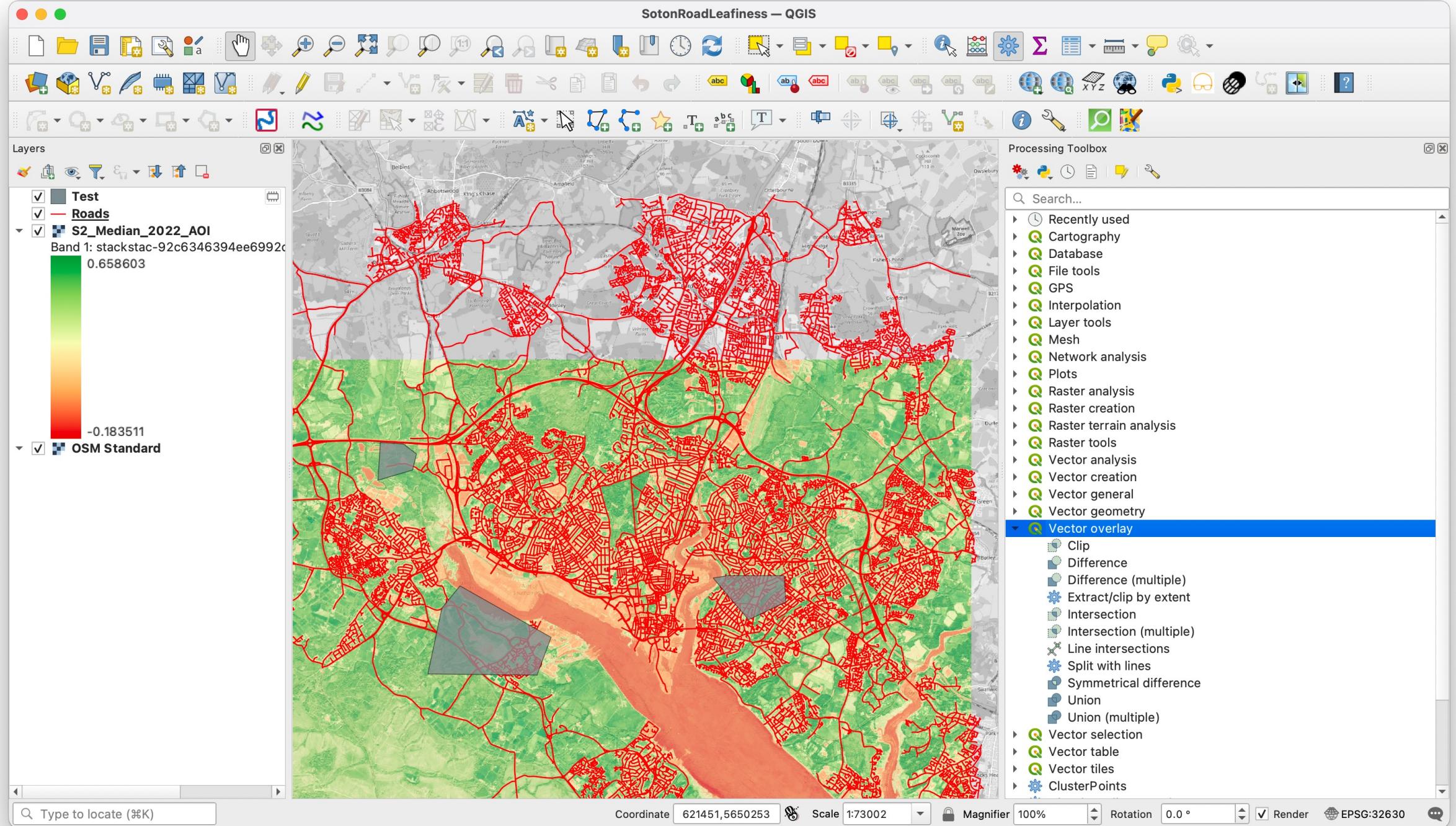


View – Edit – Process

PyQGIS & Graphical Modeler

- ▶ Cartography
- ▶ Database
- ▶ File tools
- ▶ GPS
- ▶ Interpolation
- ▶ Layer tools
- ▶ Mesh
- ▶ Network analysis
- ▶ Plots
- ▶ Raster analysis
- ▶ Raster creation
- ▶ Raster terrain analysis
- ▶ Raster tools
- ▶ Vector analysis
- ▶ Vector creation
- ▶ Vector general
- ▶ Vector geometry
- ▶ Vector overlay
- ▶ Vector selection
- ▶ Vector table
- ▶ Vector tiles
- ▶ ClusterPoints
- ▶ Dissolve adjacent polygons
- ▶ GDAL
- ▶ Geo Simplification
- ▶ GRASS
- ▶ QuickOSM

SotonRoadLeafiness — QGIS

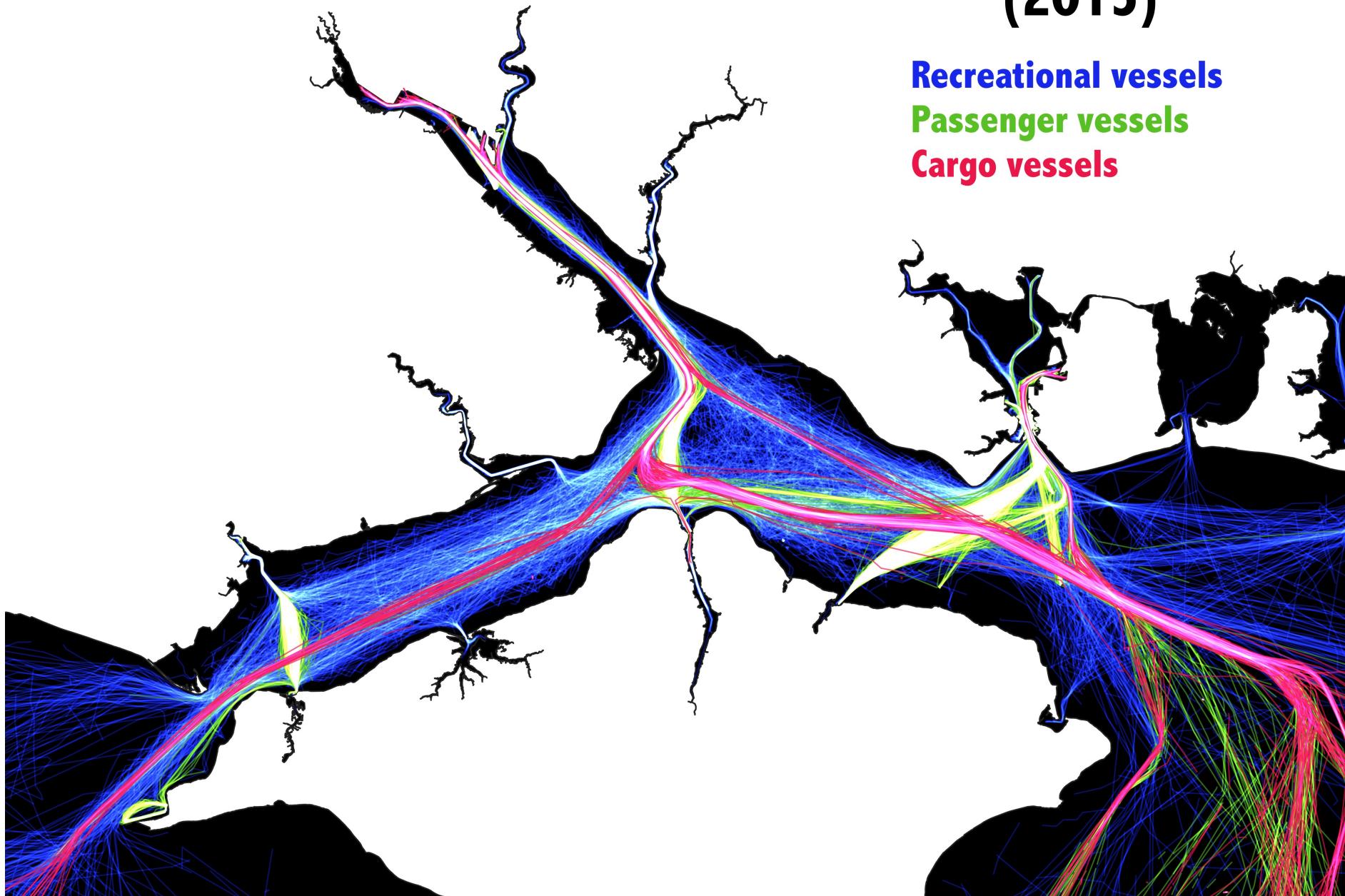


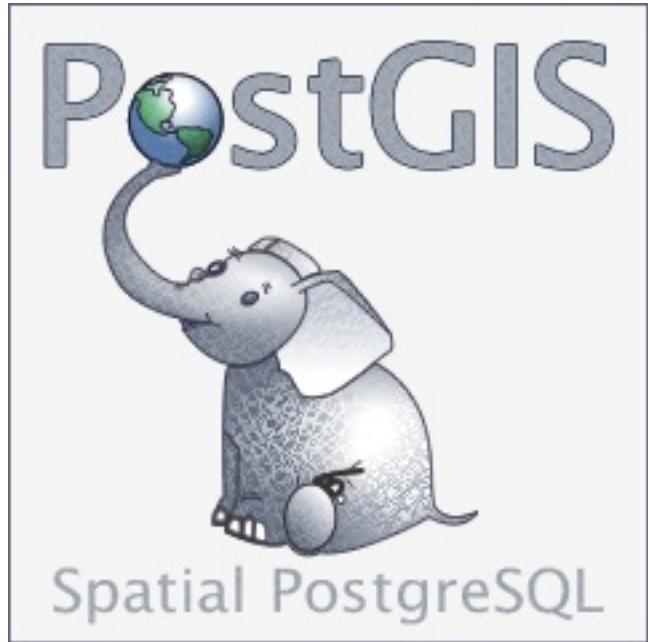
0 1 2 3 4 5 km



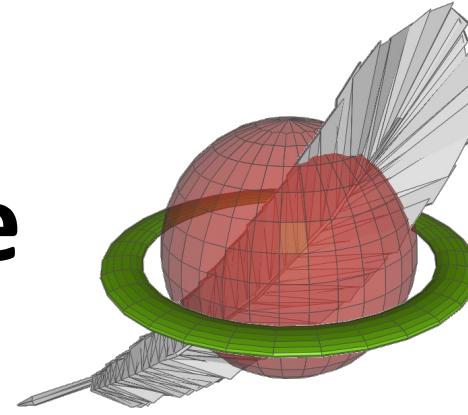
Solent Shipping Tracks (2015)

Recreational vessels
Passenger vessels
Cargo vessels





Spatialite



```
SELECT us_counties.geom , us_counties.id, COUNT(quakes.geom) AS total
FROM us_counties
JOIN quakes
  ON ST_CONTAINS(us_counties.geom, quakes.geom)
GROUP BY us_counties.id;
```

Contains / Intersects / DWithin / ...



Cloud Native Geospatial



Google Earth Engine

The screenshot shows the Google Earth Engine interface. At the top, there's a search bar and a menu bar with 'Scripts', 'Docs', and 'Assets'. Below the menu is a sidebar with navigation links like 'Owner (16)', 'Writer', 'Reader', 'Examples' (with sub-links for 'Image', 'Feature Collection', 'Charts', 'Arrays', 'Primitive', 'Cloud Masking', and specific datasets for Landsat and MODIS), and 'Sentinel2'. The main area has tabs for 'Sentinel2', 'Get Link', 'Save', 'Run', 'Reset', and 'Inspector', 'Console', 'Tasks'. The 'Console' tab contains a code editor with the following JavaScript:

```
1 // This example uses the Sentinel-2 QA band to cloud mask
2 // the collection. The Sentinel-2 cloud flags are less
3 // selective, so the collection is also pre-filtered by the
4 // CLOUDY_PIXEL_PERCENTAGE flag, to use only relatively
5 // cloud-free granules.
6
7 // Function to mask clouds using the Sentinel-2 QA band.
8 function maskS2clouds(image) {
9   var qa = image.select('QA60');
10
11   // Bits 10 and 11 are clouds and cirrus, respectively.
12   var cloudBitMask = 1 << 10;
13   var cirrusBitMask = 1 << 11;
14
15   // Both flags should be set to zero, indicating clear conditions.
16   var mask = qa.bitwiseAnd(cloudBitMask).eq(0).and(
17     qa.bitwiseAnd(cirrusBitMask).eq(0));
18
19   // Return the masked and scaled data, without the QA band.
20   return image.updateMask(mask).divide(10000)
21     .select("B.*")
22     .copyProperties(image, ["custom:time_start"]);
23 }
```

Below the code editor is a map viewer showing a satellite image of a coastal area. The bottom of the screen includes standard browser controls and a footer with copyright information.



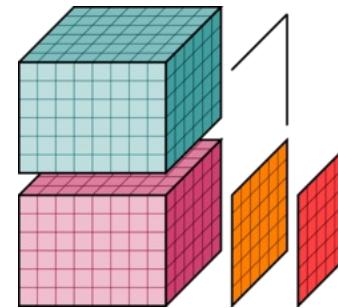
GeoParquet

Geospatial data in Parquet

Python libraries



GeoPandas



xarray

rasterstats

folium

rasterio

fiona

shapely



and lots more...



**What is the relationship
between house prices and
distance to schools?**

X & Y

House Prices

	ID	Price	Date	Postcode
0	{DBA933F9-D5BC-669D-E053-6B04A8C0AD56}	205000	2022-02-18 00:00	DL9 4RS
1	{DBA933F9-D5BE-669D-E053-6B04A8C0AD56}	220000	2022-02-14 00:00	YO12 7ND
2	{DBA933F9-D5C0-669D-E053-6B04A8C0AD56}	775000	2022-02-22 00:00	HG5 0TT
3	{DBA933F9-D5C6-669D-E053-6B04A8C0AD56}	450000	2022-03-04 00:00	YO31 1BU
4	{DBA933F9-D5CC-669D-E053-6B04A8C0AD56}	175000	2022-02-25 00:00	LA2 7EB
...
912332	{F16F63C5-D419-0491-E053-6C04A8C032ED}	150000	2022-01-17 00:00	NG31 9RH
912333	{F16F63C5-D41A-0491-E053-6C04A8C032ED}	320000	2022-01-28 00:00	PE9 3FJ
912334	{F16F63C5-D41B-0491-E053-6C04A8C032ED}	340000	2022-09-01 00:00	PE23 5RS
912335	{F16F63C5-D41C-0491-E053-6C04A8C032ED}	235000	2022-03-21 00:00	LN2 4ZJ
912336	{F16F63C5-D41D-0491-E053-6C04A8C032ED}	350000	2022-04-01 00:00	NG32 2JY

Postcodes

postcode	easting	northing
2123582	SO1 0AA	442004
2123583	SO1 0AB	441967
2123584	SO1 0AD	441909
2123585	SO1 0AE	441864
2123586	SO1 0AF	441853
...
2164040	SO97 4AT	444918
2164041	SO97 4AU	444918
2164042	SO97 4AW	444918
2164043	SO97 4AX	444918
2164044	SO97 4AY	444918

shapely
(Python vector
geospatial objects)

```
geometries = [shapely.geometry.Point(x, y)
              for x, y
              in zip(
                  postcodes.easting,
                  postcodes.northing)],
```

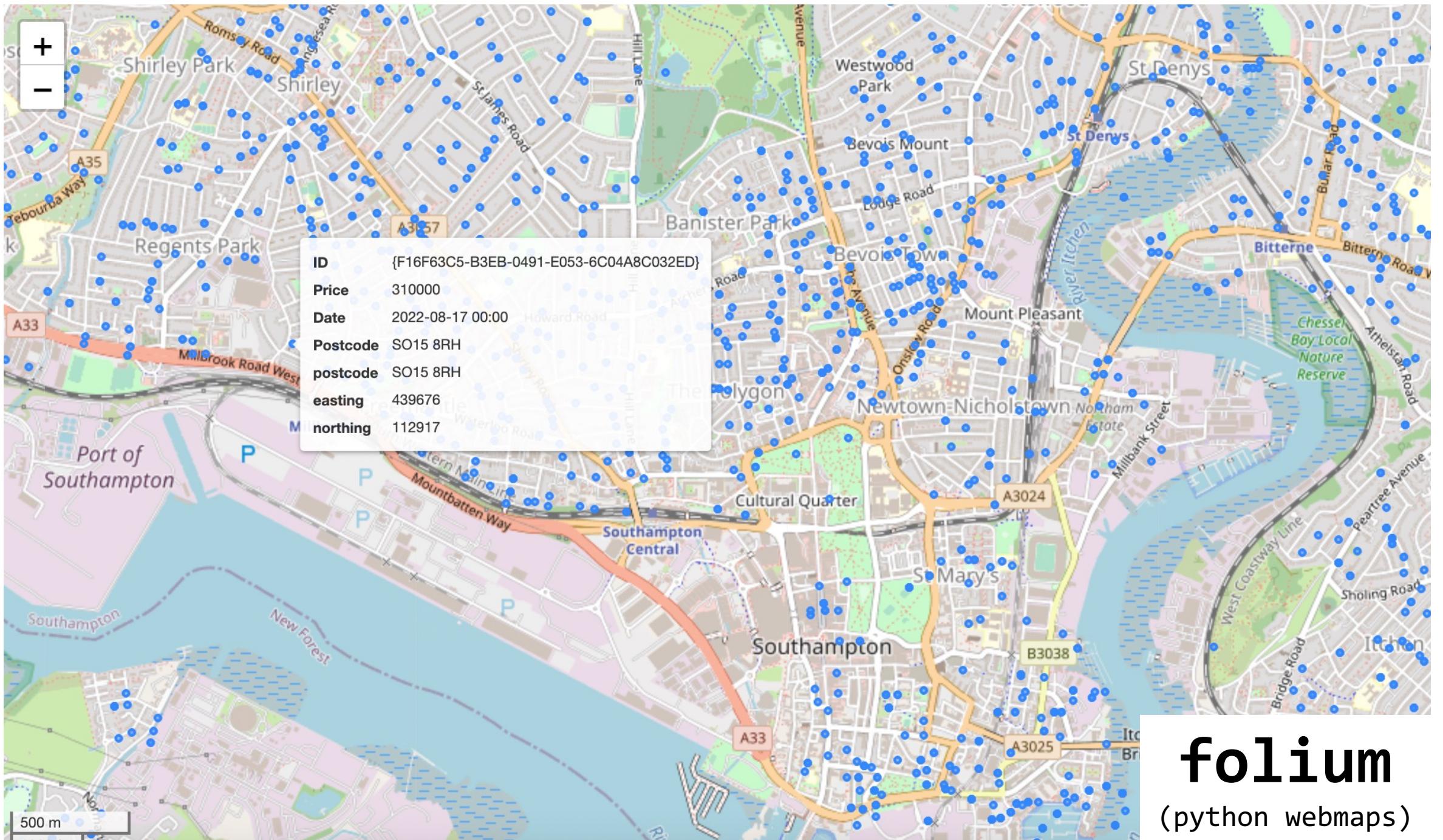
```
postcodes = gpd.GeoDataFrame(
    data=postcodes,
    geometry=geometries,
    crs=27700)
```

geopandas
(Pandas + Geo)

Index	Col1	Col2	Geometry
0	a	A	POINT(5, 9)
1	b	B	POINT(2, -3)
2	c	C	POINT(10, 7)

```
houseprices = pd.merge(  
    left=houseprices,  
    right=postcodes,  
    left_on='Postcode',  
    right_on='postcode',  
    how='inner'  
)
```

```
houseprices.explore()
```



folium
(python webmaps)

Schools

	URN	EstablishmentName	PhaseOfEducation (name)	Easting	Northing
0	100000	The Aldgate School	Primary	533498.0	181201.0
8	100008	Argyle Primary School	Primary	530238.0	182761.0
9	100009	West Hampstead Primary School	Primary	524888.0	185067.0
10	100010	Brecknock Primary School	Primary	529912.0	184835.0
11	100011	Brookfield Primary School	Primary	528706.0	186594.0
...
47950	150361	Heycroft Primary School	Primary	584687.0	189038.0
47953	150365	Field Place Infant School	Primary	511692.0	103634.0
47954	150366	Heckmondwike Primary School	Primary	422235.0	423602.0
47955	150367	Mallard Primary School	Primary	455577.0	400539.0
47956	150368	Cranleigh Church of England Primary School	Primary	505646.0	139372.0

Do the same as before...

```
joined = gpd.sjoin_nearest(houseprices,  
                           schools,  
                           distance_col='dist')
```

	Price	Postcode	dist
9410	320000	SO18 4JU	420.448570
10346	460000	SO40 3QS	794.062970
2965	115000	SO15 3SJ	396.339501
2562	185000	SO15 2NH	264.877330
1009	240000	SO19 9EH	554.582726
...
9740	481000	SO15 7QZ	497.800161
5495	270000	SO41 8YD	891.809957
1575	352000	SO19 8GB	601.658541
3780	371000	SO30 2FF	512.621693
7560	599950	SO41 0LL	1454.759430

```
count      14596.000000  
mean       586.641433  
std        453.603914  
min        0.000000  
25%        309.499999  
50%        486.834146  
75%        706.510439  
max        5307.664835  
Name: dist, dtype: float64
```

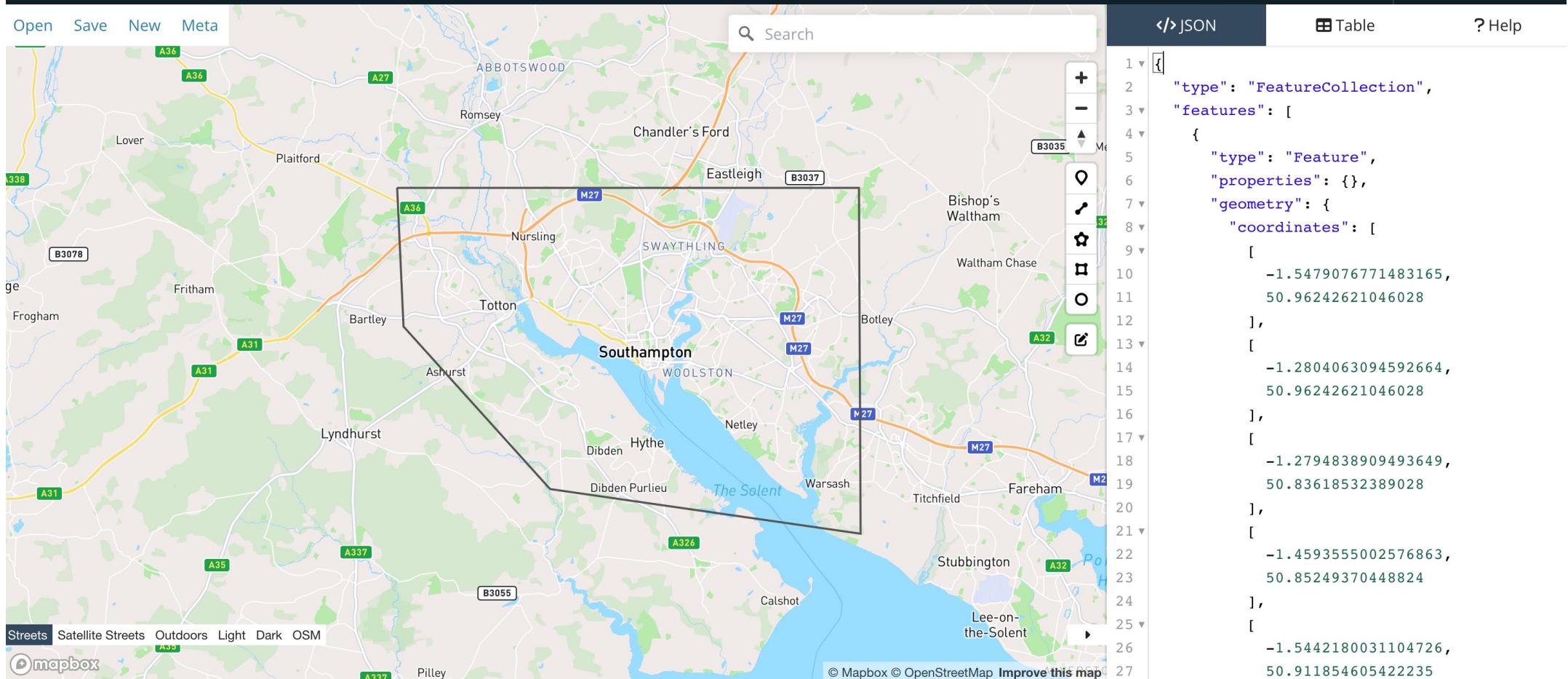
**How leafy are different
neighbourhoods of
Southampton?**





```
# Create the Dask cluster
cluster = GatewayCluster()
client = cluster.get_client()

cluster.adapt(minimum=4, maximum=24)
print(cluster.dashboard_link)
```



area of interest = <GEOJSON>

```
bbox = rasterio.features.bounds(area_of_interest)
```

rasterio

(python raster I/O)

```
stac = pystac_client.Client.open(  
    "https://planetarycomputer.microsoft.com/api/stac/v1",  
    modifier=planetary_computer.sign_inplace,  
)
```

```
search = stac.search(  
    bbox=bbox,  
    datetime="2022-01-01/2023-01-01",  
    collections=["sentinel-2-l2a"],  
    query={"eo:cloud_cover": {"lt": 10}},  
)
```

```
items = search.item_collection()
```

37 items
(individual satellite images from different times)



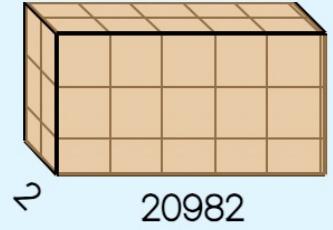
STAC



pystac
(python STAC
interface)

Near Infra-red and Red bands

```
data = stackstac.stack(  
    items,  
    assets=["B08", "B04"],  
    chunksizes=4096,  
    resolution=10,  
)
```

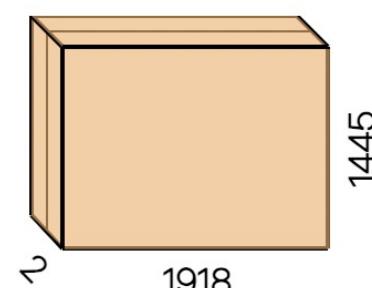
	Array	Chunk	
Bytes	127.02 GiB	128.00 MiB	 1
Shape	(37, 2, 10980, 20982)	(1, 1, 4096, 4096)	37  20982 10980
Dask graph	1332 chunks in 5 graph layers		
Data type	float64 numpy.ndarray		

xarray & stackstac

(labelled multi-dim data & combining STAC items)

```
data = stackstac.stack(  
    items,  
    assets=["B08", "B04"],  
    chunksizes=4096,  
    resolution=10,  
    bounds_latlon=bbox  
)
```

	Array	Chunk
Bytes	1.53 GiB	21.14 MiB
Shape	(37, 2, 1445, 1918)	(1, 1, 1445, 1918)
Dask graph	74 chunks in 5 graph layers	
Data type	float64 numpy.ndarray	



```
median = data.median(dim="time").compute()
```

Small: 15s

Large: 3 minutes

```
nir = median.sel(band='nir')
```

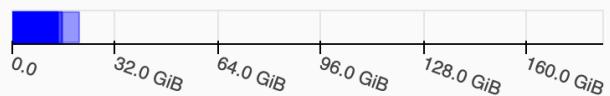
```
red = median.sel(band='red')
```

```
ndvi = (nir - red)/(nir + red)
```

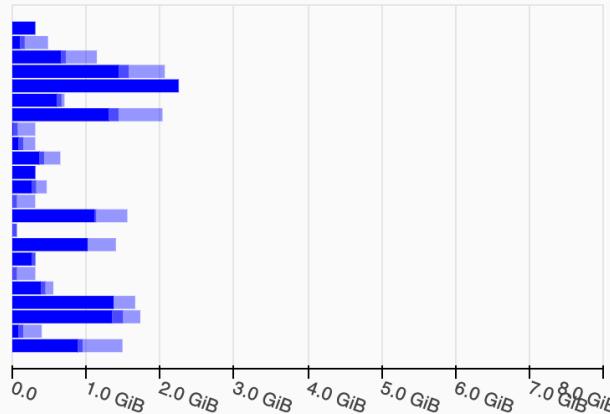
```
ndvi.rio.to_raster("S2_Median_2022_AOI.tif")
```

[Status](#) [Workers](#) [Tasks](#) [System](#)[Profile](#)[Graph](#)[Groups](#)[Info](#)[More...](#)[Documentation](#)

Bytes stored: 20.85 GiB

[?](#) [::](#)

Bytes stored per worker

[?](#) [::](#)[Processing](#) [CPU](#) [Occupancy](#) [Data Transfer](#)

Task Stream

[?](#) [::](#)[?](#) <a

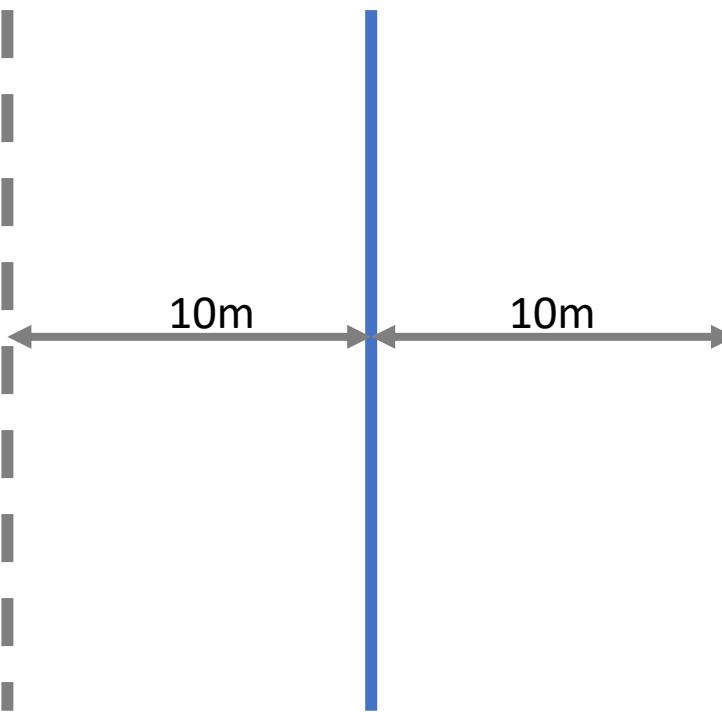


```
roads = osmnx.graph_from_point(  
    (50.91404, -1.41640),  
    dist=10000,  
    network_type="drive")
```

```
osmnx.save_graph_geopackage(roads, "SotonRoads.gpkg")
```



```
roads.geometry = roads.geometry.buffer(10)
```

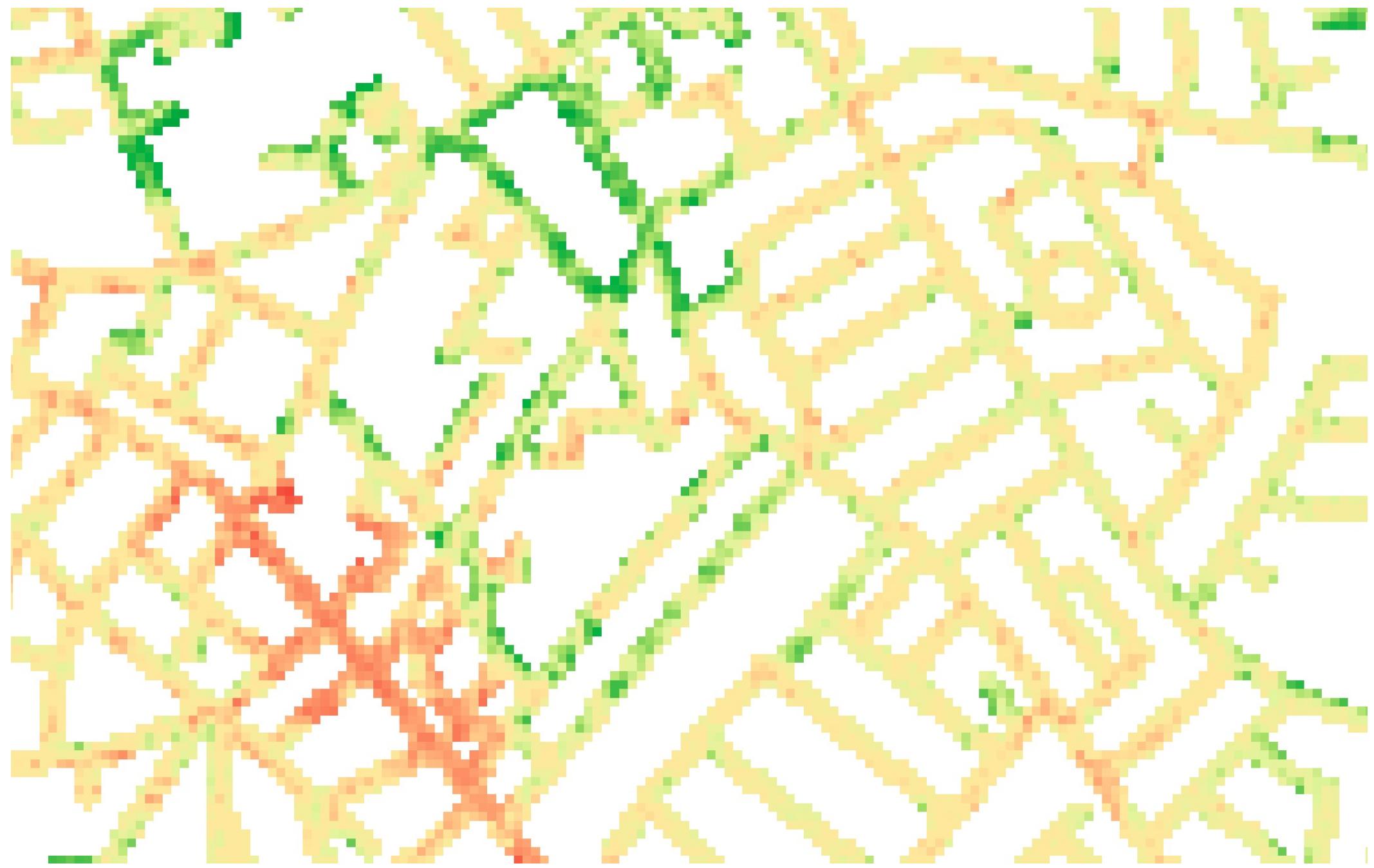




```
with rio.open("AOI_Roads.tif") as f:  
    roads_raster = f.read(1)  
    meta = f.meta  
  
with rio.open("S2_Median_2022_AOI.tif") as f:  
    ndvi_raster = f.read(1)  
  
masked = roads_raster * ndvi_raster  
  
with rio.open("Masked_NDVI.tif", 'w', **meta) as f:  
    f.write(masked, 1)
```

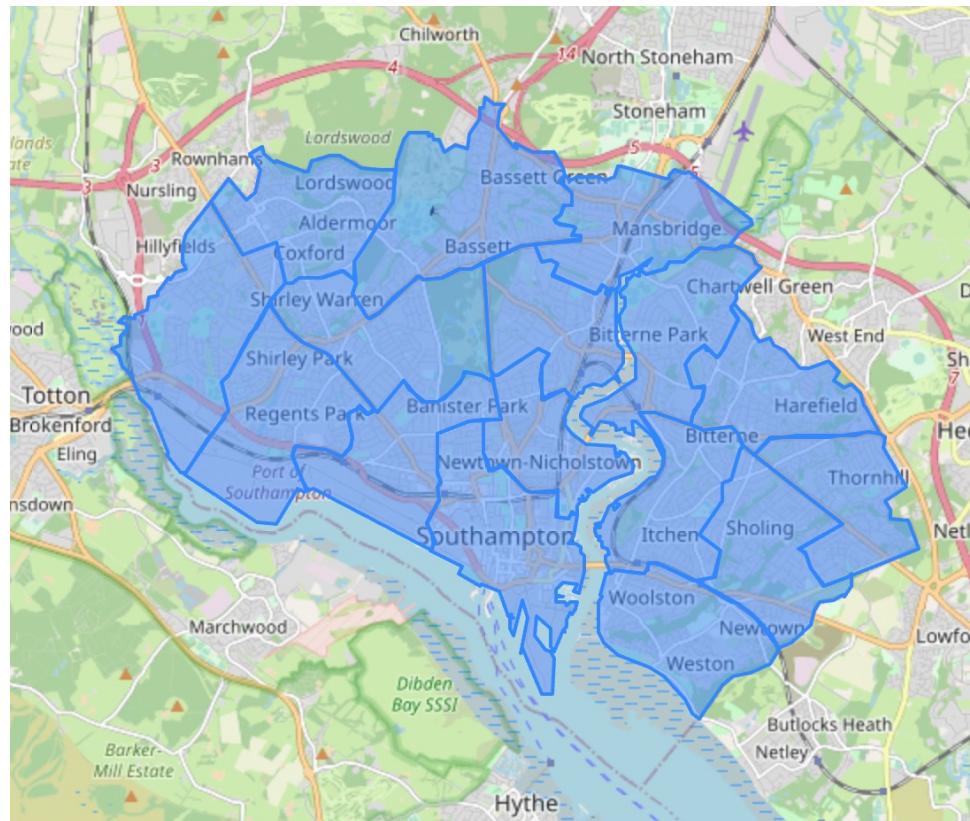
rasterio
(python raster I/O)





```
wards = gpd.read_file("SotonWards.shp")
```

```
wards = wards.to_crs(meta['crs'])
```



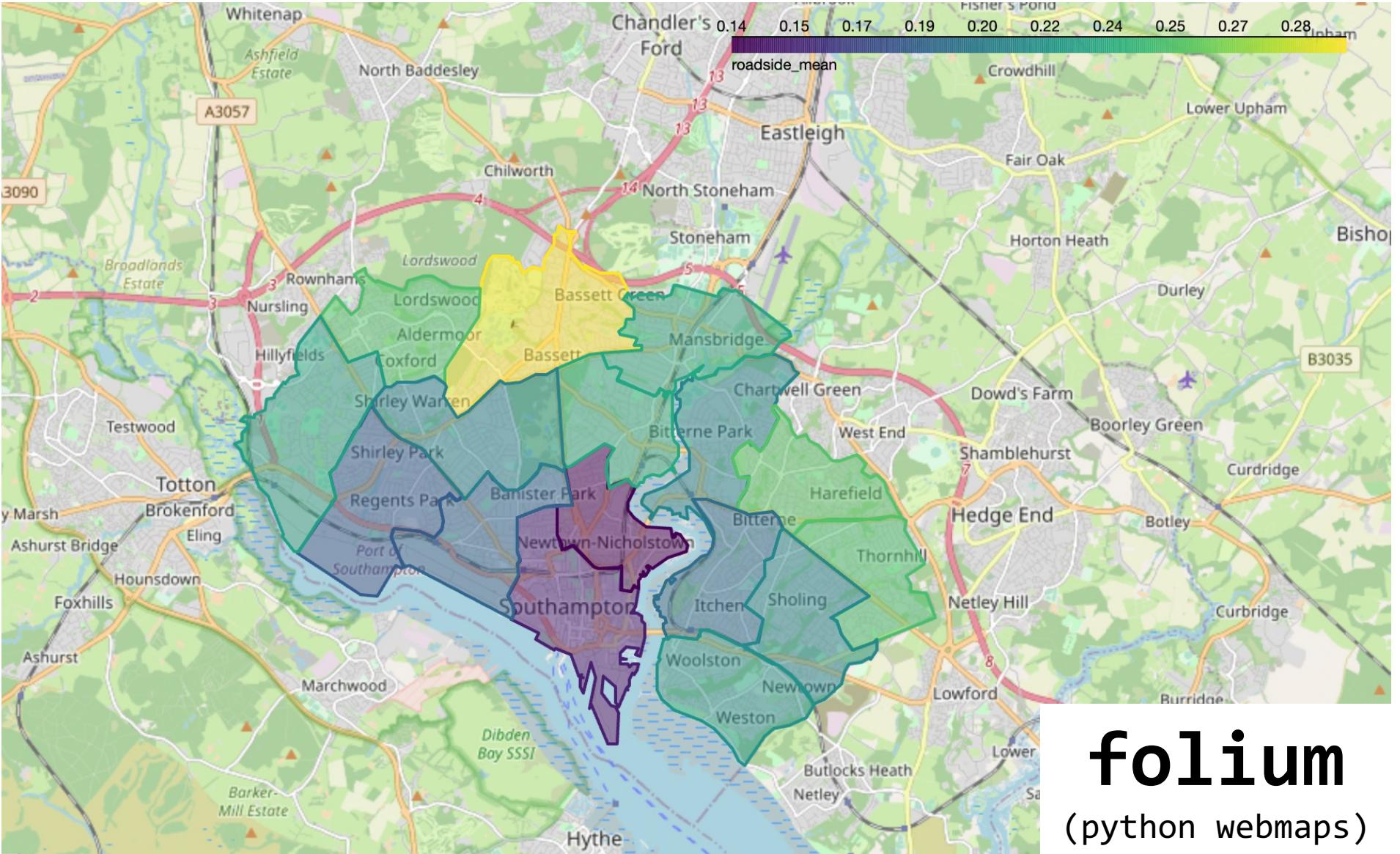
geopandas
(Pandas + Geo)

```
roadside_stats = zonal_stats(  
    vectors=wards.geometry,  
    raster='Masked_NDVI.tif',  
    stats='mean',  
    nodata=0,  
    prefix="roadside_"  
)  
  
wards = wards.join(pd.DataFrame(roadside_stats),  
    how='left')
```

rasterstats

(python zonal statistics)

```
wards.explore("roadside_mean")
```



	wd17cd	wd17nm	roadside_mean	overall_mean
0	E05002455	Bargate	0.151769	0.152316
1	E05002456	Bassett	0.297117	0.383503
2	E05002457	Bevois	0.138306	0.148619
3	E05002458	Bitterne	0.250498	0.304511
4	E05002459	Bitterne Park	0.212127	0.312092
5	E05002460	Coxford	0.252240	0.323646
6	E05002461	Freemantle	0.190042	0.179213
7	E05002462	Harefield	0.254662	0.314489
8	E05002463	Millbrook	0.183902	0.170176
9	E05002464	Peartree	0.195554	0.263064
10	E05002465	Portswood	0.235529	0.306308
11	E05002466	Redbridge	0.229053	0.264243
12	E05002467	Shirley	0.209484	0.327046
13	E05002468	Sholing	0.214263	0.300729
14	E05002469	Swaythling	0.234186	0.326982
15	E05002470	Woolston	0.220839	0.314683

...?

Any questions?

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