End-to-End Analysis of Large 3D Geospatial Datasets in RAPIDS

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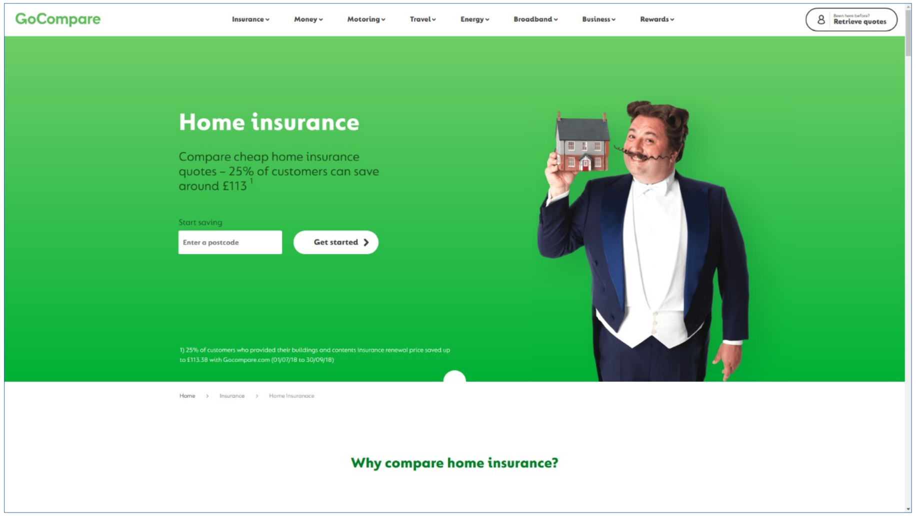
What do we mean by ‘End-to-End’ Analysis?

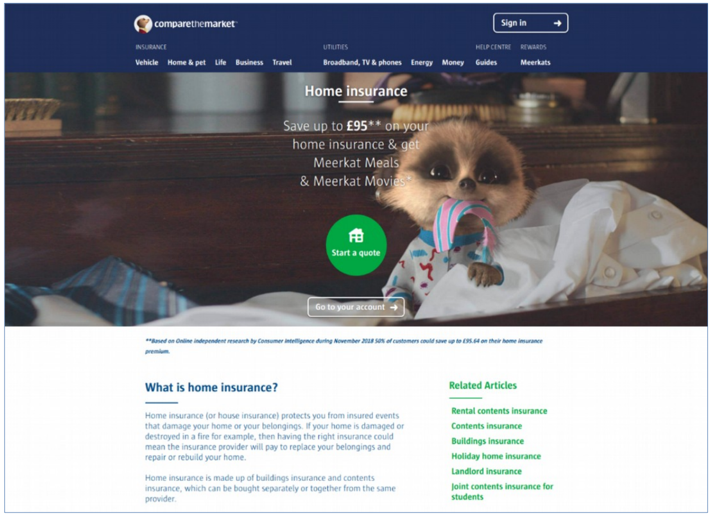
- Processing of raw data sources & ETL:
  - Data calibration
  - Conversion and standardisation
  - Load to repositories
- Combining data sources for:
  - Augmentation to enhance data
  - Attach labels to training data
- Train models
- Infer models
- Interpret and deploy results of inference
- Potentially multistage process

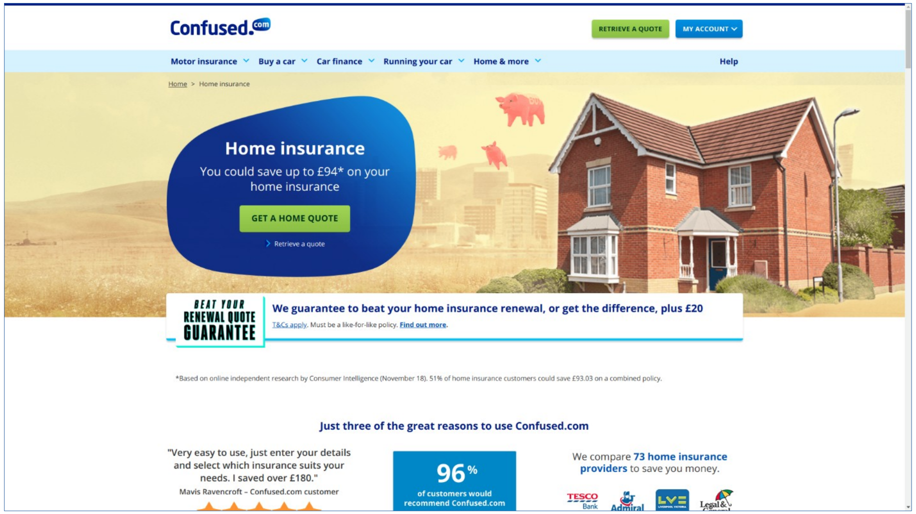
“AI is a disruptive technology”

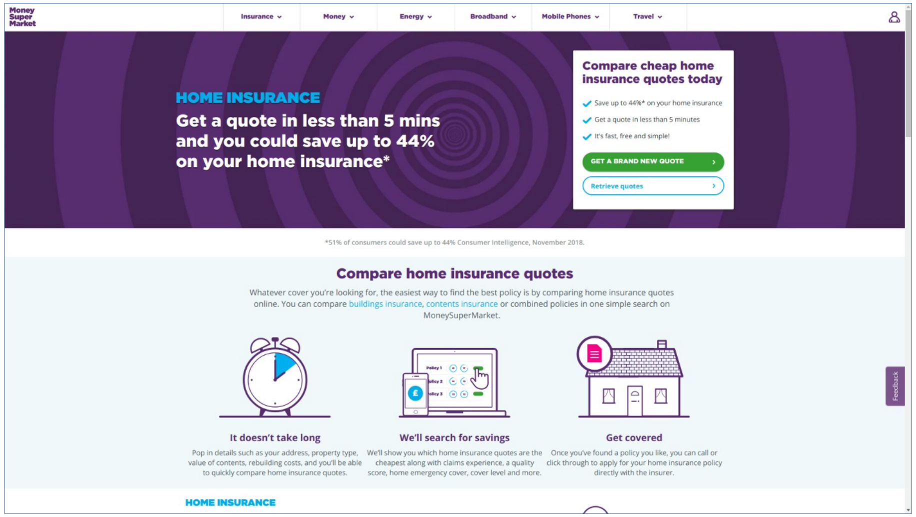
AI is also a response to other disruptive technology.

Disruption of Property Insurance Market by Price Comparison websites









The Challenge for Insurers

- Customers will not complete lengthy application forms online
- Difficult for insurer to ask customer for further information
- Customers expect instant quotations
- Potential financial loss from underwriting high risk propoerties
- Potential loss of low risk customer to a competitor
- Traditional underwriting methods no longer work

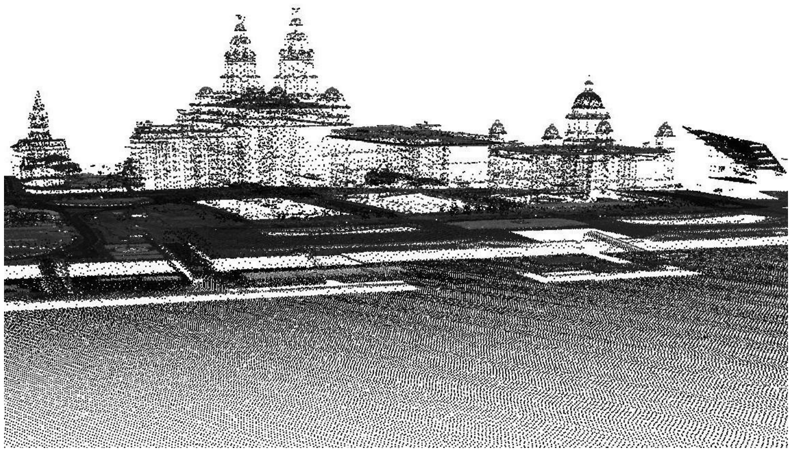
The Response

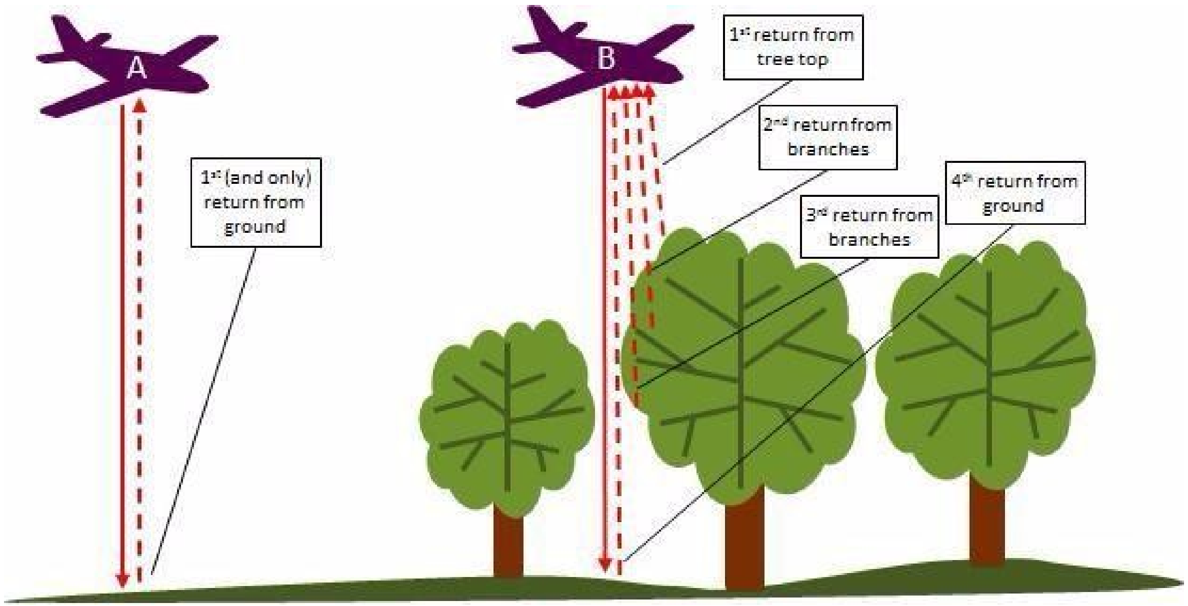
- Use AI to classify property attributes and detect risks
- Use alternative data sources to assess underwriting risk
- Minimise application form by pre-populating answers
- Move away from area based risk analysis to individual properties
- Take a 3-dimensional view of a property and its immediate environment

Geospatial Data – Data Sources

- Traditional data sources
  - Census and National Statistics
  - Mapping data as vectors and rasters
- New Data Sources
  - Satellite & Aerial Imagery
  - LiDAR data from aircraft and vehicles
  - Sensor data, e.g. SAR
  - Social Media
  - Cellphone Apps
  - Government Open Data
  - Crime location data
  - Field surveying

LiDAR Data





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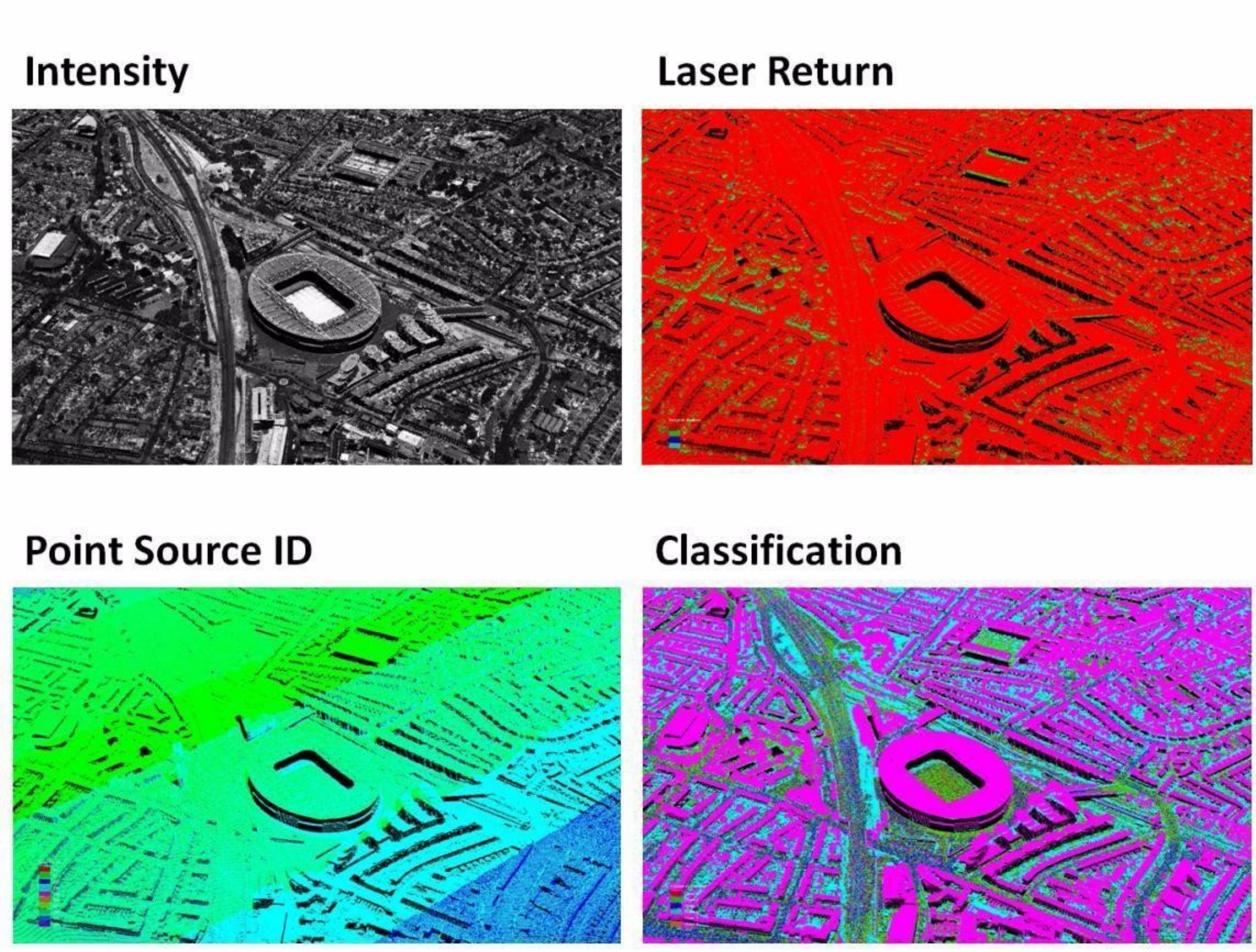
LiDAR Point Cloud Data



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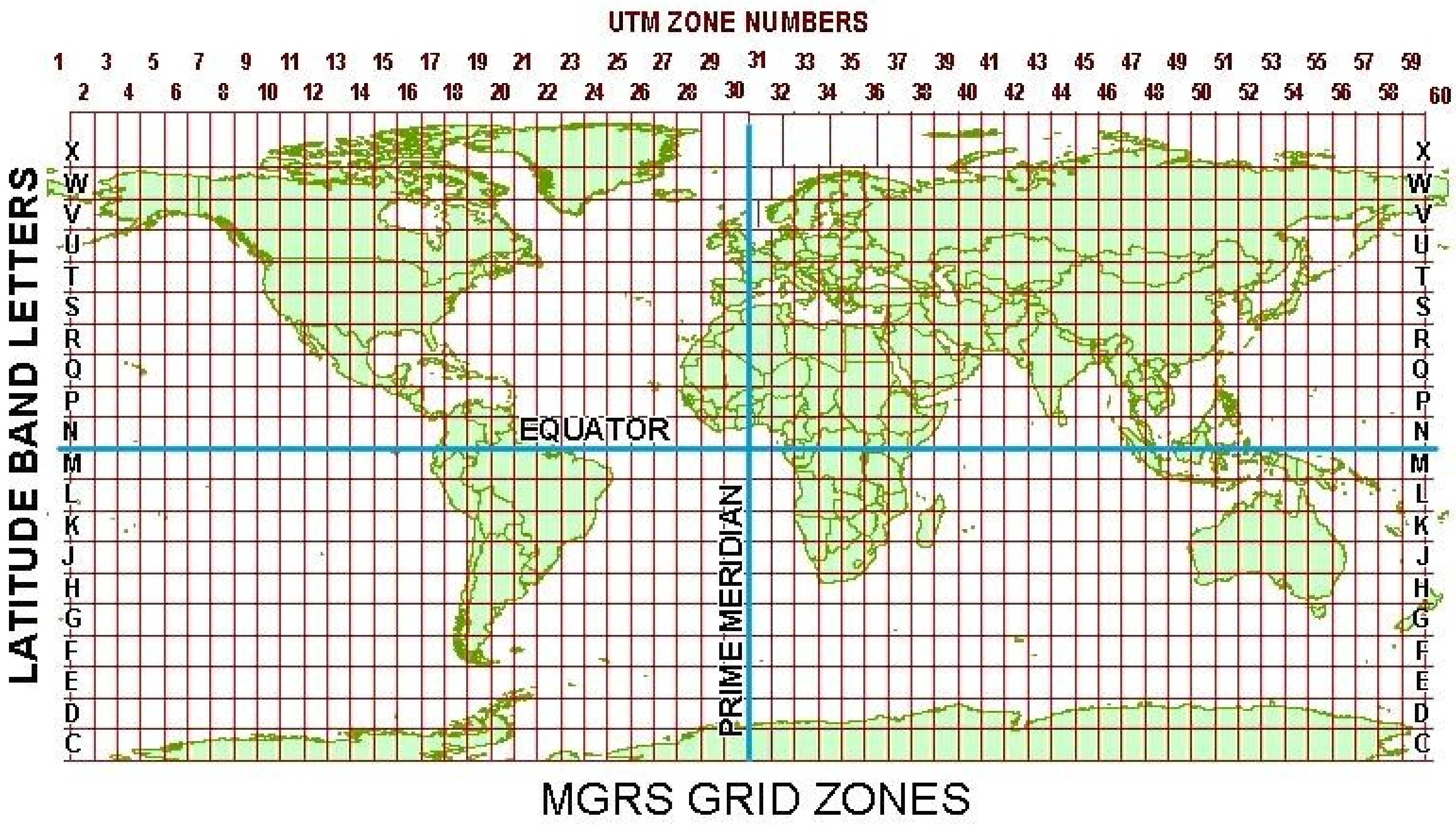
Coordinate Systems



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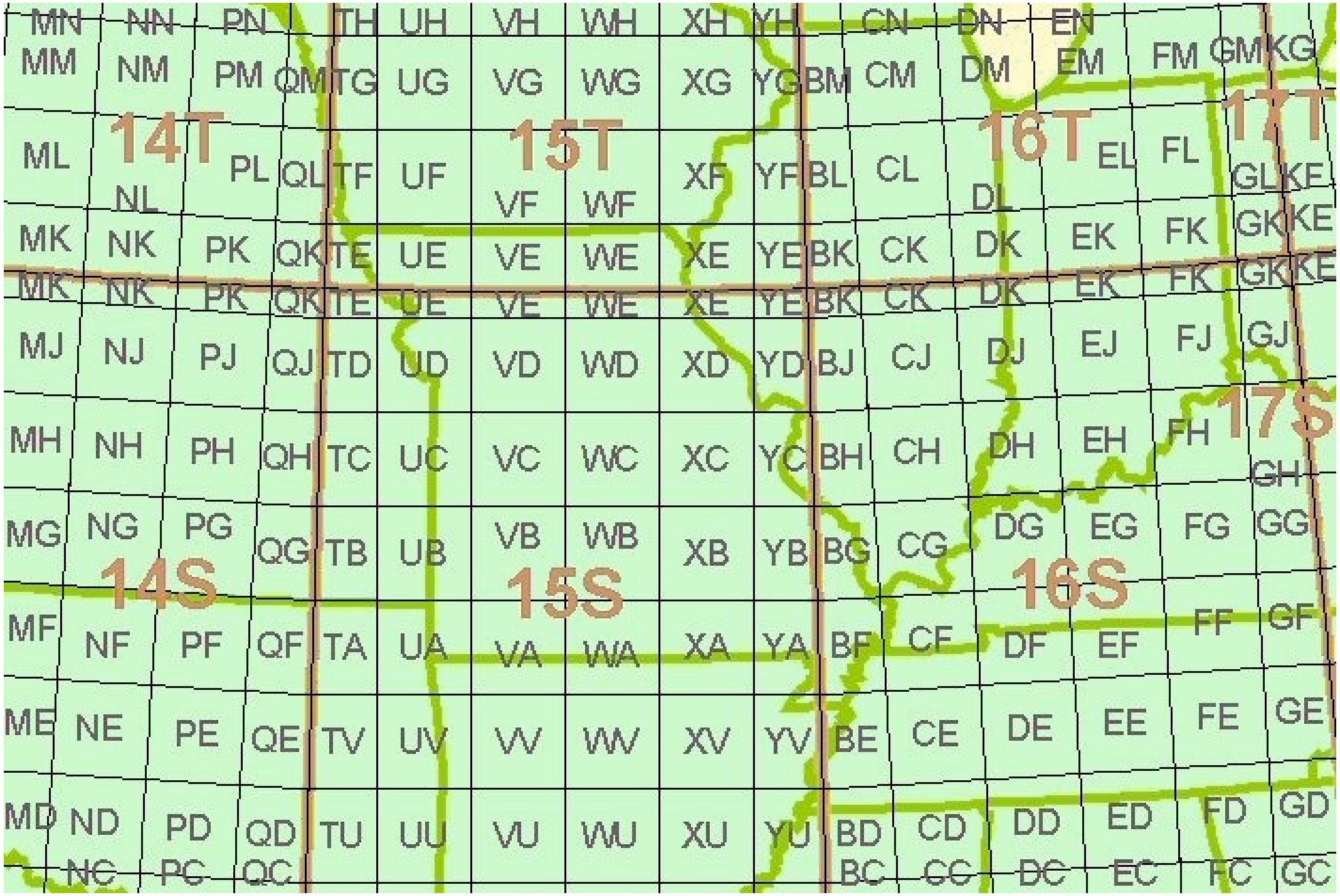
Coordinate Systems



Open Data Image US NGA Office of Geomatics

Coordinate Systems

Research – Satellite imagery

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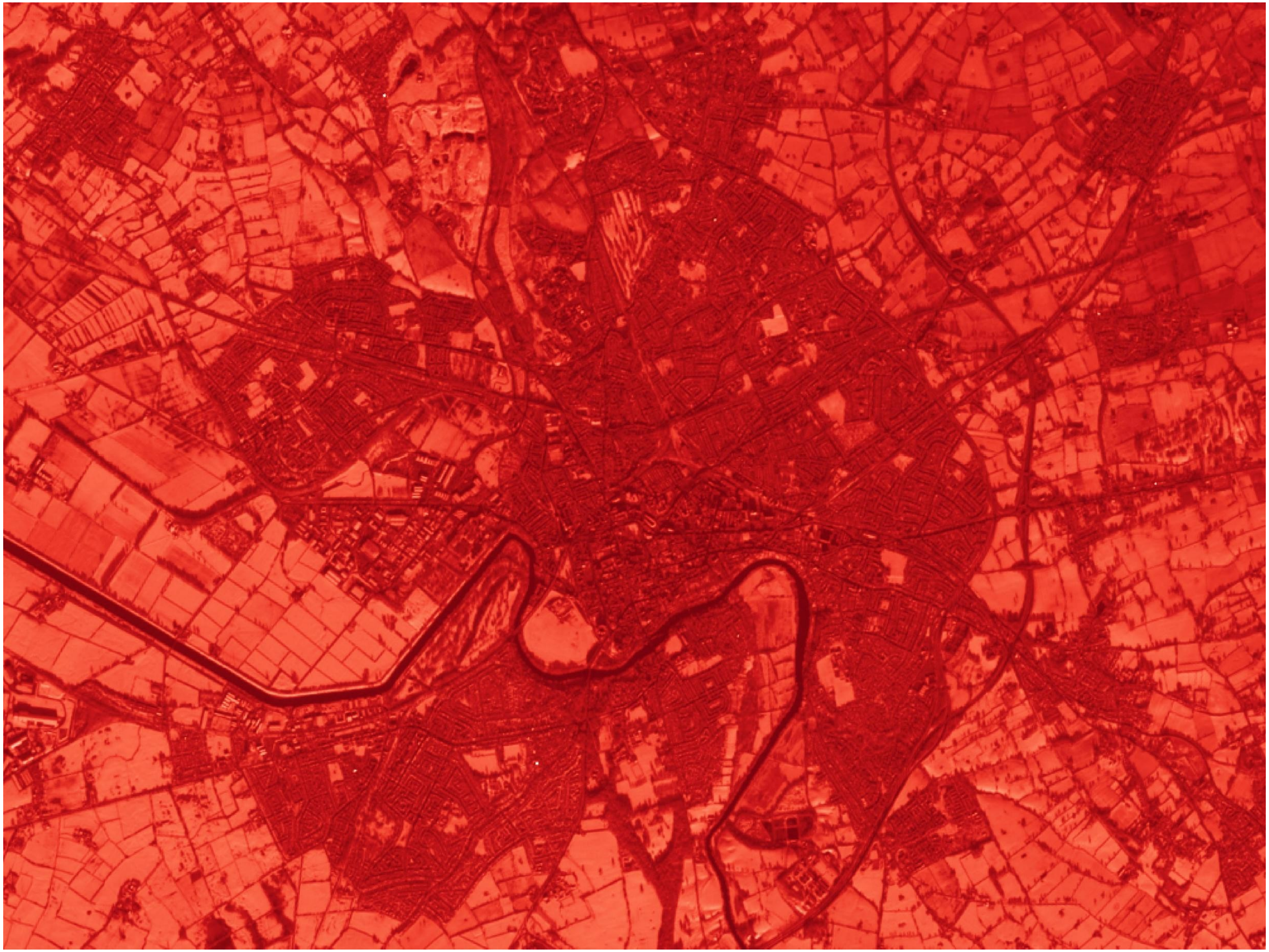
Satellite imagery



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Autoencoder Upscaled Satellite imagery

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Single Aperture Radar (SAR) Data

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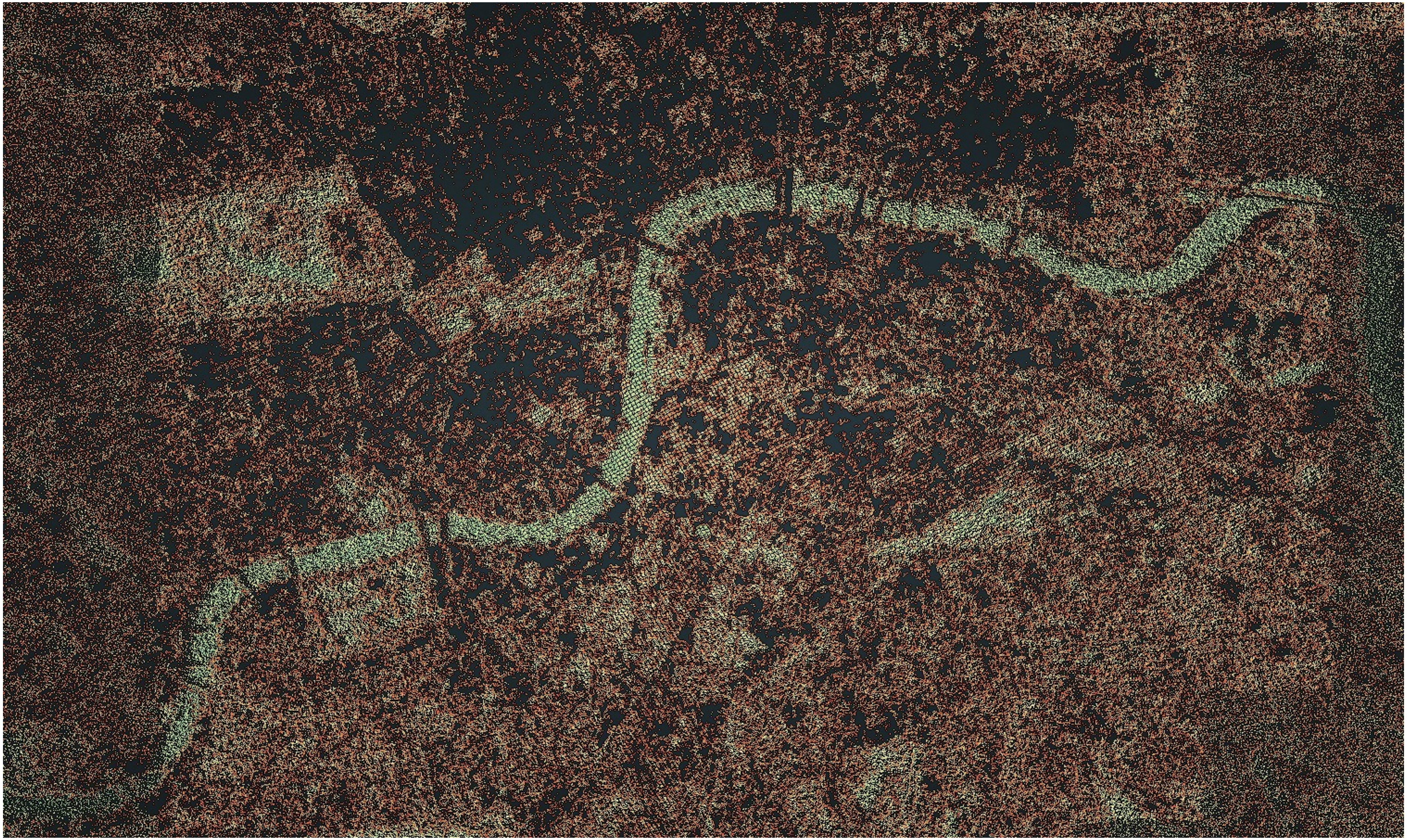
Single Aperture Radar (SAR) Data



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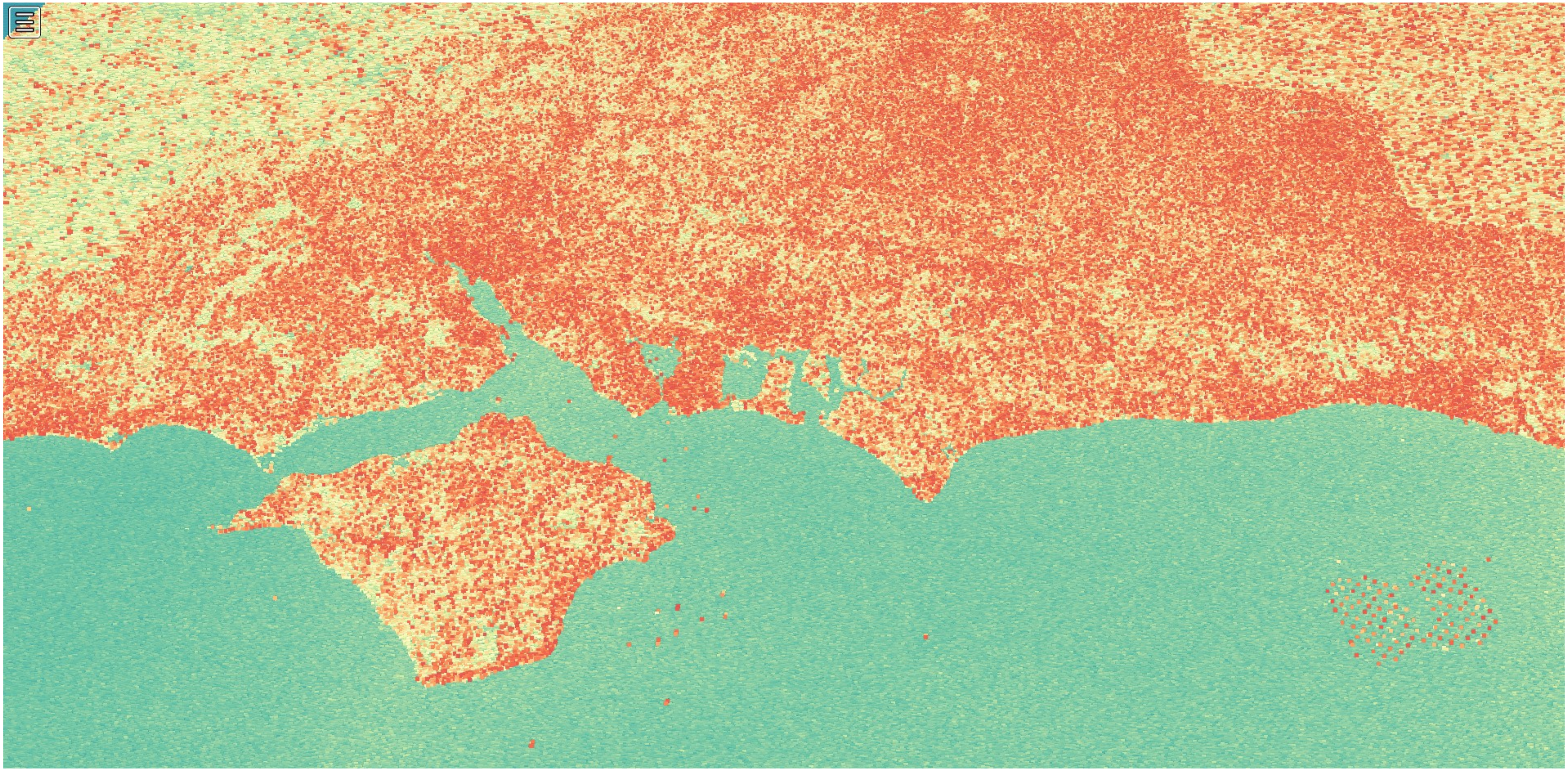
Single Aperture Radar (SAR) Data



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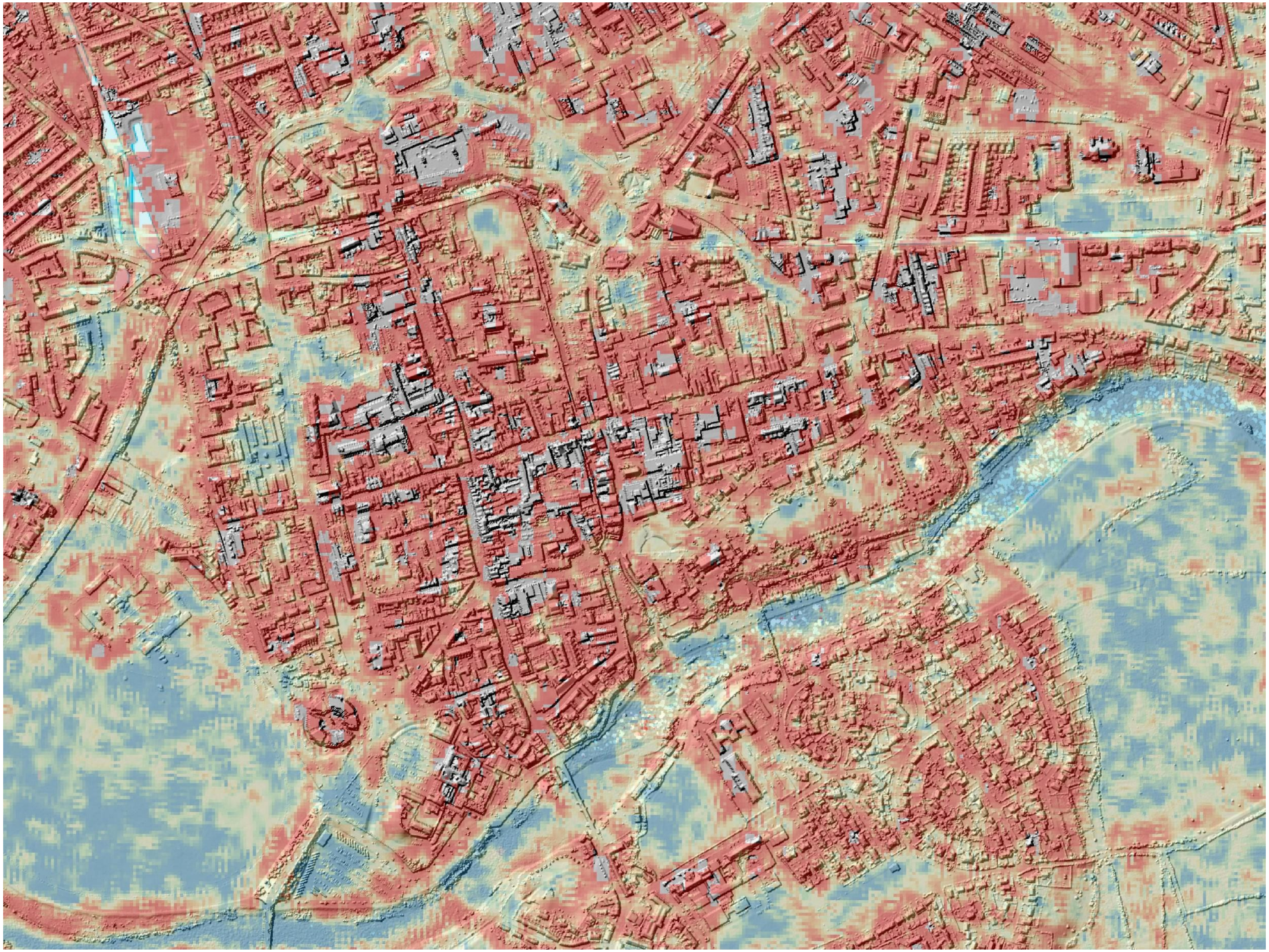
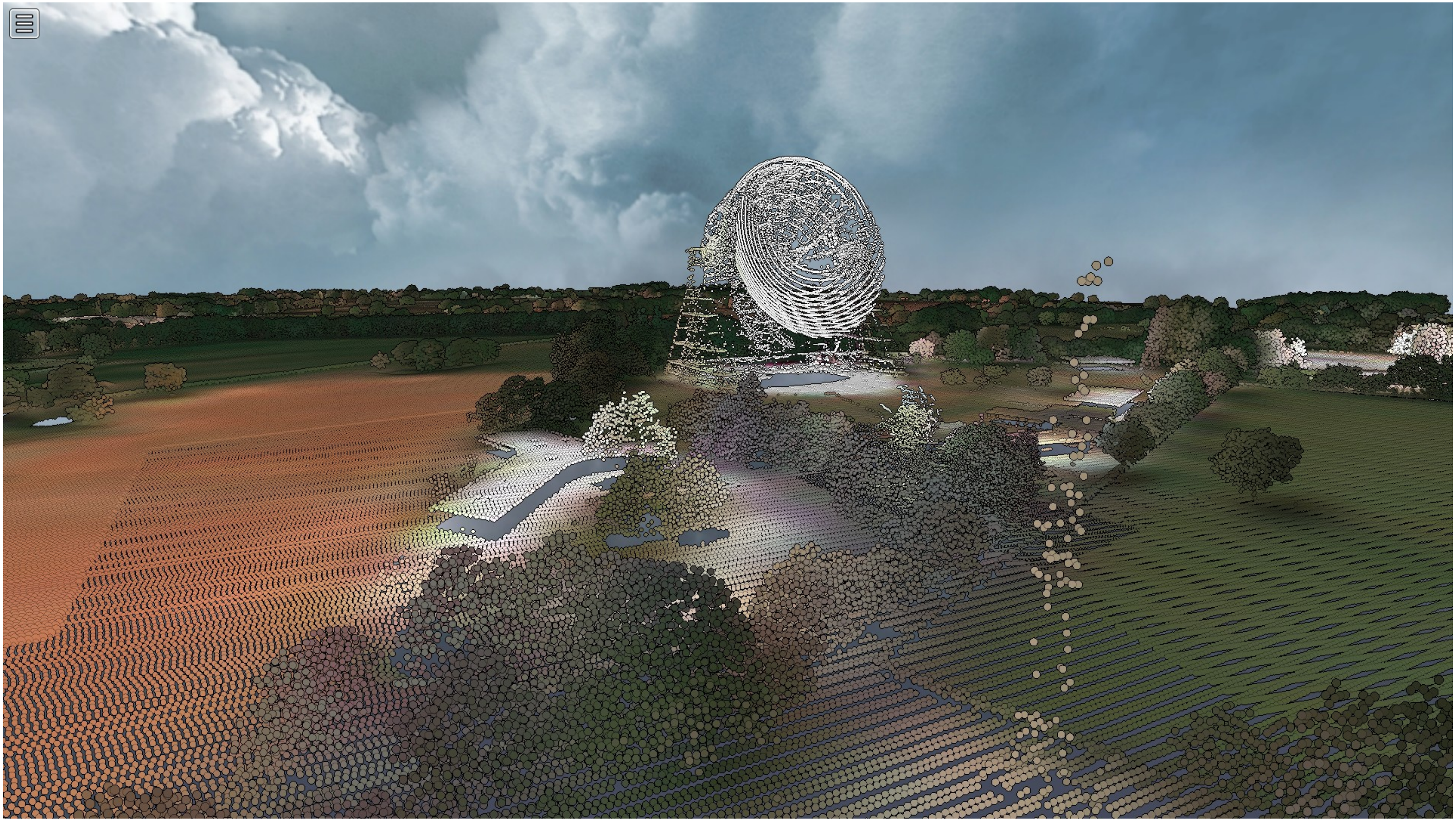
SAR and LiDAR Combined



Open Data Derived Image ESA EU Copernicus Sentinel Mission / UK Environment Agency

Satellite Imagery and LiDAR Combined



Open Data Derived Image ESA EU Copernicus Sentinel Mission / UK Environment Agency

Satellite Imagery and LiDAR Combined

Open Data Derived Image ESA EU Copernicus Sentinel Mission / USGS

Satellite Imagery and LiDAR Combined in RAPIDS

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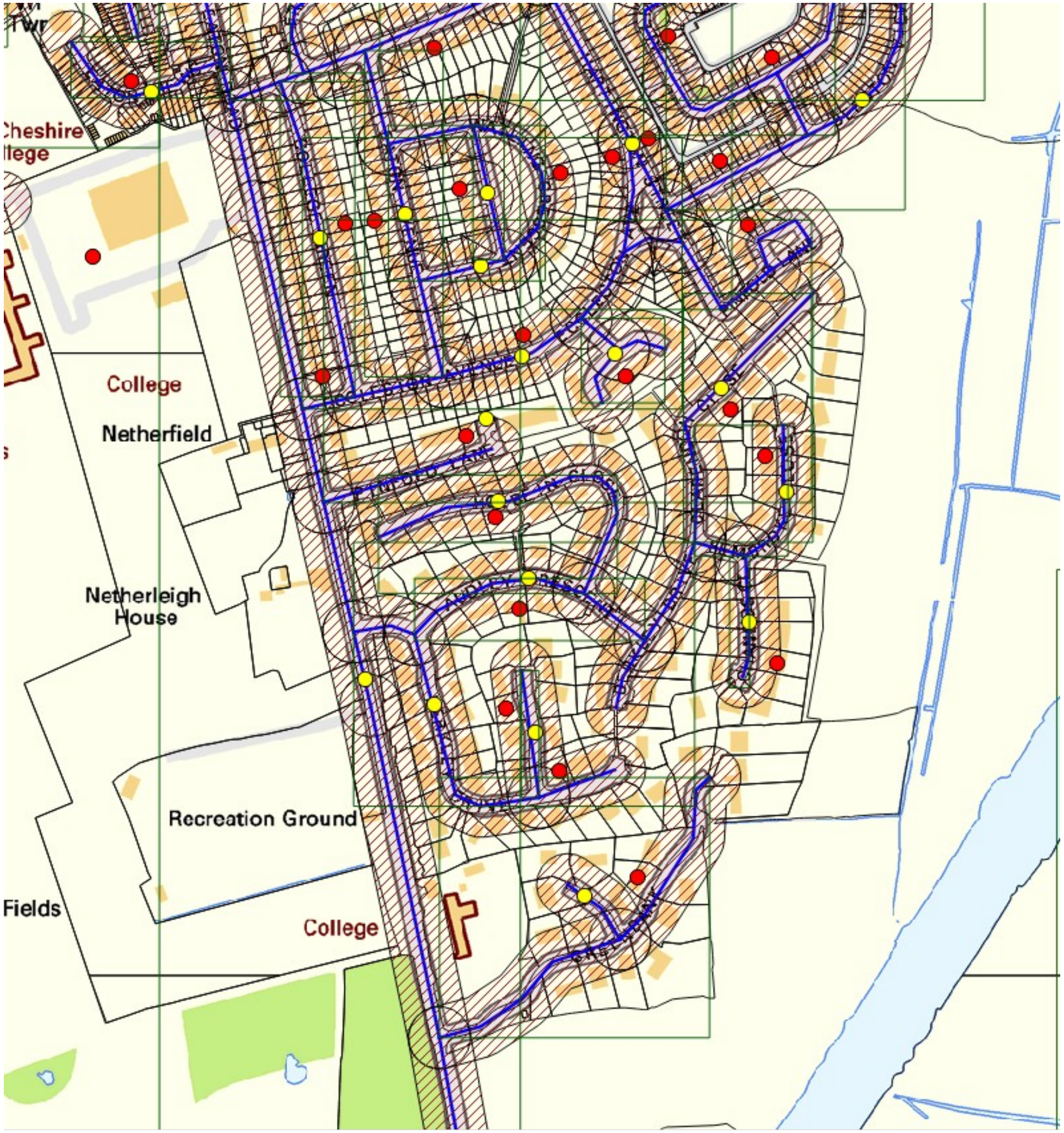
spatia_rapids_color_demo.i

Code — Python 3

```
[1]: import cudf
     from cudf.dataframe import DataFrame
     import numpy as np
     import math
     import pandas as pd
     from numba import cuda

[2]: names = ['Point_ID','ETRS89_Easting','ETRS89_Northing','ETRS89_OSGB36_EShift','ETRS89_OSGB36_NShift','ETRS89_ODN_HeightShift','Height_Datum_Flag']

[3]: dtypes = ['int64','int64','int64','float64','float64','float64','int64']

[4]: filename = '/data/ostn/OSTN15_OSGM15_DataFile.txt'

[5]: from spatia_rapids import transformations

[6]: %%time
     shift_dic = transformations.load_shifts(filename,names,dtypes,'ETRS89_Easting','ETRS89_Northing','ETRS89_OSGB36_EShift','ETRS89_OSGB36_NShift','ETRS89_ODN_HeightShift')

     CPU times: user 87.3 ms, sys: 144 ms, total: 231 ms
     Wall time: 287 ms

[7]: import laspy as lp

[8]: %%time
     lasfile = '/data/pointcloud/liv/Liverpool_Centre.las'
     inFile = lp.file.File(lasfile, mode = "r")
     print(inFile.header.min,inFile.header.max)
     print(inFile.header.get_dataformatid())

     [334000.0, 390000.0, -0.8] [335999.99, 391999.99, 139.73]
     1
     CPU times: user 2.4 ms, sys: 625 µs, total: 3.02 ms
     Wall time: 2.35 ms

[9]: origin = 496000,5913000

[10]: %%time
      point_zdf = DataFrame()
      point_zdf['x'] = inFile.x
      point_zdf['y'] = inFile.y
      point_zdf['z'] = inFile.z
      #point_zdf['n'] = inFile.num_returns[inFile.num_returns==4]

      CPU times: user 1.91 s, sys: 189 ms, total: 2.1 s
      Wall time: 911 ms

[11]: print(point_zdf)

                         x                  y     z
       0          334011.79          390001.13 -0.71
       1          334011.94          390001.26 -0.54
       2          334012.12          390001.42 -0.38
       3          334012.27          390001.54 -0.27
       4 334012.41000000003 390001.66000000003 -0.16
       5          334012.36          390001.68 -0.13
       6          334012.21          390001.55 -0.27
```

Demonstration LiDAR Processing in RAPIDS

Property Attribute Classification in LiDAR



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Property Attribute Classification in LiDAR

LMK_KEY	BUILDING_REFERENCE_NUMBER	ADDRESS1	POSTCODE	PROPERTY_TYPE	BUILT_FORM
337587020090803100814	1966065668	32, Commondale Drive	TS25 2AN	House	Semi-Detached
673146320110905030952	7035879868	6, Miers Avenue	TS24 9HL	House	Mid-Terrace
733339620120120100139	5400804968	13 Poppy Close	TS26 0YX	House	Detached
547496820100930060918	9899530868	30, Laurel Gardens	TS25 4NZ	Flat	*NULL*
279303520090512090529	3210151668	53, Mariners Point	TS24 0FB	House	End-Terrace
100721020080509110549	9252586468	3, Elderslie Walk	TS25 4BP	Flat	Detached
681296520110922070956	2432530968	72, Ridlington Way	TS24 9QB	House	Semi-Detached
586920720110211120216	8555633868	14, Fernville Close	TS25 4LN	Bungalow	Semi-Detached
690270320111018041032	4393990968	6, Barnard Grove	TS24 9SD	House	Semi-Detached
422193520100118040117	0699551768	15, Salisbury Place	TS26 0XJ	Flat	Mid-Terrace
554540820101019111021	1688680868	11, Rockpool Close	TS24 0TJ	House	Semi-Detached
1138040420140509020507	5633903278	5, Celandine Gardens	TS26 0ZJ	House	End-Terrace
74140820080215050255	0740894468	26, Burn Valley Road	TS26 9BS	House	End-Terrace
198577720090105050109	0223755568	22, Brimston Close	TS26 0QA	Bungalow	Detached
720599120111105121136	2968313968	76, Murray Street	TS26 8RQ	Flat	*NULL*
558106120101027081043	5364011868	77, Lime Crescent	TS24 8JW	House	Mid-Terrace
656450520110719030722	9025958868	6, Phoenix Close	TS25 3DH	Flat	*NULL*
639986220110609060653	5171247868	28, Lister Street	TS24 7QF	House	End-Terrace
512747420100713100718	5502987768	33, Commondale Drive	TS25 2AN	Bungalow	Semi-Detached
1467410320160801010848	2709636478	44, Northgate	TS24 0LJ	House	Mid-Terrace
616461120110412120413	0480475868	263a Raby Road	TS24 8HF	Flat	Mid-Terrace
1445200120160519100511	3080974478	50, Penarth Walk	TS26 0TW	Bungalow	Mid-Terrace
180353420081114091105	0074234568	48, Irvine Road	TS25 3HS	House	End-Terrace
948719520160915090924	4897769078	7, Regent Square	TS24 0QW	House	Mid-Terrace
190254220081125081148	9792684568	75, Challoner Road	TS24 8HY	House	Semi-Detached

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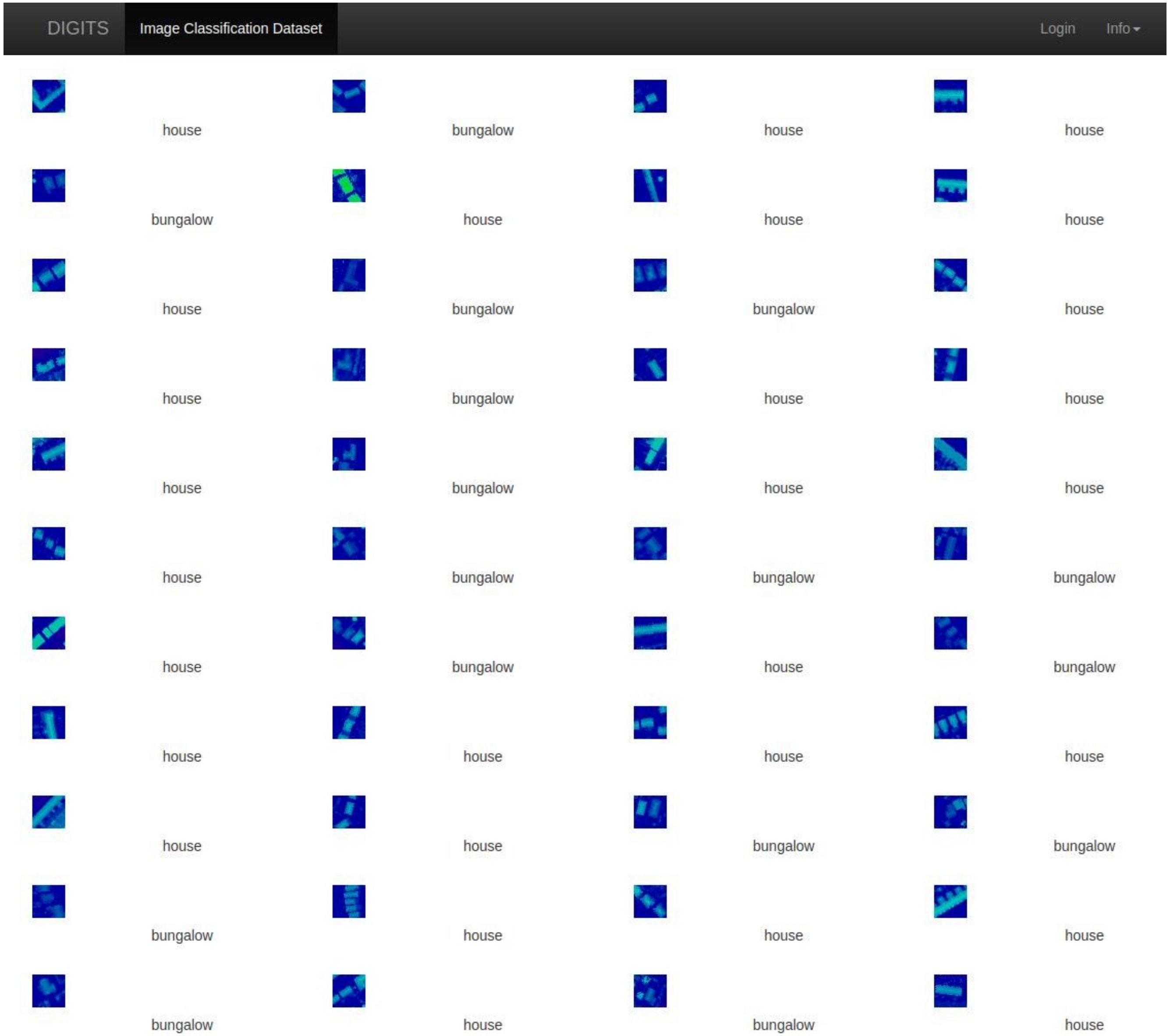
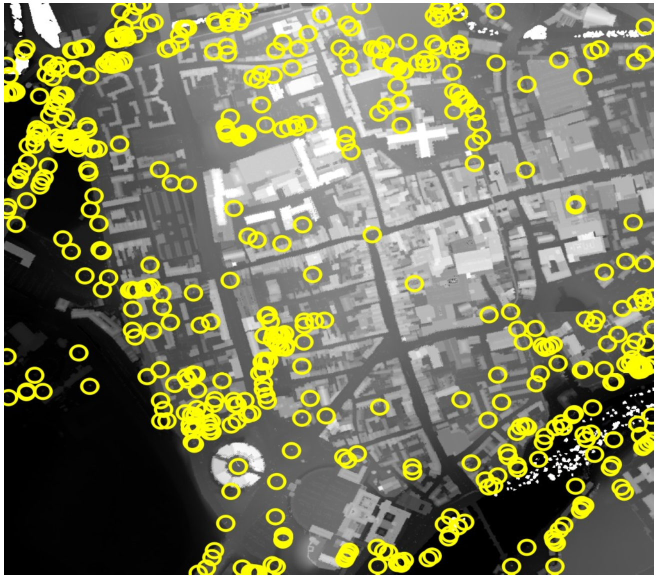
Property Attribute Classification in LiDAR

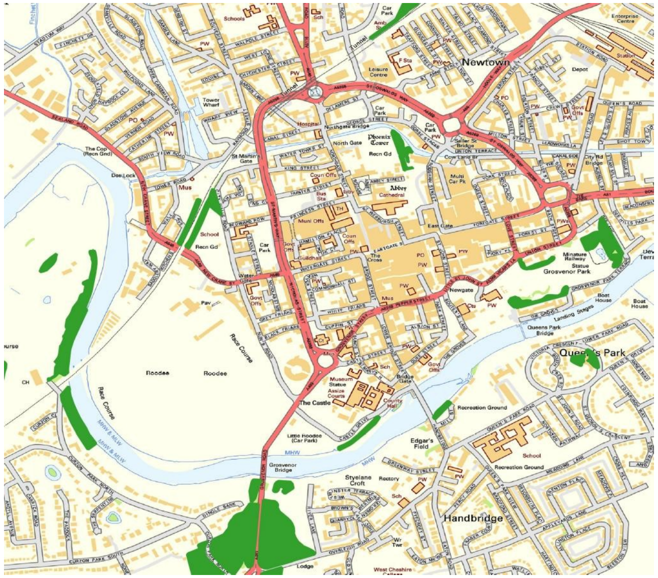


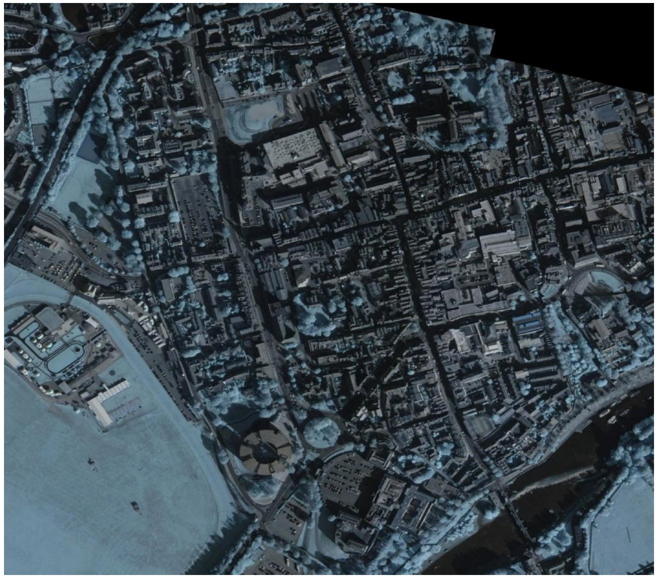
Open Data Derived Image UK Environment Agency

Demonstration Deep Learning

Deep Learning – Object Detection in LiDAR







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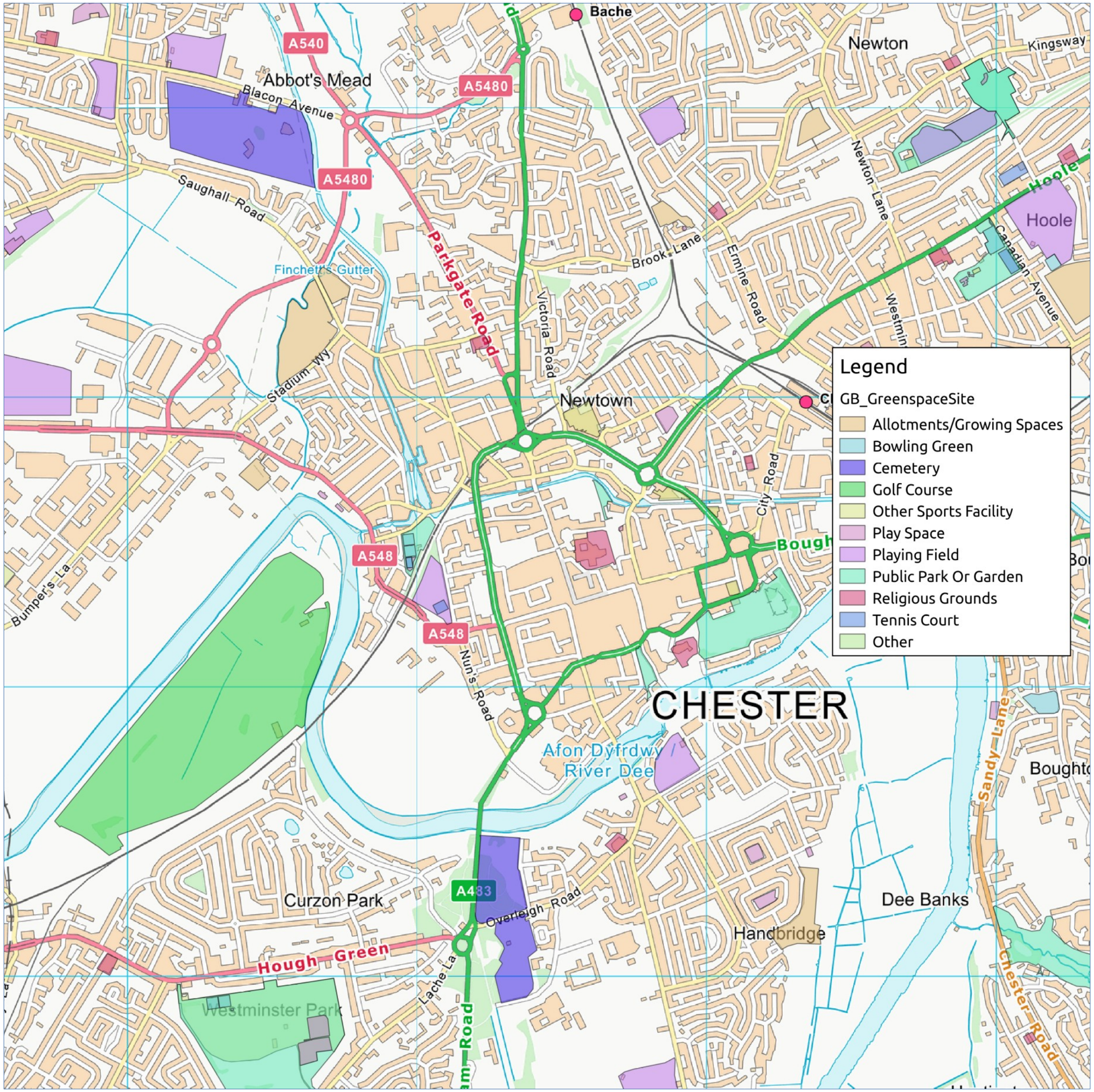
Deep Learning – OS Greenspace



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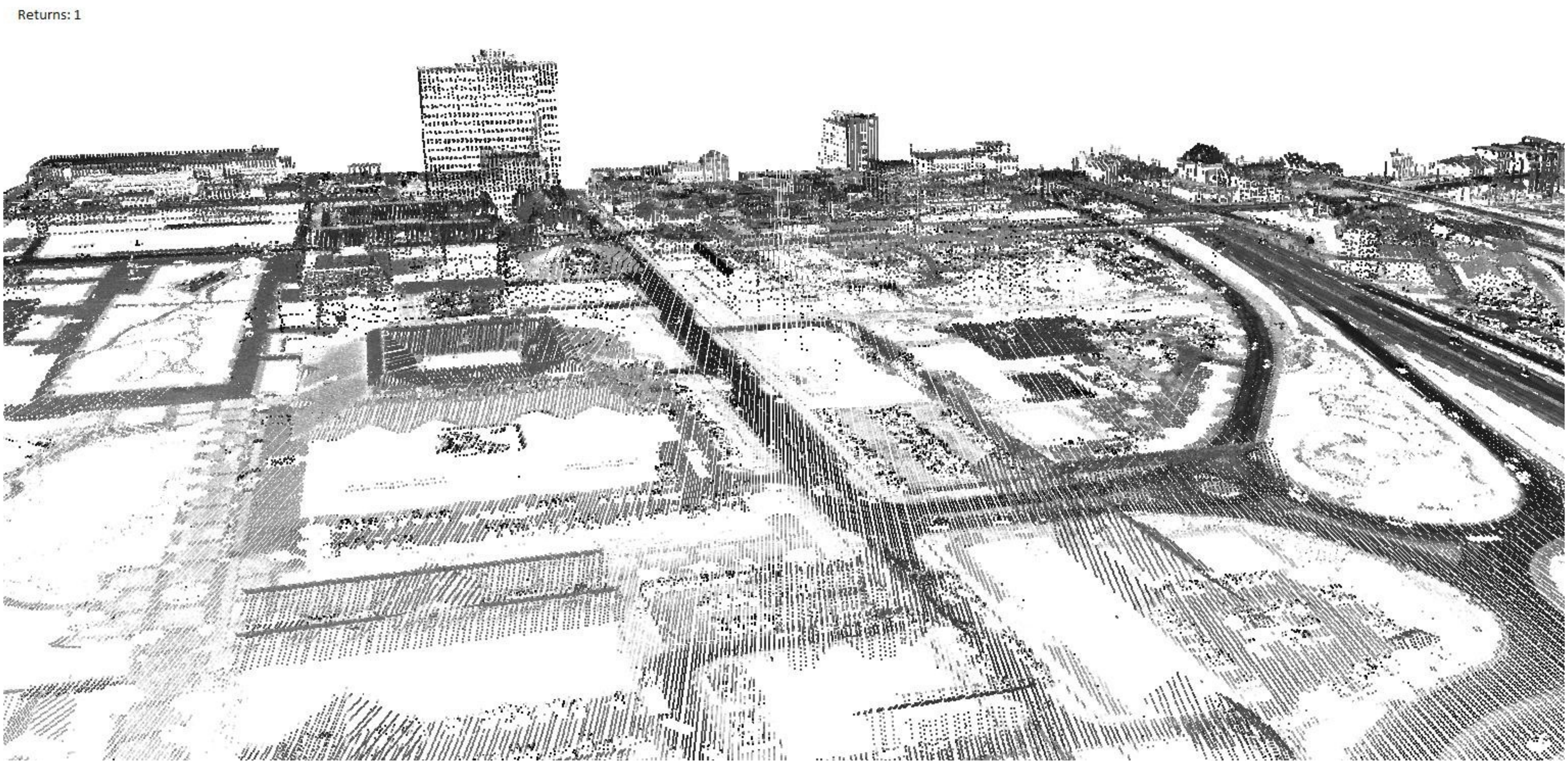
LiDAR Segmentation



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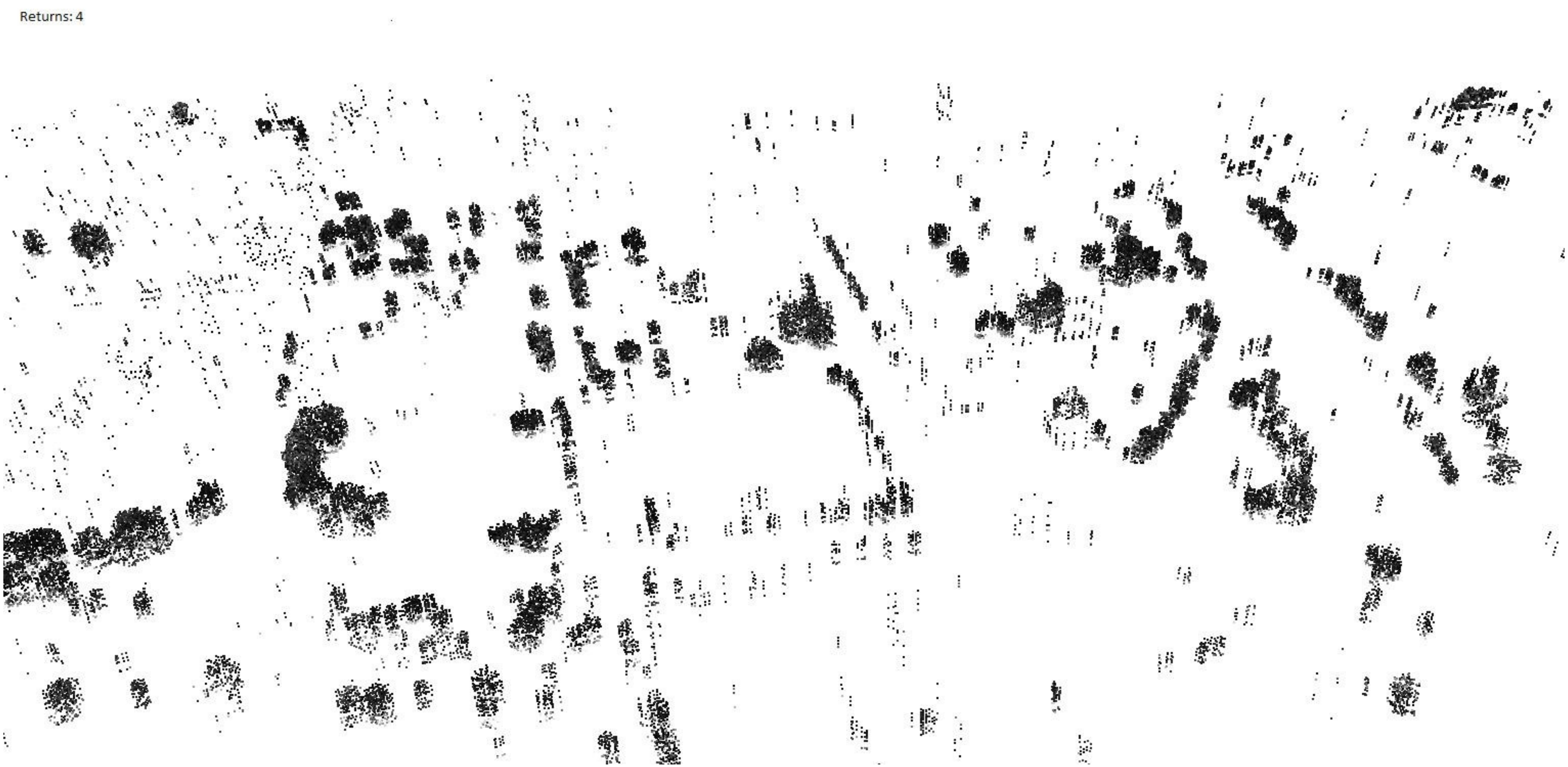
LiDAR Segmentation



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LiDAR Tree Detection in RAPIDS with CuML

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spatia_rapids_color_trees.ip

Code   Python 3

[1]:
```python
import cudf
from cudf.dataframe import DataFrame
import numpy as np
import math
import pandas as pd
from numba import cuda
from cuml import DBSCAN as cumlDBSCAN
```

[2]:
```python
import laspy as lp
```

[3]:
```python
%%time
lasfile = '/data/pointcloud/liv/Liverpool_Centre.las'
inFile = lp.file.File(lasfile, mode = "r")
```

```
CPU times: user 0 ns, sys: 2.91 ms, total: 2.91 ms
Wall time: 2.42 ms
```

[4]:
```python
%%time
point_zdf = DataFrame()
point_zdf['x'] = inFile.x[inFile.return_num==4]
point_zdf['y'] = inFile.y[inFile.return_num==4]
point_zdf['z'] = inFile.z[inFile.return_num==4]
```

```
CPU times: user 1.83 s, sys: 172 ms, total: 2 s
Wall time: 860 ms
```

[5]:
```python
eps = 3
min_samples = 2
```

[6]:
```python
%%time
clustering_cuml = cumlDBSCAN(eps = eps, min_samples = min_samples)
clustering_cuml.fit(point_zdf)
```

```
CPU times: user 629 ms, sys: 779 µs, total: 629 ms
Wall time: 187 ms
```

[7]:
```python
point_zdf["l"] = clustering_cuml.fit_predict(point_zdf)
```

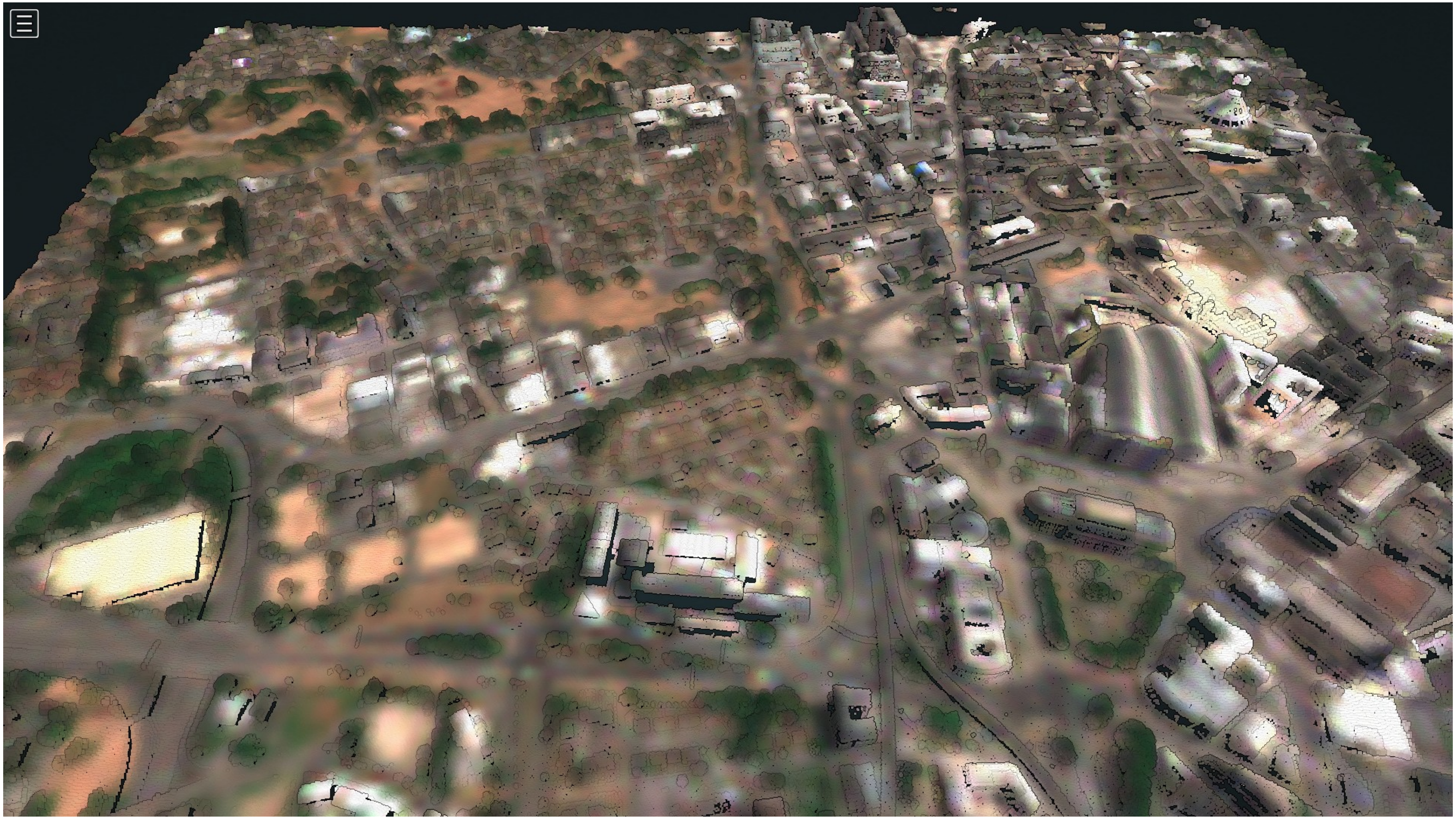
[8]:
```python
trees = point_zdf.query("l >= 0")
```

[9]:
```python
trees.drop_column("l")
```

[10]:
```python
print(trees)
```

```
                   x                 y                z
 1         334021.23         391927.01            13.52
 2         334021.21         391926.95            13.61
 3         334071.26         391837.87 14.290000000000001
 5         334015.74 391688.41000000003 16.740000000000002
 6          334015.7 391688.10000000003            16.75
14         334144.01         391663.71 19.580000000000002
15         334143.48         391663.32            19.56
25 334195.41000000003         391622.94            20.32
27         334294.52         391614.95            20.28
28 334294.85000000003         391615.19            20.32
[2087 more rows]
```

LiDAR Tree Detection in RAPIDS with CuML



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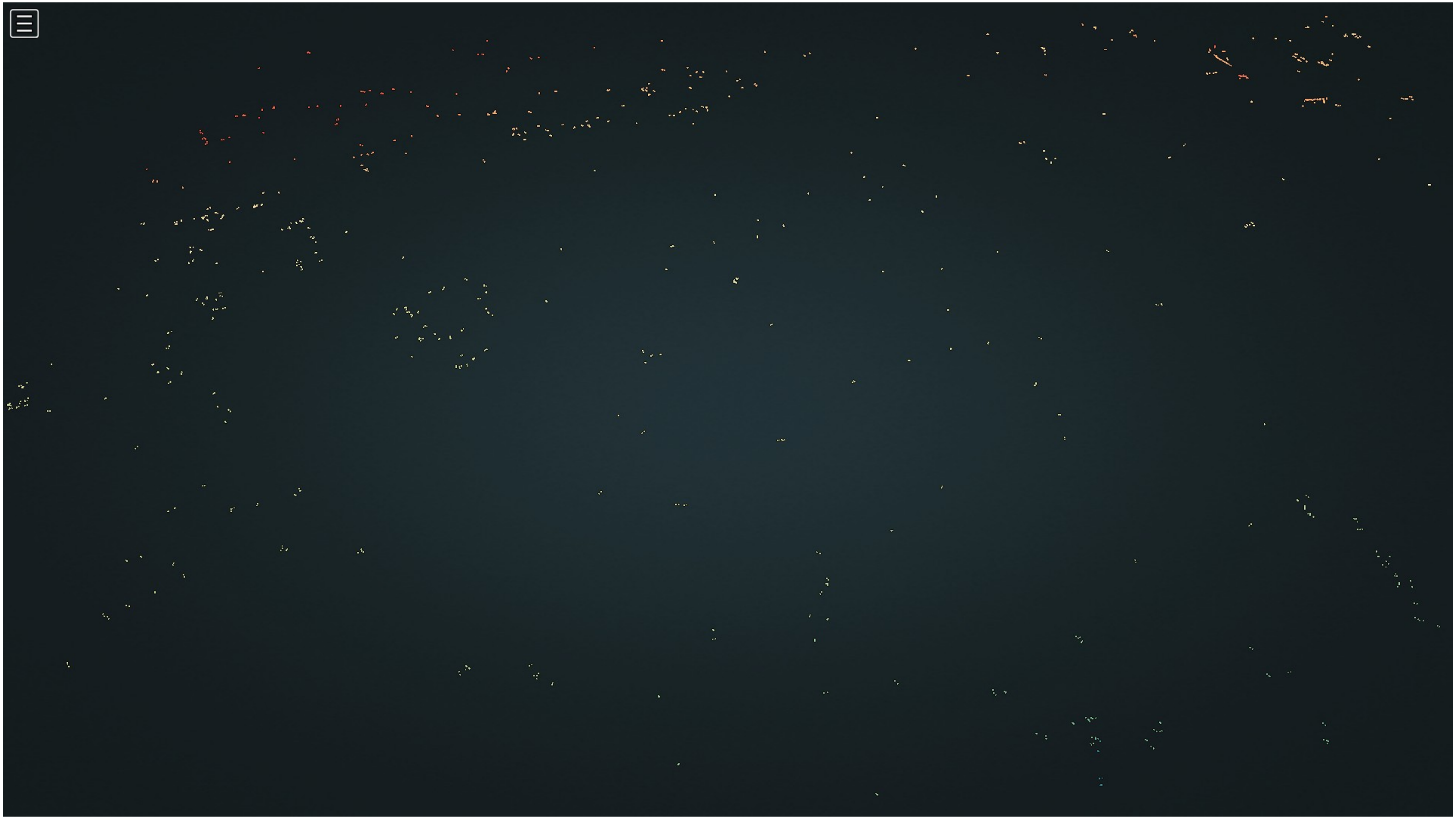
LiDAR Tree Detection in RAPIDS with CuML



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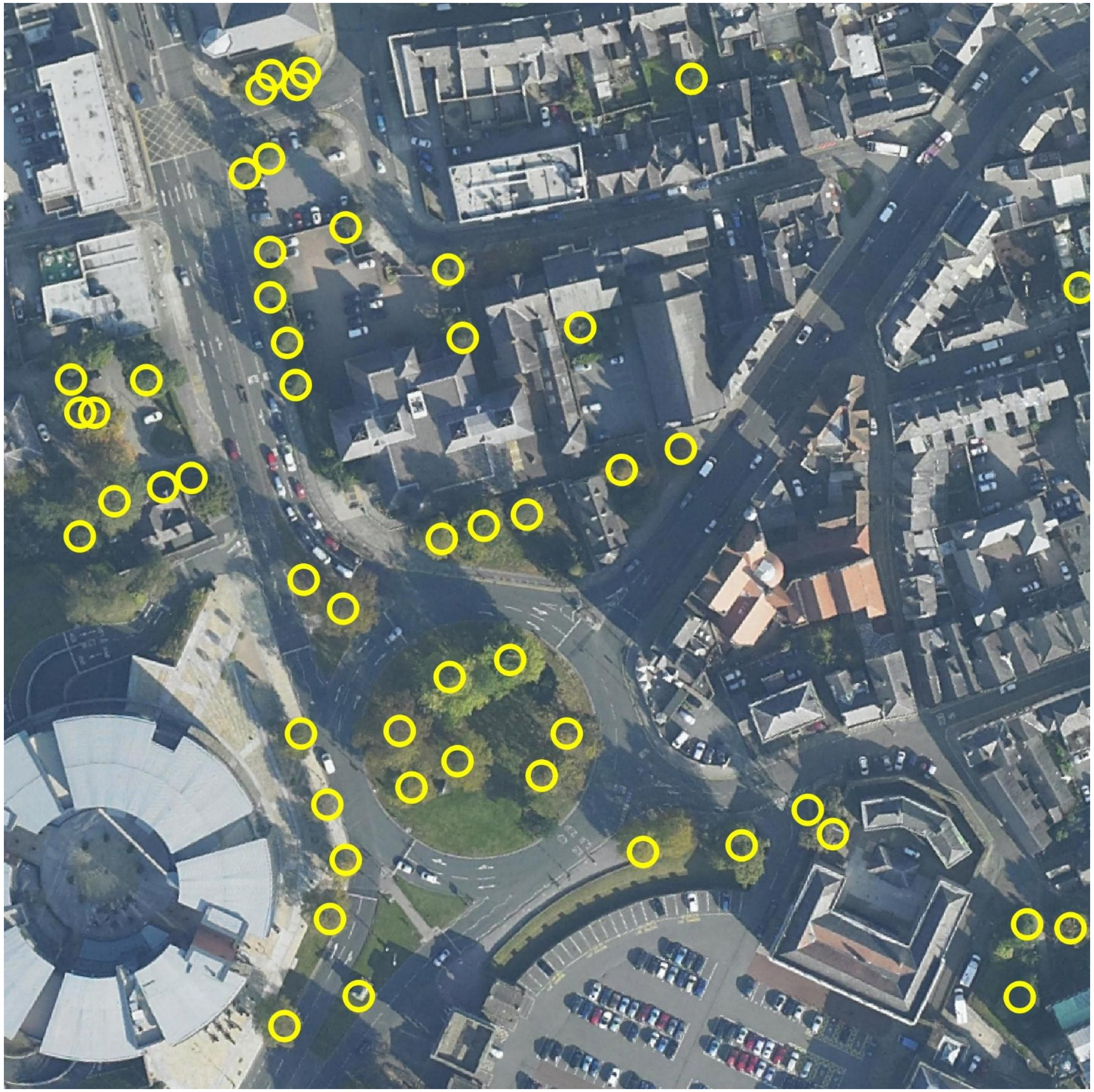
Tree Detection in LiDAR



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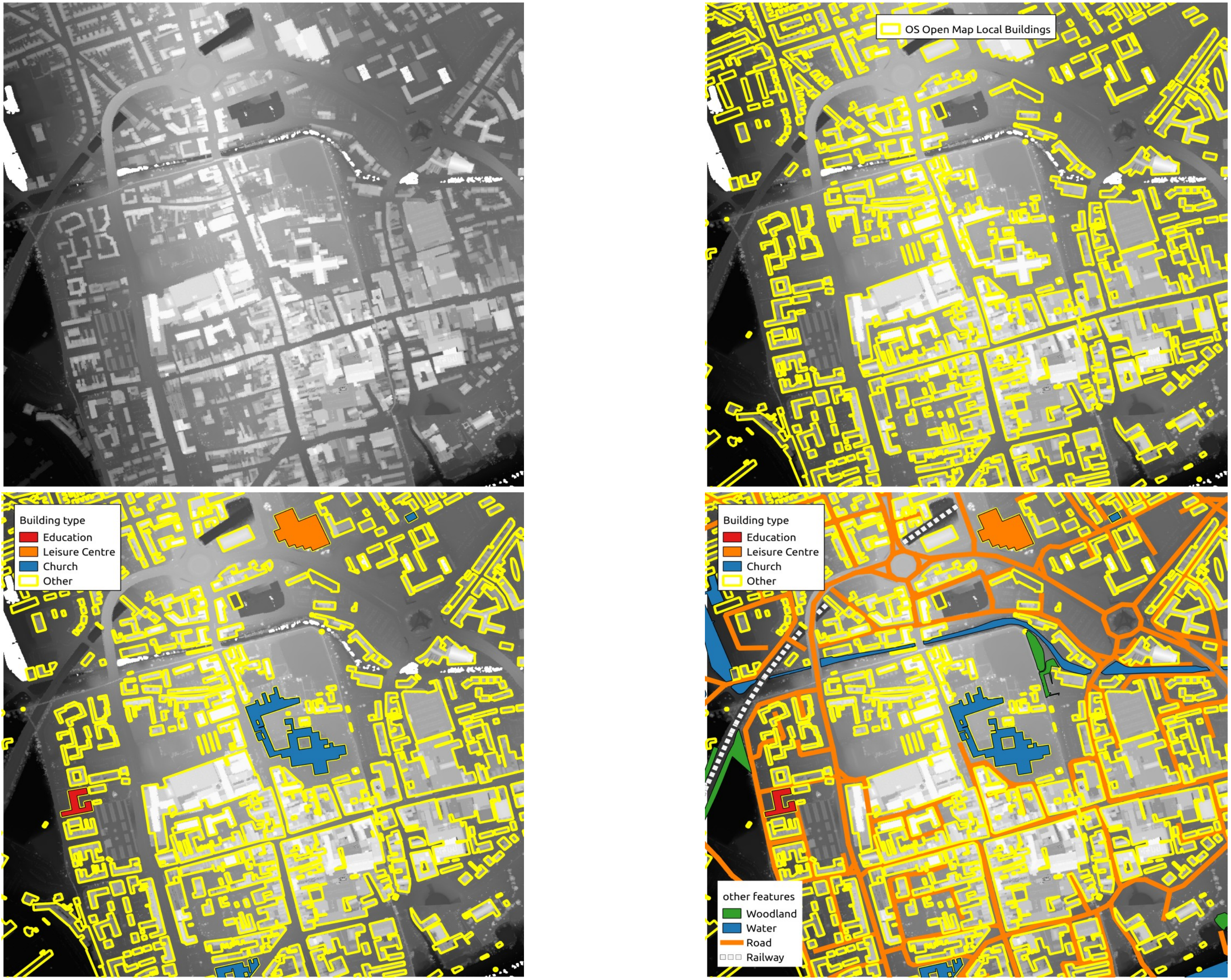
Object Detection from LiDAR



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Object Detection Labeling in RAPIDS

oml_churches_test.ipynb

Code

Python 3

```
[1]: import cudf
     from spatia_rapids import projections
     from spatia_rapids import transformations
     import numpy as np

[2]: ostn_names = ['Point_ID','ETRS89_Easting','ETRS89_Northing','ETRS89_OSGB36_EShift','ETRS89_OSGB36_NShift','ETRS89_ODN_HeightShift','Height_Datum_Flag']
     ostn_dtypes = ['int64','int64','int64','float64','float64','float64','int64']
     ostn_filename = '/data/ostn/OSTN15_OSGM15_DataFile.txt'

[3]: %%time
     shift_dic = transformations.load_shifts(ostn_filename,ostn_names,ostn_dtypes,'ETRS89_Easting','ETRS89_Northing','ETRS89_OSGB36_EShift','ETRS89_OSGB36_NShift','ETRS89_ODN_HeightShift')

     CPU times: user 99.1 ms, sys: 220 ms, total: 319 ms
     Wall time: 341 ms

[4]: names = ['ID','ring','point','x','y']
     dtypes = ["int64","int64","int64","float64","float64"]
     filename = "/data/vectors/oml_churches.csv"

[5]: %%time
     vdf = cudf.read_csv(filename,names=names,dtype=dtypes,skiprows=1)

     CPU times: user 12.9 ms, sys: 4.29 ms, total: 17.2 ms
     Wall time: 16.7 ms

[6]: %%time
     vdf = vdf.apply_rows(transformations.rapids_etrs2osgb,incols=['x', 'y'],outcols=dict(es=np.float64,ns=np.float64,hs=np.float64,adj=np.int8),kwargs=shift_dic)

     CPU times: user 636 ms, sys: 15 ms, total: 651 ms
     Wall time: 649 ms

[7]: vdf['east'] = vdf['x']-vdf['es']
     vdf['north'] = vdf['y']-vdf['ns']

[8]: proj_etrs = projections.get_proj_parameters(27700,ellipsoid=4258)
     proj_utm30 = projections.get_proj_parameters(25830)

     ('GRS_1980', 6378137.0, 6356752.314140356, '298.257222101', 0.003352810681182319)
     {'n': 0.0016792203946287211, 'PHI0': 0.8552113334772214, 'N0': -100000.0, 'a': 6378137.0, 'e_sqr': 0.006694380022900686, 'bF0': 6354217.697096618, 'LAMBDA0': -0.03490658503988659, 'aF0': 6375593.8562768
     23, 'E0': 400000.0, 'F0': 0.9996012717, 'b': 6356752.314140356}
     ('GRS_1980', 6378137.0, 6356752.314140356, '298.257222101', 0.003352810681182319)
     {'n': 0.0016792203946287211, 'PHI0': 0.0, 'N0': 0.0, 'a': 6378137.0, 'e_sqr': 0.006694380022900686, 'bF0': 6354209.6132147005, 'LAMBDA0': -0.05235987755982988, 'aF0': 6375585.745200001, 'E0': 500000.0,
     'F0': 0.9996, 'b': 6356752.314140356}

[9]: %%time
     vdf = vdf.apply_rows(projections.rapids_en2latlon,incols=['east', 'north'],outcols=dict(lat=np.float64,lon=np.float64),kwargs=proj_etrs)

     CPU times: user 709 ms, sys: 36 ms, total: 745 ms
     Wall time: 741 ms

[10]: print(vdf)

        ID ring point                 x            y adj               es ...                  lon
     0   1    0     0 460054.5900000001   1201094.46   1 102.93099739657141 ... -0.9022432882672774
     1   1    0     1          460066.9   1201094.96   1 102.93117743282399 ... -0.9020177824183705
     2   1    0     2         460067.81    1201072.7   1   102.930899369787 ... -0.9020079284275687
     3   1    0     3          460055.5    1201072.2   1 102.93071960710002 ... -0.9022334328822663
     4   1    0     4 460054.5900000001   1201094.46   1 102.93099739657141 ... -0.9022432882672774
```

Object Detection Labeling in RAPIDS

oml_churches_test.ipynb

```
CPU times: user 709 ms, sys: 36 ms, total: 745 ms
Wall time: 741 ms
```

[10]:
```
print(vdf)
```

```
     ID ring point                 x                  y  adj                es ...                  lon
 0    1    0     0 460054.5900000001         1201094.46    1 102.93099739657141 ... -0.9022432882672774
 1    1    0     1          460066.9         1201094.96    1 102.93117743282399 ... -0.9020177824183705
 2    1    0     2         460067.81          1201072.7    1   102.930899369787 ... -0.9020079284275687
 3    1    0     3          460055.5          1201072.2    1 102.93071960710002 ... -0.9022334328822663
 4    1    0     4 460054.5900000001         1201094.46    1 102.93099739657141 ... -0.9022432882672774
 5    6    0     0         461447.13         1208836.01    1 103.05450175515129 ... -0.8743238732757238
 6    6    0     1         461448.27 1208846.6800000004    1 103.05466216124361 ... -0.8742996054706821
 7    6    0     2         461471.36         1208844.22    1 103.05497183153919 ... -0.8738767738085924
 8    6    0     3         461470.22         1208833.55    1 103.05481118188099 ... -0.8739010428465085
 9    6    0     4         461447.13         1208836.01    1 103.05450175515129 ... -0.8743238732757238
[192755 more rows]
[5 more columns]
```

[11]:
```
%%time
vdf = vdf.apply_rows(projections.rapids_latlon2en,incols=['lat', 'lon'],outcols=dict(east=np.float64,north=np.float64),kwargs=proj_utm30)
```

```
CPU times: user 499 ms, sys: 11.3 ms, total: 510 ms
Wall time: 509 ms
```

[12]:
```
print(vdf[['east','north']])
```

```
                east              north
 0 614554.7220852895 6729927.903818589
 1 614567.0242868561 6729928.591401609
 2 614568.2734215639 6729906.345545966
 3 614555.9712196725 6729905.657963582
 4 614554.7220852895 6729927.903818589
 5 615829.2509406238 6737690.593149093
 6  615830.228243363 6737701.280419619
 7 615853.3554255705 6737699.172567375
 8 615852.3781230241  6737688.48529628
 9 615829.2509406238 6737690.593149093
[192755 more rows]
```

[13]:
```
pdf = vdf.to_pandas()
```

[14]:
```
gb = pdf.groupby(['ID'])
bb = gb.agg({'east' : [np.min, np.max],'north' : [np.min, np.max]})
```

[15]:
```
gb = pdf.groupby(['ID'])
bb.to_csv("/data/vectors/church_bb.csv")
```

Object Detection Labeling in RAPIDS

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Terrain Interpolation & Analysis in RAPIDS

```
from spatia_rapids import projections
```

```
from spatia_rapids import dem
```

```
d = dem.dem()
```

```
import os.path
import fnmatch

folder = '/data/dem/'

matches = []
for root, dirnames, filenames in os.walk(folder):
  for filename in fnmatch.filter(filenames, '*.asc'):
    matches.append(os.path.join(root, filename))
```

```
idx_array = np.full((9301), -1, dtype=int)
grid_array = []
```

```
def getOSGridRecNo(e,n):
    east_index = int(e/10000);
    north_index = int(n/10000);
    return east_index + (71 * north_index) + 1;
```

```
%%time
for i,f in enumerate(sorted(matches)):
    d.loadASCII(f)
    idx = getOSGridRecNo(d.metadata['xllcorner'],d.metadata['yllcorner'])-1
    idx_array[idx] = i
    #print(i,idx,f)
    grid_array += [d.data]
```

```
CPU times: user 15.9 s, sys: 209 ms, total: 16.2 s
Wall time: 16.1 s
```

```
from numba import cuda
cuda_grid = cuda.to_device(np.array(grid_array))
```

```
cuda_idx = cuda.to_device(idx_array)
```

```
cuda_grid.shape
```

Terrain Interpolation & Analysis in RAPIDS

```
@cuda.jit(device=True)
def cu_getOSGridRecNo(e,n):
    east_index = int(e/10000);
    north_index = int(n/10000);
    return east_index + (71 * north_index) + 1;
```

```
@cuda.jit(device=True)
def cu_calc_height(E, N, grid,idx):
    # Calculate point offset within grid square
    grid_rec = cu_getOSGridRecNo(E,N) - 1
    if grid_rec < 0 or grid_rec > idx.shape[0] or idx[grid_rec] < 0:
        return 0.0
    east_origin = math.floor((E + 25) / 50) * 50 - 25
    north_origin = math.floor((N + 25) / 50) * 50 - 25
    east_offset = int((east_origin - int(east_origin / 10000) * 10000) / 50)
    north_offset = 199 - int((north_origin - int(north_origin / 10000) * 10000) / 50)
    print (east_origin,north_origin)
    print (east_offset,north_offset)
    t = (E - east_origin) / 50
    u = (N - north_origin) / 50
    # If point is a grid corner, return the shift
    if (E + 25) % 50 == 0 and (N + 25) % 50 == 0:
        return grid[idx[grid_rec]][north_offset][east_offset]
    # Else use bilinear interpolation to estimate shift within the grid.
    else:
        height = 0.0
        # Calculate point offset within grid square
        # For each corner of the enclosing grid square
        for xi in range(0,2):
            for yi in range(0,2):
                grid_rec = cu_getOSGridRecNo(east_origin+xi*50,north_origin+yi*50) -1
                if idx[grid_rec] < 0:
                    return 0.0
                eidx = (east_offset + xi) % 200
                nidx = (north_offset - yi) % 200
                print(east_origin+xi*50,north_origin+yi*50,grid_rec,eidx,nidx)
                # Calculate bilinear adjustment factor (area of rectangle define by point and corner) and apply it to shift at relevant corner
                factor = ((1 - xi) + (2 * xi - 1) * t) * ((1 - yi) + (2 * yi - 1) * u)
                h = grid[idx[grid_rec]][nidx][eidx]
                height += factor * h
                print(grid[idx[grid_rec]][nidx][eidx])

        return (height)
```

```
def rapids_calc_heights(x, y, h, cuda_grid,cuda_idx):
    for i, (E, N) in enumerate(zip(x,y)):
        h[i] = cu_calc_height(E,N,cuda_grid,cuda_idx)
```

```
%%time
hdf = adf.apply_rows(rapids_calc_heights,incols=['x', 'y'],outcols=dict(h=np.float64),kwargs=dict(cuda_grid=cuda_grid,cuda_idx=cuda_idx))
```

```
CPU times: user 3min 13s, sys: 2min 17s, total: 5min 31s
Wall time: 5min 13s
```

Terrain Interpolation & Analysis in RAPIDS

```
print(hdf[['x','y','h']])
```

```
                    x          y                  h
 0 358263.47000000003 172798.15 14.971814348801894
 1           352967.0  181077.0  6.812000163269042
 2           352967.0  181077.0  6.812000163269042
 3           354800.0  180469.0               6.97
 4           354796.0  180460.0  6.911400001525879
 5           353473.0  180409.0  7.487519968414307
 6           352548.0  180308.0  7.708360050964355
 7           352515.0  180360.0   7.50000002861023
 8           352462.0  180401.0 7.3659998798370365
 9           354662.0  180364.0  6.717719916343689
[37961339 more rows]
```

Terrain Interpolation & Analysis in RAPIDS

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By using RAPIDS & TensorFlow

- We have processed large 3D datasets
- Re-projected coordinate systems with high accuracy
- Merged datasets in different formats & coordinates to enrich training data
- Labelled LiDAR & satellite images for training
- Been able to interpret and deploy the results of AI

In terms of our business objectives

- AI models have accurately predicted property attributes
- These remove the need to ask questions
- Removes the risk of incorrect information being supplied by the customer due to fraud or subjectivity
- Provided additional insights to the insurance companies
- Considerably enhance the accuracy of underwriting decisions

Other applications under development

- Spatial microsimulation of small-area statistics estimates
- Using cuML clustering on autoencoder output for unsupervised classification of imagery
- Creating 3D deep learning models with TensorFlow Sparse Tensors and Conv3D layers
- Using hybrid image and sensor data combined objects as training data

Conclusions

- RAPIDS simplifies the process of GPU acceleration of computationally intensive applications
- RAPIDS protects your legacy investments by allowing code to be reused with minimal adaptation
- RAPIDS is extensible
- RAPIDS is a versatile ~~data~~ science accelation platform