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REGRESSION-BASED UNMIXING OF URBAN LAND COVER

ASSIGNMENT HYPERSPECTRAL IMAGERY

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CONTENTS

OBJECTIVES

- Overview the basic functionalities of the EnMAP-Box QGIS Plugin through the inspection and assessment of hyperspectral and high-resolution images
- Get an insight of how to create urban spectral libraries using EnMAP-Box QGIS Plugin
- Familiarize with the process of mapping urban land cover fractions employing the Regression based unmixing application of EnMAP-Box QGIS Plugin

USED SOFTWARE

- QGIS 3.26.1
- EnMAP-Box 3 (3.11.0) Plugin

USED DATA

The example data provided by EnMAP Plugin

- "enmap_berlin.bsq" spaceborne hyperspectral image from EnMap sensor simulated from HyMap
    - Spatial Resolution: 30m
    - It has **177 bands**

enmap_berlin.bsq	
Path	C:/Users/mprod/AppData/Roaming/QGIS/QGIS3/profiles/def...
Size	31.2MB 220x400x177x2 (Int16)
CRS	WGS 84 / UTM zone 33N
Bands	177

Figure 1 Bands of the enmap_berlin.bsq hyperspectral image

- "hires_berlin.bsq" high resolution true color image
    - Spatial Resolution: 3.6m
    - It has **3 bands**

hires_berlin.bsq	
Path	C:/Users/mprod/AppData/Roaming/QGIS/QGIS3/profiles/def...
Size	8.0MB 800x3327x3x1 (Byte)
CRS	WGS 84 / UTM zone 33N
Bands	3

Figure 2 Bands of the hires_berlin.bsq high-resolution image

- "landcover_berlin_point" vector layer with detailed land cover information at the point level

OBESERVATIONS

TASK 1: CALCULATE THE STATISTICS OF THE ENMAP_BERLIN.BSQ IMAGE

- **Tools → Image Statistics → Select the image as a raster → Run**
- The number of Bands of the ***enmap_berlin.bsq*** hyperspectral image was also displayed when calculating the statistics→ it has **177 bands**
- Additionally, the image spectral range goes from **460** to **2409 nanometers**

	Band	Histogram	Min	Max	Mean	StdDev
1	Band 001: band 8 (0.460000 Micrometers)		110.0	3759.0	418.4	202.1
177	Band 177: band 239 (2.409000 Micrometers)		0.0	4491.0	702.7	341.2

Figure 3 Statistics for the Band 1 and Band 177 of the enmap_belin.bsq image

TASK 2: CREATE SPECTRAL SIGNATURES OF DIFFERENT REGIONS OF THE ENMAP_BERLIN.BSQ HYPERSPECTRAL IMAGE

The spectral signatures were created for the following urban land cover classes: water, soil, tree, low vegetation, pavement, and roof. Additionally, in order to double check if the selected pixels in the hyperspectral image belonged to the classes of interest, they were validated with the high-resolution image.

LOCATION OF THE FEATURES SELECTED TO TAKE THE SPECTRAL SIGNATURES

Water 1

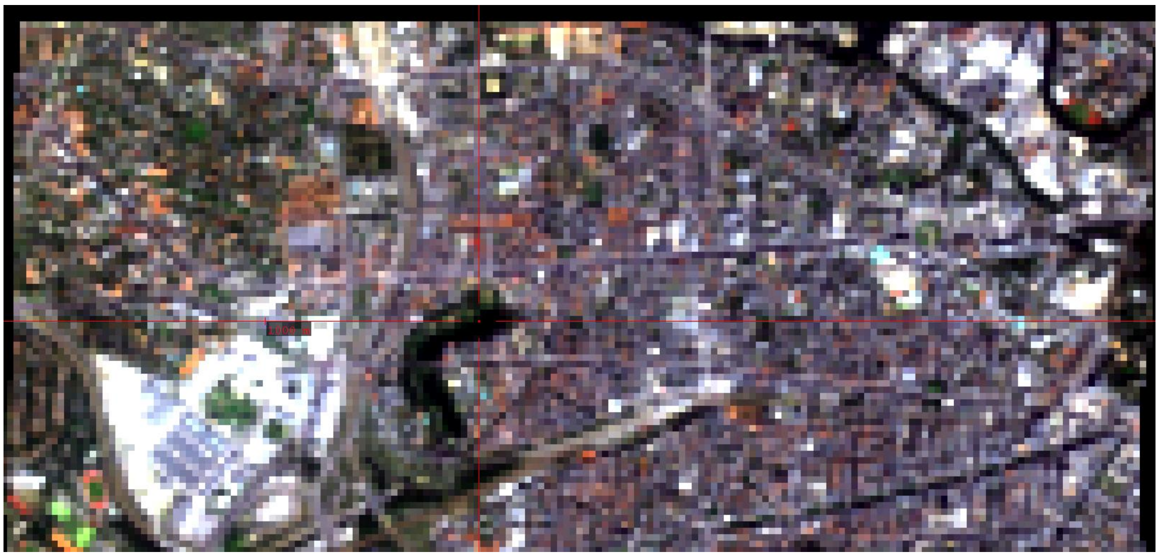


Figure 4 Crosshair pointing to the pixel where the "Water 1" spectrum was collected in the enmap_belin.bsq image

Water 2

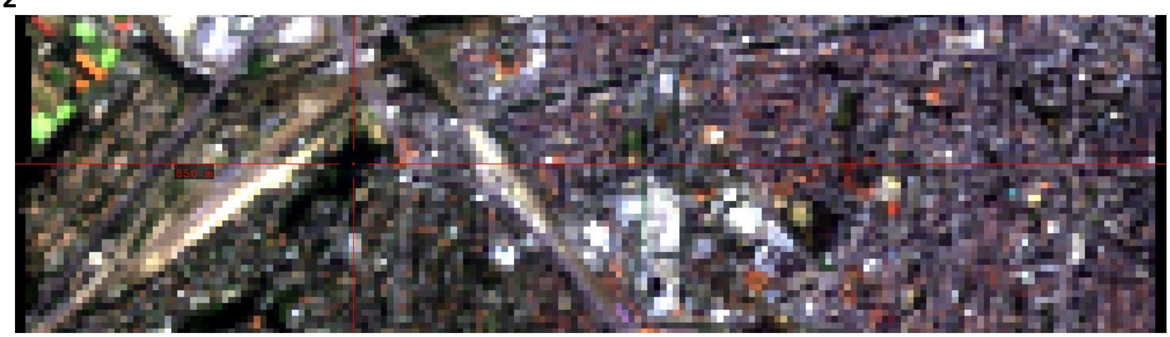


Figure 5 Crosshair pointing to the pixel where the "Water 2" spectrum was collected in the enmap_belin.bsq image

Water 3

Figure 6 Crosshair pointing to the pixel where the "Water 3" spectrum was collected in the enmap_belin.bsq image

Water 4

Figure 7 Crosshair pointing to the pixel where the "Water 4" spectrum was collected in the enmap_belin.bsq image

Soil 1

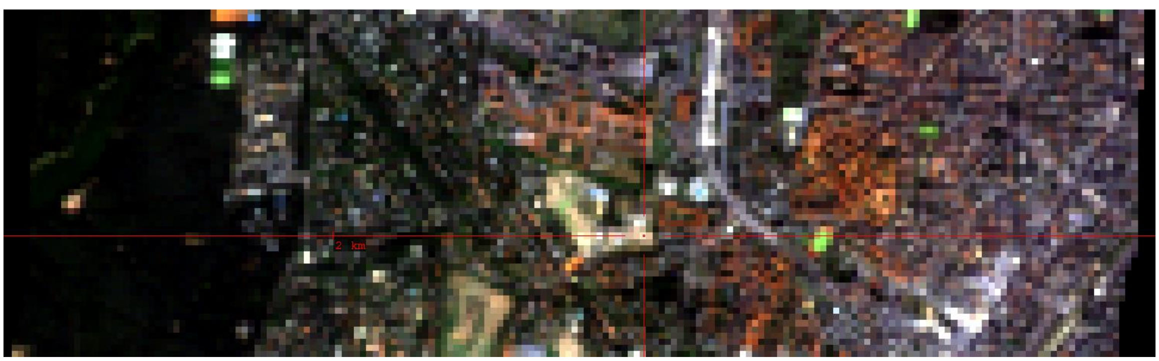


Figure 8 Crosshair pointing to the pixel where the "Soil 1" spectrum was collected in the enmap_belin.bsq image

Soil 2

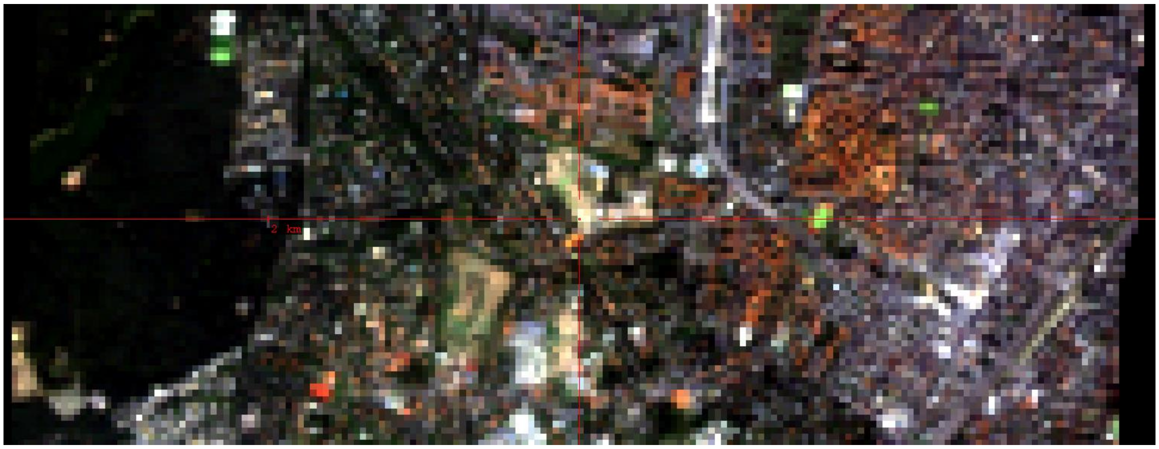


Figure 9 Crosshair pointing to the pixel where the "Soil 2" spectrum was collected in the enmap_belin.bsq image

Soil 3

Figure 10 Crosshair pointing to the pixel where the "Soil 3" spectrum was collected in the enmap_belin.bsq image

Soil 4

Figure 11 Crosshair pointing to the pixel where the "Soil 4" spectrum was collected in the enmap_belin.bsq image

Tree 1

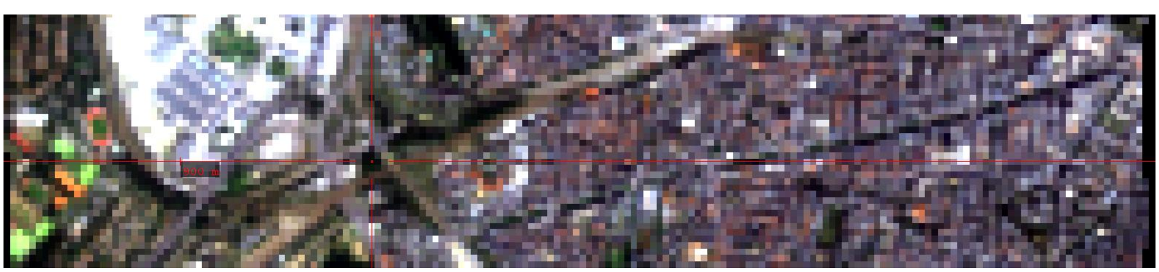


Figure 12 Crosshair pointing to the pixel where the "Tree 1" spectrum was collected in the enmap_belin.bsq image

Tree 2

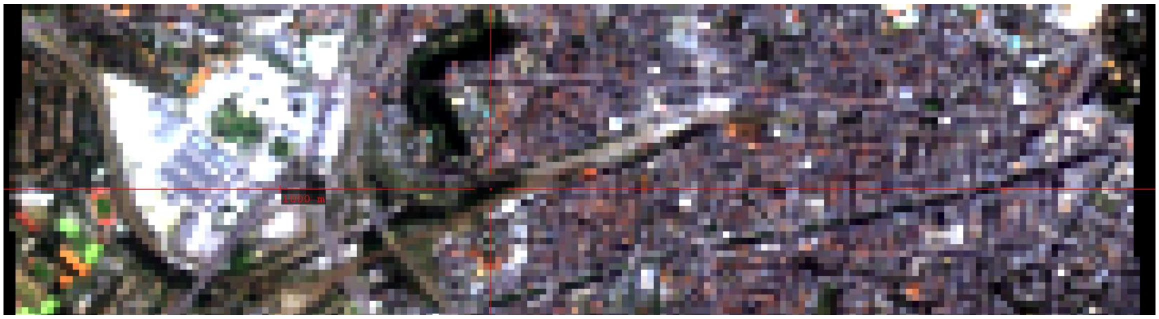


Figure 13 Crosshair pointing to the pixel where the "Tree 2" spectrum was collected in the enmap_belin.bsq image

Tree 3

Figure 14 Crosshair pointing to the pixel where the "Tree 3" spectrum was collected in the enmap_belin.bsq image

Tree 4

Figure 15 Crosshair pointing to the pixel where the "Tree 4" spectrum was collected in the enmap_belin.bsq image

Low Vegetation 1

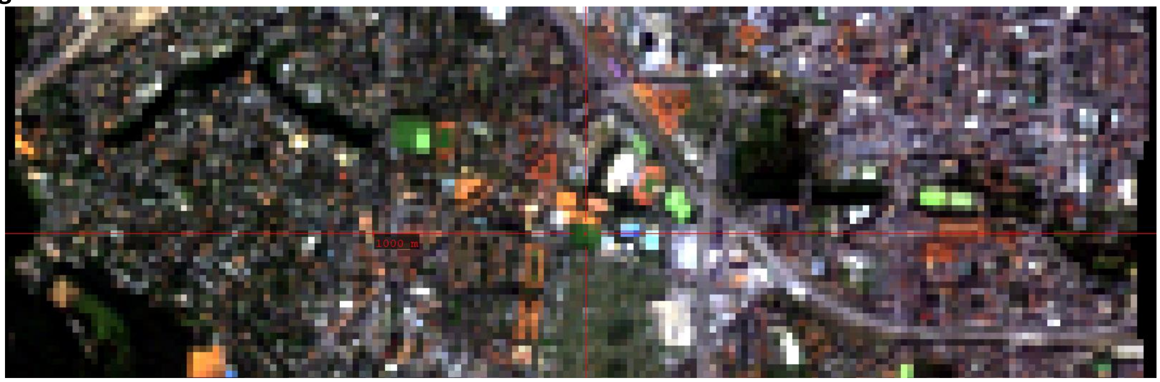


Figure 16 Crosshair pointing to the pixel where the "Low Vegetation 1" spectrum was collected in the enmap_belin.bsq image

Low Vegetation 2

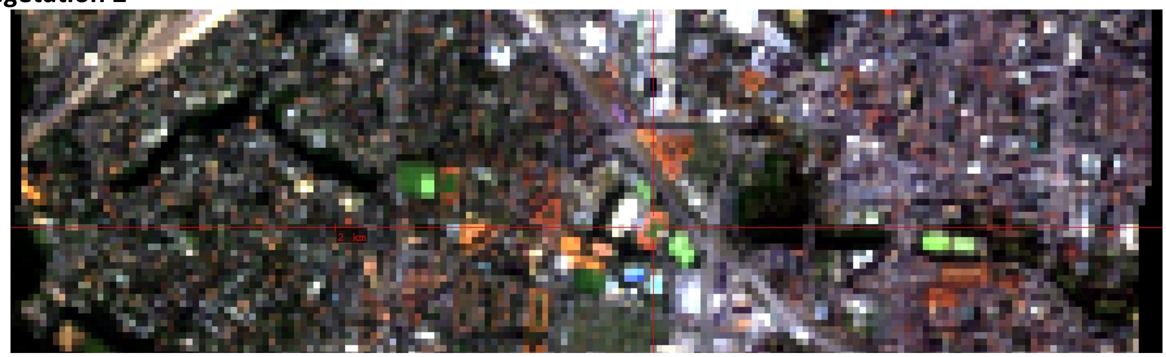


Figure 17 Crosshair pointing to the pixel where the "Low Vegetation 2" spectrum was collected in the enmap_belin.bsq image

Low Vegetation 3

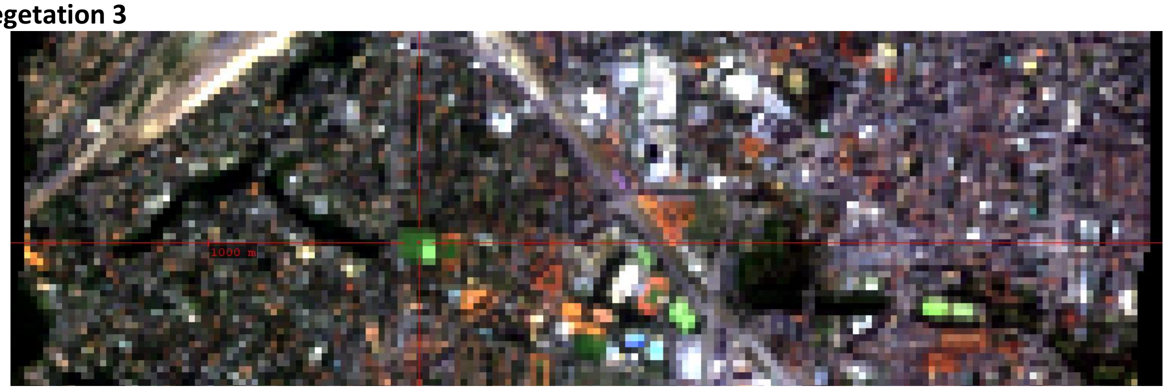


Figure 18 Crosshair pointing to the pixel where the "Low Vegetation 3" spectrum was collected in the enmap_belin.bsq image

Low Vegetation 4

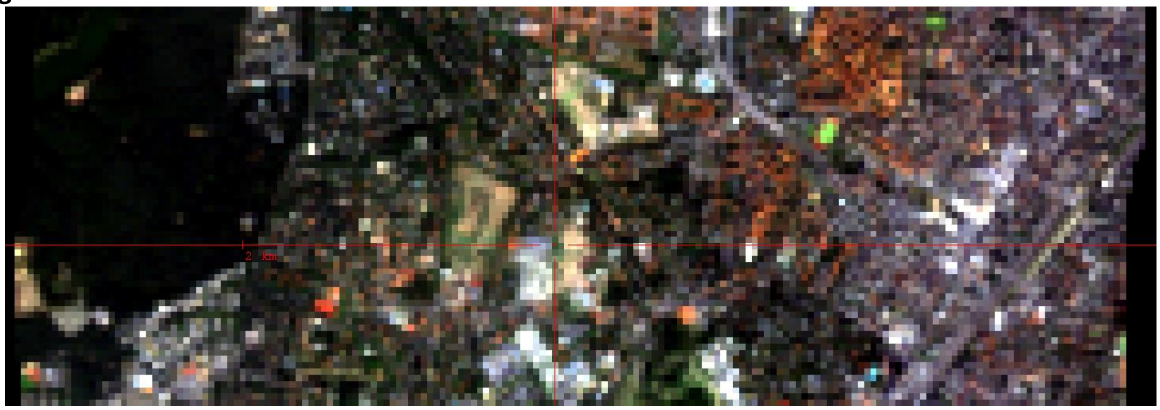


Figure 19 Crosshair pointing to the pixel where the "Low Vegetation 4" spectrum was collected in the enmap_belin.bsq image

Pavement 1

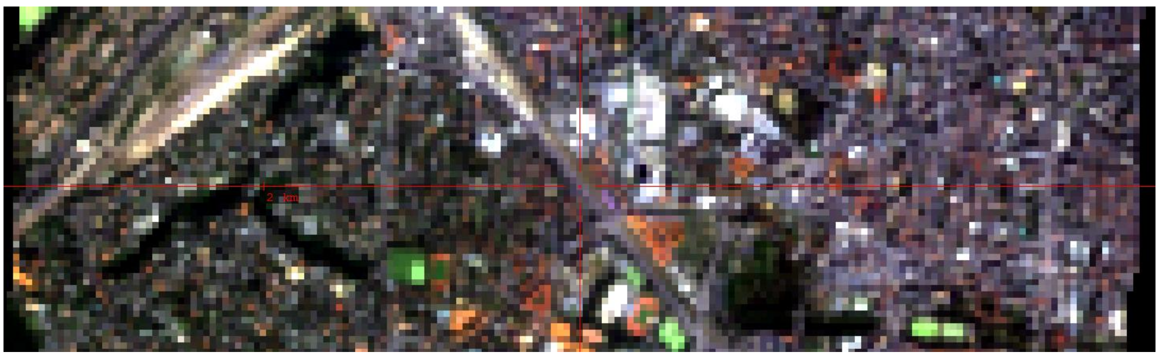


Figure 20 Crosshair pointing to the pixel where the "Pavement 1" spectrum was collected in the enmap_belin.bsq image

Pavement 2

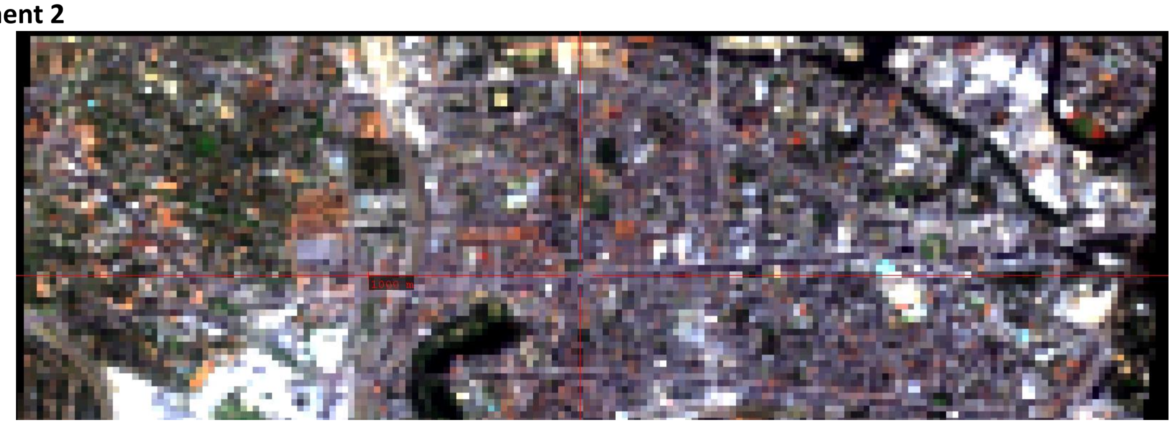


Figure 21 Crosshair pointing to the pixel where the "Pavement 2" spectrum was collected in the enmap_belin.bsq image

Pavement 3

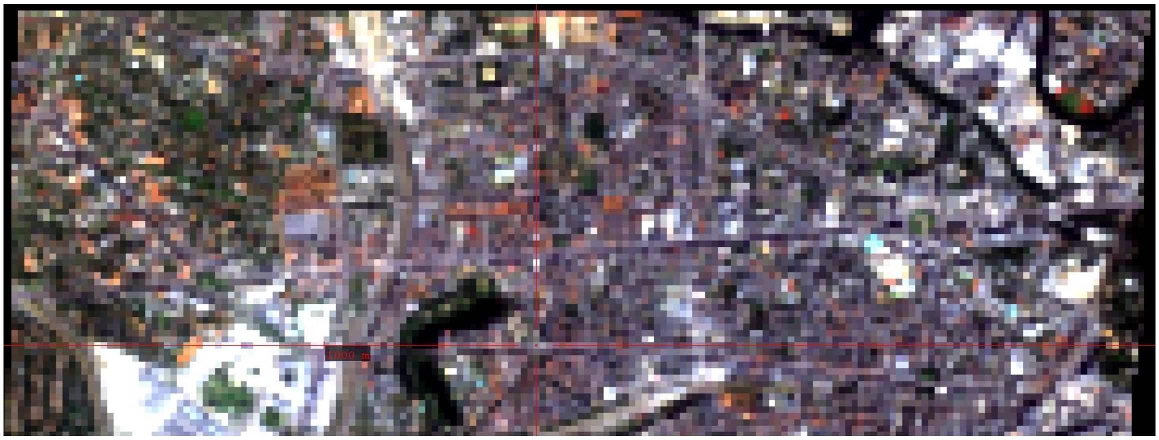


Figure 22 Crosshair pointing to the pixel where the "Pavement 3" spectrum was collected in the enmap_belin.bsq image

Roof 1

Figure 23 Crosshair pointing to the pixel where the "Roof 1" spectrum was collected in the enmap_belin.bsq image

Roof 2

Figure 24 Crosshair pointing to the pixel where the "Roof 2" spectrum was collected in the enmap_belin.bsq image

Roof 3

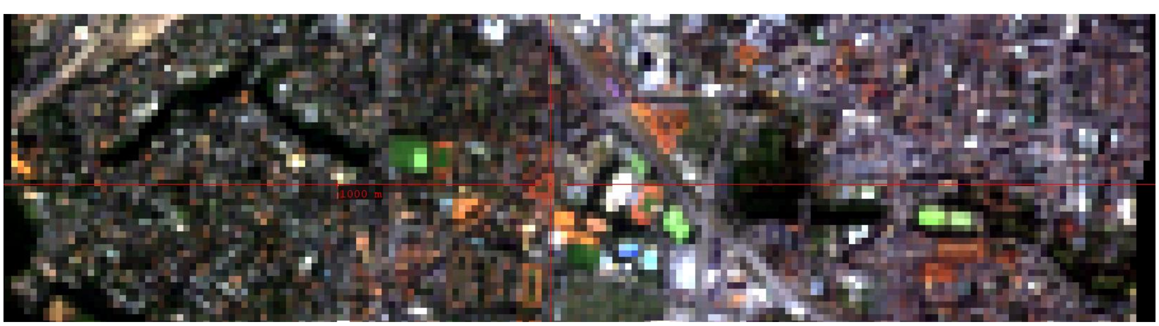


Figure 25 Crosshair pointing to the pixel where the "Roof 3" spectrum was collected in the enmap_belin.bsq image

Created Spectral Library

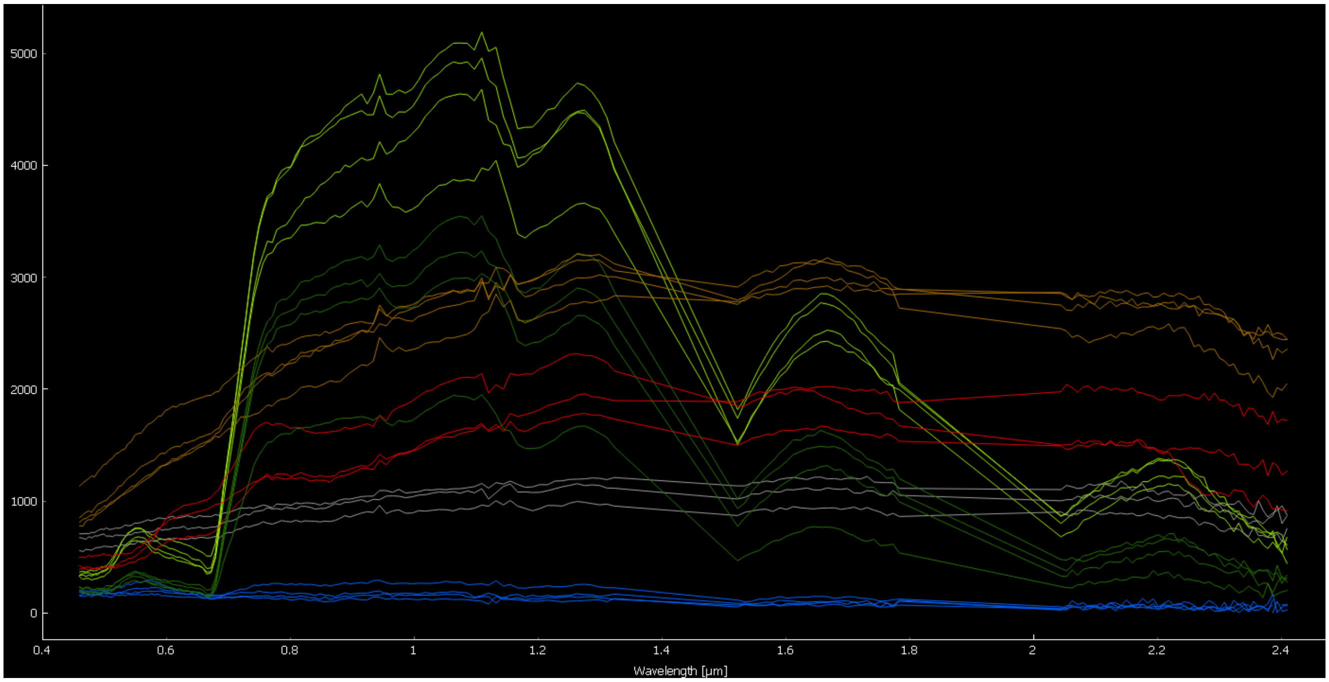


Figure 26 Created Spectral Library

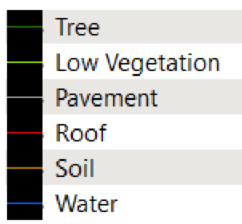


Figure 27 Legend Spectral Library

Differences between the collected spectra

- Low Vegetation and Trees: the spectral signatures show low reflectance values in the visible portion of the electromagnetic spectrum and the highest reflectance in the near infrared portion. It is important to highlight that even if the the Low Vegetation and Trees spectra have similar trends in the collected range, the reflectance values of the Trees spectra are in general smaller than the Low Vegetation values
- Soil: reflectance values continuously increase from the visible to the near infrared portion. In the short-wavelength infrared portion, reflectance values are continuous except for small local valleys probably due to water absorption.
- Roof: like the soil spectra, roof reflectance values increase from the visible to the near infrared portion and are mainly constant for the short infrared portion. However, roof reflectance values are always smaller than the soil reflectance values along the whole range. The reflectance variations within the roof's collected spectra are possibly due to the different type of materials
- Pavement: similar reflectance values within the spectral range. Reflectance values are slightly lower for the optical portion
- Water: low reflectance values (close to cero) can be observed for the water spectra. Most of the incident radiant flux is absorbed

TASK 3: APPLY REGRESSION-BASED UNMIXING FOR LAND COVER FRACTION MAPPING

- **Applications→ Regression-based unmixing**

The Regression Based Unmixing Application was run two times using different Regressors in each: first with the **Linear Regression Regressor** and then with the **Random Forest Regressor**. The output Class Fraction Layer in each case consisted of 5 bands, where each band represented a fraction map of the defined target classes (impervious, low vegetation, soil, tree, and water).

The band statistics of the Output Class Fraction Layers were the following:

Band Statistics

Raster layer: ClassFractionLayerLR.tif

	Band	Histogram	Min	Max	Mean	StdDev
1	Band 1: impervious (Gray)		-2.4	2.8	0.36	0.3396
2	Band 2: low vegetation		-1.24	1.66	0.125	0.1625
3	Band 3: soil		-2.48	3.47	0.0559	0.1567
4	Band 4: tree		-2.01	3.41	0.3267	0.3174
5	Band 5: water		-1.33	2.18	0.1545	0.1897

Figure 28 Band Statistics Output Class Fraction Layer. Used Regressor: Linear Regression

Band Statistics

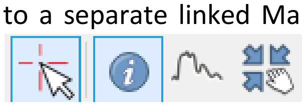
Raster layer: ClassFractionLayerRF.tif

	Band	Histogram	Min	Max	Mean	StdDev
1	Band 1: impervious (Gray)		0.0	0.9994	0.4458	0.2669
2	Band 2: low vegetation		0.0	1.0	0.2665	0.1403
3	Band 3: soil		0.0	1.0	0.1602	0.1109
4	Band 4: tree		0.0006	1.0	0.4637	0.2565
5	Band 5: water		0.0014	1.0	0.3286	0.1229

Figure 29 Band Statistics Output Class Fraction Layer. Used Regressor: Random Forest

Hence, for the Linear Regression Regressor, the fractions per pixel for all the classes can have negative values or values greater than 1 (Figure 28). However, these values are in the physically meaningful range **between 0 and 1.**

PERFORMANCE OF EACH CLASS WITH EXAMPLES FOR EACH FRACTION LAYER

The evaluation was performed for the Output Class Fraction Layer of the Random Forest Regressor (Figure 29). Specifically, each of the **singlegray** images (one per target) were compared with the high-res_berlin.bsq image added to a separate linked Map Window. The **Identify tool** together with the **Identify cursor location values option**  were used to display fraction values of sample pixels.

Band 1: Impervious

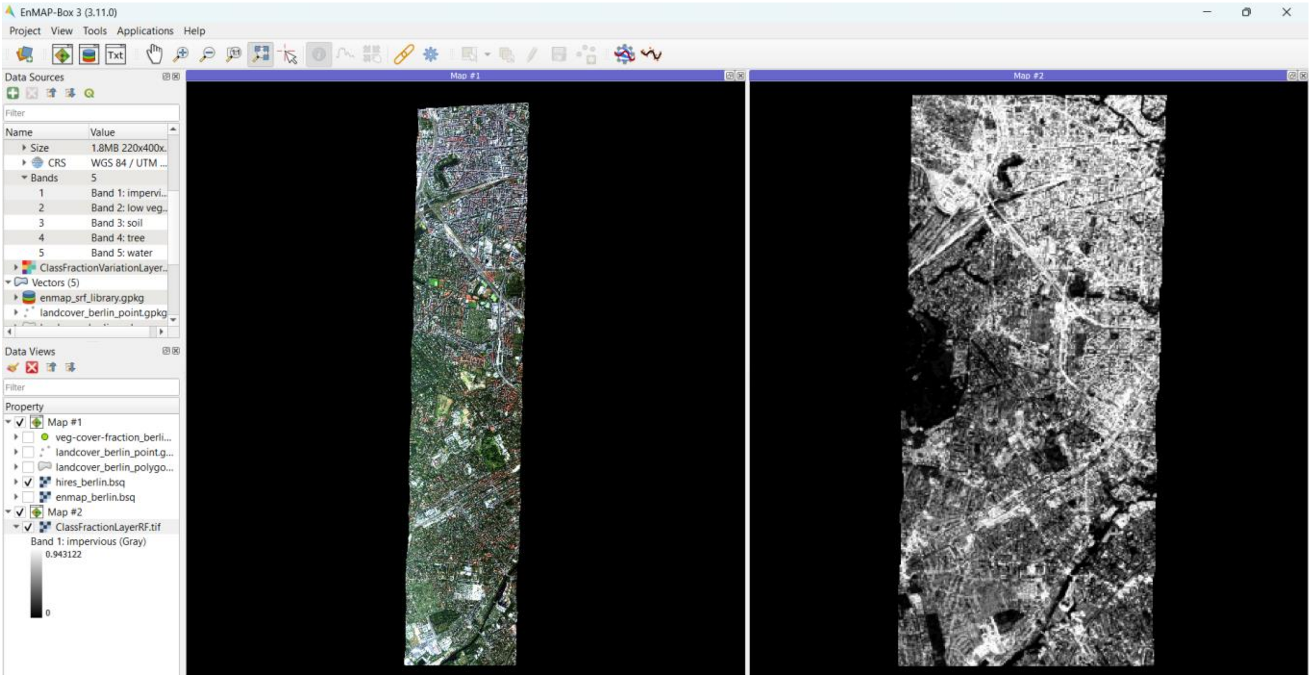


Figure 30 Left: high-res_berlin.bsq image. Right: singlegray image for the Impervious class

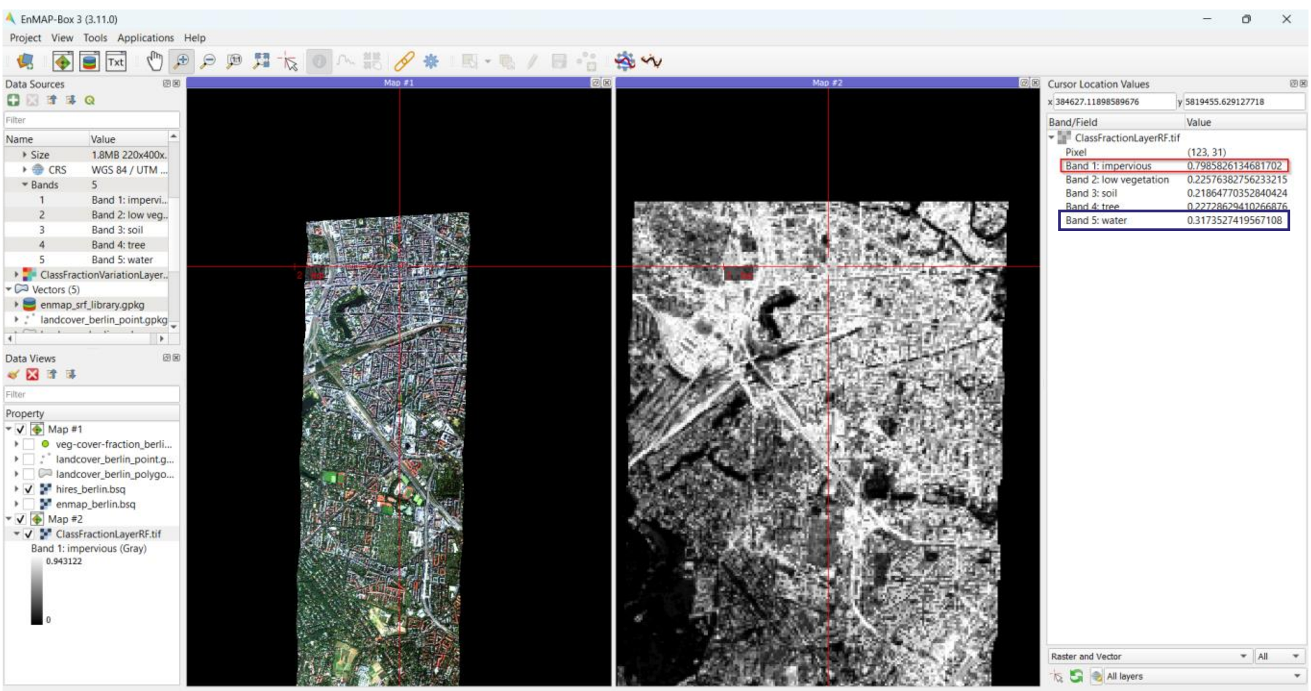


Figure 31 Example 1 of the fraction values obtained for a pixel associated with an Impervious Object

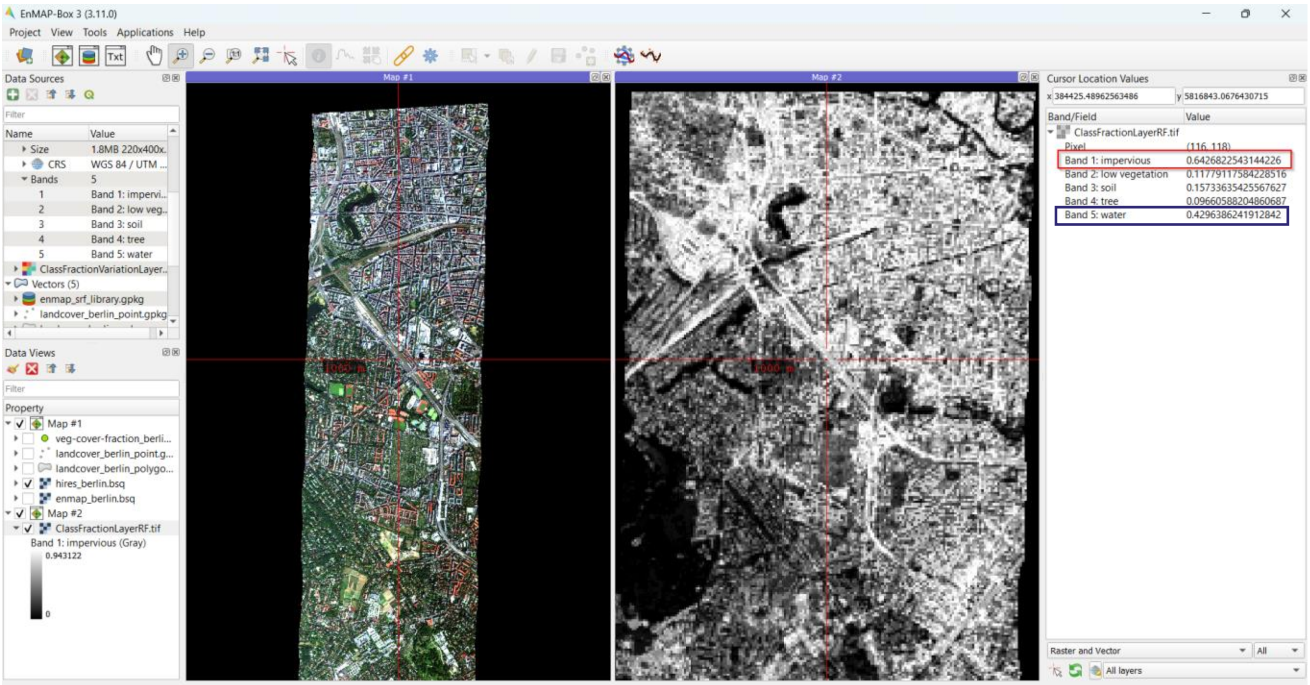


Figure 32 Example 2 of the fraction values obtained for a pixel associated with an Impervious Object

A great number of impervious features can be observed along the image, with a greater concentration on the city center (Figure 30). Additionally, the impervious fraction estimation for the sample selected pixels, based on the High-Resolution Image, are correctly retrieved. However, the water fraction values for these pixels are also high, suggesting a possible overestimation of the water class (Figures 31 and 32).

Band 2: Low Vegetation

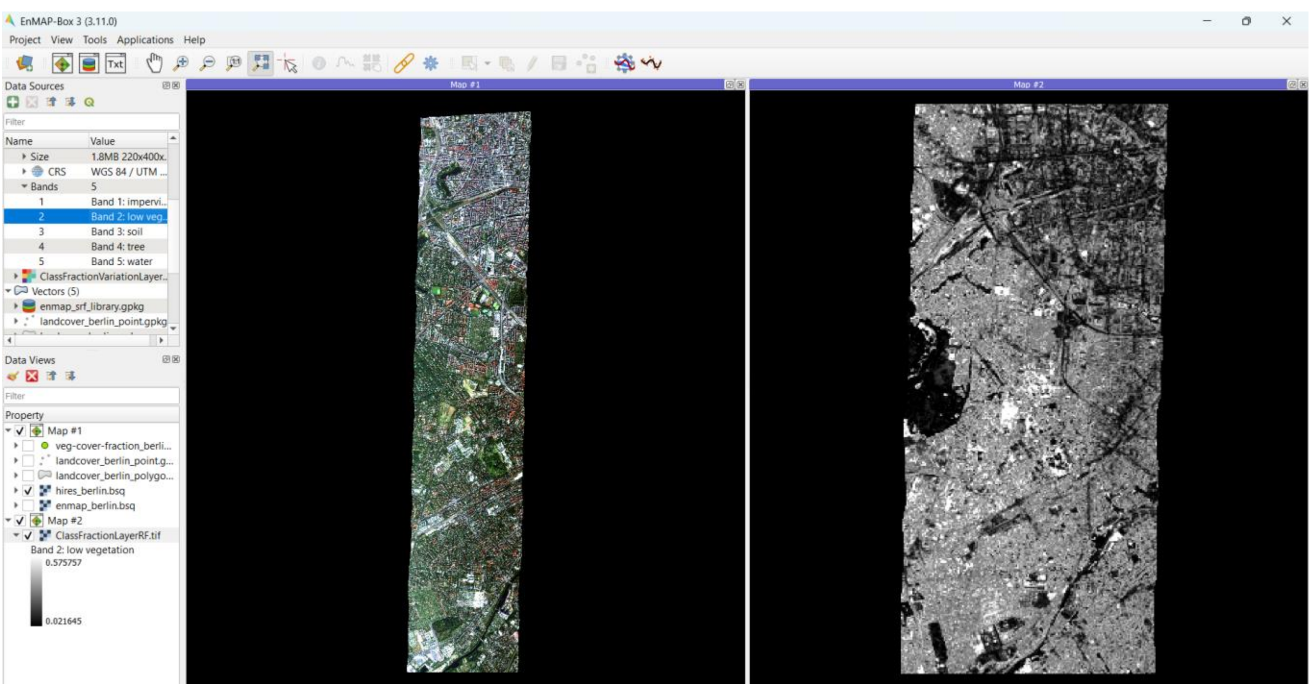


Figure 33 Left: high-res_berlin.bsq image. Right: singlegray image for the Low Vegetation class

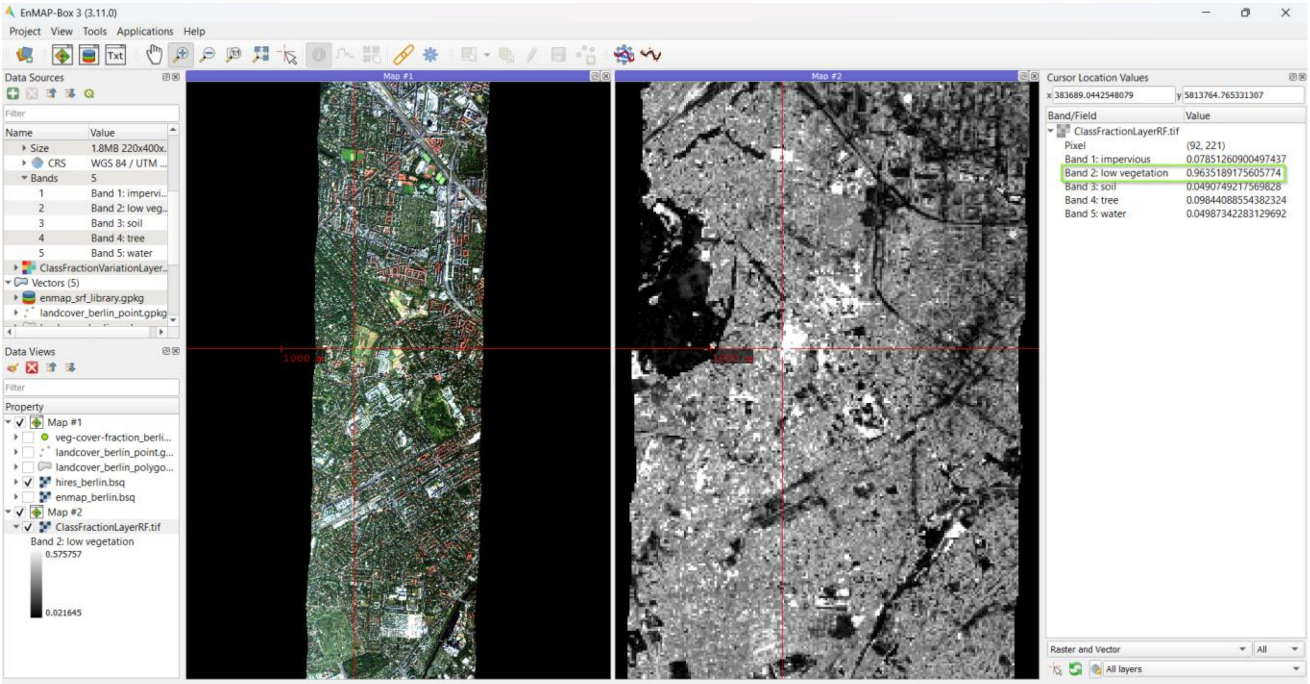


Figure 34 Example 1 of the fraction values obtained for a pixel associated with a Low Vegetation Feature

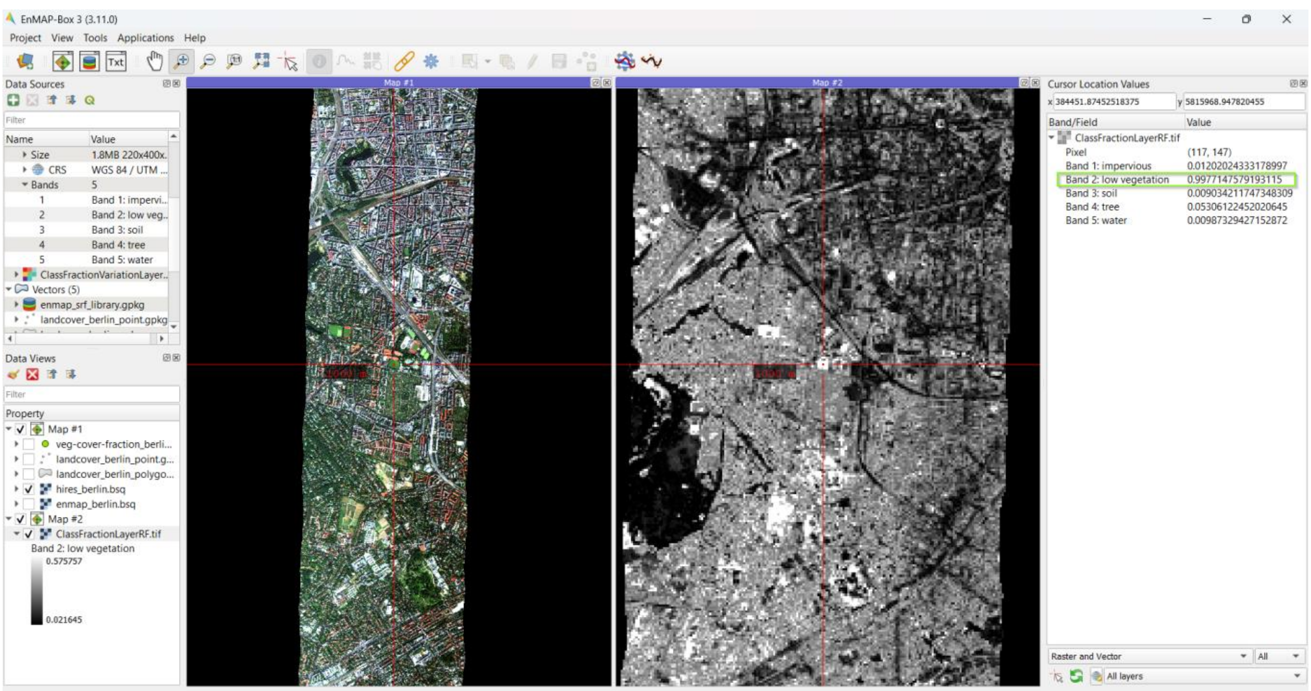


Figure 35 Example 2 of the fraction values obtained for a pixel associated with a Low Vegetation Feature

The vegetation coverage increases in the suburban areas (Figure 33). As it can be checked on the Figures 34 and 35, Low Vegetation fraction values are correctly estimated for the pixels where the High-Resolution Image indicates that effectively there is Low Vegetation presence.

Band 3: Soil

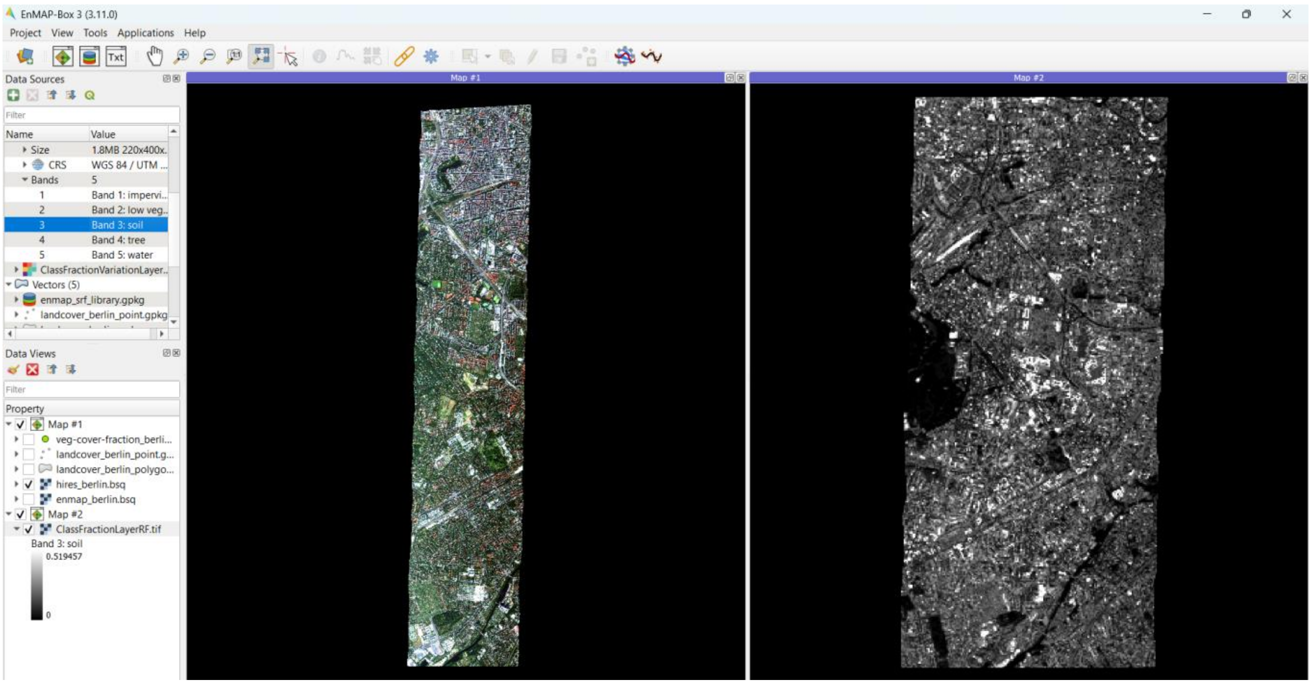


Figure 36 Left: high-res_berlin.bsq image. Right: singlegray image for the Soil class

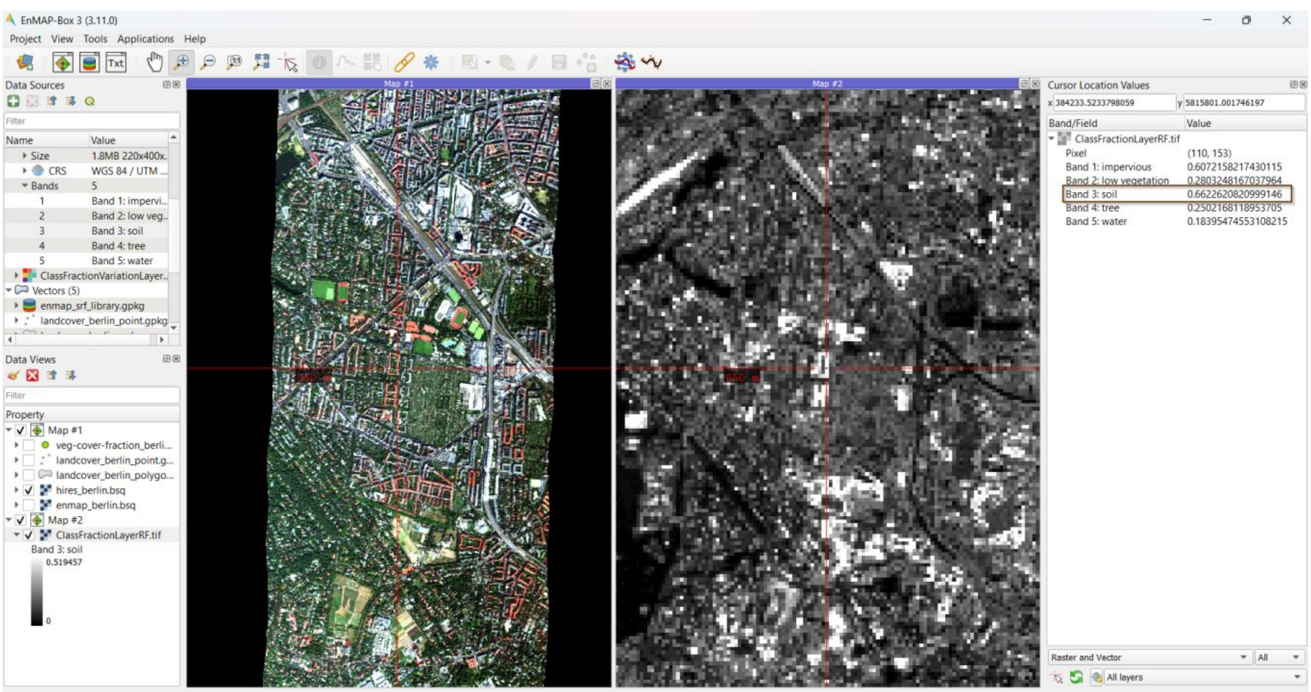


Figure 37 Fraction values obtained for a pixel associated with an Impervious Feature

Soil distribution is in patches along the image (Figure 36). Soil fraction values are overestimated in certain areas where the high-resolution image indicates that there are not soil surfaces, but instead roofs. The latter can be possibly explained because the composition/materials of the roofs (Figure 37).

Band 4: Tree

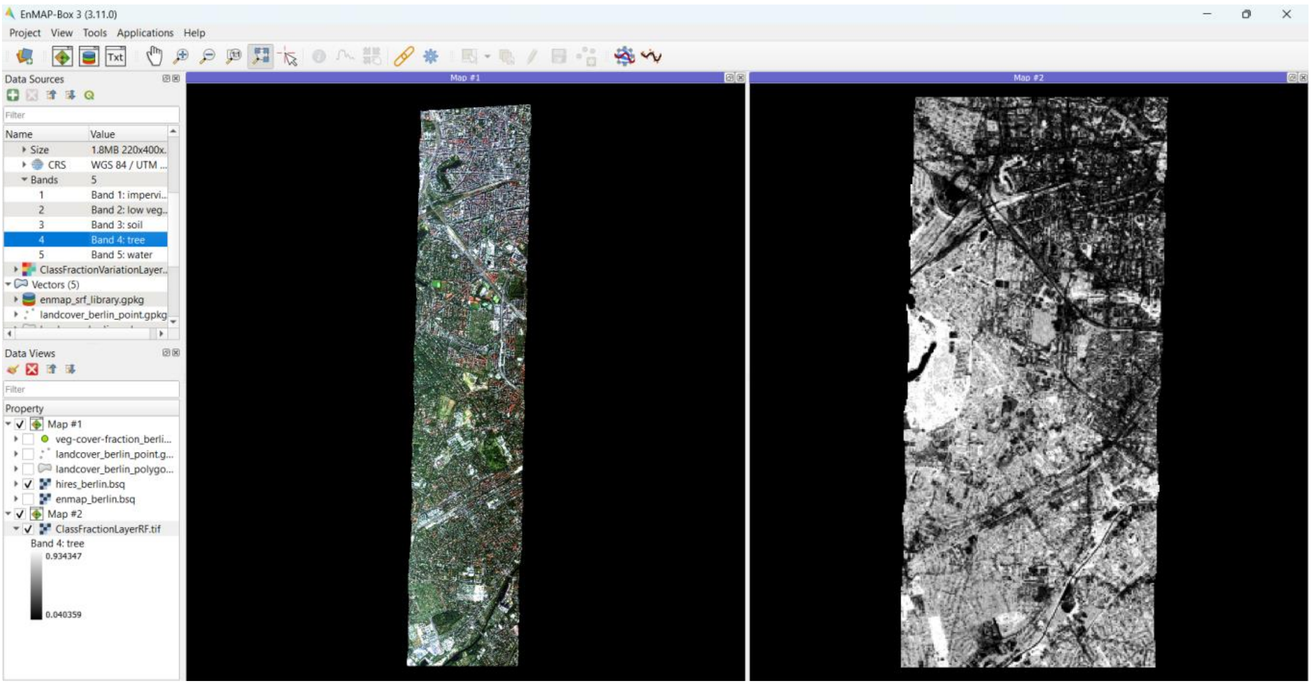


Figure 38 Left: high-res_berlin.bsq image. Right: singlegray image for the Tree class

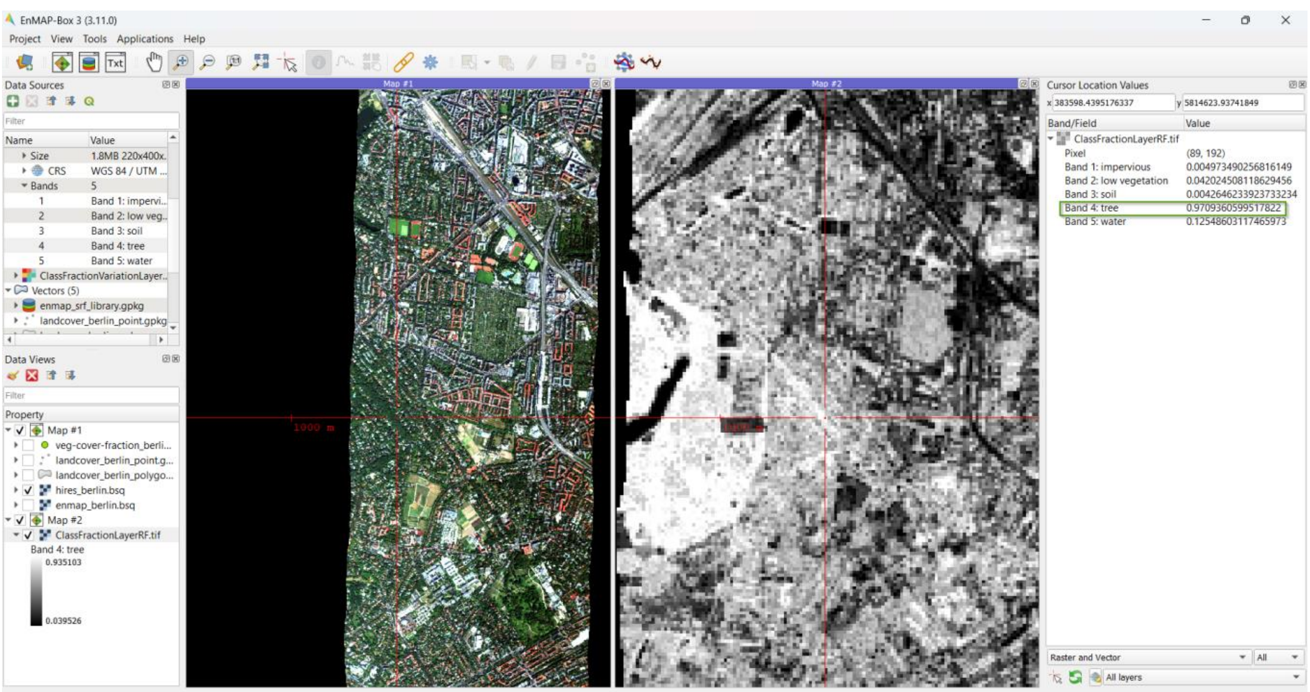


Figure 39 Fraction values obtained for a pixel associated with Trees

Like the Low Vegetation class, Trees class increases its abundance while moving towards suburban areas (Figure 38). The fraction values for the Trees class are coherent to what is observed in the High-resolution Image. Thus, brighter areas on the singlegray image for the Tree class successfully correspond with Trees presence in the high-resolution image.

Band 5: Water

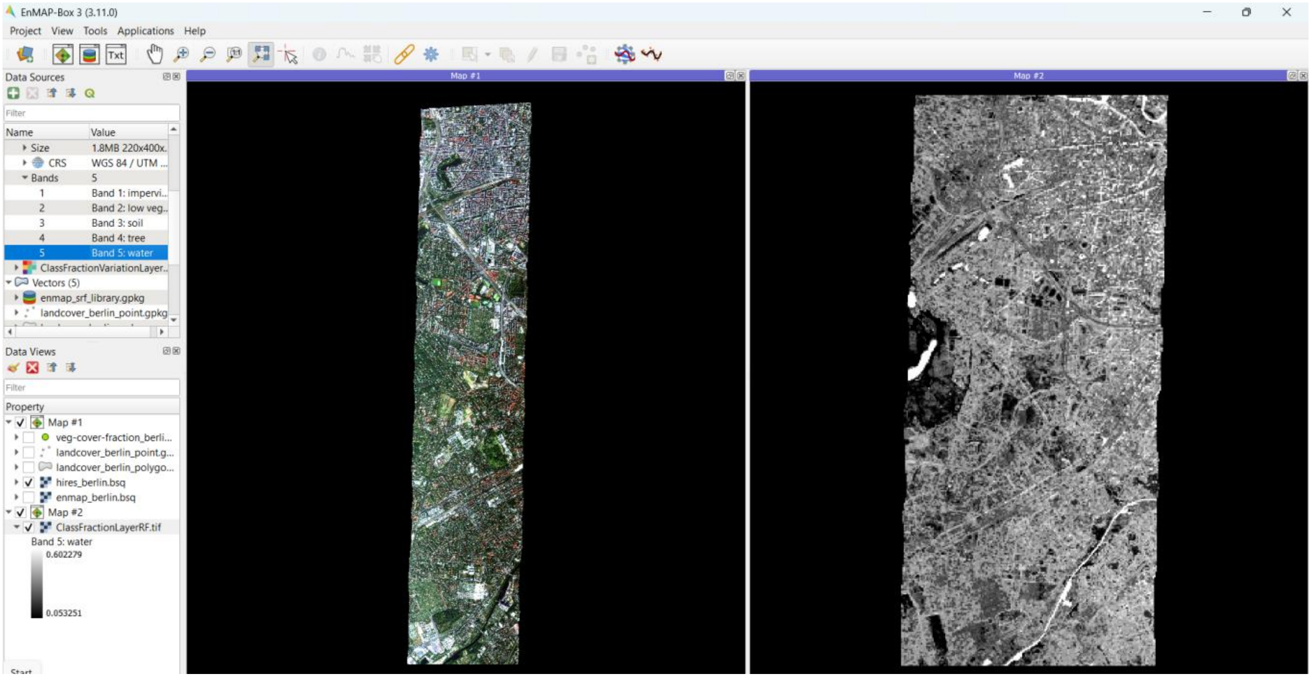


Figure 40 Left: high-res_berlin.bsq image. Right: singlegray image for the Water class

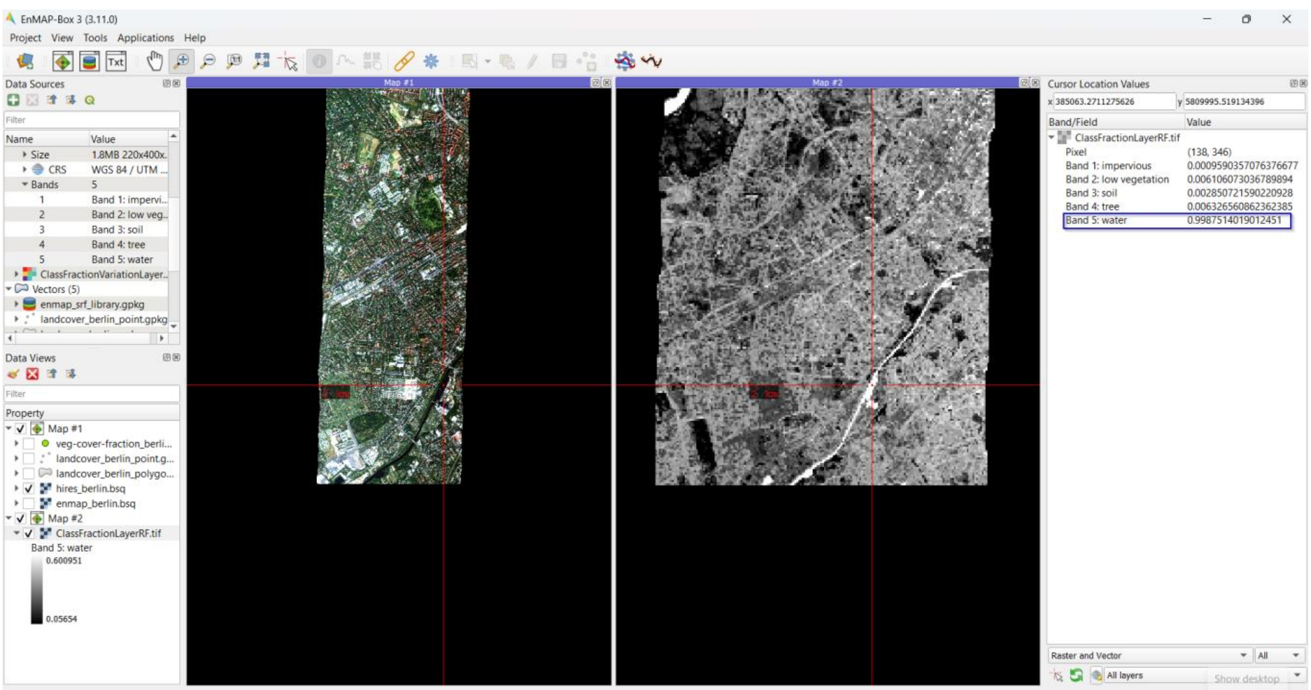


Figure 41 Example 1 of the fraction values obtained for a pixel associated with a Water Body

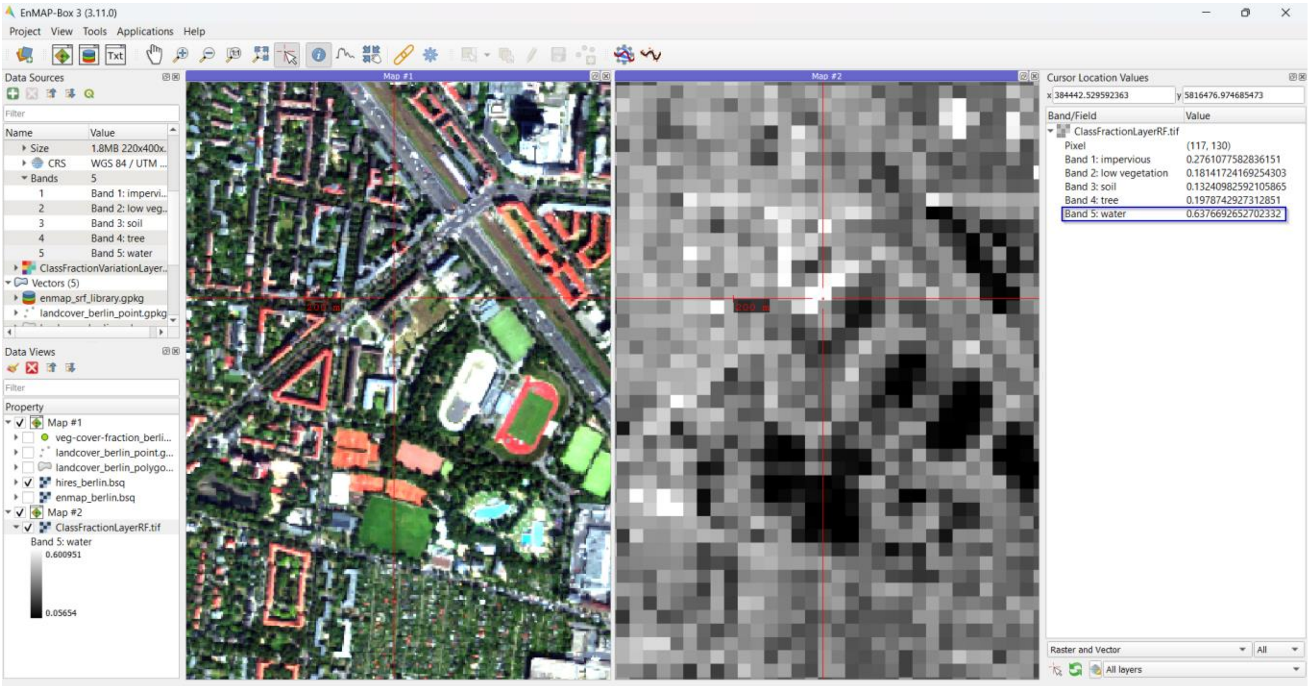


Figure 42 Example 2 of the fraction values obtained for a pixel associated with a Water Body

The fractional values displayed on the singlegray image appropriately estimate the presence of water bodies in the scene (Figure 41). However, as previously indicated, water fractional values are overestimated for impervious features (Figure 42).

CONCLUSIONS

- The Class Fraction Layer obtained from the Unmixing Process using the Random Forest Regressor and the reference points vector layer as the endmember dataset had a good performance when visually comparing it with the High-Resolution Image. Only the Water and Soil fraction values resulted to be slightly overestimated for some features in the scene.
- Fraction Mapping based on the Regression-based unmixing approach is useful to discriminate different surface types in urban heterogenous environments. Particularly, when the spatial resolution of the images is coarse, and pixels have mixed information.

REFERENCES

A. Okujeni, S. van der Linden (2021). Regression-based unmixing of urban land cover. HYPERedu, EnMAP education initiative, 1st revision January 2021, originally published March 2019, Humboldt-Universität zu Berlin.

[Regression-based unmixing of urban land cover — EnMAP-Box 3 3.10.3.20220824T155109 documentation]