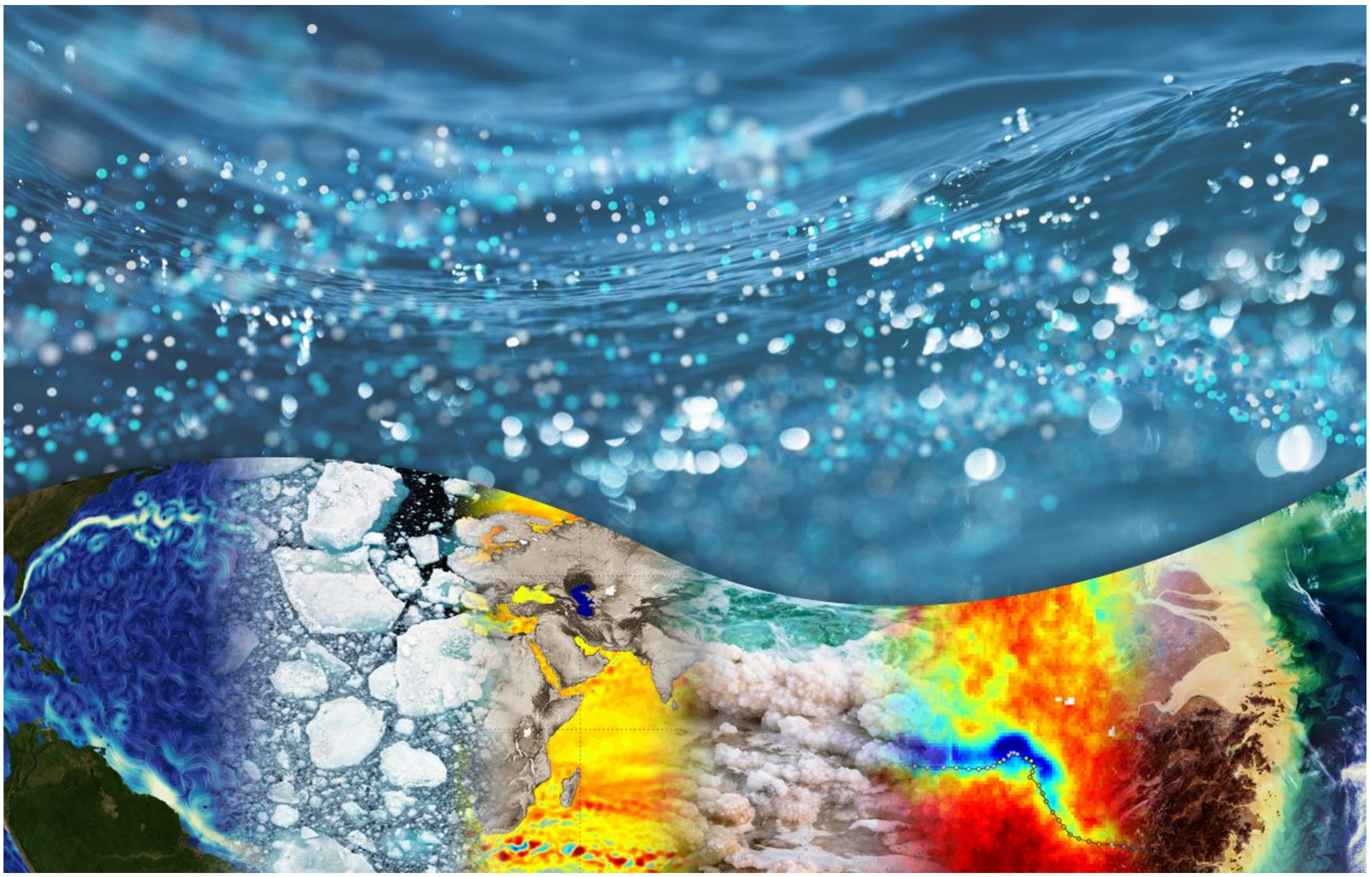
ADVANCE REMOTE SENSING

COPERNICUS MASTER'S IN DIGITAL EARTH



REGRESSION BASED SPECTRAL UNMIXING

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Introduction:

This document elaborates the simple process of regression based spectral unmixing using the EnMap-Box python plugin. The revolutionary hyperspectral imaging phenomena has given a new turn around in the field of remote sensing. It offers high spectral and very often high spatial resolution that makes the observation of ground materials extremely convenient from the space. However, the higher number of the spectral bands may lead to the overestimation of one material over the other at the pixel level. To address this spectral mixing of the end members, an unmixing technique has been introduced to apply the dimensionality reduction and/or the band redundancy to utilize only the bands that are relevant for the studied endmembers and avoid spectral mixing. The following section will discuss the regression based spectral unmixing using the linear regression model.

Hyperspectral unmixing:

As it was discussed previously, hyperspectral unmixing is a technique to distinguish end members based on their spectral signature in the mixed spectral image. “Hyperspectral unmixing (HU) refers to any process that separates the pixel spectra from a hyperspectral image into a collection of spectral signature called endmembers and a set of fractional abundances, one set per pixel” (Bioucas-Dias et al., 2012).

Unmixing exercise (EnMap-Box):

The following description and the screenshots will guide you through the regression based unmixing, while explaining some of the important parameters along the way.

There are many tools that can help you perform the spectral unmixing technique, but for this particular instance, the EnMap-Box plugin of QGIS has been used with the pre-existing example data for berlin. In this example we have deployed the linear regression model to estimate the fraction value for the endmembers present per pixel in the image. See figure 1. The dimensionality reduction has been done through the creation of classification dataset that takes the predefined classes of the objects present in the image. This step holds huge significance particularly for the performance of the deployed machine learning models. This does not overburden the model with the extravagant spectral information. The linear regression model was run under the default parameters, see figure 2, with the ensemble activated (for extra help).

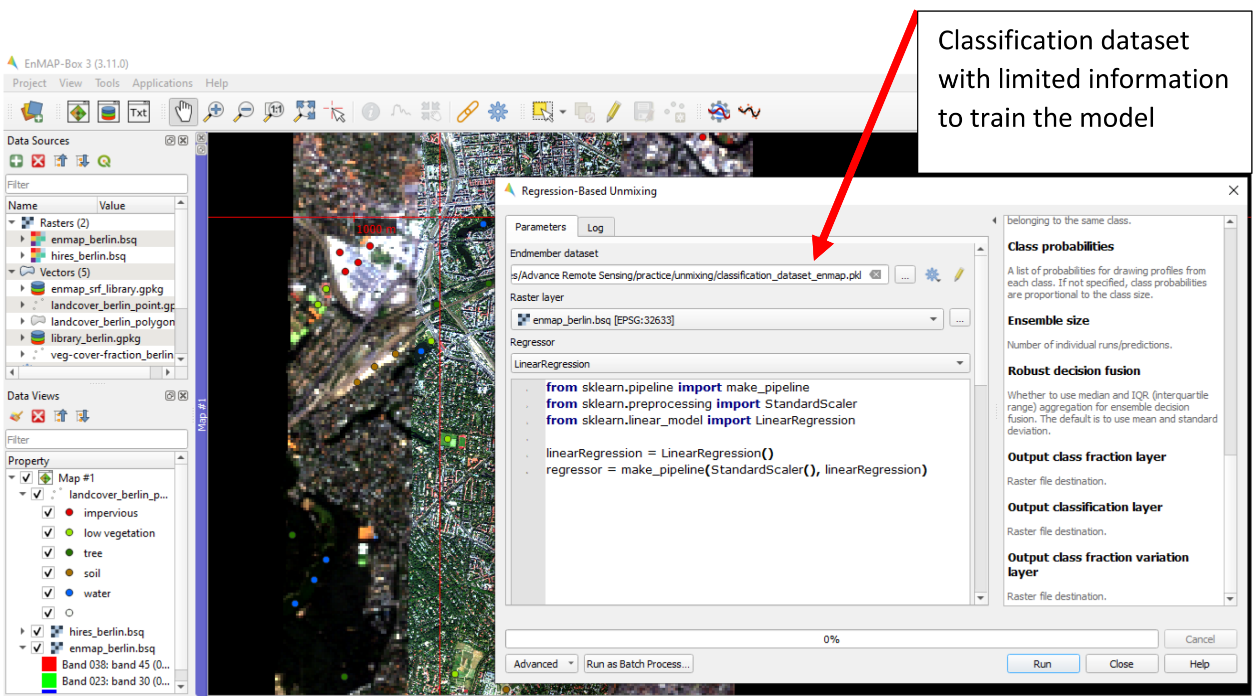

Figure 1. Represents the classification dataset to train the model

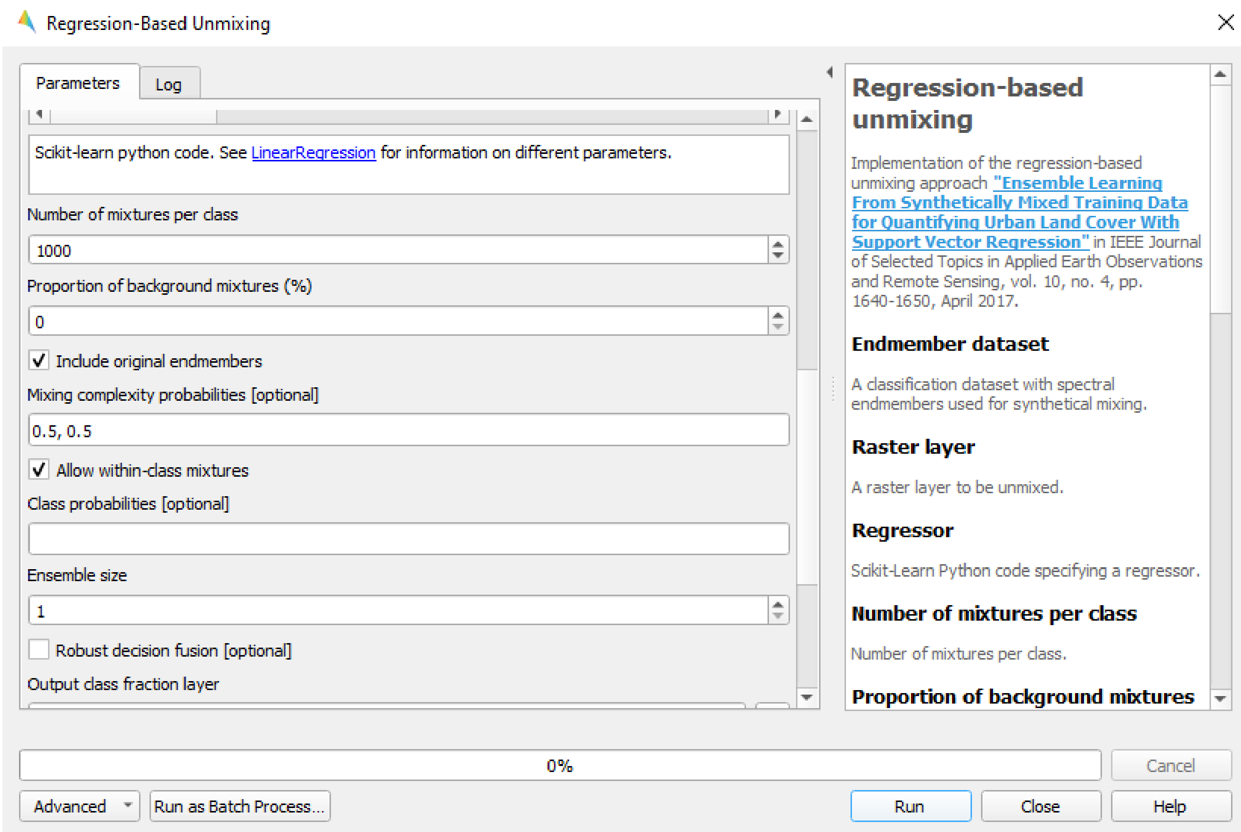

Figure 2. Shows the parameterization of the regression model for the unmixing

The purpose of preparing a fraction layer is very understandable from the definition of hyperspectral unmixing that each pixel can have more than one endmember however it is essential to identify the percentage or the fraction they occupy in each pixel to estimate the endmember contribution in the pixel and then in the whole image.

The following segment will depict the fraction layer with reduced bands and fraction value(s) in each pixel and for specific classes through a series of screenshots.

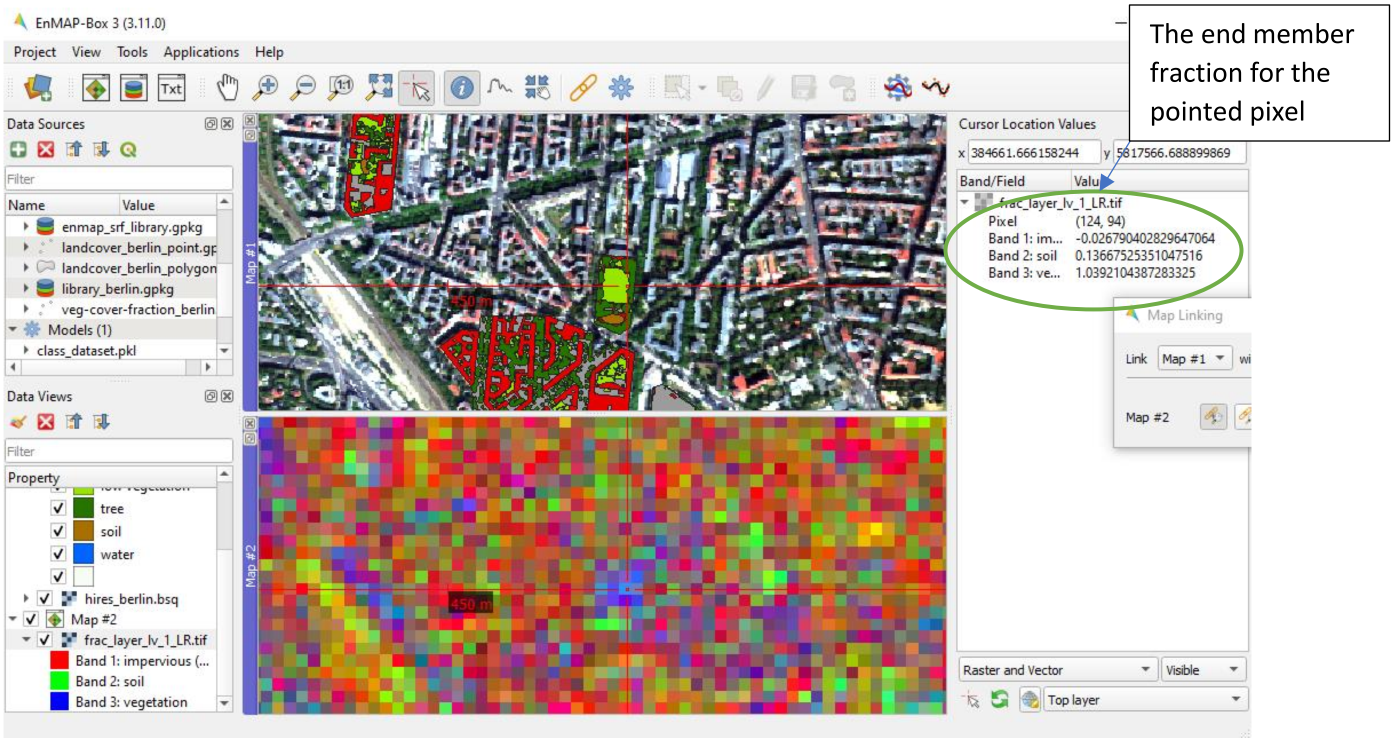

Figure 3. Example of the end member fractions after the dimensionality reduction

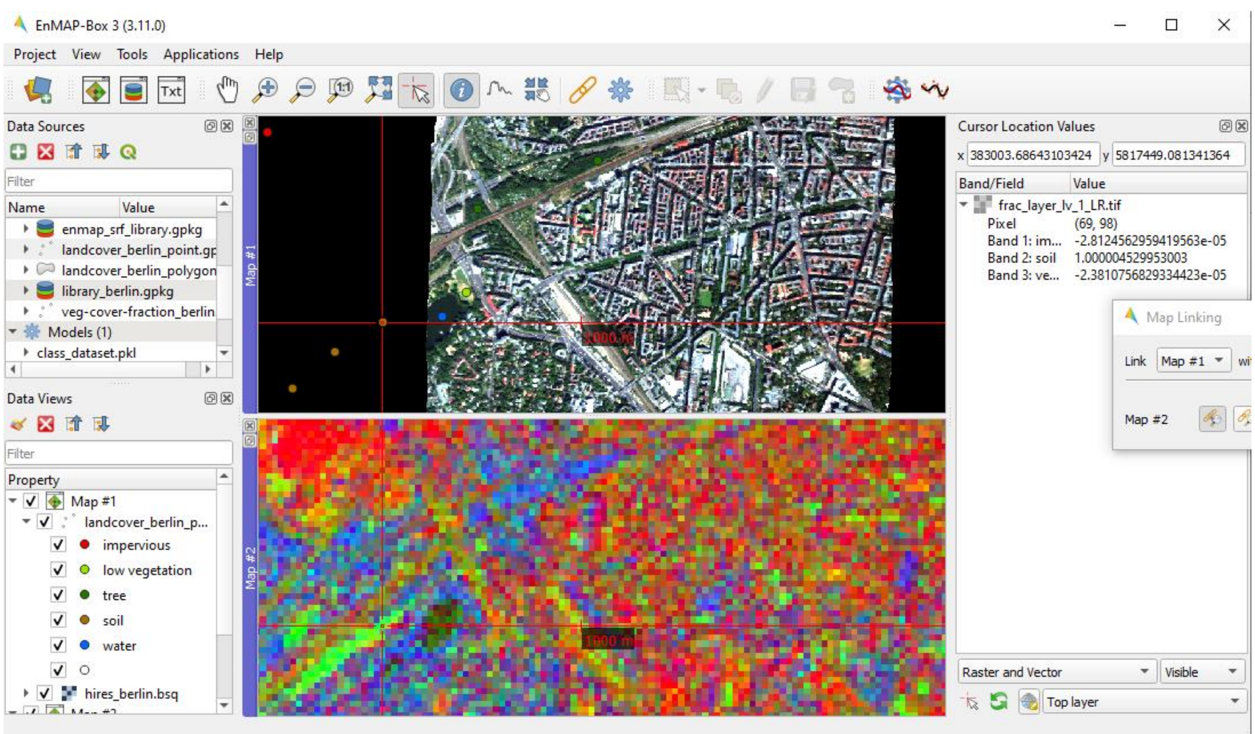

Figure 4. Example of the end member fractions using the landcover points from the example data

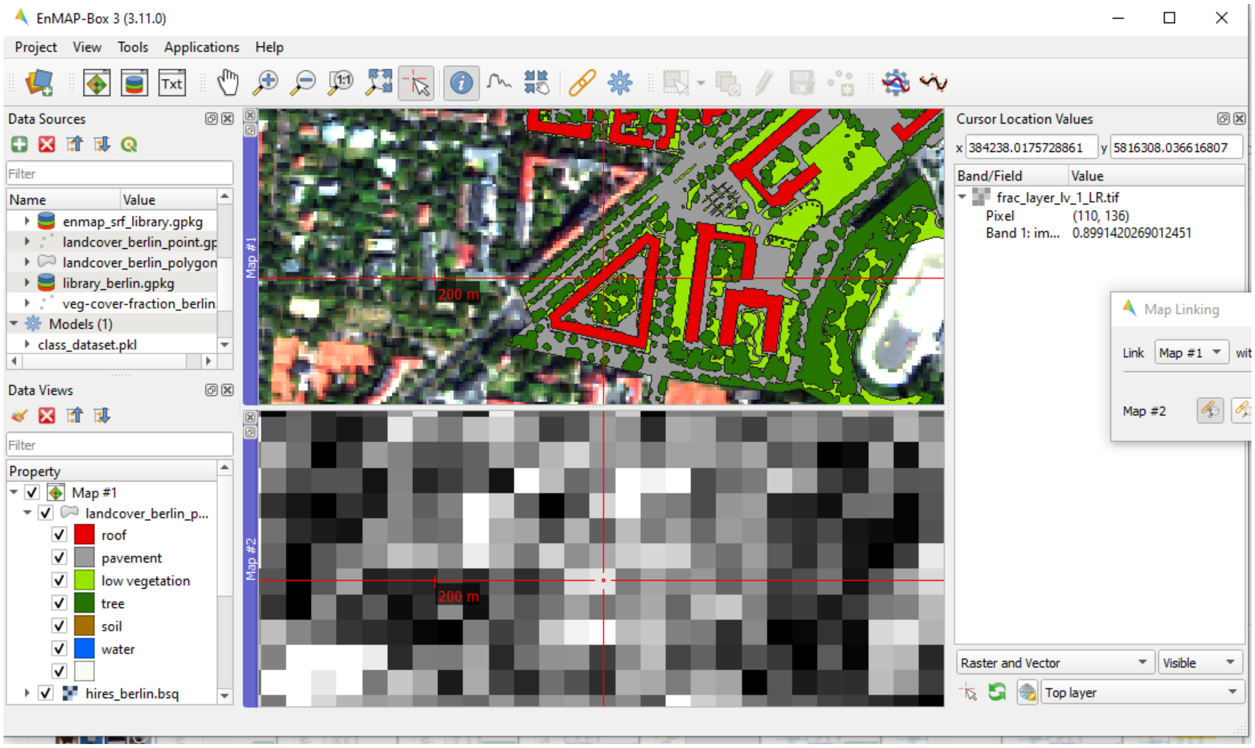

Figure 5. Validating the fractionation for the impervious class

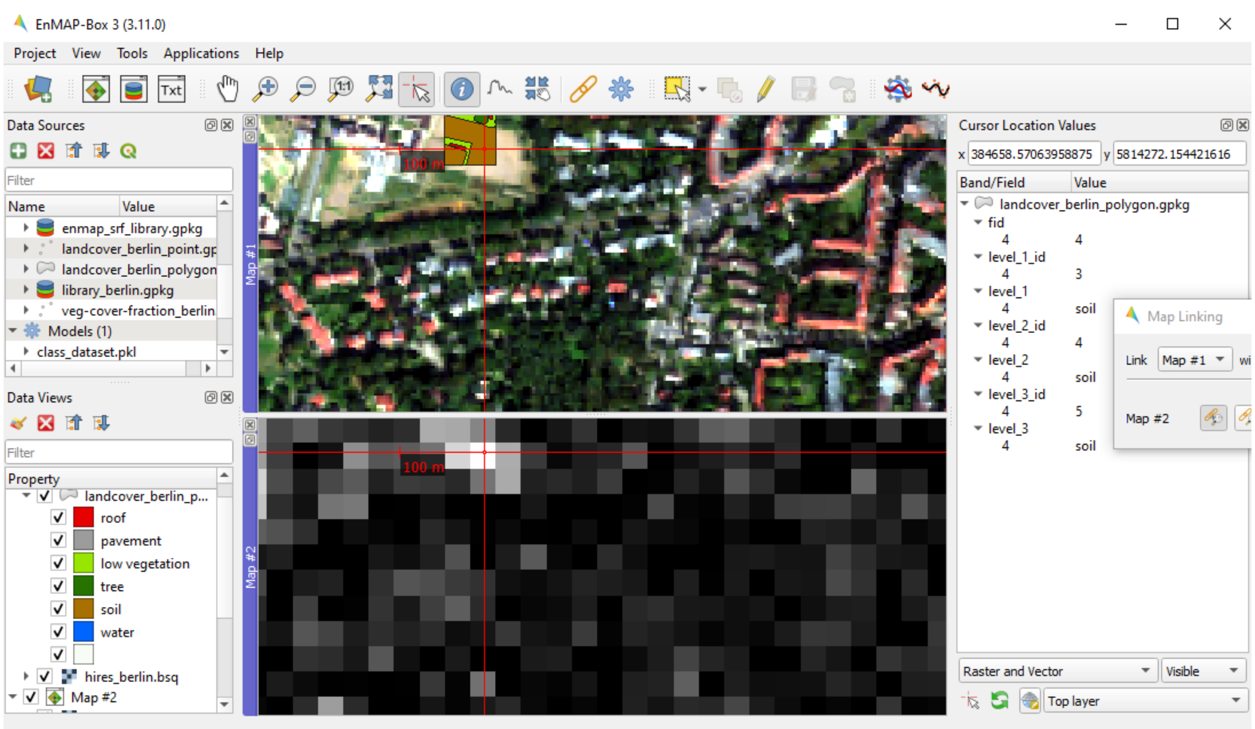

Figure 6. Validating the fractionation for the soil class

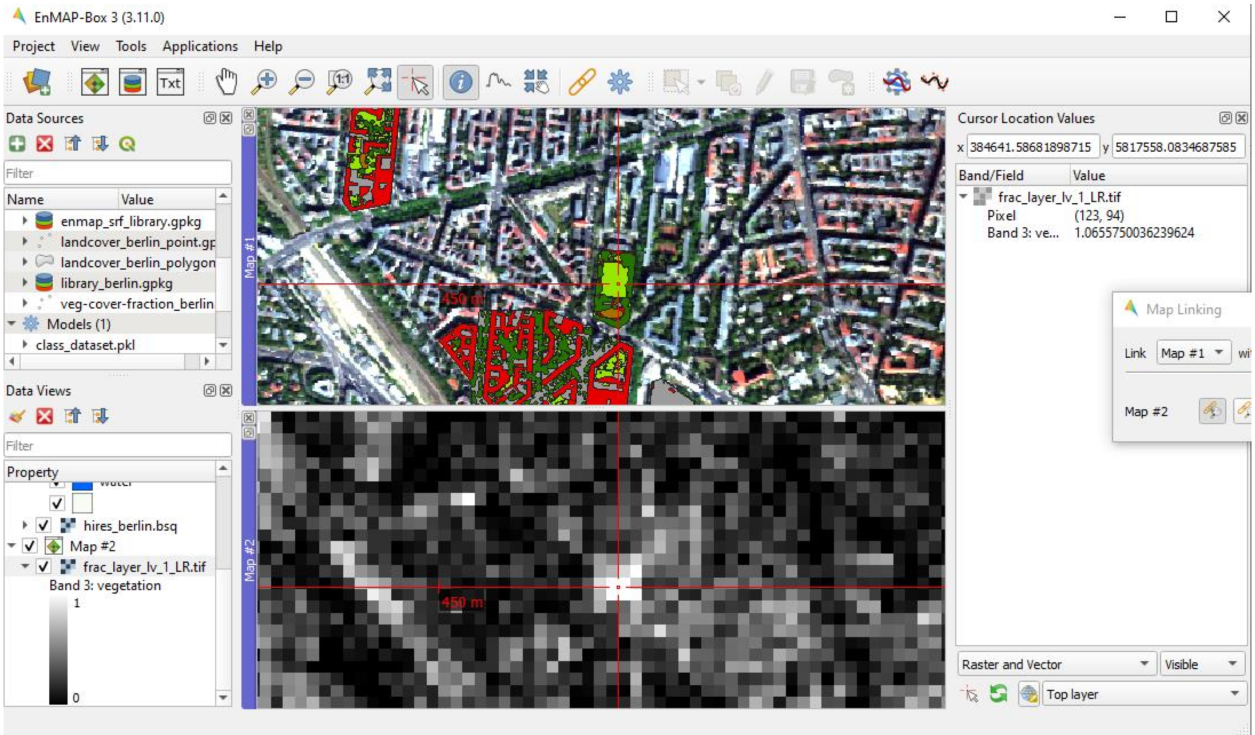

Figure 7. Validating the fractionation for the vegetation class

The comparison with the high-resolution image for the area of interest seems like a job well done. As we look at the pixel value either by isolating each class or for the whole fraction layer, the results look relatively coherent; however, a regression analysis report or the error estimation will give us a better insight on how well did the regressors perform while fractionizing the end members pixel by pixel.

Accuracy report for regression:

To generate a regression analysis report, the reference layer and fraction layer are the prerequisites. You make the fraction layer by the rasterization of the landcover polygon available in the example data. See figure 8 & 9.

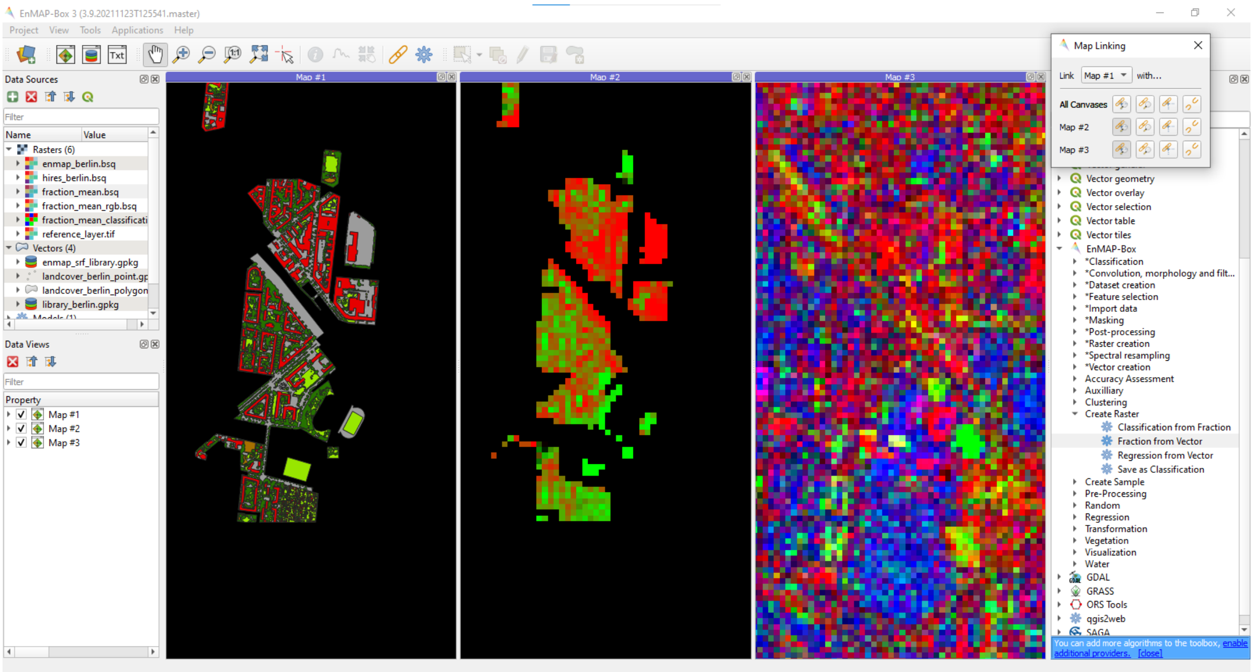

Figure 8. Left to Right: The pre-defined landcover polygons; the reference layer (to validate the accuracy of the regressors); the fraction layer

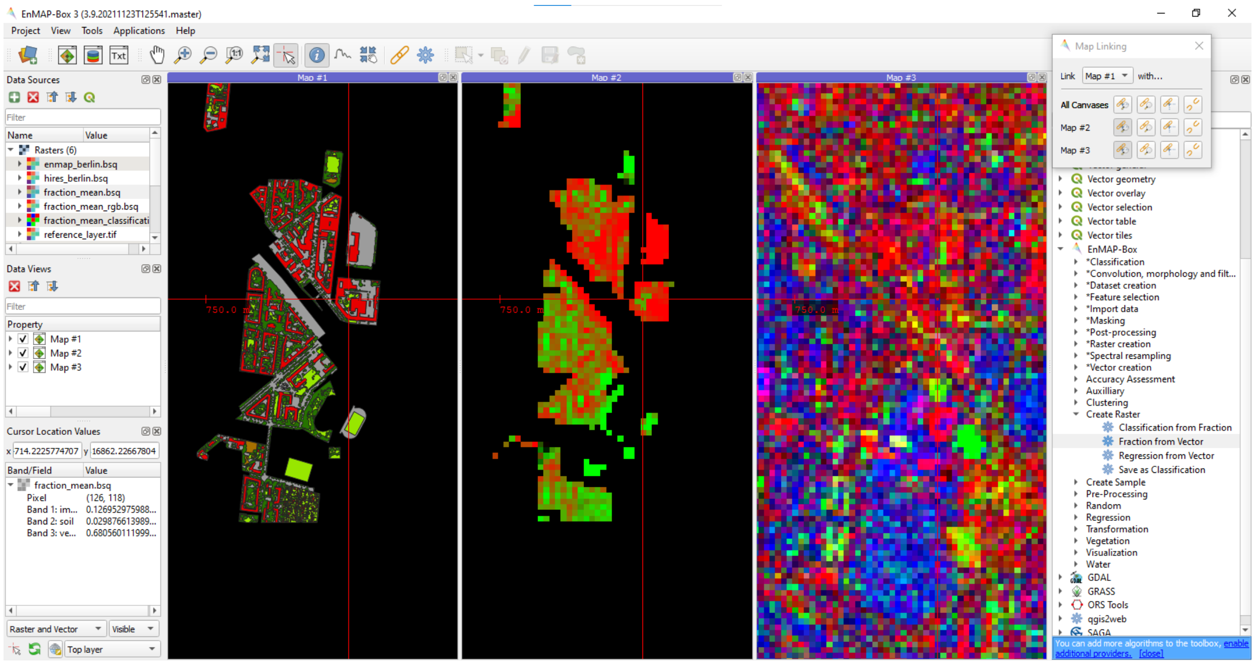

Figure 9. Fraction value observation w.r.t the reference layer

The accuracy assessment might not be very different for the spectral analysis than a conventional data analysis, instead of usual numbers the former uses the pixel/band values/wavelengths. For this example, the attached accuracy report can be accessed to peak into the main assessment parameters and the performance of the regression model for each class. However, the overall performance of the regression model in this unmixing exercise has been summarized well in the following figure 10.

Regression Performance

Outputs Overview

	Outputs			
Reference	class 1	class 2	class 3	class 4
Prediction	impervious	soil	vegetation	water

Metrics

Number of samples: 1610

	Outputs			
	class 1	**class 2**	**class 3**	**class 4**
Mean absolute error (MAE)	0.2205	0.4047	0.3466	0.2191
Root MSE (RMSE)	0.2834	0.5023	0.4426	0.2794
Ratio of performance to deviation (RPD)	1.1447	0.6125	0.3068	0.488
Mean error (ME)	-0.083	-0.351	0.3116	0.207
Mean squared error (MSE)	0.0803	0.2523	0.1959	0.0781
Median absolute error (MedAE)	0.1758	0.36	0.3028	0.2031
Squared pearson correlation (r^2)	0.3791	0.0268	0.0082	0.1277
Explained variance score	0.3023	-0.3636	-4.3569	-0.8945
Coefficient of determination (R^2)	0.2369	-1.6655	-9.6234	-3.1991

Figure 10. Summary of the Regression Model Assessment

Conclusion:

In conclusion, the dimensionality reduction through the formation of classification dataset really helped the regression model to prepare a respectable and comparable fraction layer for level_1 class of the observed endmembers. The isolated fraction layer for each class helped validate the performance of the model to the naked eye; however, the integration of the reference layer and the fraction layer provided the quantitative assessment of the deployed regression model. All in all, the unmixing techniques holds great significance for the true translation of the pixel values to identify the pure endmembers present in the image. This technique might also come in handy to reduce the overestimation of some endmembers in the pixel to get the true pixel information.