1 Introduction to hyperspectral data

Three different data sets, 'Vegetation.txt', 'Urban.txt' and 'Geology_Soil.txt', are available for your first steps in hyperspectral remote sensing. Copy these data sets from moodle to your personal directory. Pick one that matches your favorite subject. The data set 'Vegetation.txt' contains spectra of ten different plant species. 'Urban.txt' consists of reflectance spectra of ten different materials typically present in urban areas. 'Geology_Soil.txt' includes spectra of ten minerals. The data sets have been compiled from the USGS spectral library (http://speclab.cr.usgs.gov/spectral-lib.html) that we will explore in an upcoming training. Table 1.1 lists the content of the data sets in detail.

Table 1.1: Content of the three spectral data sets.

Spectrum #	Vegetation	Urban	Geology_Soil
1	Aspen	Old asphalt	Alunite
2	Blackbrush	New asphalt	Calcite
3	Blue spruce	Blue spruce	Chlorite
4	Engelmann spruce	Brick	Goethite
5	Fir	Concrete	Hematite
6	Dry grass	Fiberglass	Illite
7	Juniper	Dry grass	Kaolinite
8	Maple	Lawn grass	Muscovite
9	Oak	Swallow water	Olivine
10	Walnut	Metal roof	Quarz

Aim

In this session, we learn

- (1) How to read spectral data in your environment
- (2) How to handle and visualize the data
- (3) How to deal with imaging spectroscopy data

Prepare a spectral library

Read the data sets you want to explore in your work space. In R this is done with the following code (all script in the working sheets are R). Assign the data to the object 'specs.'

The data set is organized in rows and columns. Each row represents a spectrum, each column a spectral band corresponding to a distinct wavelength region.

Q1.1: Are the wavelength given in nm or in μ m? Which wavelength range is covered? Are the reflectance values scaled [0,1] or in [0,100]%?

in nanometers raning from 400 nm to 2445 nm; scaled [0,1]

Spectral data in combination with the wavelength information and additional attributes (such as an ID or the measured target) are referred to as spectral library. A spectral library is hence a compilation of information, including at least the reflectance spectra and the wavelength information of the spectral bands. Additional information, for example an attribute table, can also be included.

In our data sets, the spectral bands cover the range from 400 nm to 2445 nm and have a bandwidth of 5 nm. We create a vector with the wavelength information to build the spectral library. The target information is contained in the rownames of the spectral data set.

Plotting the spectral library

To get a first impression, we can simply plot the reflectance values of the spectra against the corresponding wavelengths. For this purpose, we need a general plot function that enables line-plots with two axes, such as the generic plot() function in R.

In the human perception, the color blue corresponds roughly to 450 nm, green to 550 nm, and red to 630 nm.

```
abline (v=450, col="blue") ## add a blue vertical line at 450 nm abline (v=550, col="green") ## add a green vertical line at 450 nm abline (v=630, col="red") ## add a red vertical line at 450 nm ^{\circ}
```

Q1.2: What color would the measured object have if you would be seeing it in reality?

We thus see the object (Aspen foliage) in a dark greenish color. Minerals: Reflectance in the blue, green, and red region is rather high (45-80%). The reflectance values increase from blue to red. The color of the object (Alunite) is thus a slightly brownish white.

Urban: Reflectance in the blue, green, and red region is rather low (< 10%). Reflectance increases slightly from blue to red. The color of the object (old, withered asphalt) is a slightly brownish (mixture of red and green) dark gray. Vegetation: Reflectance in the green region is low (approximately 15%), in blue and red region even lower (< 10%).

We combine all spectra to a single plot for a better comparison.

Q1.3: Compare the spectra of the different objects regarding their shape and magnitude. Which characteristic (dis-)similarities can be observed? Urban: take a look at spectra belonging to similar materials (asphalt, vegetation, etc.). Vegetation: take into consideration the different leaf traits (needleleaf, broadleaf) and water content (dry vegetation). Minerals: can you identify characteristic features in the SWIR region?

Visualizing the inter-correlation of spectral bands

If you take a closer look at the spectra, you will realize that neighboring bands have in general similar reflectance values. This similarity of neighboring bands is the so-called inter-correlation, a characteristic feature of spectral data that interferes with many analysis techniques. The inter-correlation strongly depends on the kind of spectra we are analyzing. Often, we can identify distinct spectral regions that show a high inter-correlation and thus a similar behavior. The inter-correlation can be assessed by calculating the mutual, pairwise correlations of all bands in a correlation matrix. This correlation matrix is a square matrix with as many rows and columns as there are bands. Because the correlation of band 1 and band 2 is the same as for band 2 and band 1, the inter-correlation pattern is symmetric with the diagonal being the rotation axis. The upper half, being redundant, can hence be eliminated.

```
cm <- cor (speclib$specs) ## calculate the correlation matrix cm[row (cm) > col (cm)] <- NA ## eliminate the upper half
```

The terra-package in R enables the conversion of data tables (matrices) into gridded raster data for further analysis and visualization and makes the GDAL. We will use it later for handling image data sets and explore this functionality for the visualization of the correlation matrix, too.

Q1.4: Describe the inter-correlation of spectral bands in your data set. Can you identify distinct regions with a similar spectral behavior (R>0.7)?

spectrum are highly inter-correlated.

the 1410-1650 nm and 1880-2100 nm regions are inter-correlated with the visible region. Vegetation: Bands within the following spectral regions show a very high inter-correlation: 450-710 nm (the visible region), 730-1380 nm (near infrared, NIR), 1400-1880 nm (SWIR), 1900-2450 nm (SWIR). In addition, the distinct SWIR regions are inter-correlated to a lesser degree and also show some inter-correlation with the visible region. Geology: There are no distinct regions that can be separated. In general, all neighboring bands across the whole Geology:

Urban: Bands within the following spectral regions show a very high inter-correlation: 450-730 nm (the visible region), 740-1380 nm (near infrared, SWIR), 1410-1650 nm, 1670-1850 nm (short wave infrared, SWIR), 1880-2100 nm (SWIR), 2150-2450 nm (SWIR). In addition, the distinct SWIR regions are also inter-correlated to a lesser degree and

Q1.5: If you were a engineer and asked to design a multispectral sensor with five bands for urban / vegetation / geology & soil mapping, where would you place the bands based on the observed intercorrelation patterns?

characteristics.

Urban: One in the visible, one in the VIR, and one in each SWIR region. Yegetation: Two bands in the visible region, one in the VIR, and one in each SWIR region. Geology: There are no distinct spectral regions and five bands are not sufficient for providing the main spectral

Image data

Now that you have seen some spectra, we want to take a look at a hyperspectral image cube. Again, three different data sets are available. The data have been sampled with the airborne AISA sensor (full-range) and are provided free of charge from the SecTIR web page (http://www.spectir.com/free-data-samples/). The geology data set covers the Cuperite site in Nevada (USA), a well-known test site for geological applications. The vegetation (and water) data set was taken in the lower Suwannee National Wildlife Reserve in the Gulf of Mexico. The urban data set covers parts of the city of Reno in Nevada (USA). Note that this image has not been flightline corrected. Because the AISA sensor comes in different configurations, the number of bands included in the data as well as the wavelengths corresponding to the bands differ between the data sets. Figure 1.1 illustrates the distribution of the bands across the solar electromagnetic spectrum. All images have been processed to reflectance data; the digital numbers are reflectance values [% * 100]. The wavelength information related to the images comes in corresponding *.txt files and provides the wavelengths of the bands in µm.

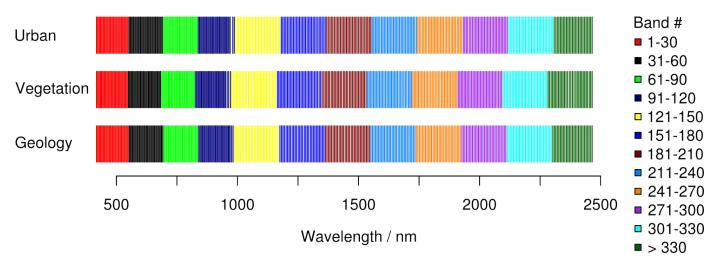


Fig. 1.1: Distribution of the AISA bands across the solar electromagnetic spectrum for the three different configurations used in the data sets.

Again, select a data set that you want to work with and assign it to the object 'im.' Assign the corresponding wavlength information to the object 'im.wl.'

```
im <- geo.im / 100 \#\# or veg.im or urb.im, /100 to scale reflectance in % im.wl <- geo.wl \#\# or veg.wl or urb.wl
```

The plotRGB function combines three bands of the image cube to a color composite. The combination 51, 34, and 13 results in a true color image.

```
plotRGB (im, r=51, g=34, b=13, stretch="lin") \#\# plot a color composite of band \#\# 51(red), 34 (green), and 13 (blue)
```

Q1.6: Use your newly gained knowledge on spectral properties of the surface to select three bands that enhance the main differences of the materials that you expect in your image. Which bands do you select? Why?

Find a way to extract the spectral profiles from the pixels. In R this can be done interactively. As long as the image is still displayed in the graphic panel, we can extract the spectra of individual pixels by using the interactive click() function and clicking on pixels in the plotted image. A simple graphic function plots the spectral profiles in a new panel for examination.

Extract the spectra of multiple pixels (e.g., by by repeatedly executing the previous line of code and clicking into the image).

Q1.7: Are you already familiar with the shape of some spectra? Can you identify some materials present in the image?