Spectrometer accuracy assesment using validation tarps

Background

In this lesson we will be examing the accuracy of the Neon Imaging Spectrometer (NIS) against targets with known reflectance. The targets consist of two 10 x 10 m tarps which have been specially designed to have 3% reflectance (black tarp) and 48% reflectance (white tarp) across all of the wavelengths collected by the NIS (see images below). During the Sept. 12 2016 flight over the Chequamegon-Nicolet National Forest, an area in D05 which is part of Steigerwaldt (STEI) site, these tarps were deployed in a gravel pit. During the airborne overflight, observations were also taken over the tarps with an ASD field spectrometer. The ASD measurments provide a validation source against the the airborne measurements.





Reflectance tarps

To test the accuracy, we will utilize reflectance curves from the tarps as well as from the associated flight line and execute absolute and relative comparisons. The major error sources in the NIS can be generally categorized into the following sources

- 1) Calibration of the sensor
- 2) Quality of ortho-rectification
- 3) Accuracy of radiative transfer code and subsequent ATCOR interpolation
- 4) Selection of atmospheric input parameters
- 5) Terrain relief
- 6) Terrain cover

Note that the manual for ATCOR, the atmospheric correction software used by AOP, specifies the accuracy of reflectance retrievals to be between 3 and 5% of total reflectance. The tarps are located in a flat area, therefore, influences by terrain releif should be minimal. We will ahve to keep the remining errors in mind as we analyze the data.

Objective

In this lesson we will learn how to retrieve reflectance curves from a pre-specified coordainte in a NEON AOP HDF 5 file, learn how to read a tab delimited text file, retrive bad bad window indexes and mask portions of a reflectance curve, plot reflectance curves on a graph and save the file, gain an understanding of some sources of uncertainty in NIS data.

Suggested pre-requisites

Working with NEON AOP Hyperspectral Data in Python Jupyter Notebooks

Learn to Efficiently Process NEON Hyperspectral Data

We'll start by adding all of the necessary libraries to our python script

```
In [2]: import h5py
import csv
import numpy as np
import os
import gdal
import matplotlib.pyplot as plt
import sys
from math import floor
import time
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

As well as our function to read the hdf5 reflectance files and associated metadata

```
In [3]: def h5refl2array(h5 filename):
            hdf5 file = h5py.File(h5 filename, 'r')
            #Get the site name
            file attrs string = str(list(hdf5 file.items()))
            file_attrs_string_split = file_attrs_string.split("'")
            sitename = file attrs string split[1]
            refl = hdf5 file[sitename]['Reflectance']
            reflArray = refl['Reflectance Data']
            refl shape = reflArray.shape
            wavelengths = refl['Metadata']['Spectral Data']['Wavelength']
            #Create dictionary containing relevant metadata information
            metadata = {}
            metadata['shape'] = reflArray.shape
            metadata['mapInfo'] = refl['Metadata']['Coordinate System']['Map Info']
            #Extract no data value & set no data value to NaN\n",
            metadata['scaleFactor'] = float(reflArray.attrs['Scale_Factor'])
            metadata['noDataVal'] = float(reflArray.attrs['Data Ignore Value'])
            metadata['bad_band_window1'] = (refl.attrs['Band_Window_1_Nanometers'])
            metadata['bad band window2'] = (refl.attrs['Band Window 2 Nanometers'])
            metadata['projection'] = refl['Metadata']['Coordinate System']['Proj4'].value
            metadata['EPSG'] = int(refl['Metadata']['Coordinate_System']['EPSG Code'].val
            mapInfo = refl['Metadata']['Coordinate System']['Map Info'].value
            mapInfo_string = str(mapInfo); #print('Map Info:',mapInfo_string)\n",
            mapInfo split = mapInfo string.split(",")
            #Extract the resolution & convert to floating decimal number
            metadata['res'] = {}
            metadata['res']['pixelWidth'] = mapInfo_split[5]
            metadata['res']['pixelHeight'] = mapInfo_split[6]
            #Extract the upper left-hand corner coordinates from mapInfo\n",
            xMin = float(mapInfo_split[3]) #convert from string to floating point number\
            yMax = float(mapInfo split[4])
            #Calculate the xMax and yMin values from the dimensions\n",
            xMax = xMin + (refl_shape[1]*float(metadata['res']['pixelWidth'])) #xMax = Le
            yMin = yMax - (refl_shape[0]*float(metadata['res']['pixelHeight'])) #yMin = t
            metadata['extent'] = (xMin,xMax,yMin,yMax),
            metadata['ext_dict'] = {}
            metadata['ext_dict']['xMin'] = xMin
            metadata['ext dict']['xMax'] = xMax
            metadata['ext dict']['yMin'] = yMin
            metadata['ext_dict']['yMax'] = yMax
            hdf5 file.close
            return reflArray, metadata, wavelengths
```

Define the location where you are holding the data for the data institute. The h5_filename will be the flightline which contains the tarps, and the tarp_48_filename and tarp_03_filename contain the field validated spectra for the white and black tarp respectively, organized by wavelength and reflectance.

In [4]: print('Start CHEQ tarp uncertainty script')

h5_filename = 'C:/RSDI_2017/data/CHEQ/H5/NEON_D05_CHEQ_DP1_20160912_160540_reflectarp_48_filename = 'C:/RSDI_2017/data/CHEQ/H5/CHEQ_Tarp_48_01_refl_bavg.txt'
 tarp_03_filename = 'C:/RSDI_2017/data/CHEQ/H5/CHEQ_Tarp_03_02_refl_bavg.txt'

Start CHEQ tarp uncertainty script

We want to pull the spectra from the airborne data from the center of the tarp to minimize any errors introduced by infiltrating light in adjecent pixels, or through errors in ortho-rectification (source 2). We have pre-determined the coordinates for the center of each tarp which are as follows:

48% reflectance tarp UTMx: 727487, UTMy: 5078970

3% reflectance tarp UTMx: 727497, UTMy: 5078970

Reflectance tarp centers

Let's define these coordaintes

```
In [5]: tarp_48_center = np.array([727487,5078970])
tarp_03_center = np.array([727497,5078970])
```

Now we'll use our function designed for NEON AOP's HDF5 files to access the hyperspectral data

```
In [6]: [reflArray,metadata,wavelengths] = h5refl2array(h5_filename)
```

Within the reflectance curves there are areas with noisey data due to atmospheric windows in the water absorption bands. For this exercise we do not want to plot these areas as they obscure detailes in the plots due to their anamolous values. The meta data assocaited with these band locations is contained in the metadata gatherd by our function. We will pull out these areas as 'bad band windows' and determine which indexes in the reflectance curves contain the bad bands

```
In [7]: bad_band_window1 = (metadata['bad_band_window1'])
bad_band_window2 = (metadata['bad_band_window2'])

index_bad_window1 = [i for i, x in enumerate(wavelengths) if x > bad_band_window1
index_bad_window2 = [i for i, x in enumerate(wavelengths) if x > bad_band_window2
```

Now join the list of indexes together into a single variable

```
In [8]: index_bad_windows = index_bad_window1+index_bad_window2
```

The reflectance data is saved in files which are 'tab delimited.' We will use a numpy function (genfromtxt) to quickly import the tarp reflectance curves observed with the ASD using the '\t'.

delimeter to indicate tabs are used.

```
In [9]: tarp_48_data = np.genfromtxt(tarp_48_filename, delimiter = '\t')
tarp_03_data = np.genfromtxt(tarp_03_filename, delimiter = '\t')
```

Now we'll set all the data inside of those windows to NaNs (not a number) so they will not be included in the plots

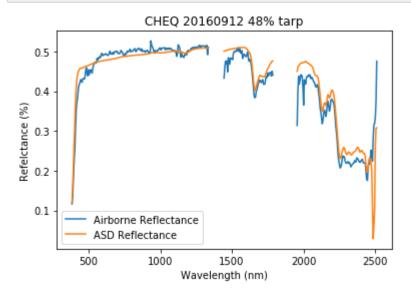
```
In [10]: tarp_48_data[index_bad_windows] = np.nan
tarp_03_data[index_bad_windows] = np.nan
```

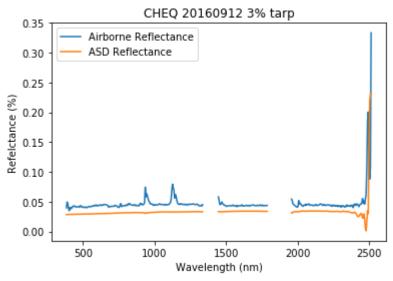
The next step is to determine which pixel in the reflectance data belongs to the center of each tarp. To do this, we will subtract the tarp center pixel location from the upper left corner pixels specified in the map info of the H5 file. This information is saved in the metadata dictionary output from our function that reads NEON AOP HDF5 files. The difference between these coordaintes gives us the x and y index of the reflectance curve.

```
In [11]: x_tarp_48_index = int((tarp_48_center[0] - metadata['ext_dict']['xMin'])/float(metarp_48_index = int((metadata['ext_dict']['yMax'] - tarp_48_center[1])/float(metarp_03_index = int((tarp_03_center[0] - metadata['ext_dict']['xMin'])/float(metarp_03_index = int((metadata['ext_dict']['yMax'] - tarp_03_center[1])/float(metarp_03_index = int((metadata['ext_dict']['yMax'] - tarp_03_center[1])/float(metadata['ext_dict']['yMax'] - ta
```

Next, we will plot both the curve from the airborne data taken at the center of the tarps as well as the curves obtained from the ASD data to provide a visualisation of thier consistency for both tarps. Once generated, we will also save the figure to a pre-determined location.

```
In [14]:
         plt.figure(1)
         tarp 48 reflectance = np.asarray(reflArray[y tarp 48 index,x tarp 48 index,:], dt
         tarp 48 reflectance[index bad windows] = np.nan
         plt.plot(wavelengths,tarp 48 reflectance,label = 'Airborne Reflectance')
         plt.plot(wavelengths,tarp_48_data[:,1], label = 'ASD Reflectance')
         plt.title('CHEQ 20160912 48% tarp')
         plt.xlabel('Wavelength (nm)'); plt.ylabel('Refelctance (%)')
         plt.legend()
         plt.savefig('CHEQ 20160912 48 tarp.png',dpi=300,orientation='landscape',bbox inch
         plt.figure(2)
         tarp_03_reflectance = np.asarray(reflArray[y_tarp_03_index,x_tarp_03_index,:], dt
         tarp_03_reflectance[index_bad_windows] = np.nan
         plt.plot(wavelengths,tarp 03 reflectance,label = 'Airborne Reflectance')
         plt.plot(wavelengths,tarp 03 data[:,1],label = 'ASD Reflectance')
         plt.title('CHEQ 20160912 3% tarp')
         plt.xlabel('Wavelength (nm)'); plt.ylabel('Refelctance (%)')
         plt.legend()
         plt.savefig('CHEQ_20160912_3_tarp.png',dpi=300,orientation='landscape',bbox_inche
```



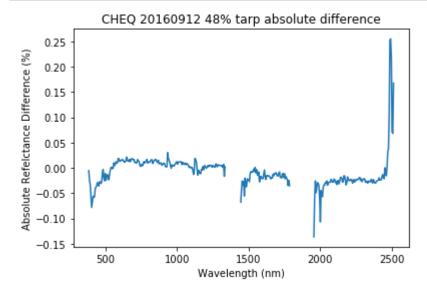


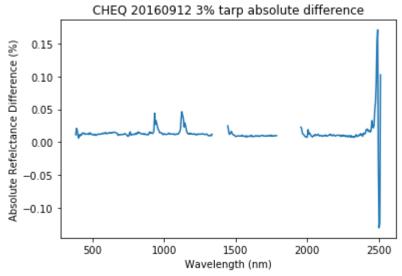
This produces plots showing the results of the ASD and airborne measurements over the 48% tarp. Visually, the comparison between the two appears to be fairly good. However, over the 3% tarp we appear to be over-estimating the reflectance. Large absolute differences could be associated with ATCOR input parameters (source 4). For example, the user must input the local visibility, which is related to aerosal optical thickness (AOT). We don't measure this at every site, therefore input a standard parameter for all sites.

Given the 3% reflectance tarp has much lower overall reflactance, it may be more informative to determine what the absolute difference between the two curves are and plot that as well.

```
In [15]: plt.figure(3)
   plt.plot(wavelengths,tarp_48_reflectance-tarp_48_data[:,1])
   plt.title('CHEQ 20160912 48% tarp absolute difference')
   plt.xlabel('Wavelength (nm)'); plt.ylabel('Absolute Refelctance Difference (%)')
   plt.savefig('CHEQ_20160912_48_tarp_absolute_diff.png',dpi=300,orientation='landsc

   plt.figure(4)
   plt.plot(wavelengths,tarp_03_reflectance-tarp_03_data[:,1])
   plt.title('CHEQ 20160912 3% tarp absolute difference')
   plt.xlabel('Wavelength (nm)'); plt.ylabel('Absolute Refelctance Difference (%)')
   plt.savefig('CHEQ_20160912_3_tarp_absolute_diff.png',dpi=300,orientation='landsca
```



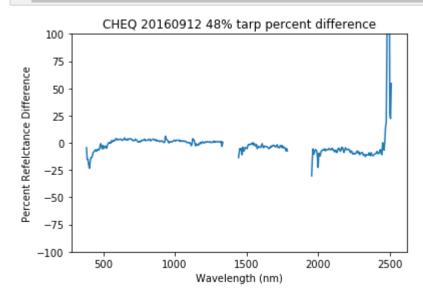


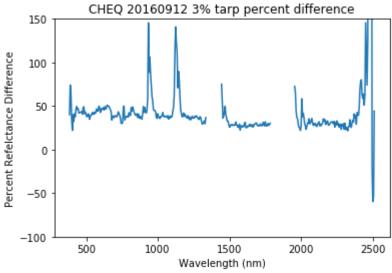
From this we are able to see that the 48% tarp actually has larger absolute differences than the 3% tarp. The 48% tarp performs poorly at the shortest and longest waveleghts as well as near the edges of the 'bad band windows.' This is related to difficulty in calibrating the sensor in these sensitive areas (source 1).

Let's now determine the result of the percent difference, which is the metric used by ATCOR to report accuracy. We can do this by calculating the ratio of the absolute difference between curves to the total reflectance

In [16]:
 plt.figure(5)
 plt.plot(wavelengths,100*np.divide(tarp_48_reflectance-tarp_48_data[:,1],tarp_48_
 plt.title('CHEQ 20160912 48% tarp percent difference')
 plt.xlabel('Wavelength (nm)'); plt.ylabel('Percent Refelctance Difference')
 plt.ylim((-100,100))
 plt.savefig('CHEQ_20160912_48_tarp_relative_diff.png',dpi=300,orientation='landsc

plt.figure(6)
 plt.plot(wavelengths,100*np.divide(tarp_03_reflectance-tarp_03_data[:,1],tarp_03_
 plt.title('CHEQ 20160912 3% tarp percent difference')
 plt.xlabel('Wavelength (nm)'); plt.ylabel('Percent Refelctance Difference')
 plt.ylim((-100,150))
 plt.savefig('CHEQ_20160912_3_tarp_relative_diff.png',dpi=300,orientation='landsca')





From these plots we can see that even though the absolute error on the 48% tarp was larger, the relative error on the 48% tarp is generally much smaller. The 3% tarp can have errors exceeding 50% for most of the tarp. This indicates that targets with low reflectance values may have higher relative errors.