MAP - Hyperspectral Remote Sensing

May 20, 2021

Dominic Hewitt do6743he-s

I had quite some troubles with Matlab and so, as I am learning Python, decided to complete the exercise in a Jupyter notebook

1 Import modules

[1]:
```
import numpy as np
import pandas as pd
from scipy import io
from scipy.stats import linregress, describe
import matplotlib.pyplot as plt
```

2 Load and check data

[2]:
```
subplots_data = io.loadmat('subplots.mat')
subplots = subplots_data['subplots']
np.shape(subplots)
```

[2]:
```
(584, 60)
```

[3]:
```
lai_data = io.loadmat('fieldlai.mat')
lai = lai_data['fieldlai'][0]
```

[4]:
```
lai
```

[4]:
```
array([2.54, 2.88, 2.13, 1.58, 1.94, 2.69, 3.6 , 5.11, 2.06, 5.09, 3.72,
       3.45, 3.3 , 2.76, 5.54, 6.16, 5.26, 4.47, 2.82, 1.63, 2.42, 2.33,
       2.84, 2.12, 1.65, 2.82, 1.64, 1.95, 2.46, 1.62, 2.02, 1.76, 1.31,
       2.25, 2.23, 4.94, 2.96, 3.33, 4.15, 4.13, 3.12, 2.76, 3.53, 3.09,
       5.43, 5.29, 4.39, 4.24, 2.74, 1.98, 3.05, 3.02, 1.96, 1.09, 1.43,
       2.2 , 1.4 , 1.08, 1.38, 1.36])
```

[5]:
```
np.shape(subplots)
```

[5]:
```
(584, 60)
```

[6]:
```
subplots[0]
```

[6]:
```
array([1.63317647, 1.38608824, 1.62261765, 1.79544118, 1.68752941,
       1.67151471, 1.47005882, 1.59147059, 1.82079412, 1.59147059,
       1.57344118, 1.50098529, 1.68394118, 1.57008824, 1.08202941,
       1.20861765, 1.25638235, 1.08070588, 1.57085294, 2.16738235,
       1.95238235, 1.81352941, 2.08175   , 1.90726471, 2.09808824,
       2.08175   , 2.33644118, 2.22614706, 2.57552941, 2.33644118,
       1.86614706, 2.0985    , 2.11570588, 1.97244118, 1.97244118,
       1.40517647, 1.28297059, 1.16147059, 1.22147059, 1.22147059,
       1.31923529, 1.57044118, 1.5285    , 1.31923529, 1.80142647,
       1.80820588, 2.04101471, 1.59355882, 1.36820588, 1.83016176,
       1.79188235, 1.79188235, 1.83016176, 2.00617647, 1.58475   ,
       1.91720588, 1.58475   , 2.21720588, 2.12017647, 1.88023529])
```

3 Calculate the Standard NDVI

Note: indeces in python always begin at 0; so in this case the bands will always be minus 1

[7]:
```
# NDVI=(infrared - red)/(infrared + red)

nir = subplots[298]
red = subplots[194]

NDVIs = (nir - red)/(nir + red)
```

[8]:
```
NDVIs
```

[8]:
```
array([0.80124622, 0.81770987, 0.76473776, 0.72382544, 0.64873222,
       0.75548466, 0.89082889, 0.89531476, 0.7884871 , 0.89531476,
       0.81173747, 0.80333766, 0.77236223, 0.80382923, 0.85751949,
       0.8580105 , 0.87559191, 0.86222756, 0.80474732, 0.57425708,
       0.66968322, 0.78267067, 0.75507011, 0.76554682, 0.68010971,
       0.75507011, 0.67566579, 0.71202606, 0.62519671, 0.67566579,
       0.67060712, 0.60581282, 0.64227121, 0.64010997, 0.64010997,
       0.86753392, 0.84236327, 0.85384694, 0.85905979, 0.85905979,
       0.78285882, 0.7369968 , 0.79290395, 0.78285882, 0.84722039,
       0.84686323, 0.74473159, 0.83565894, 0.853673  , 0.78758038,
       0.85288855, 0.85288855, 0.78758038, 0.75434658, 0.82933658,
       0.74444646, 0.82933658, 0.75425191, 0.75075183, 0.82470582])
```

4 Calculate the coefficient of determination (R squared)

[9]:
```
def r2(SVI):
    coeff = linregress(SVI, lai) # calculate linear regression
    return coeff.rvalue**2 #square the r_value to get coefficient of␣
 ↪determination

r2(NDVIs)
```

[9]:
```
0.4111413434942934
```

5 Calculate R squared for all band combinations

First I reate a dictionary and then with a for loop, append each r2 value as well as index of band 1 and 2 (the if statement avoids the calculation for the same bands. i.e.(B1-B1)/(B1+B1)

[10]:
```
NDVIn = {'R2':[], 'band1':[], 'band2':[]}
for i,j in [(i, j) for i in enumerate(subplots) for j in enumerate(subplots)]:
    if i[0] != j[0]:
        NDVI = (i[1]-j[1])/(i[1]+j[1])
        NDVIn['R2'].append(r2(NDVI))
        NDVIn['band1'].append(i[0])
        NDVIn['band2'].append(j[0])
```

Convert to data frame for visualisation

[11]:
```
band_combi = pd.DataFrame(NDVIn)
band_combi.head()
```

[11]:

	R2	band1	band2
0	0.081155	0	1
1	0.082572	0	2
2	0.083652	0	3
3	0.084325	0	4
4	0.084516	0	5

#Find the optimal bands and corresponding wavelenghts

[12]:
```
optimal_bands = band_combi.loc[band_combi['R2'].idxmax()]
optimal_bands
```

[12]:
```
R2          0.689201
band1      72.000000
band2     451.000000
Name: 42426, dtype: float64
```

```
[13]: wl_data = io.loadmat('wl.mat')
wl = wl_data['wl']

optimal_wl = f'{wl[71][0]} nm, {wl[450][0]} nm'
optimal_wl
```

```
[13]: '502.16 nm, 1362.62 nm'
```

Excersise question Compare the R 2 obtained between LAI and standard NDVI (NDVIs) and R 2 obtained using best narrow band NDVI (NDVIn). What are their differences? How do you explain these dif- ferences?

The R squared value for the relationship between the optimal bands and Lai is significantly higher (stronger) than that of the standard DNVI bands. This is because the variance in these bands (and index calculated from them) is more similar to the variance in LAI and is more likely an effect of the reflectance of LAI.

6 Calculate NDVI using optimal bands

```
[14]: #NDVI=(infrared - red)/(infrared + red)
nir = subplots[int(optimal_bands.band2)]
red = subplots[int(optimal_bands.band1)]

NDVIn = (nir - red)/(nir + red)
```

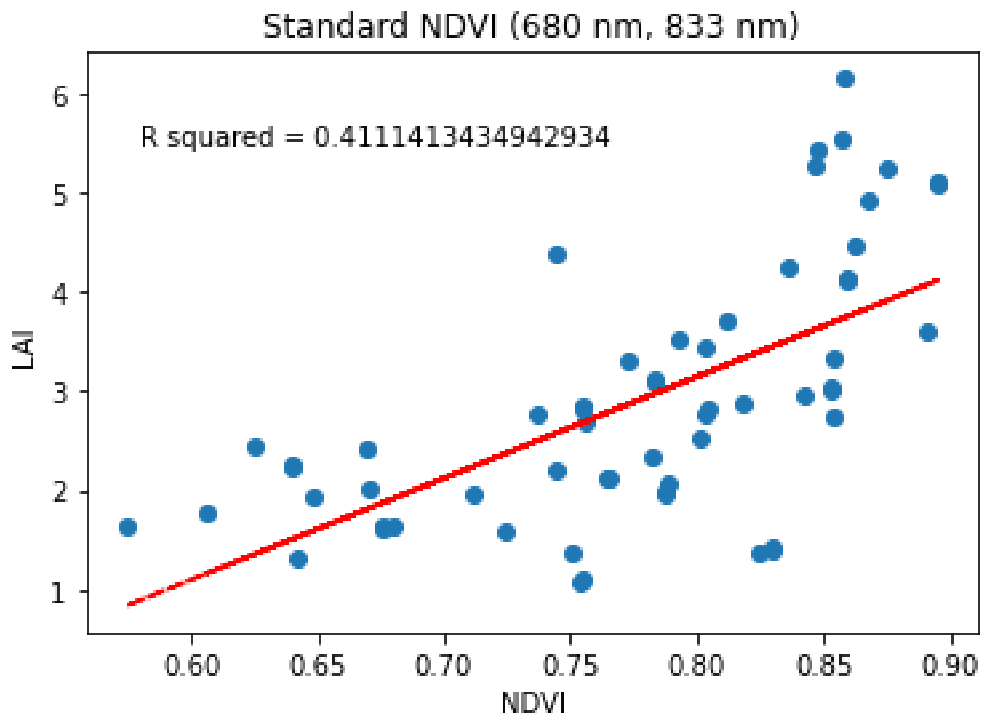
```
[15]: NDVIn
```

```
[15]: array([0.76244576, 0.76017196, 0.72922792, 0.72148529, 0.71753213,
       0.72971254, 0.78177368, 0.8181748 , 0.73535594, 0.8181748 ,
       0.76083886, 0.77232423, 0.74663598, 0.75563119, 0.82166839,
       0.8228885 , 0.81618218, 0.82159369, 0.73077345, 0.64335051,
       0.69850748, 0.74577437, 0.73777418, 0.75284599, 0.73843788,
       0.73777418, 0.71027831, 0.73140727, 0.69705952, 0.71027831,
       0.74977976, 0.70719718, 0.73330682, 0.73185483, 0.73185483,
       0.78180428, 0.75777199, 0.77170557, 0.76530315, 0.76530315,
       0.7431252 , 0.76533426, 0.76300681, 0.7431252 , 0.81998579,
       0.79419873, 0.70620363, 0.78881396, 0.73034947, 0.71167705,
       0.75507705, 0.75507705, 0.71167705, 0.69905312, 0.74064528,
       0.70071674, 0.74064528, 0.69574097, 0.69646747, 0.72235465])
```

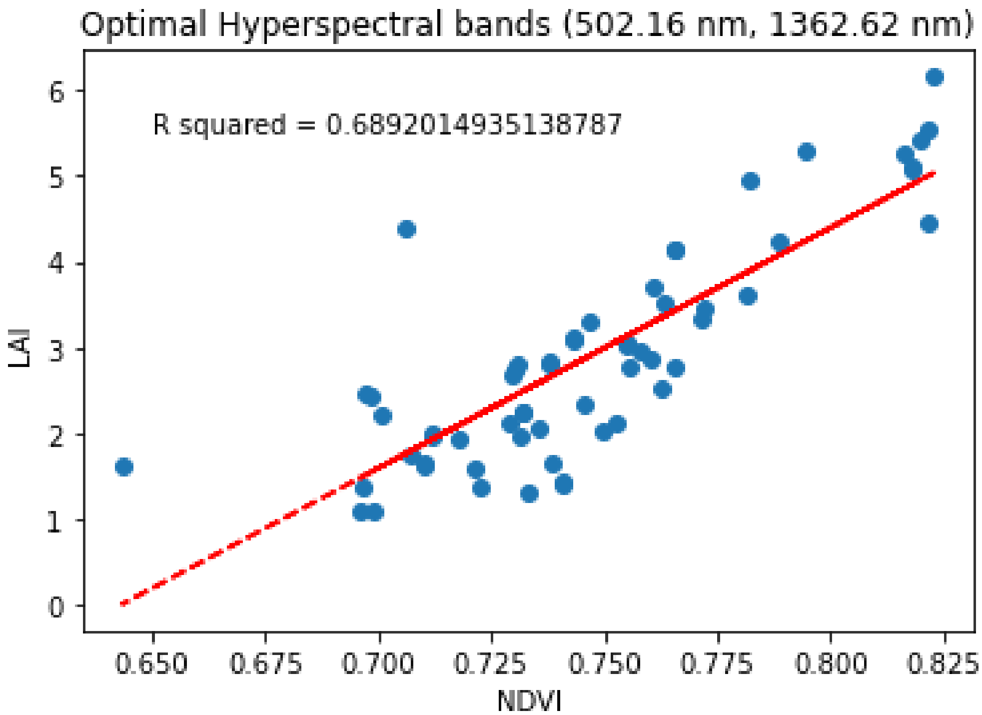
7 Plot the two SVIs (standard and optimal NDVI)

```
[16]: plt.scatter(NDVIs, lai)
plt.xlabel('NDVI')
plt.ylabel('LAI')
```

```
plt.title('Standard NDVI (680 nm, 833 nm)')

z = np.polyfit(NDVIs, lai, 1) # plot the regession line
p = np.poly1d(z)
plt.plot(NDVIs,p(NDVIs),"r--")

plt.text(0.58, 5.5, f'R squared = {r2(NDVIs)}')
plt.show()
```



[17]:
```
plt.scatter(NDVIn, lai)
plt.xlabel('NDVI')
plt.ylabel('LAI')
plt.title(f'Optimal Hyperspectral bands ({optimal_wl})')

z = np.polyfit(NDVIn, lai, 1) # plot the regression line
p = np.poly1d(z)
plt.plot(NDVIn,p(NDVIn),"r--")

plt.text(0.65, 5.5, f'R squared = {r2(NDVIn)}')
plt.show()
```



8 Challenge: Estimate LAI and calculate RMSE for each SVI

First I create a new dictionary called 'results', then I define two functions: one for estimating LAI and the other for calculating RMSE. The function for calculating R squared is above in a previous section. Then I calculate the variables for each SVI in a for loop and add everything the dictionary

[18]:
```
results = {'SVI Name':['standard NDVI', 'narrowband NDVI'],
           'Bands':['680 nm, 833 nm', optimal_wl],
           'SVI Values':[NDVIs, NDVIn],
           'Estimated LAI':[],
           'R2':[],
           'RMSE':[]
          }


def est_lai(NDVI):
    return reg.intercept + (reg.slope * NDVI)


def RMSE(estimated, measured):
    return np.sqrt(np.mean((estimated-measured)**2))
```

```python
for SVI in results['SVI Values']:
    reg = linregress(SVI, lai) # calculate linear regression
    est = est_lai(SVI) # estimate lai using the regression equation
    R2 = r2(SVI) # calculate coeficcient of determination
    rmse = RMSE(est, lai) #calculate the RMSE

    #append results to dict
    results['R2'].append(R2)
    results['Estimated LAI'].append(est)
    results['RMSE'].append(rmse)
```

Finally I converted the above dictionary into a Pandas dataframe for visualising.

[19]:
```python
results = pd.DataFrame(results)
results
```

[19]:
```
          SVI Name                  Bands  \
0    standard NDVI          680 nm, 833 nm
1  narrowband NDVI  502.16 nm, 1362.62 nm

                                          SVI Values  \
0  [0.801246223380298, 0.817709867447483, 0.76473…
1  [0.7624457645768697, 0.7601719591513552, 0.729…

                                       Estimated LAI        R2      RMSE
0  [3.159798814946276, 3.3286804244131414, 2.7853…  0.411141  0.977018
1  [3.3431423447176662, 3.2794123880761212, 2.412…  0.689201  0.709801
```