遙感探測--作業六

監督式影像分類--精度評估

使用工具

- ArcGIS Pro
- QGIS
- SAGA GIS
- Python
 - Numpy
 - PIL
 - pandas

使用資料

- EO-1 ALI
- EO1A1170442016203110K0
- 同學提供的地真資料 (108207406、108207408、108207411)

前情提要

Kappa係數反應的是跟隨機分類成果比較的優劣(-1 <= κ <= 1)

κ=(該次分類正確程度-隨機分類的正確程度)/(1-隨機分類的正確程度)

隨機分類的正確程度=分類時挑中第i類的機率*被分為第i類的機率

=(地真資料第i類的個數/總數)*(分類成果第i類的個數/總數)

(假設分類間獨立不相干. 為獨立事件

κ=1→完美 0<κ<1→還行 κ=0→跟隨機分的差不多 κ<0→比隨機分的還糟糕

ArcGIS SVM

ClassValue

P_Accuracy

Kappa

C_10	15	0	0	0	15	1	0
C_12	0	0	1	0	1	0	0
C_20	0	0	13	0	13	1	0
C_42	0	0	0	30	30	1	0
Total	15	0	14	30	59	0	0

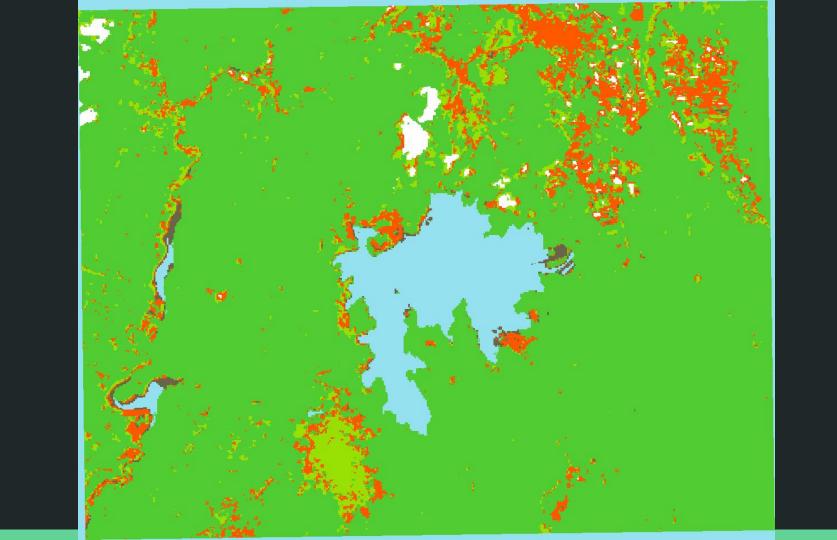
U_Accuracy Kappa

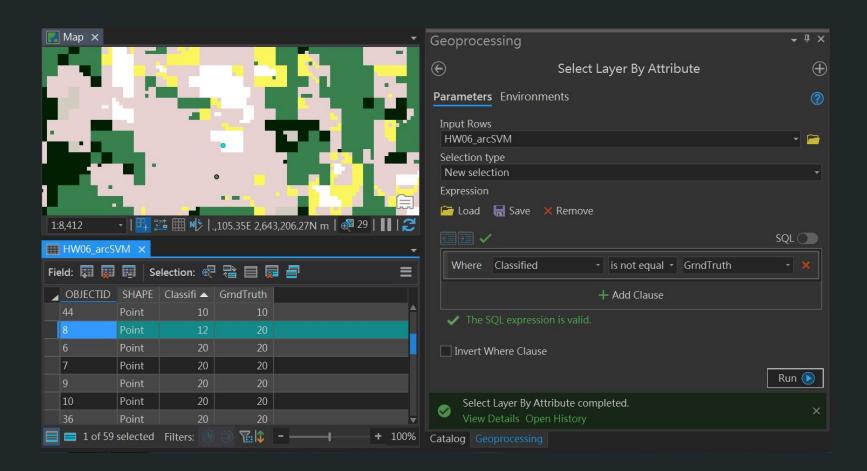
0.98305085

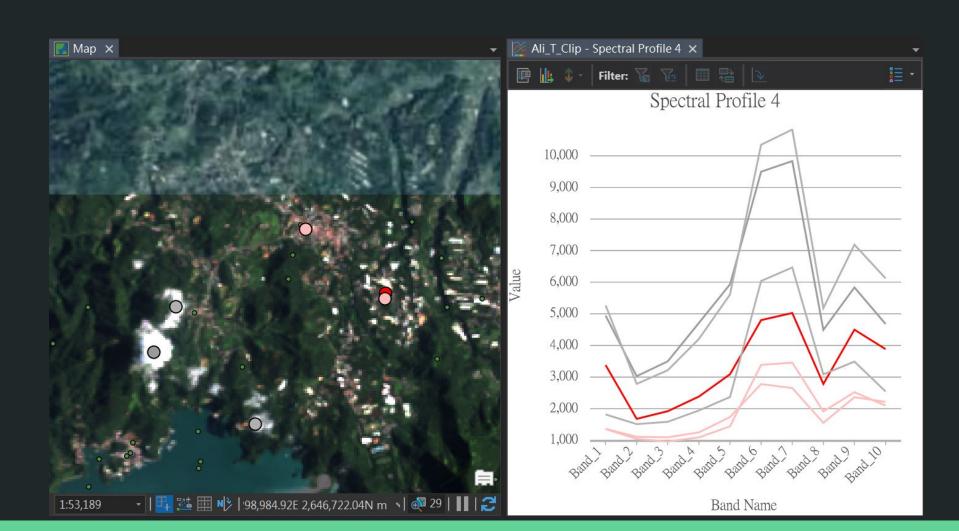
0 0.97286109

C_10 (水) C_12 (雲) C_20 (建物) C_42 (植被) Total

0.92857143

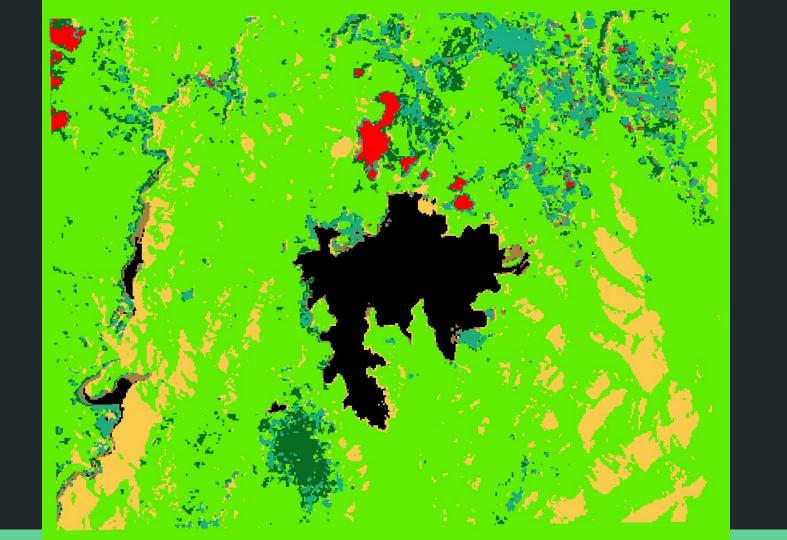






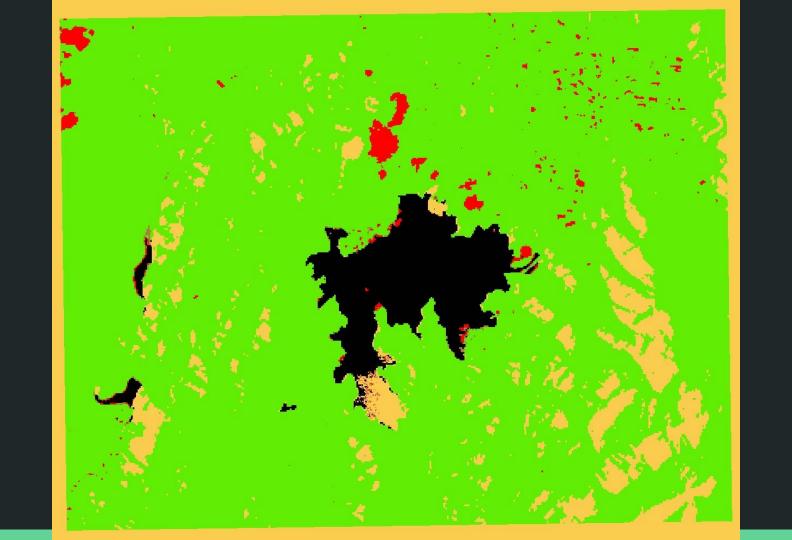
SAGA GIS -- ANN (OpenCV) 15x2

ClassValue	C_0(水)	C_2(建物)	C_4(植被)	Total	U_Accuracy	Kappa
C_0	15	0	0	15	1	0
C_2	0	14	0	14	1	0
C_4	0	0	30	30	1	0
Total	15	14	30	59	0	0
P_Accuracy	1	1	1	0	1	0
Kappa	0	0	0	0	0	1



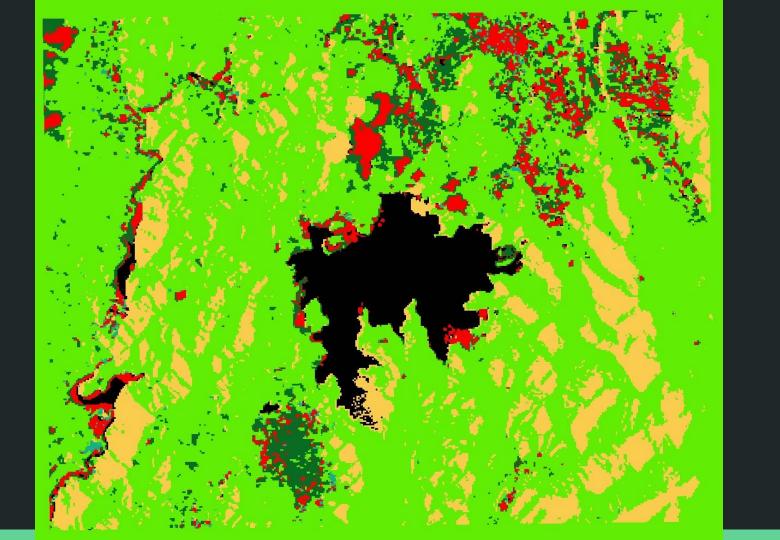
ANN (OpenCV) 6x5

ClassValue	C_0(水)	C_1(雲)	C_2(建物)	C_4(植被)	Total	U_Accuracy	Kappa
C_0	13	0	0	0	13	1	0
C_1	0	0	1	0	1	0	0
C_2	0	0	0	0	0	0	0
C_4	2	0	13	30	45	0.66666667	0
Total	15	0	14	30	59	0	0
P_Accuracy	0.86666667	0	0	1	0	0.72881356	0
Kappa	0	0	0	0	0	0	0.51239669



ANN (OpenCV) 3x3

ClassValue	C_0(水)	C_1(雲)	C_2(建物)	C_4(植被)	Total	U_Accuracy	Kappa
C_0	14	0	0	0	14	1	0
C_1	0	0	12	0	12	0	0
C_2	0	0	2	0	2	1	0
C_4	1	0	0	30	31	0.967741935	0
Total	15	0	14	30	59	0	0
P_Accuracy	0.933333333	0	0.142857143	1	0	0.779661017	0
Kappa	0	0	0	0	0	0	0.668396022



Numpy – Confusion matrix

```
import numpy as np
from PIL import Image
                                                                    Actual
                                                                    Predicted
import pandas as pd
                                                   #GroundTruth
GT=np.asarray(Image.open('Rasterize_HW06.tif'))
Classified='ANN 15x2.tif'
Clsf=np.asarray(Image.open(Classified))
GTclasses=[0,1,2] #0:water 1:building 2:forest
ClassTable={0:0,1:2,2:4} # ground_truth : classified
VdDict={} #validation pixel's class and [col,row]
Clsf=np.where(Clsf==5,4,Clsf) #merge class
Class_Truth=[]
Class Predicted=[]
for Gclass in GTclasses:
       VdDict[Gclass]=np.argwhere(GT==Gclass).tolist()
       for index in VdDict[Gclass]:
              indices=index[0],index[1]
              cla=Clsf[indices]
              Class_Truth.append(ClassTable[Gclass])
              Class_Predicted.append(cla)
              if cla!=ClassTable[Gclass]:
                      print(indices,Gclass,cla)
df=pd.DataFrame(list(zip(Class_Truth,Class_Predicted)),columns =['Truth', 'Predicted'])
CM=pd.crosstab(df|'Truth'],df|'Predicted'],rownames=['Actual'], colnames=['Predicted'],margins=True)
print(CM.transpose())
```

```
E:\Homework\RemoteSensing\Reference>py ConfusionMatrix.py
(450, 539) 0 2
(505, 886) 0 4
(704, 545) 0 4
(767, 439) 0 2
(801, 641) 0 4
(181, 1154) 1 4
(195, 353) 1 4
(424, 590) 1 4
(445, 581) 1 0
(829, 437) 1 6
Actual 0 2 4 All
Predicted
0 10 1 0 11
2 2 9 0 11
4 3 3 30 36
6 0 1 0 1
All 15 14 30 59
```

Numpy 改

```
import numpy as np
from PIL import Image
import pandas as pd
def ConfusionMatrix(GrndTruth, Classified): #Rasterize_GrndTruth.tif, Classified.tif
  GT=np.asarray(Image.open(GrndTruth))
  Clsf=np.asarray(Image.open(Classified))
GTclasses={0:'water',1:'building',2:'forest'}
ClassTable={0:'water',1:'cloud',2:'building',3:'other',4:'forest',5:'forest',6:'other'} #All classes
  VdDict={} #validation pixel's class and [col,row]
  Class Truth=[]
  Class Predicted=[]
  for Gvalue in GTclasses:
     VdDict[Gvalue]=np.argwhere(GT==Gvalue).tolist() #index.type(np.array->list)
     Gclass=GTclasses[Gvalue] #Classname(Ground Truth)
     for index in VdDict[Gvalue]:
       indices=index[0],index[1] #row,colum
       Cvalue=Clsf[indices] #Corresponed pixel value in 'Classified'
       cla=ClassTable[Cvalue] #Classname(Classified)
       Class_Truth.append(Gclass)
       Class_Predicted.append(cla)
       if cla!=Gclass:
          print(indices.Gclass.cla)
  df=pd.DataFrame(list(zip(Class_Truth,Class_Predicted)),columns =['Truth', 'Predicted'])
  CM=pd.crosstab(dff'Predicted'].dff'Truth'].margins=True)
  print(CM)
  0=1a:0=0a
  n=CM['All']['All']
  for cla in GTclasses.values():
     p0+=CM[cla][cla]/n
     p1+=CM[cla][All']/n*CM[All'][cla]/n
  kappa=(p0-p1)/(1-p1)
  print("Cohen's Kappa:%.5f"%kappa)
  return CM,kappa
ConfusionMatrix('Rasterize_HW06.tif','ANN_15x2.tif')
```

	7) water for			
(76, 835) building a	cloud		
(163. 11	40) building	g cloud		
	9) building			
	9) building			
(179, 110	06) building	g cloud		
(207, 66	7) building	cloud		
(406, 576	3) building	cloud		
(422, 57)	2) building	cloud		
(427, 56	7) building	cloud		
(611, 77	7) building	cloud		
(618, 78	1) building	cloud		
(811, 423	3) building	cloud		
Truth	building	forest	water	All
Predicted	d ,			
building	2	0	0	2
cloud	12	0	0	12
forest		30	1	31
water	0	0	14	14
All	14	30	15	59
~				

Numpy – For loop

```
CMdict={}
Kappadict={}
from pathlib import Path
dir='Classified'
tifs=Path(dir).glob('*.tif')
for file in tifs:
  filename=str(file)[len(dir)+1:-4]
```

print(KappaDF.sort_values(by=['Kappa']))

```
ANN 15\times2
                                                                              1.000000
                                                                    ANN 20×2
                                                                               1.000000
                                                                     ANN 7\times4
                                                                              1.000000
  CMdict[filename], Kappadict[filename]=ConfusionMatrix('Rasterize_HW06.tif', file)
KappaDF=pd.DataFrame({'Node x Layer':Kappadict.keys(),'Kappa':Kappadict.values()})
```

Node x Layer

ANN 6×5 ANN 3×1

ANN 15×3

ANN 10×3

ANN 7×3

Kappa

0.512397

0.668396

0.972861

0.972861

0.972874

ANN 3×3 0.668396

ANN 10×2 0.972861

小結

1. 預處裡

a. 雲、雲影 → CloudMask or 取一段時間的中位數
https://gis.stackexchange.com/guestions/393828/median-vs-mean-in-gee

但因sensor通過時間相同, 日照條件相近, 地形造成的陰影尚未除去

b. 地形陰影 → Topographic Correction (DEM+太陽位置)
Review of Shadow Detection and De-shadowing Methods in RemoteSensing

2. ANN

- a. Layer不是越多越好, 這次的資料大約 2層就夠
- b. 各Layer的Node也不是越多越好,大約7~20個較為合適

報告結束

謝謝大家