In [1]:

```
from osgeo import gdal, gdalconst
from osgeo.gdalconst import *
import numpy as np
from matplotlib import pyplot as plt
import pandas as pd
from sklearn.metrics import classification_report
from tensorflow import keras
```

```
C:\Users\Lay\Anaconda3\envs\ai\lib\site-packages\tensorflow\python\framework\dtypes.py:
526: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a fu
ture version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\Lay\Anaconda3\envs\ai\lib\site-packages\tensorflow\python\framework\dtypes.py:
527: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a fu
ture version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\Lay\Anaconda3\envs\ai\lib\site-packages\tensorflow\python\framework\dtypes.py:
528: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a fu
ture version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\Lay\Anaconda3\envs\ai\lib\site-packages\tensorflow\python\framework\dtypes.py:
529: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a fu
ture version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\Lay\Anaconda3\envs\ai\lib\site-packages\tensorflow\python\framework\dtypes.py:
530: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a fu
ture version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\Lay\Anaconda3\envs\ai\lib\site-packages\tensorflow\python\framework\dtypes.py:
535: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a fu
ture version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

In [2]:

```
img_path = './FinalQ4Image.jpg'
```

In [3]:

```
ds = gdal.Open(img_path, GA_ReadOnly)
```

In [4]:

```
n_band = ds.RasterCount
```

In [5]:

```
img_width = 2448
img_height = 2448
```

In [6]:

```
img = np.zeros((img_width,img_height,n_band))
for i in range(n_band):
    band = ds.GetRasterBand(i+1)
    data = band.ReadAsArray()
    img[:,:,i] = data
data = None
band = None
```

In [7]:

```
#mgU = img.mean()
#imgStd = img.std()
img = (img)/255
```

In [8]:

```
pointWater = pd.read_csv('./water_samples.csv').values
pointUrban = pd.read_csv('./urban_samples.csv').values
pointAgri = pd.read_csv('./agriculture_samples.csv').values
pointRange = pd.read_csv('./Range_samples.csv').values
pointBarren = pd.read_csv('./barren_samples.csv').values
```

In [9]:

```
def imgPointToData(img,point):
    dataOut = []
    for i in range(len(point)):
        dataOut.append(img[point[i,0],point[i,1]])
    return np.array(dataOut)
```

In [10]:

```
dataWater = imgPointToData(img,pointWater)
dataUrban = imgPointToData(img,pointUrban)
dataAgri = imgPointToData(img,pointAgri)
dataRange = imgPointToData(img,pointRange)
dataBarren = imgPointToData(img,pointBarren)
```

In [11]:

```
X_train = np.concatenate((dataWater[:8000],dataUrban[:8000],dataAgri[:8000],dataRange[:8000],dataBarr
en[:8000]))
y_train = np.ones((len(X_train)))
y_train[:8000] *= 0
y_train[8000:16000] *= 1
y_train[16000:24000] *= 2
y_train[24000:36000] *= 3
y_train[36000:40000] *= 4

X_test = np.concatenate((dataWater[8000:],dataUrban[8000:],dataAgri[8000:],dataRange[8000:],dataBarre
n[8000:]))
y_test = np.ones((len(X_test)))
y_test[:2000] *= 0
y_test[2000:4000] *= 1
y_test[4000:6000] *= 2
y_test[6000:8000] *= 3
y_test[8000:10000] *= 4
```

In [12]:

```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(40000, 3)
(40000,)
(10000, 3)
(10000,)
```

In [13]:

```
idx1 = np.random.permutation(len(X_train))
X_train = X_train[idx1]
y_train = y_train[idx1]

idx2 = np.random.permutation(len(X_test))
X_test = X_test[idx2]
y_test = y_test[idx2]

#X_train = X_train/255
#X_test = X_test/255
```

In [14]:

```
X_train1 = np.concatenate((dataWater[:8000],dataUrban[:8000],dataAgri[:8000],dataRange[:8000],dataBar
ren[:8000]))
y_train1 = np.ones((len(X_train)))
y_train1[:8000] *= 0
y_train1[8000:40000] *= 1


X_test1  = np.concatenate((dataWater[8000:],dataUrban[8000:],dataAgri[8000:],dataRange[8000:],dataBar
ren[8000:]))
y_test1 = np.ones((len(X_test1)))
y_test1[:2000] *= 0
y_test1[2000:10000] *= 1

idx1 = np.random.permutation(len(X_train1))
X_train1 = X_train1[idx1]
y_train1 = y_train1[idx1]

idx2 = np.random.permutation(len(X_test1))
X_test1 = X_test1[idx2]
y_test1 = y_test1[idx2]
```

In [15]:

```
X_train2 = np.concatenate((dataUrban[:8000],dataAgri[:8000],dataRange[:8000],dataBarren[:8000]))
y_train2 = np.ones((len(X_train2)))
y_train2[:8000] *= 0
y_train2[8000:16000] *= 1
y_train2[16000:24000] *= 2
y_train2[24000:36000] *= 3


X_test2 = np.concatenate((dataUrban[8000:],dataAgri[8000:],dataRange[8000:],dataBarren[8000:]))
y_test2 = np.ones((len(X_test2)))
y_test2[:2000] *= 0
y_test2[2000:4000] *= 1
y_test2[4000:6000] *= 2
y_test2[6000:8000] *= 3


idx1 = np.random.permutation(len(X_train2))
X_train2 = X_train2[idx1]
y_train2 = y_train2[idx1]

idx2 = np.random.permutation(len(X_test2))
X_test2 = X_test2[idx2]
y_test2 = y_test2[idx2]

#X_train2 = X_train2/255
#X_test2 = X_test2/255

print(X_train2.shape)
print(y_train2.shape)
print(X_test2.shape)
print(y_test2.shape)
```

```
(32000, 3)
(32000,)
(8000, 3)
(8000,)
```

In [16]:

```
y_train_encode = keras.utils.to_categorical(y_train)
y_test_encode = keras.utils.to_categorical(y_test)
y_train_encode2 = keras.utils.to_categorical(y_train2)
y_test_encode2 = keras.utils.to_categorical(y_test2)
```

In [26]:

```
def nnmodel(input_shape):
    X_input = keras.layers.Input((input_shape))
    X = keras.layers.Dense(128,activation='relu')(X_input)
    X = keras.layers.Dense(32,activation='relu')(X)
    X = keras.layers.Dense(1,activation='sigmoid')(X)
    model = keras.models.Model(inputs=X_input, outputs=X, name='model')
    return model
```

In [27]:

```
mymodel = nnmodel(X_train1[0].shape)
mymodel.compile(optimizer="adam", loss="binary_crossentropy", metrics=['accuracy'])
mymodel.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_3 (InputLayer)         (None, 3)                 0         
_________________________________________________________________
dense_6 (Dense)              (None, 128)               512       
_________________________________________________________________
dense_7 (Dense)              (None, 32)                4128      
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 33        
=================================================================
Total params: 4,673
Trainable params: 4,673
Non-trainable params: 0
_________________________________________________________________
```

In [28]:

```
mymodel.fit(X_train1,y_train1,batch_size=32,epochs=10,validation_data=(X_test1,y_test1))
```

```
Train on 40000 samples, validate on 10000 samples
Epoch 1/10
40000/40000 [==============================] - 5s 124us/sample - loss:
0.1427 - acc: 0.9418 - val_loss: 0.0721 - val_acc: 0.9742
Epoch 2/10
40000/40000 [==============================] - 5s 120us/sample - loss:
0.0673 - acc: 0.9753 - val_loss: 0.0606 - val_acc: 0.9777
Epoch 3/10
40000/40000 [==============================] - 5s 120us/sample - loss:
0.0582 - acc: 0.9786 - val_loss: 0.0526 - val_acc: 0.9811
Epoch 4/10
40000/40000 [==============================] - 5s 121us/sample - loss:
0.0534 - acc: 0.9807 - val_loss: 0.0503 - val_acc: 0.9823
Epoch 5/10
40000/40000 [==============================] - 5s 127us/sample - loss:
0.0516 - acc: 0.9817 - val_loss: 0.0485 - val_acc: 0.9819
Epoch 6/10
40000/40000 [==============================] - 5s 132us/sample - loss:
0.0504 - acc: 0.9814 - val_loss: 0.0488 - val_acc: 0.9815
Epoch 7/10
40000/40000 [==============================] - 5s 136us/sample - loss:
0.0495 - acc: 0.9824 - val_loss: 0.0494 - val_acc: 0.9815
Epoch 8/10
40000/40000 [==============================] - 6s 147us/sample - loss:
0.0495 - acc: 0.9821 - val_loss: 0.0468 - val_acc: 0.9828
Epoch 9/10
40000/40000 [==============================] - 6s 141us/sample - loss:
0.0488 - acc: 0.9819 - val_loss: 0.0486 - val_acc: 0.9822
Epoch 10/10
40000/40000 [==============================] - 5s 130us/sample - loss:
0.0483 - acc: 0.9826 - val_loss: 0.0460 - val_acc: 0.9832
```

Out[28]:

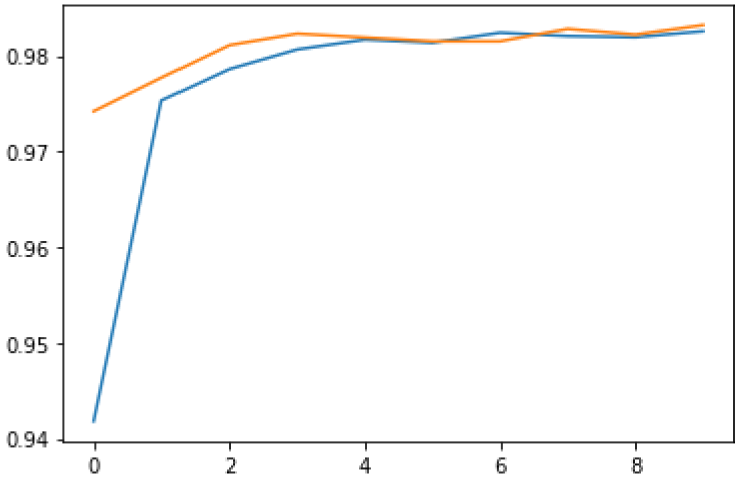
```
<tensorflow.python.keras.callbacks.History at 0x15f8fc7e048>
```

In [29]:

```
his = mymodel.history.history
plt.plot(his['acc'])
plt.plot(his['val_acc'])
```

Out[29]:

```
[<matplotlib.lines.Line2D at 0x15f8e3acc48>]
```



In [30]:

```
pred1 = mymodel.predict(X_test1)
pred1 = (pred1>0.5)*1
```

In [31]:

```
print(classification_report(y_test1,pred1))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.96      0.96      2000
         1.0       0.99      0.99      0.99      8000

    accuracy                           0.98     10000
   macro avg       0.97      0.97      0.97     10000
weighted avg       0.98      0.98      0.98     10000
```

In [32]:

```
def nnmodel2(input_shape):
    X_input = keras.layers.Input((input_shape))
    X = keras.layers.Dense(1024,activation='relu')(X_input)
    X = keras.layers.Dense(256,activation='relu')(X)
    X = keras.layers.Dense(4,activation='softmax')(X)
    model = keras.models.Model(inputs=X_input, outputs=X, name='model')
    return model
```

In [34]:

```
mymodel2 = nnmodel2(X_train2[0].shape)
opt = keras.optimizers.Adam(lr=0.0005)
mymodel2.compile(optimizer=opt, loss="categorical_crossentropy", metrics=['accuracy'])
mymodel2.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_5 (InputLayer)         (None, 3)                 0         
_________________________________________________________________
dense_12 (Dense)             (None, 1024)              4096      
_________________________________________________________________
dense_13 (Dense)             (None, 256)               262400    
_________________________________________________________________
dense_14 (Dense)             (None, 4)                 1028      
=================================================================
Total params: 267,524
Trainable params: 267,524
Non-trainable params: 0
_________________________________________________________________
```

In [35]:

```
mymodel2.fit(X_train2,y_train_encode2,batch_size=32,epochs=50,validation_data=(X_test2,y_test_encode2
))
```

```
Train on 32000 samples, validate on 8000 samples
Epoch 1/50
32000/32000 [==============================] - 5s 160us/sample - loss:
1.0615 - acc: 0.5530 - val_loss: 1.0056 - val_acc: 0.5775
Epoch 2/50
32000/32000 [==============================] - 4s 135us/sample - loss:
1.0065 - acc: 0.5820 - val_loss: 1.0167 - val_acc: 0.5680
Epoch 3/50
32000/32000 [==============================] - 4s 127us/sample - loss:
0.9999 - acc: 0.5869 - val_loss: 0.9989 - val_acc: 0.5866
Epoch 4/50
32000/32000 [==============================] - 4s 126us/sample - loss:
0.9939 - acc: 0.5878 - val_loss: 0.9967 - val_acc: 0.5764
Epoch 5/50
32000/32000 [==============================] - 4s 125us/sample - loss:
0.9857 - acc: 0.5934 - val_loss: 0.9806 - val_acc: 0.5844
Epoch 6/50
32000/32000 [==============================] - 4s 125us/sample - loss:
0.9784 - acc: 0.5970 - val_loss: 0.9850 - val_acc: 0.5946
Epoch 7/50
32000/32000 [==============================] - 5s 147us/sample - loss:
0.9746 - acc: 0.6000 - val_loss: 0.9744 - val_acc: 0.6018
Epoch 8/50
32000/32000 [==============================] - 5s 144us/sample - loss:
0.9686 - acc: 0.6019 - val_loss: 0.9894 - val_acc: 0.5775
Epoch 9/50
32000/32000 [==============================] - 4s 129us/sample - loss:
0.9632 - acc: 0.6021 - val_loss: 0.9587 - val_acc: 0.5989
Epoch 10/50
32000/32000 [==============================] - 4s 130us/sample - loss:
0.9627 - acc: 0.6056 - val_loss: 0.9538 - val_acc: 0.6051
Epoch 11/50
32000/32000 [==============================] - 4s 130us/sample - loss:
0.9566 - acc: 0.6080 - val_loss: 0.9534 - val_acc: 0.6041
Epoch 12/50
32000/32000 [==============================] - 4s 128us/sample - loss:
0.9548 - acc: 0.6088 - val_loss: 0.9498 - val_acc: 0.6037
Epoch 13/50
32000/32000 [==============================] - 4s 129us/sample - loss:
0.9511 - acc: 0.6103 - val_loss: 0.9588 - val_acc: 0.6012
Epoch 14/50
32000/32000 [==============================] - 4s 127us/sample - loss:
0.9494 - acc: 0.6084 - val_loss: 0.9414 - val_acc: 0.6105
Epoch 15/50
32000/32000 [==============================] - 4s 125us/sample - loss:
0.9466 - acc: 0.6099 - val_loss: 0.9524 - val_acc: 0.6053
Epoch 16/50
32000/32000 [==============================] - 4s 126us/sample - loss:
0.9450 - acc: 0.6128 - val_loss: 0.9491 - val_acc: 0.6115
Epoch 17/50
32000/32000 [==============================] - 4s 126us/sample - loss:
0.9393 - acc: 0.6156 - val_loss: 0.9479 - val_acc: 0.6083
Epoch 18/50
32000/32000 [==============================] - 4s 128us/sample - loss:
0.9346 - acc: 0.6177 - val_loss: 0.9369 - val_acc: 0.6120
Epoch 19/50
32000/32000 [==============================] - 4s 127us/sample - loss:
0.9320 - acc: 0.6179 - val_loss: 0.9435 - val_acc: 0.6086
Epoch 20/50
32000/32000 [==============================] - 4s 126us/sample - loss:
0.9263 - acc: 0.6238 - val_loss: 0.9257 - val_acc: 0.6175
```

```
Epoch 21/50
32000/32000 [==============================] - 4s 129us/sample - loss:
0.9253 - acc: 0.6228 - val_loss: 0.9375 - val_acc: 0.6100
Epoch 22/50
32000/32000 [==============================] - 4s 134us/sample - loss:
0.9234 - acc: 0.6245 - val_loss: 0.9201 - val_acc: 0.6183
Epoch 23/50
32000/32000 [==============================] - 5s 144us/sample - loss:
0.9211 - acc: 0.6251 - val_loss: 0.9270 - val_acc: 0.6144
Epoch 24/50
32000/32000 [==============================] - 4s 140us/sample - loss:
0.9178 - acc: 0.6275 - val_loss: 0.9186 - val_acc: 0.6174
Epoch 25/50
32000/32000 [==============================] - 4s 134us/sample - loss:
0.9171 - acc: 0.6265 - val_loss: 0.9168 - val_acc: 0.6187
Epoch 26/50
32000/32000 [==============================] - 4s 134us/sample - loss:
0.9152 - acc: 0.6249 - val_loss: 0.9134 - val_acc: 0.6187
Epoch 27/50
32000/32000 [==============================] - 4s 134us/sample - loss:
0.9138 - acc: 0.6276 - val_loss: 0.9331 - val_acc: 0.6101
Epoch 28/50
32000/32000 [==============================] - 4s 134us/sample - loss:
0.9115 - acc: 0.6277 - val_loss: 0.9249 - val_acc: 0.6141
Epoch 29/50
32000/32000 [==============================] - 4s 133us/sample - loss:
0.9105 - acc: 0.6266 - val_loss: 0.9422 - val_acc: 0.6112
Epoch 30/50
32000/32000 [==============================] - 4s 133us/sample - loss:
0.9092 - acc: 0.6285 - val_loss: 0.9067 - val_acc: 0.6216
Epoch 31/50
32000/32000 [==============================] - 4s 132us/sample - loss:
0.9079 - acc: 0.6276 - val_loss: 0.9033 - val_acc: 0.6242
Epoch 32/50
32000/32000 [==============================] - 4s 133us/sample - loss:
0.9071 - acc: 0.6295 - val_loss: 0.9137 - val_acc: 0.6240
Epoch 33/50
32000/32000 [==============================] - 4s 133us/sample - loss:
0.9068 - acc: 0.6271 - val_loss: 0.9406 - val_acc: 0.6028
Epoch 34/50
32000/32000 [==============================] - 4s 133us/sample - loss:
0.9066 - acc: 0.6283 - val_loss: 0.9171 - val_acc: 0.6159
Epoch 35/50
32000/32000 [==============================] - 4s 133us/sample - loss:
0.9063 - acc: 0.6277 - val_loss: 0.9028 - val_acc: 0.6200
Epoch 36/50
32000/32000 [==============================] - 4s 131us/sample - loss:
0.9040 - acc: 0.6299 - val_loss: 0.9121 - val_acc: 0.6166
Epoch 37/50
32000/32000 [==============================] - 4s 131us/sample - loss:
0.9039 - acc: 0.6309 - val_loss: 0.9179 - val_acc: 0.6168
Epoch 38/50
32000/32000 [==============================] - 4s 130us/sample - loss:
0.9042 - acc: 0.6296 - val_loss: 0.9095 - val_acc: 0.6191
Epoch 39/50
32000/32000 [==============================] - 4s 131us/sample - loss:
0.9031 - acc: 0.6280 - val_loss: 0.9248 - val_acc: 0.6125
Epoch 40/50
32000/32000 [==============================] - 4s 131us/sample - loss:
0.9019 - acc: 0.6295 - val_loss: 0.9022 - val_acc: 0.6226
Epoch 41/50
```

```
32000/32000 [==============================] - 4s 131us/sample - loss: 0.9007 - acc: 0.6301 - val_loss: 0.9035 - val_acc: 0.6190
Epoch 42/50
32000/32000 [==============================] - 4s 131us/sample - loss: 0.9006 - acc: 0.6302 - val_loss: 0.9098 - val_acc: 0.6196
Epoch 43/50
32000/32000 [==============================] - 4s 130us/sample - loss: 0.9012 - acc: 0.6309 - val_loss: 0.8995 - val_acc: 0.6235
Epoch 44/50
32000/32000 [==============================] - 4s 131us/sample - loss: 0.8981 - acc: 0.6331 - val_loss: 0.9016 - val_acc: 0.6220
Epoch 45/50
32000/32000 [==============================] - 4s 131us/sample - loss: 0.8989 - acc: 0.6320 - val_loss: 0.9169 - val_acc: 0.6189
Epoch 46/50
32000/32000 [==============================] - 4s 132us/sample - loss: 0.8988 - acc: 0.6303 - val_loss: 0.8991 - val_acc: 0.6246
Epoch 47/50
32000/32000 [==============================] - 4s 131us/sample - loss: 0.8994 - acc: 0.6319 - val_loss: 0.8935 - val_acc: 0.6259
Epoch 48/50
32000/32000 [==============================] - 4s 132us/sample - loss: 0.8995 - acc: 0.6302 - val_loss: 0.8979 - val_acc: 0.6234
Epoch 49/50
32000/32000 [==============================] - 4s 135us/sample - loss: 0.9002 - acc: 0.6307 - val_loss: 0.8972 - val_acc: 0.6242
Epoch 50/50
32000/32000 [==============================] - 4s 131us/sample - loss: 0.8984 - acc: 0.6323 - val_loss: 0.8940 - val_acc: 0.6242
```

Out[35]:

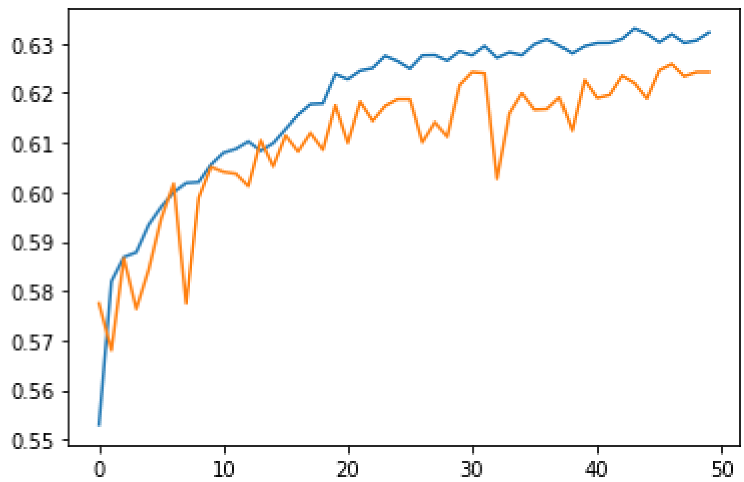
<tensorflow.python.keras.callbacks.History at 0x15f92552308>

In [36]:

```
his2 = mymodel2.history.history
plt.plot(his2['acc'])
plt.plot(his2['val_acc'])
```

Out[36]:

[<matplotlib.lines.Line2D at 0x15f935bf588>]



In [37]:

```
pred2 = np.argmax(mymodel2.predict(X_test2),axis=1)
```

In [38]:

```
print(classification_report(y_test2,pred2))
```

```
              precision    recall  f1-score   support

         0.0       0.69      0.50      0.58      2000
         1.0       0.54      0.58      0.56      2000
         2.0       0.56      0.64      0.59      2000
         3.0       0.74      0.78      0.76      2000

    accuracy                           0.62      8000
   macro avg       0.63      0.62      0.62      8000
weighted avg       0.63      0.62      0.62      8000
```

In [39]:

```
def commodel(data):
    l1 = np.round(mymodel.predict(data))
    l2 = np.argmax(mymodel2.predict(data),axis=1)
    outdata = []
    for i in range(len(data)):
        if(l1[i]==0):
            outdata.append(0)
        else:
            outdata.append(l2[i]+1)
    return np.array(outdata)
```

In [40]:

```
pred = commodel(X_test)
```

In [41]:

```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.96      0.96      2000
         1.0       0.68      0.50      0.58      2000
         2.0       0.52      0.55      0.53      2000
         3.0       0.56      0.64      0.59      2000
         4.0       0.74      0.78      0.76      2000

    accuracy                           0.69     10000
   macro avg       0.69      0.69      0.69     10000
weighted avg       0.69      0.69      0.69     10000
```

In [64]:

```
img = img.reshape(((2448* 2448, 3)))
#img = img*255
```

In [66]:

```
predimg = commodel(img)
```

In [67]:

```
predimg_dec = predimg
```

In [68]:

```
colormap = np.zeros_like(img).astype(int)
```

In [69]:

```
for i in range(len(colormap)):
    if(predimg_dec[i] == 0):
        #water
        colormap[i] = [0,0,255]
    elif(predimg_dec[i]==1):
        #urban
        colormap[i] = [0,255,255]
    elif (predimg_dec[i] ==2):
        #argi
        colormap[i] = [255,255,0]
    elif (predimg_dec[i] == 3):
        #range
        colormap[i] = [255,0,255]
    elif (predimg_dec[i] == 4):
        #barren
        colormap[i] = [255,255,255]
```

In [70]:

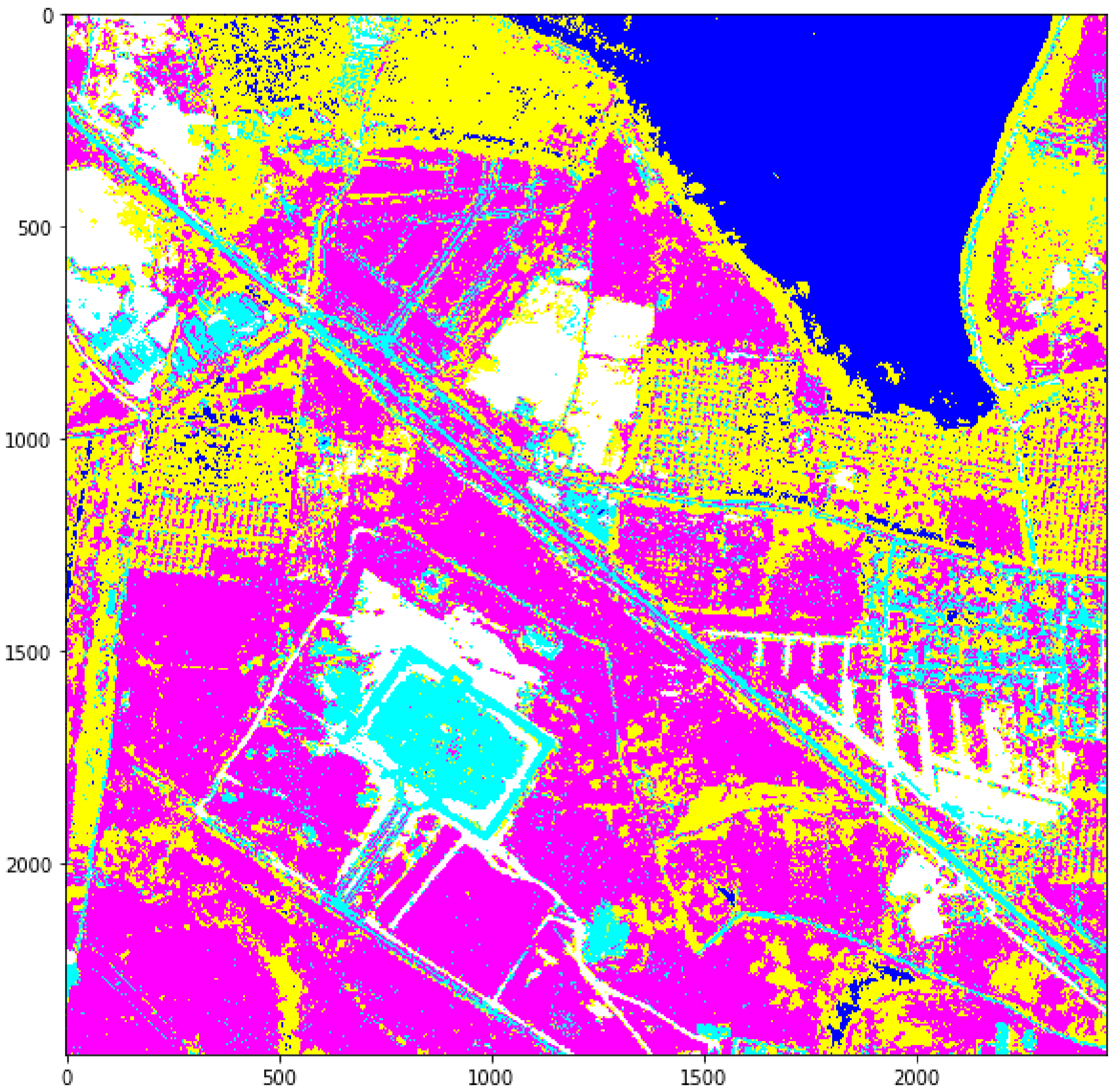
```
colormap = colormap.reshape((2448,2448,3))
```

In [71]:

```
plt.figure(figsize=(10,10))
plt.imshow(colormap)
```

Out[71]:

<matplotlib.image.AxesImage at 0x15ee41095c8>



In [72]:

```
from PIL import Image
```

In [73]:

```
im = Image.fromarray(colormap.astype(np.uint8))
im.save('./final4-lcm.png')
print('saved "./final4-lcm.png" ')
```

```
saved "./final4-lcm.png"
```

In [74]:

```
from sklearn.metrics import confusion_matrix,cohen_kappa_score
```

In [75]:

```
confmat = confusion_matrix(y_test,pred)
print('----- Confusion matrix -----')
print(confmat)
```

```
----- Confusion matrix -----
[[1916    4   80    0    0]
 [  19 1007  415  373  186]
 [  49  148 1106  499  198]
 [  16  156  400 1274  154]
 [   0  156  145  142 1557]]
```

In [84]:

```
user_acc = [confmat[0,0],confmat[1,1],confmat[2,2],confmat[3,3],confmat[4,4]]/np.sum(confmat,axis=1)*
100
print(f'User accuracy : {user_acc} %')
```

```
User accuracy : [95.8  50.35 55.3  63.7  77.85] %
```

In [88]:

```
prod_acc = [confmat[0,0],confmat[1,1],confmat[2,2],confmat[3,3],confmat[4,4]]/np.sum(confmat,axis=0)*
100
print(f'Producer accuracy : {prod_acc} %')
```

```
Producer accuracy : [95.8        68.45683209 51.53774464 55.68181818 74.31980907] %
```

In [87]:

```
overall_acc = np.sum([confmat[0,0],confmat[1,1],confmat[2,2],confmat[3,3],confmat[4,4]])/100
print(f'Overall accuracy : {overall_acc} %')
```

```
Overall accuracy : 68.6 %
```

In [79]:

```
(overall_acc-1/5)/(1-1/5)
```

Out[79]:

```
0.6075
```

In [80]:

```
kappa = cohen_kappa_score(y_test,pred)
print(f'Kappa Score : {kappa}')
```

Kappa Score : 0.6074999999999999

In [81]:

```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.96      0.96      2000
         1.0       0.68      0.50      0.58      2000
         2.0       0.52      0.55      0.53      2000
         3.0       0.56      0.64      0.59      2000
         4.0       0.74      0.78      0.76      2000

    accuracy                           0.69     10000
   macro avg       0.69      0.69      0.69     10000
weighted avg       0.69      0.69      0.69     10000
```

In [82]:

```
confmat[0]
```

Out[82]:

array([1916,   4,   80,   0,   0], dtype=int64)

In [83]:

```
np.sum(confmat,axis=0)
```

Out[83]:

array([2000, 1471, 2146, 2288, 2095], dtype=int64)

In [ ]: