

```
In [20]: %load_ext autoreload
         %autoreload 2
```

The autoreload extension is already loaded. To reload it, use:
%reload_ext autoreload

```
In [21]: ##autoreload # When utils.py is updated
         from utils_unet_resunet import *
         from tensorflow.keras.preprocessing.image import ImageDataGenerator
         root_path = 'imgs/'
```

```
In [3]: # Define data type (L8-Landsat8, S2-Sentinel2, S1-Sentinel1)
         img_type = 'S2'

         if img_type == 'L8':
             # Load images
             ref_2019 = load_tif_image(root_path+'New_Images/References/res_10m/r10m_def_2019
             opt_2018 = load_tif_image(root_path+'New_Images/Landsat8/'+cut_land8_2018.tif')
             opt_2019 = load_tif_image(root_path+'New_Images/Landsat8/'+cut_land8_2019.tif')

             # Resize images
             opt_2018 = resize_image(opt_2018.copy(), ref_2019.shape[0], ref_2019.shape[1])
             opt_2019 = resize_image(opt_2019.copy(), ref_2019.shape[0], ref_2019.shape[1])

             # Filter outliers
             opt_2018 = filter_outliers(opt_2018.copy())
             opt_2019 = filter_outliers(opt_2019.copy())

             image_stack = np.concatenate((opt_2018, opt_2019), axis=-1)
             print('landsat_resize:', image_stack.shape)
             del opt_2018, opt_2019

         if img_type == 'S2':
             # Load images
             sent2_2018_1 = load_tif_image(root_path+'New_Images/Sentinel2/'+2018_10m_b2348.
             #sent2_2018_2 = load_tif_image(root_path+'New_Images/Sentinel2/'+2018_20m_b5678

             # Resize bands of 20m
             #sent2_2018_2 = resize_image(sent2_2018_2.copy(), sent2_2018_1.shape[0], sent2_2
             #sent2_2018 = np.concatenate((sent2_2018_1, sent2_2018_2), axis=-1)
             sent2_2018 = sent2_2018_1.copy()
             del sent2_2018_1#, sent2_2018_2

             sent2_2019_1 = load_tif_image(root_path+'New_Images/Sentinel2/'+2019_10m_b2348.
             #sent2_2019_2 = load_tif_image(root_path+'New_Images/Sentinel2/'+2019_20m_b5678

             # Resize bands of 20m
             #sent2_2019_2 = resize_image(sent2_2019_2.copy(), sent2_2019_1.shape[0], sent2_2
             #sent2_2019 = np.concatenate((sent2_2019_1, sent2_2019_2), axis=-1)
             sent2_2019 = sent2_2019_1.copy()
             del sent2_2019_1#, sent2_2019_2

             # Filter outliers
             sent2_2018 = filter_outliers(sent2_2018.copy())
             sent2_2019 = filter_outliers(sent2_2019.copy())

             image_stack = np.concatenate((sent2_2018, sent2_2019), axis=-1)
             print('Image stack:', image_stack.shape)
             del sent2_2018, sent2_2019

         if img_type == 'S1':
```

```

# Load images
sar_2018_vh = np.expand_dims(load_SAR_image(root_path+'New_Images/Sentinel1/'+c
sar_2018_vv = np.expand_dims(load_SAR_image(root_path+'New_Images/Sentinel1/'+c
sar_2019_vh = np.expand_dims(load_SAR_image(root_path+'New_Images/Sentinel1/'+c
sar_2019_vv = np.expand_dims(load_SAR_image(root_path+'New_Images/Sentinel1/'+c

sar_2018 = np.concatenate((sar_2018_vh, sar_2018_vv), axis=-1)
sar_2019 = np.concatenate((sar_2019_vh, sar_2019_vv), axis=-1)
del sar_2018_vh, sar_2018_vv, sar_2019_vh, sar_2019_vv

# Filter outliers
sar_2018 = filter_outliers(sar_2018.copy())
sar_2019 = filter_outliers(sar_2019.copy())

image_stack = np.concatenate((sar_2018, sar_2019), axis=-1)
print('Image stack:', image_stack.shape)
del sar_2018, sar_2019

# Load references
# Load current reference
#ref_2019 = load_tif_image(root_path+'New_Images/References/res_10m/r10m_def_2019.tif')
# Load past references
#past_ref = np.load(root_path+'New_Images/References/past_ref_and_clouds.npy').astype
#past_ref1 = load_tif_image(root_path+'New_Images/References/res_10m/r10m_def_1988_2
#past_ref2 = load_tif_image(root_path+'New_Images/References/res_10m/r10m_def_2008_2
#clouds_2018 = load_tif_image(root_path+'New_Images/References/cut_b10_2018.tif').as
#clouds_2018 = resize_image(np.expand_dims(clouds_2018.copy(), axis = -1), ref_2019.
#clouds_2018 = binary_mask_cloud(clouds_2018.copy(), 50)
#clouds_2019 = load_tif_image(root_path+'New_Images/References/cut_b10_2019.tif').as
#clouds_2019 = resize_image(np.expand_dims(clouds_2019.copy(), axis = -1), ref_2019.
#clouds_2019 = binary_mask_cloud(clouds_2019.copy(), 50)

```

```

imgs/New_Images/Sentinel2/2018_10m_b2348.tif
imgs/New_Images/Sentinel2/2019_10m_b2348.tif
Image stack: (17729, 9202, 8)

```

In [4]:

```

# Create label mask
#past_ref = past_ref1 + past_ref2 + clouds_2018 + clouds_2019
#past_ref[past_ref>=1] = 1
#buffer = 2
#final_mask1 = mask_no_considered(ref_2019, buffer, past_ref)
#del past_ref1, past_ref2, clouds_2018, clouds_2019
final_mask1 = np.load(root_path+'New_Images/ref/'++'labels.npy')

lim_x = 10000
lim_y = 7000
image_stack = image_stack[:lim_x, :lim_y, :]
final_mask1 = final_mask1[:lim_x, :lim_y]
#ref_2019 = ref_2019[:lim_x, :lim_y]

h_, w_, channels = image_stack.shape
print('image stack size: ', image_stack.shape)

# Normalization
type_norm = 1
image_array = normalization(image_stack.copy(), type_norm)
print(np.min(image_array), np.max(image_array))
del image_stack

# Print pertengate of each class (whole image)
print('Total no-deforestaion class is {}'.format(len(final_mask1[final_mask1==0])))
print('Total deforestaion class is {}'.format(len(final_mask1[final_mask1==1])))
print('Total past deforestaion class is {}'.format(len(final_mask1[final_mask1==2])))
print('Percentage of deforestaion class is {:.2f}'.format((len(final_mask1[final_mas

```

```

image stack size: (10000, 7000, 8)
-4.987141 5.626766
Total no-deforestation class is 36326397
Total deforestation class is 1048775
Total past deforestation class is 32624828
Percentage of deforestation class is 2.89

```

In [5]:

```

# Create tile mask
mask_tiles = create_mask(final_mask1.shape[0], final_mask1.shape[1], grid_size=(5, 4)
image_array = image_array[:mask_tiles.shape[0], :mask_tiles.shape[1],:]
final_mask1 = final_mask1[:mask_tiles.shape[0], :mask_tiles.shape[1]]

print('mask: ', mask_tiles.shape)
print('image stack: ', image_array.shape)
print('ref :', final_mask1.shape)
#plt.imshow(mask_tiles)

```

```

Tiles size: 2000 1750
Mask size: (10000, 7000)
mask: (10000, 7000)
image stack: (10000, 7000, 8)
ref : (10000, 7000)

```

In [6]:

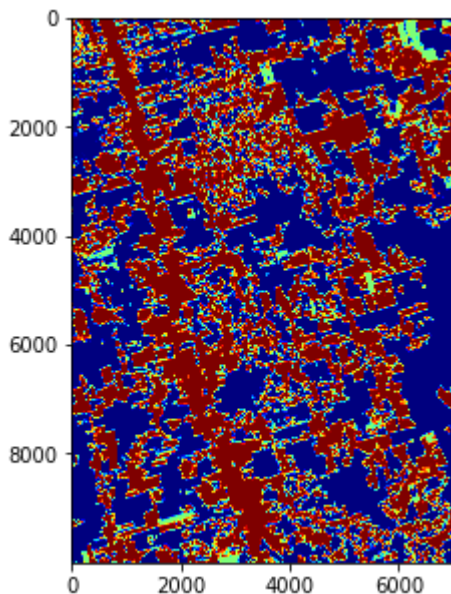
```

plt.figure(figsize=(10,5))
plt.imshow(final_mask1, cmap = 'jet')

```

Out[6]:

```
<matplotlib.image.AxesImage at 0x1ec52b747f0>
```



In [7]:

```

# Define tiles for training, validation, and test sets
tiles_tr = [1,3,5,8,11,13,14,20]
tiles_val = [6,19]
tiles_ts = (list(set(np.arange(20)+1)-set(tiles_tr)-set(tiles_val)))

mask_tr_val = np.zeros((mask_tiles.shape)).astype('float32')
# Training and validation mask
for tr_ in tiles_tr:
    mask_tr_val[mask_tiles == tr_] = 1

for val_ in tiles_val:
    mask_tr_val[mask_tiles == val_] = 2

mask_amazon_ts = np.zeros((mask_tiles.shape)).astype('float32')

```

```
for ts_ in tiles_ts:
    mask_amazon_ts[mask_tiles == ts_] = 1
```

```
In [8]: # Create idx image to extract patches
overlap = 0.7
patch_size = 128
batch_size = 32
im_idx = create_idx_image(final_mask1)
patches_idx = extract_patches(im_idx, patch_size=(patch_size, patch_size), overlap=0.7)
patches_mask = extract_patches(mask_tr_val, patch_size=(patch_size, patch_size), overlap=0.7)
del im_idx
```

```
In [9]: # Selecting index trn val and test patches idx
idx_trn = np.squeeze(np.where(patches_mask.sum(axis=(1, 2)) == patch_size**2))
idx_val = np.squeeze(np.where(patches_mask.sum(axis=(1, 2)) == 2*patch_size**2))
del patches_mask

patches_idx_trn = patches_idx[idx_trn]
patches_idx_val = patches_idx[idx_val]
del idx_trn, idx_val

print('Number of training patches: ', len(patches_idx_trn), 'Number of validation patches: ', len(patches_idx_val))
```

Number of training patches: 17110 Number of validation patches 4116

```
In [10]: # Extract patches with at least 2% of deforestation class
X_train = retrieve_idx_percentage(final_mask1, patches_idx_trn, patch_size, percentage=0.02)
X_valid = retrieve_idx_percentage(final_mask1, patches_idx_val, patch_size, percentage=0.02)
print(X_train.shape, X_valid.shape)
del patches_idx_trn, patches_idx_val
```

(1158, 128, 128) (341, 128, 128)

```
In [11]: def batch_generator(batches, image, reference, target_size, number_class):
    """Take as input a Keras ImageGen (Iterator) and generate random
    crops from the image batches generated by the original iterator.
    """
    image = image.reshape(-1, image.shape[-1])
    reference = reference.reshape(final_mask1.shape[0]*final_mask1.shape[1])
    while True:
        batch_x, batch_y = next(batches)
        batch_x = np.squeeze(batch_x.astype('int64'))
        #print(batch_x.shape)
        batch_img = np.zeros((batch_x.shape[0], target_size, target_size, image.shape[-1]))
        batch_ref = np.zeros((batch_x.shape[0], target_size, target_size, number_class))

        for i in range(batch_x.shape[0]):
            if np.random.rand() > 0.5:
                batch_x[i] = np.rot90(batch_x[i], 1)
            batch_img[i] = image[batch_x[i]]
            batch_ref[i] = tf.keras.utils.to_categorical(reference[batch_x[i]], number_class)

        yield (batch_img, batch_ref)

train_datagen = ImageDataGenerator(horizontal_flip = True,
                                    vertical_flip = True)
valid_datagen = ImageDataGenerator(horizontal_flip = True,
                                    vertical_flip = True)

y_train = np.zeros((len(X_train)))
y_valid = np.zeros((len(X_valid)))
```

```

train_gen = train_datagen.flow(np.expand_dims(X_train, axis = -1), y_train,
                               batch_size=batch_size,
                               shuffle=True)

valid_gen = valid_datagen.flow(np.expand_dims(X_valid, axis = -1), y_valid,
                                batch_size=batch_size,
                                shuffle=False)

number_class = 3
train_gen_crops = batch_generator(train_gen, image_array, final_mask1, patch_size, n
valid_gen_crops = batch_generator(valid_gen, image_array, final_mask1, patch_size, n

```

In [12]:

```

exp = 1
path_exp = root_path+'experiments/exp'+str(exp)
path_models = path_exp+'/models'
path_maps = path_exp+'/pred_maps'

if not os.path.exists(path_exp):
    os.makedirs(path_exp)
if not os.path.exists(path_models):
    os.makedirs(path_models)
if not os.path.exists(path_maps):
    os.makedirs(path_maps)

```

In [22]:

```

# Define model
input_shape = (patch_size, patch_size, channels)
nb_filters = [32, 64, 128]

method = 'unet'
if method == 'unet':
    model = build_unet(input_shape, nb_filters, number_class)

if method == 'resunet':
    model = build_resunet(input_shape, nb_filters, number_class)

```

In [23]:

```

# Parameters of the model
weights = [0.2, 0.8, 0]
adam = Adam(lr = 1e-3 , beta_1=0.9)
loss = weighted_categorical_crossentropy(weights)

```

In [24]:

```

time_tr = []
times = 5
for tm in range(0,times):
    print('time: ', tm)

    model.compile(optimizer=adam, loss=loss, metrics=['accuracy'])
    model.summary()

    earllystop = EarlyStopping(monitor='val_loss', min_delta=0.0001, patience=10, ver
    checkpoint = ModelCheckpoint(path_models+ '/' + method + '_' +str(tm)+'.h5', monit
    lr_reduce = ReduceLROnPlateau(factor=0.9, min_delta=0.0001, patience=5, verbose=
    callbacks_list = [earllystop, checkpoint]
    # train the model
    start_training = time.time()
    history = model.fit_generator(train_gen_crops,
                                steps_per_epoch=len(X_train)*3//train_gen.batch_size,
                                validation_data=valid_gen_crops,
                                validation_steps=len(X_valid)*3//valid_gen.batch_size,

```

```

        epochs=100,
        callbacks=callbacks_list)
    end_training = time.time() - start_training
    time_tr.append(end_training)
    time_tr_array = np.asarray(time_tr)
    # Save training time
    np.save(path_exp+'/metrics_tr.npy', time_tr_array)

```

time: 0
Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_3 (InputLayer)	[(None, 128, 128, 8) 0		
conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_3[0][0]
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]
conv2 (Conv2D)	(None, 64, 64, 64) 18496		max_pooling2d[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64) 0		conv2[0][0]
conv3 (Conv2D) [0]	(None, 32, 32, 128) 73856		max_pooling2d_1[0]
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 128) 0		conv3[0][0]
conv4 (Conv2D) [0]	(None, 16, 16, 128) 147584		max_pooling2d_2[0]
conv5 (Conv2D)	(None, 16, 16, 128) 147584		conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128) 147584		conv5[0][0]
up_sampling2d (UpSampling2D)	(None, 32, 32, 128) 0		conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128) 147584		up_sampling2d[0][0]
concatenate3 (Concatenate)	(None, 32, 32, 256) 0		conv3[0][0] upsampling3[0][0]
up_sampling2d_1 (UpSampling2D)	(None, 64, 64, 256) 0		concatenate3[0][0]
upsampling2 (Conv2D) [0]	(None, 64, 64, 64) 147520		up_sampling2d_1[0]
concatenate2 (Concatenate)	(None, 64, 64, 128) 0		conv2[0][0]

upsampling2[0][0]

up_sampling2d_2 (UpSampling2D)	(None, 128, 128, 128) 0	concatenate2[0][0]
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upsampling1 (Conv2D)	(None, 128, 128, 32) 36896	up_sampling2d_2[0][0]
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concatenate1 (Concatenate)	(None, 128, 128, 64) 0	conv1[0][0] upsampling1[0][0]
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conv2d (Conv2D)	(None, 128, 128, 3) 195	concatenate1[0][0]
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```
=====
Total params: 869,635
Trainable params: 869,635
Non-trainable params: 0
```

Epoch 1/100



```
C:\Users\felferrari\AppData\Roaming\Python\Python38\site-packages\tensorflow\python\keras\engine\training.py:1844: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.
```

```
warnings.warn("`Model.fit_generator` is deprecated and '
108/108 [=====] - 12s 56ms/step - loss: 0.0908 - accuracy: 0.7706 - val_loss: 0.1033 - val_accuracy: 0.7722
```

```
Epoch 00001: val_loss improved from inf to 0.10332, saving model to imgs/experiments/exp1/models/unet_0.h5
```

Epoch 2/100

```
108/108 [=====] - 5s 46ms/step - loss: 0.0656 - accuracy: 0.8252 - val_loss: 0.1161 - val_accuracy: 0.7735
```

```
Epoch 00002: val_loss did not improve from 0.10332
```

Epoch 3/100

```
108/108 [=====] - 5s 46ms/step - loss: 0.0599 - accuracy: 0.8358 - val_loss: 0.1093 - val_accuracy: 0.7830
```

```
Epoch 00003: val_loss did not improve from 0.10332
```

Epoch 4/100

```
108/108 [=====] - 5s 46ms/step - loss: 0.0580 - accuracy: 0.8411 - val_loss: 0.1128 - val_accuracy: 0.7837
```

```
Epoch 00004: val_loss did not improve from 0.10332
```

Epoch 5/100

```
108/108 [=====] - 5s 45ms/step - loss: 0.0524 - accuracy: 0.8521 - val_loss: 0.1238 - val_accuracy: 0.7878
```

```
Epoch 00005: val_loss did not improve from 0.10332
```

Epoch 6/100

```
108/108 [=====] - 5s 46ms/step - loss: 0.0504 - accuracy: 0.8549 - val_loss: 0.1584 - val_accuracy: 0.7884
```

```
Epoch 00006: val_loss did not improve from 0.10332
```

Epoch 7/100

```
108/108 [=====] - 5s 47ms/step - loss: 0.0450 - accuracy: 0.8620 - val_loss: 0.1584 - val_accuracy: 0.7828
```

```
Epoch 00007: val_loss did not improve from 0.10332
```

Epoch 8/100

108/108 [=====] - 5s 47ms/step - loss: 0.0409 - accuracy: 0.8728 - val_loss: 0.1516 - val_accuracy: 0.7759

Epoch 00008: val_loss did not improve from 0.10332

Epoch 9/100

108/108 [=====] - 5s 46ms/step - loss: 0.0392 - accuracy: 0.8751 - val_loss: 0.1537 - val_accuracy: 0.7970

Epoch 00009: val_loss did not improve from 0.10332

Epoch 10/100

108/108 [=====] - 5s 47ms/step - loss: 0.0408 - accuracy: 0.8712 - val_loss: 0.1750 - val_accuracy: 0.7867

Epoch 00010: val_loss did not improve from 0.10332

Epoch 11/100

108/108 [=====] - 5s 47ms/step - loss: 0.0334 - accuracy: 0.8866 - val_loss: 0.1722 - val_accuracy: 0.7887

Epoch 00011: val_loss did not improve from 0.10332

Epoch 00011: early stopping

time: 1

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_3 (InputLayer)	[(None, 128, 128, 8) 0		
conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_3[0][0]
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]
conv2 (Conv2D)	(None, 64, 64, 64) 18496		max_pooling2d[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64) 0		conv2[0][0]
conv3 (Conv2D)	(None, 32, 32, 128) 73856		max_pooling2d_1[0][0]
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 128) 0		conv3[0][0]
conv4 (Conv2D)	(None, 16, 16, 128) 147584		max_pooling2d_2[0][0]
conv5 (Conv2D)	(None, 16, 16, 128) 147584		conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128) 147584		conv5[0][0]
up_sampling2d (UpSampling2D)	(None, 32, 32, 128) 0		conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128) 147584		up_sampling2d[0][0]

concatenate3 (Concatenate)	(None, 32, 32, 256)	0	conv3[0][0] upsampling3[0][0]
up_sampling2d_1 (UpSampling2D)	(None, 64, 64, 256)	0	concatenate3[0][0]
upsampling2 (Conv2D)	(None, 64, 64, 64)	147520	up_sampling2d_1[0] [0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_2 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D)	(None, 128, 128, 32)	36896	up_sampling2d_2[0] [0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d (Conv2D)	(None, 128, 128, 3)	195	concatenate1[0][0]
=====			
Total params: 869,635			
Trainable params: 869,635			
Non-trainable params: 0			

Epoch 1/100

108/108 [=====] - 6s 50ms/step - loss: 0.0318 - accuracy: 0.8912 - val_loss: 0.1972 - val_accuracy: 0.7895

Epoch 00001: val_loss improved from inf to 0.19716, saving model to imgs/experiments/exp1/models/unet_1.h5

Epoch 2/100

108/108 [=====] - 5s 49ms/step - loss: 0.0291 - accuracy: 0.8966 - val_loss: 0.1919 - val_accuracy: 0.7952

Epoch 00002: val_loss improved from 0.19716 to 0.19192, saving model to imgs/experiments/exp1/models/unet_1.h5

Epoch 3/100

108/108 [=====] - 5s 50ms/step - loss: 0.0277 - accuracy: 0.9009 - val_loss: 0.1663 - val_accuracy: 0.7914

Epoch 00003: val_loss improved from 0.19192 to 0.16634, saving model to imgs/experiments/exp1/models/unet_1.h5

Epoch 4/100

108/108 [=====] - 5s 49ms/step - loss: 0.0290 - accuracy: 0.8971 - val_loss: 0.1731 - val_accuracy: 0.7854

Epoch 00004: val_loss did not improve from 0.16634

Epoch 5/100

108/108 [=====] - 5s 50ms/step - loss: 0.0252 - accuracy: 0.9074 - val_loss: 0.1915 - val_accuracy: 0.7872

Epoch 00005: val_loss did not improve from 0.16634

Epoch 6/100

108/108 [=====] - 6s 52ms/step - loss: 0.0238 - accuracy:

0.9121 - val_loss: 0.2250 - val_accuracy: 0.7724

Epoch 00006: val_loss did not improve from 0.16634

Epoch 7/100

108/108 [=====] - 6s 57ms/step - loss: 0.0234 - accuracy:

0.9133 - val_loss: 0.2329 - val_accuracy: 0.7839

Epoch 00007: val_loss did not improve from 0.16634

Epoch 8/100

108/108 [=====] - 6s 56ms/step - loss: 0.0223 - accuracy:

0.9168 - val_loss: 0.2319 - val_accuracy: 0.7839

Epoch 00008: val_loss did not improve from 0.16634

Epoch 9/100

108/108 [=====] - 6s 58ms/step - loss: 0.0214 - accuracy:

0.9181 - val_loss: 0.2385 - val_accuracy: 0.7823

Epoch 00009: val_loss did not improve from 0.16634

Epoch 10/100

108/108 [=====] - 6s 58ms/step - loss: 0.0207 - accuracy:

0.9217 - val_loss: 0.2355 - val_accuracy: 0.7873

Epoch 00010: val_loss did not improve from 0.16634

Epoch 11/100

108/108 [=====] - 6s 57ms/step - loss: 0.0199 - accuracy:

0.9244 - val_loss: 0.2587 - val_accuracy: 0.7810ss:

Epoch 00011: val_loss did not improve from 0.16634

Epoch 12/100

108/108 [=====] - 6s 57ms/step - loss: 0.0182 - accuracy:

0.9300 - val_loss: 0.2534 - val_accuracy: 0.7848

Epoch 00012: val_loss did not improve from 0.16634

Epoch 13/100

108/108 [=====] - 6s 54ms/step - loss: 0.0186 - accuracy:

0.9291 - val_loss: 0.2600 - val_accuracy: 0.7844

Epoch 00013: val_loss did not improve from 0.16634

Epoch 00013: early stopping

time: 2

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_3 (InputLayer)	[(None, 128, 128, 8) 0		

conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_3[0][0]

max_pooling2d (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]

conv2 (Conv2D)	(None, 64, 64, 64) 18496		max_pooling2d[0][0]

max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64) 0		conv2[0][0]

conv3 (Conv2D)	(None, 32, 32, 128) 73856		max_pooling2d_1[0][0]

max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 128)	0	conv3[0][0]
conv4 (Conv2D)	(None, 16, 16, 128)	147584	max_pooling2d_2[0]
conv5 (Conv2D)	(None, 16, 16, 128)	147584	conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128)	147584	conv5[0][0]
up_sampling2d (UpSampling2D)	(None, 32, 32, 128)	0	conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128)	147584	up_sampling2d[0][0]
concatenate3 (Concatenate)	(None, 32, 32, 256)	0	conv3[0][0] upsampling3[0][0]
up_sampling2d_1 (UpSampling2D)	(None, 64, 64, 256)	0	concatenate3[0][0]
upsampling2 (Conv2D)	(None, 64, 64, 64)	147520	up_sampling2d_1[0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_2 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D)	(None, 128, 128, 32)	36896	up_sampling2d_2[0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d (Conv2D)	(None, 128, 128, 3)	195	concatenate1[0][0]
=====			
Total params: 869,635			
Trainable params: 869,635			
Non-trainable params: 0			

Epoch 1/100

108/108 [=====] - 7s 55ms/step - loss: 0.0183 - accuracy: 0.9295 - val_loss: 0.2424 - val_accuracy: 0.7773

Epoch 00001: val_loss improved from inf to 0.24236, saving model to imgs/experiments/exp1/models/unet_2.h5

Epoch 2/100

108/108 [=====] - 6s 55ms/step - loss: 0.0184 - accuracy: 0.9305 - val_loss: 0.2229 - val_accuracy: 0.7835

Epoch 00002: val_loss improved from 0.24236 to 0.22294, saving model to imgs/experiments/exp1/models/unet_2.h5

Epoch 3/100
 108/108 [=====] - 6s 56ms/step - loss: 0.0163 - accuracy: 0.9370 - val_loss: 0.2340 - val_accuracy: 0.7834

Epoch 00003: val_loss did not improve from 0.22294

Epoch 4/100
 108/108 [=====] - 6s 56ms/step - loss: 0.0165 - accuracy: 0.9362 - val_loss: 0.2691 - val_accuracy: 0.7766

Epoch 00004: val_loss did not improve from 0.22294

Epoch 5/100
 108/108 [=====] - 6s 57ms/step - loss: 0.0167 - accuracy: 0.9360 - val_loss: 0.2799 - val_accuracy: 0.7700

Epoch 00005: val_loss did not improve from 0.22294

Epoch 6/100
 108/108 [=====] - 6s 59ms/step - loss: 0.0156 - accuracy: 0.9390 - val_loss: 0.2741 - val_accuracy: 0.7736

Epoch 00006: val_loss did not improve from 0.22294

Epoch 7/100
 108/108 [=====] - 6s 59ms/step - loss: 0.0146 - accuracy: 0.9433 - val_loss: 0.2866 - val_accuracy: 0.7732

Epoch 00007: val_loss did not improve from 0.22294

Epoch 8/100
 108/108 [=====] - 6s 60ms/step - loss: 0.0146 - accuracy: 0.9430 - val_loss: 0.2920 - val_accuracy: 0.7737

Epoch 00008: val_loss did not improve from 0.22294

Epoch 9/100
 108/108 [=====] - 6s 58ms/step - loss: 0.0143 - accuracy: 0.9443 - val_loss: 0.2609 - val_accuracy: 0.7719

Epoch 00009: val_loss did not improve from 0.22294

Epoch 10/100
 108/108 [=====] - 6s 60ms/step - loss: 0.0151 - accuracy: 0.9416 - val_loss: 0.2816 - val_accuracy: 0.7757

Epoch 00010: val_loss did not improve from 0.22294

Epoch 11/100
 108/108 [=====] - 7s 61ms/step - loss: 0.0145 - accuracy: 0.9436 - val_loss: 0.2611 - val_accuracy: 0.7786

Epoch 00011: val_loss did not improve from 0.22294

Epoch 12/100
 108/108 [=====] - 6s 60ms/step - loss: 0.0183 - accuracy: 0.9342 - val_loss: 0.2428 - val_accuracy: 0.7857

Epoch 00012: val_loss did not improve from 0.22294

Epoch 00012: early stopping

time: 3

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_3 (InputLayer)	[(None, 128, 128, 8) 0		
<hr/>			
conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_3[0][0]
<hr/>			
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]

conv2 (Conv2D)	(None, 64, 64, 64)	18496	max_pooling2d[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64)	0	conv2[0][0]
conv3 (Conv2D)	(None, 32, 32, 128)	73856	max_pooling2d_1[0][0]
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 128)	0	conv3[0][0]
conv4 (Conv2D)	(None, 16, 16, 128)	147584	max_pooling2d_2[0][0]
conv5 (Conv2D)	(None, 16, 16, 128)	147584	conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128)	147584	conv5[0][0]
up_sampling2d (UpSampling2D)	(None, 32, 32, 128)	0	conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128)	147584	up_sampling2d[0][0]
concatenate3 (Concatenate)	(None, 32, 32, 256)	0	conv3[0][0] upsampling3[0][0]
up_sampling2d_1 (UpSampling2D)	(None, 64, 64, 256)	0	concatenate3[0][0]
upsampling2 (Conv2D)	(None, 64, 64, 64)	147520	up_sampling2d_1[0][0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_2 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D)	(None, 128, 128, 32)	36896	up_sampling2d_2[0][0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d (Conv2D)	(None, 128, 128, 3)	195	concatenate1[0][0]
=====			
Total params: 869,635			
Trainable params: 869,635			
Non-trainable params: 0			

```

Epoch 1/100
108/108 [=====] - 8s 66ms/step - loss: 0.0156 - accuracy:
0.9408 - val_loss: 0.2439 - val_accuracy: 0.7756

Epoch 00001: val_loss improved from inf to 0.24389, saving model to imgs/experiment
s/exp1/models\unet_3.h5
Epoch 2/100
108/108 [=====] - 7s 64ms/step - loss: 0.0134 - accuracy:
0.9479 - val_loss: 0.2624 - val_accuracy: 0.7769

Epoch 00002: val_loss did not improve from 0.24389
Epoch 3/100
108/108 [=====] - 7s 62ms/step - loss: 0.0130 - accuracy:
0.9493 - val_loss: 0.2969 - val_accuracy: 0.7700

Epoch 00003: val_loss did not improve from 0.24389
Epoch 4/100
108/108 [=====] - 7s 62ms/step - loss: 0.0124 - accuracy:
0.9515 - val_loss: 0.2965 - val_accuracy: 0.7747

Epoch 00004: val_loss did not improve from 0.24389
Epoch 5/100
108/108 [=====] - 7s 64ms/step - loss: 0.0124 - accuracy:
0.9515 - val_loss: 0.2937 - val_accuracy: 0.7750

Epoch 00005: val_loss did not improve from 0.24389
Epoch 6/100
108/108 [=====] - 7s 66ms/step - loss: 0.0123 - accuracy:
0.9513 - val_loss: 0.2949 - val_accuracy: 0.7742

Epoch 00006: val_loss did not improve from 0.24389
Epoch 7/100
108/108 [=====] - 7s 68ms/step - loss: 0.0122 - accuracy:
0.9530 - val_loss: 0.2989 - val_accuracy: 0.7684

Epoch 00007: val_loss did not improve from 0.24389
Epoch 8/100
108/108 [=====] - 7s 68ms/step - loss: 0.0119 - accuracy:
0.9532 - val_loss: 0.2945 - val_accuracy: 0.7750

Epoch 00008: val_loss did not improve from 0.24389
Epoch 9/100
108/108 [=====] - 7s 68ms/step - loss: 0.0117 - accuracy:
0.9542 - val_loss: 0.2989 - val_accuracy: 0.7741

Epoch 00009: val_loss did not improve from 0.24389
Epoch 10/100
108/108 [=====] - 7s 68ms/step - loss: 0.0118 - accuracy:
0.9536 - val_loss: 0.2806 - val_accuracy: 0.7789

Epoch 00010: val_loss did not improve from 0.24389
Epoch 11/100
108/108 [=====] - 7s 69ms/step - loss: 0.0127 - accuracy:
0.9502 - val_loss: 0.2836 - val_accuracy: 0.7800

Epoch 00011: val_loss did not improve from 0.24389
Epoch 00011: early stopping
time: 4
Model: "model"

```

Layer (type)	Output Shape	Param #	Connected to
=====			
=====			
input_3 (InputLayer)	[(None, 128, 128, 8) 0		

conv1 (Conv2D)	(None, 128, 128, 32)	2336	input_3[0][0]
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32)	0	conv1[0][0]
conv2 (Conv2D)	(None, 64, 64, 64)	18496	max_pooling2d[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64)	0	conv2[0][0]
conv3 (Conv2D) [0]	(None, 32, 32, 128)	73856	max_pooling2d_1[0] [0]
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 128)	0	conv3[0][0]
conv4 (Conv2D) [0]	(None, 16, 16, 128)	147584	max_pooling2d_2[0] [0]
conv5 (Conv2D)	(None, 16, 16, 128)	147584	conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128)	147584	conv5[0][0]
up_sampling2d (UpSampling2D)	(None, 32, 32, 128)	0	conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128)	147584	up_sampling2d[0][0]
concatenate3 (Concatenate)	(None, 32, 32, 256)	0	conv3[0][0] upsampling3[0][0]
up_sampling2d_1 (UpSampling2D)	(None, 64, 64, 256)	0	concatenate3[0][0]
upsampling2 (Conv2D) [0]	(None, 64, 64, 64)	147520	up_sampling2d_1[0] [0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_2 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D) [0]	(None, 128, 128, 32)	36896	up_sampling2d_2[0] [0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d (Conv2D)	(None, 128, 128, 3)	195	concatenate1[0][0]

=====

Total params: 869,635
Trainable params: 869,635
Non-trainable params: 0

Epoch 1/100

108/108 [=====] - 8s 69ms/step - loss: 0.0121 - accuracy: 0.9534 - val_loss: 0.2605 - val_accuracy: 0.7742

Epoch 00001: val_loss improved from inf to 0.26045, saving model to imgs/experiments/exp1/models/unet_4.h5

Epoch 2/100

108/108 [=====] - 7s 68ms/step - loss: 0.0114 - accuracy: 0.9552 - val_loss: 0.2789 - val_accuracy: 0.77120.0114 - ETA: 1s - loss: 0.0114 - accuracy: 0.9552 - val_loss: 0.2789 - val_accuracy: 0.7712

Epoch 00002: val_loss did not improve from 0.26045

Epoch 3/100

108/108 [=====] - 7s 69ms/step - loss: 0.0114 - accuracy: 0.9556 - val_loss: 0.3120 - val_accuracy: 0.7703

Epoch 00003: val_loss did not improve from 0.26045

Epoch 4/100

108/108 [=====] - 8s 71ms/step - loss: 0.0112 - accuracy: 0.9565 - val_loss: 0.3032 - val_accuracy: 0.7698 3s - loss: 0.0112 - accuracy: 0.9565 - val_loss: 0.3032 - val_accuracy: 0.7698 - ETA: 3s - loss: 0.0112 - accuracy: 0.9565 - val_loss: 0.3032 - val_accuracy: 0.7698

Epoch 00004: val_loss did not improve from 0.26045

Epoch 5/100

108/108 [=====] - 8s 73ms/step - loss: 0.0109 - accuracy: 0.9569 - val_loss: 0.3099 - val_accuracy: 0.7727

Epoch 00005: val_loss did not improve from 0.26045

Epoch 6/100

108/108 [=====] - 8s 71ms/step - loss: 0.0107 - accuracy: 0.9585 - val_loss: 0.3182 - val_accuracy: 0.7738

Epoch 00006: val_loss did not improve from 0.26045

Epoch 7/100

108/108 [=====] - 8s 74ms/step - loss: 0.0107 - accuracy: 0.9581 - val_loss: 0.3247 - val_accuracy: 0.7658

Epoch 00007: val_loss did not improve from 0.26045

Epoch 8/100

108/108 [=====] - 8s 74ms/step - loss: 0.0105 - accuracy: 0.9586 - val_loss: 0.2955 - val_accuracy: 0.7727

Epoch 00008: val_loss did not improve from 0.26045

Epoch 9/100

108/108 [=====] - 8s 74ms/step - loss: 0.0111 - accuracy: 0.9566 - val_loss: 0.3106 - val_accuracy: 0.7724

Epoch 00009: val_loss did not improve from 0.26045

Epoch 10/100

108/108 [=====] - 8s 75ms/step - loss: 0.0105 - accuracy: 0.9591 - val_loss: 0.3016 - val_accuracy: 0.7765

Epoch 00010: val_loss did not improve from 0.26045

Epoch 11/100

108/108 [=====] - 8s 78ms/step - loss: 0.0107 - accuracy: 0.9587 - val_loss: 0.2961 - val_accuracy: 0.7772

Epoch 00011: val_loss did not improve from 0.26045

Epoch 00011: early stopping

In [26]:

```

# Test Loop
time_ts = []
n_pool = 3
n_rows = 5
n_cols = 4
rows, cols = image_array.shape[:2]
pad_rows = rows - np.ceil(rows/(n_rows*2**n_pool))*n_rows*2**n_pool
pad_cols = cols - np.ceil(cols/(n_cols*2**n_pool))*n_cols*2**n_pool
print(pad_rows, pad_cols)

npad = ((0, int(abs(pad_rows))), (0, int(abs(pad_cols))), (0, 0))
image1_pad = np.pad(image_array, pad_width=npad, mode='reflect')

h, w, c = image1_pad.shape
patch_size_rows = h//n_rows
patch_size_cols = w//n_cols
num_patches_x = int(h/patch_size_rows)
num_patches_y = int(w/patch_size_cols)

input_shape=(patch_size_rows,patch_size_cols, c)

if method == 'unet':
    new_model = build_unet(input_shape, nb_filters, number_class)

if method == 'resunet':
    new_model = build_resunet(input_shape, nb_filters, number_class)

for tm in range(0,times):
    print('time: ', tm)
    model = load_model(path_models+ '/' + method + '_' +str(tm)+'.h5', compile=False)

    for l in range(1, len(model.layers)):
        new_model.layers[l].set_weights(model.layers[l].get_weights())

    start_test = time.time()
    patch_t = []

    for i in range(0,num_patches_y):
        for j in range(0,num_patches_x):
            patch = image1_pad[patch_size_rows*j:patch_size_rows*(j+1), patch_size_c
            predictions_ = new_model.predict(np.expand_dims(patch, axis=0))
            del patch
            patch_t.append(predictions_[::,:,1])
            del predictions_
    end_test = time.time() - start_test
    patches_pred = np.asarray(patch_t).astype(np.float32)

    prob_reconstructed = pred_reconstruct(h, w, num_patches_x, num_patches_y, patch_s
    np.save(path_maps+'/'+'prob_'+str(tm)+'.npy',prob_reconstructed)

    time_ts.append(end_test)
    del prob_reconstructed, model, patches_pred
time_ts_array = np.asarray(time_ts)
# Save test time
np.save(path_exp+'/metrics_ts.npy', time_ts_array)

```

```

0.0 -8.0
time: 0
time: 1
time: 2
time: 3
time: 4

```

```
In [27]: # Compute mean of the tm predictions maps
prob_rec = np.zeros((image1_pad.shape[0], image1_pad.shape[1], times))

for tm in range(0, times):
    print(tm)
    prob_rec[:, :, tm] = np.load(path_maps+'/'+'prob_'+str(tm)+'.npy').astype(np.float)

mean_prob = np.mean(prob_rec, axis = -1)
np.save(path_maps+'/'+'prob_mean.npy', mean_prob)
```

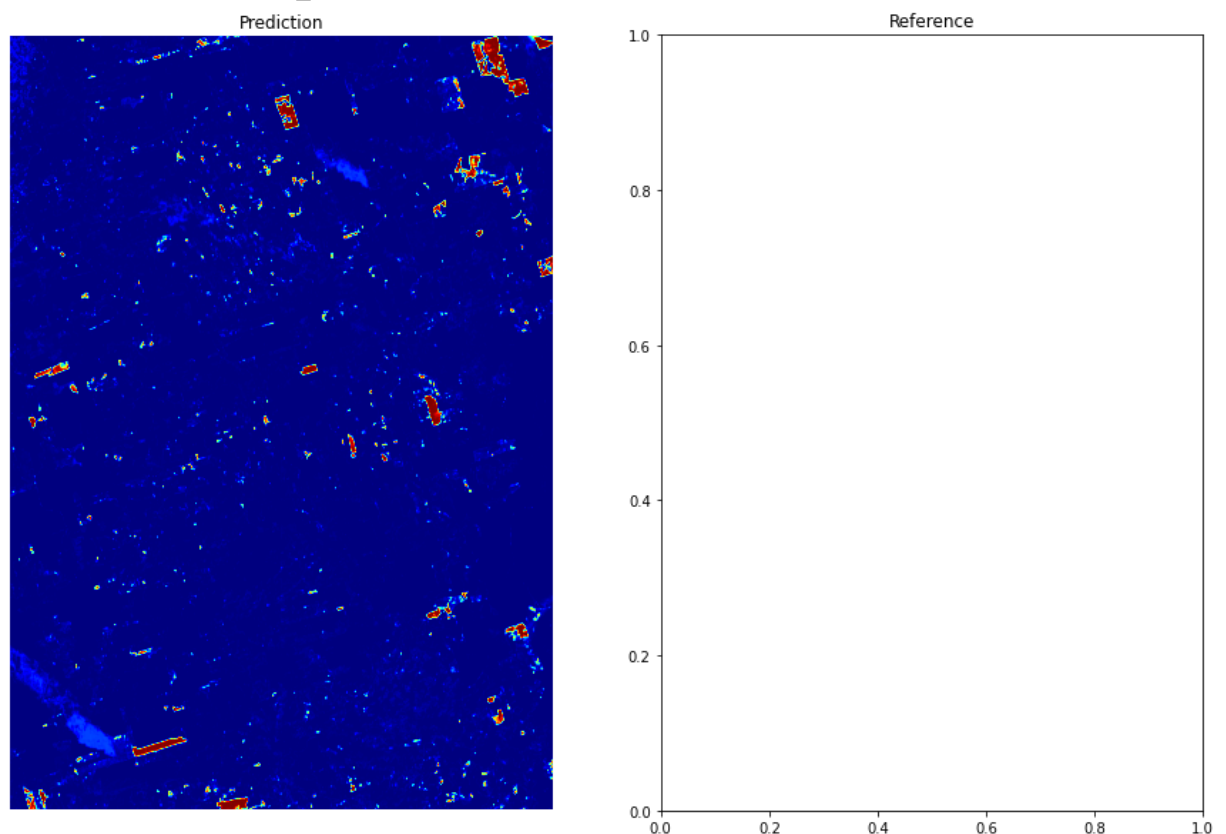
0
1
2
3
4

```
In [28]: # Plot mean map and reference
fig = plt.figure(figsize=(15,10))
ax1 = fig.add_subplot(121)
plt.title('Prediction')
ax1.imshow(mean_prob, cmap = 'jet')
ax1.axis('off')

ax2 = fig.add_subplot(122)
plt.title('Reference')
ax2.imshow(ref_2019, cmap = 'jet')
ax2.axis('off')
```

```
-----
NameError                                Traceback (most recent call last)
C:\Users\FELFER~1\AppData\Local\Temp\ipykernel_12872\3622215040.py in <module>
      8 ax2 = fig.add_subplot(122)
      9 plt.title('Reference')
--> 10 ax2.imshow(ref_2019, cmap = 'jet')
     11 ax2.axis('off')
```

NameError: name 'ref_2019' is not defined



```
In [29]: # Computing metrics
mean_prob = mean_prob[:final_mask1.shape[0], :final_mask1.shape[1]]
ref1 = np.ones_like(final_mask1).astype(np.float32)

ref1 [final_mask1 == 2] = 0
TileMask = mask_amazon_ts * ref1
GTTruePositives = final_mask1==1

Npoints = 50
Pmax = np.max(mean_prob[GTTruePositives * TileMask ==1])
ProbList = np.linspace(Pmax,0,Npoints)

metrics_ = matrices_AA_recall(ProbList, mean_prob, final_mask1, mask_amazon_ts, 625)
np.save(path_exp+'/acc_metrics.npy',metrics_)
```

```
0.9987759828567505
```

```
D:\Ferrari\proj_1\Mabel_original\utils_unet_resunet.py:200: RuntimeWarning: invalid
value encountered in longlong_scalars
```

```
precision_ = TP/(TP+FP)
```

```
0.9783927995331434
```

```
0.9580096162095362
```

```
0.9376264328859291
```

```
0.917243249562322
```

```
0.8968600662387147
```

```
0.8764768829151076
```

```
0.8560936995915005
```

```
0.8357105162678933
```

```
0.815327332944286
```

```
0.7949441496206789
```

```
0.7745609662970718
```

```
0.7541777829734646
```

```
0.7337945996498575
```

```
0.7134114163262504
```

```
0.6930282330026432
```

```
0.672645049679036
```

```
0.6522618663554289
```

```
0.6318786830318217
```

```
0.6114954997082146
```

```
0.5911123163846075
```

```
0.5707291330610003
```

```
0.5503459497373931
```

```
0.529962766413786
```

```
0.5095795830901788
```

```
0.4891963997665717
```

```
0.4688132164429645
```

```
0.44843003311935736
```

```
0.42804684979575025
```

```
0.407663666472143
```

```
0.3872804831485359
```

```
0.3668972998249287
```

```
0.3465141165013216
```

```
0.32613093317771447
```

```
0.30574774985410724
```

```
0.28536456653050013
```

```
0.2649813832068929
```

```
0.2445981998832858
```

```
0.22421501655967868
```

```
0.20383183323607146
```

```
0.18344864991246435
```

```
0.16306546658885723
```

```
0.14268228326525
```

```
0.1222990999416429
```

```
0.10191591661803578
```

```
0.08153273329442856
```

```
0.06114954997082145
0.040766366647214225
0.020383183323607112
0.0
```

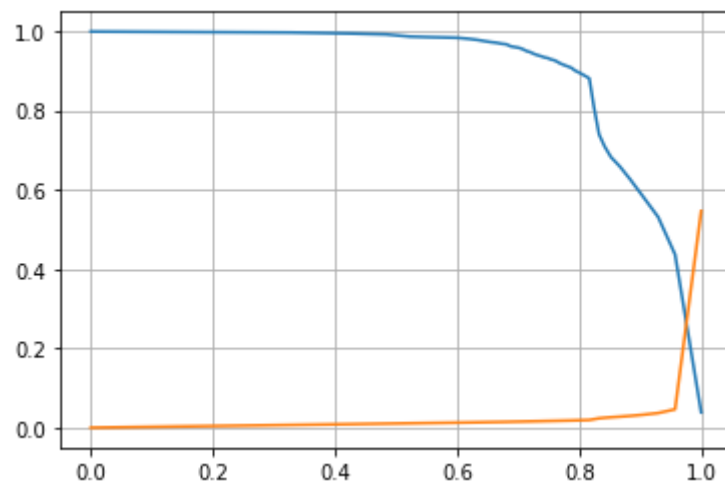
```
In [30]: # Complete NaN values
metrics_copy = metrics_.copy()
metrics_copy = complete_nan_values(metrics_copy)
```

```
In [31]: # Compute Mean Average Precision (mAP) score
Recall = metrics_copy[:,0]
Precision = metrics_copy[:,1]
AA = metrics_copy[:,2]

DeltaR = Recall[1:]-Recall[:-1]
AP = np.sum(Precision[:-1]*DeltaR)
print('mAP', AP)

# Plot Recall vs. Precision curve
plt.close('all')
plt.plot(metrics_copy[:,0],metrics_copy[:,1])
plt.plot(metrics_copy[:,0],metrics_copy[:,2])
plt.grid()
```

mAP 0.9124369937467522



In []: