

```
In [1]: %load_ext autoreload
        %autoreload 2
```

```
In [2]: ##autoreload # When utils.py is updated
        from utils_unet_resunet import *
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from model.models import Model_3
        from model.losses import WBCE
        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]:

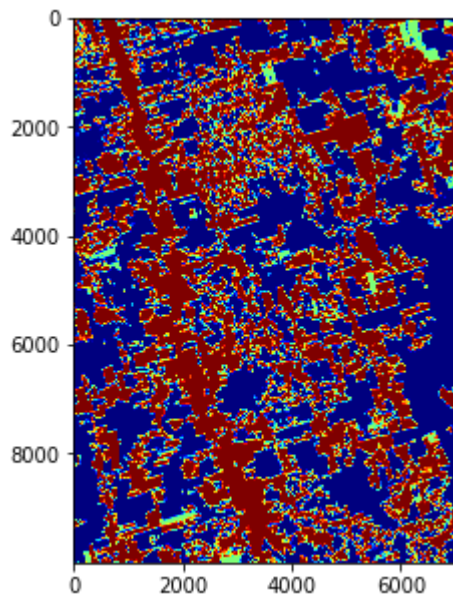
```

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

```

Out[6]:

```
<matplotlib.image.AxesImage at 0x1a71e9c71c0>
```



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 [26]:

```

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 [32]:

```

# 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)

#model = Model_3(nb_filters, number_class)
#model.build((None, 128,128,8))

```

In [33]:

```

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

loss = weighted_categorical_crossentropy(weights)
#loss = WBCE(weights)

```

In [34]:

```

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', save
    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_7"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_8 (InputLayer)	[(None, 128, 128, 8) 0		
conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_8[0][0]
max_pooling2d_21 (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]
conv2 (Conv2D)	(None, 64, 64, 64) 18496		max_pooling2d_21[0][0]
max_pooling2d_22 (MaxPooling2D)	(None, 32, 32, 64) 0		conv2[0][0]
conv3 (Conv2D)	(None, 32, 32, 128) 73856		max_pooling2d_22[0][0]
max_pooling2d_23 (MaxPooling2D)	(None, 16, 16, 128) 0		conv3[0][0]
conv4 (Conv2D)	(None, 16, 16, 128) 147584		max_pooling2d_23[0][0]
conv5 (Conv2D)	(None, 16, 16, 128) 147584		conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128) 147584		conv5[0][0]
up_sampling2d_21 (UpSampling2D)	(None, 32, 32, 128) 0		conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128) 147584		up_sampling2d_21[0][0]
concatenate3 (Concatenate)	(None, 32, 32, 256) 0		conv3[0][0] upsampling3[0][0]
up_sampling2d_22 (UpSampling2D)	(None, 64, 64, 256) 0		concatenate3[0][0]

upsampling2 (Conv2D)	(None, 64, 64, 64)	147520	up_sampling2d_22[0][0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_23 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D)	(None, 128, 128, 32)	36896	up_sampling2d_23[0][0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d_8 (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 [=====] - 18s 166ms/step - loss: 0.1003 - accuracy: 0.7463 - val_loss: 0.0939 - val_accuracy: 0.7857

Epoch 00001: val_loss improved from inf to 0.09390, saving model to imgs/experiments/exp1/models/unet_0.h5

Epoch 2/100

108/108 [=====] - 17s 161ms/step - loss: 0.0666 - accuracy: 0.8225 - val_loss: 0.1026 - val_accuracy: 0.7789

Epoch 00002: val_loss did not improve from 0.09390

Epoch 3/100

108/108 [=====] - 17s 161ms/step - loss: 0.0621 - accuracy: 0.8334 - val_loss: 0.1251 - val_accuracy: 0.7941

Epoch 00003: val_loss did not improve from 0.09390

Epoch 4/100

108/108 [=====] - 17s 161ms/step - loss: 0.0590 - accuracy: 0.8367 - val_loss: 0.1607 - val_accuracy: 0.7731

Epoch 00004: val_loss did not improve from 0.09390

Epoch 5/100

108/108 [=====] - 17s 160ms/step - loss: 0.0539 - accuracy: 0.8485 - val_loss: 0.1381 - val_accuracy: 0.7863

Epoch 00005: val_loss did not improve from 0.09390

Epoch 6/100

108/108 [=====] - 17s 160ms/step - loss: 0.0506 - accuracy: 0.8556 - val_loss: 0.1500 - val_accuracy: 0.7970

Epoch 00006: val_loss did not improve from 0.09390

Epoch 7/100

108/108 [=====] - 17s 160ms/step - loss: 0.0466 - accuracy: 0.8623 - val_loss: 0.1455 - val_accuracy: 0.7963

Epoch 00007: val_loss did not improve from 0.09390

Epoch 8/100

108/108 [=====] - 17s 162ms/step - loss: 0.0423 - accuracy: 0.8707 - val_loss: 0.1424 - val_accuracy: 0.7970

Epoch 00008: val_loss did not improve from 0.09390

Epoch 9/100

108/108 [=====] - 17s 159ms/step - loss: 0.0376 - accuracy: 0.8798 - val_loss: 0.1559 - val_accuracy: 0.7967

Epoch 00009: val_loss did not improve from 0.09390

Epoch 10/100

108/108 [=====] - 18s 164ms/step - loss: 0.0374 - accuracy: 0.8777 - val_loss: 0.1772 - val_accuracy: 0.7991

Epoch 00010: val_loss did not improve from 0.09390

Epoch 11/100

108/108 [=====] - 18s 168ms/step - loss: 0.0370 - accuracy: 0.8796 - val_loss: 0.1705 - val_accuracy: 0.8036

Epoch 00011: val_loss did not improve from 0.09390

Epoch 00011: early stopping

time: 1

Model: "model_7"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_8 (InputLayer)	[(None, 128, 128, 8) 0		
conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_8[0][0]
max_pooling2d_21 (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]
conv2 (Conv2D)	(None, 64, 64, 64) 18496		max_pooling2d_21[0][0]
max_pooling2d_22 (MaxPooling2D)	(None, 32, 32, 64) 0		conv2[0][0]
conv3 (Conv2D)	(None, 32, 32, 128) 73856		max_pooling2d_22[0][0]
max_pooling2d_23 (MaxPooling2D)	(None, 16, 16, 128) 0		conv3[0][0]
conv4 (Conv2D)	(None, 16, 16, 128) 147584		max_pooling2d_23[0][0]
conv5 (Conv2D)	(None, 16, 16, 128) 147584		conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128) 147584		conv5[0][0]
up_sampling2d_21 (UpSampling2D)	(None, 32, 32, 128) 0		conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128) 147584		up_sampling2d_21[0]

[0]

concatenate3 (Concatenate)	(None, 32, 32, 256)	0	conv3[0][0] upsampling3[0][0]
up_sampling2d_22 (UpSampling2D)	(None, 64, 64, 256)	0	concatenate3[0][0]
upsampling2 (Conv2D)	(None, 64, 64, 64)	147520	up_sampling2d_22[0] [0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_23 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D)	(None, 128, 128, 32)	36896	up_sampling2d_23[0] [0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d_8 (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 [=====] - 18s 162ms/step - loss: 0.0318 - accuracy:
 0.8902 - val_loss: 0.1494 - val_accuracy: 0.7999

Epoch 00001: val_loss improved from inf to 0.14944, saving model to imgs/experiments/exp1/models/unet_1.h5

Epoch 2/100

108/108 [=====] - 17s 157ms/step - loss: 0.0296 - accuracy:
 0.8946 - val_loss: 0.1651 - val_accuracy: 0.7938

Epoch 00002: val_loss did not improve from 0.14944

Epoch 3/100

108/108 [=====] - 17s 159ms/step - loss: 0.0286 - accuracy:
 0.8973 - val_loss: 0.1804 - val_accuracy: 0.7880

Epoch 00003: val_loss did not improve from 0.14944

Epoch 4/100

108/108 [=====] - 17s 161ms/step - loss: 0.0270 - accuracy:
 0.9011 - val_loss: 0.2099 - val_accuracy: 0.7895

Epoch 00004: val_loss did not improve from 0.14944

Epoch 5/100

108/108 [=====] - 17s 157ms/step - loss: 0.0255 - accuracy:
 0.9059 - val_loss: 0.2023 - val_accuracy: 0.7971

Epoch 00005: val_loss did not improve from 0.14944

Epoch 6/100

108/108 [=====] - 17s 160ms/step - loss: 0.0252 - accuracy:

0.9061 - val_loss: 0.2033 - val_accuracy: 0.7890

Epoch 00006: val_loss did not improve from 0.14944

Epoch 7/100

108/108 [=====] - 18s 171ms/step - loss: 0.0239 - accuracy:

0.9103 - val_loss: 0.2182 - val_accuracy: 0.7835

Epoch 00007: val_loss did not improve from 0.14944

Epoch 8/100

108/108 [=====] - 17s 161ms/step - loss: 0.0228 - accuracy:

0.9139 - val_loss: 0.2200 - val_accuracy: 0.7898

Epoch 00008: val_loss did not improve from 0.14944

Epoch 9/100

108/108 [=====] - 17s 160ms/step - loss: 0.0228 - accuracy:

0.9143 - val_loss: 0.1793 - val_accuracy: 0.7855

Epoch 00009: val_loss did not improve from 0.14944

Epoch 10/100

108/108 [=====] - 17s 162ms/step - loss: 0.0227 - accuracy:

0.9142 - val_loss: 0.1980 - val_accuracy: 0.7855

Epoch 00010: val_loss did not improve from 0.14944

Epoch 11/100

108/108 [=====] - 18s 164ms/step - loss: 0.0210 - accuracy:

0.9200 - val_loss: 0.1976 - val_accuracy: 0.7954

Epoch 00011: val_loss did not improve from 0.14944

Epoch 00011: early stopping

time: 2

Model: "model_7"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_8 (InputLayer)	[(None, 128, 128, 8) 0		
=====			
conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_8[0][0]
=====			
max_pooling2d_21 (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]
=====			
conv2 (Conv2D)	(None, 64, 64, 64) 18496		max_pooling2d_21[0][0]
=====			
max_pooling2d_22 (MaxPooling2D)	(None, 32, 32, 64) 0		conv2[0][0]
=====			
conv3 (Conv2D)	(None, 32, 32, 128) 73856		max_pooling2d_22[0][0]
=====			
max_pooling2d_23 (MaxPooling2D)	(None, 16, 16, 128) 0		conv3[0][0]
=====			
conv4 (Conv2D)	(None, 16, 16, 128) 147584		max_pooling2d_23[0][0]
=====			
conv5 (Conv2D)	(None, 16, 16, 128) 147584		conv4[0][0]

conv6 (Conv2D)	(None, 16, 16, 128)	147584	conv5[0][0]
up_sampling2d_21 (UpSampling2D)	(None, 32, 32, 128)	0	conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128)	147584	up_sampling2d_21[0][0]
concatenate3 (Concatenate)	(None, 32, 32, 256)	0	conv3[0][0] upsampling3[0][0]
up_sampling2d_22 (UpSampling2D)	(None, 64, 64, 256)	0	concatenate3[0][0]
upsampling2 (Conv2D)	(None, 64, 64, 64)	147520	up_sampling2d_22[0][0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_23 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D)	(None, 128, 128, 32)	36896	up_sampling2d_23[0][0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d_8 (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 [=====] - 18s 165ms/step - loss: 0.0197 - accuracy: 0.9231 - val_loss: 0.1974 - val_accuracy: 0.7882

Epoch 00001: val_loss improved from inf to 0.19741, saving model to imgs/experiments/exp1/models/unet_2.h5

Epoch 2/100

108/108 [=====] - 17s 159ms/step - loss: 0.0186 - accuracy: 0.9272 - val_loss: 0.2131 - val_accuracy: 0.7873

Epoch 00002: val_loss did not improve from 0.19741

Epoch 3/100

108/108 [=====] - 17s 158ms/step - loss: 0.0181 - accuracy: 0.9288 - val_loss: 0.2495 - val_accuracy: 0.7782

Epoch 00003: val_loss did not improve from 0.19741

Epoch 4/100

108/108 [=====] - 17s 159ms/step - loss: 0.0176 - accuracy: 0.9312 - val_loss: 0.2474 - val_accuracy: 0.7803

Epoch 00004: val_loss did not improve from 0.19741
 Epoch 5/100
 108/108 [=====] - 17s 161ms/step - loss: 0.0175 - accuracy: 0.9311 - val_loss: 0.2371 - val_accuracy: 0.7872

Epoch 00005: val_loss did not improve from 0.19741
 Epoch 6/100
 108/108 [=====] - 17s 158ms/step - loss: 0.0168 - accuracy: 0.9337 - val_loss: 0.2448 - val_accuracy: 0.7804

Epoch 00006: val_loss did not improve from 0.19741
 Epoch 7/100
 108/108 [=====] - 17s 160ms/step - loss: 0.0160 - accuracy: 0.9374 - val_loss: 0.2632 - val_accuracy: 0.7825

Epoch 00007: val_loss did not improve from 0.19741
 Epoch 8/100
 108/108 [=====] - 17s 161ms/step - loss: 0.0157 - accuracy: 0.9382 - val_loss: 0.2664 - val_accuracy: 0.7788

Epoch 00008: val_loss did not improve from 0.19741
 Epoch 9/100
 108/108 [=====] - 17s 160ms/step - loss: 0.0153 - accuracy: 0.9391 - val_loss: 0.2506 - val_accuracy: 0.7847

Epoch 00009: val_loss did not improve from 0.19741
 Epoch 10/100
 108/108 [=====] - 17s 163ms/step - loss: 0.0207 - accuracy: 0.9262 - val_loss: 0.2336 - val_accuracy: 0.7871

Epoch 00010: val_loss did not improve from 0.19741
 Epoch 11/100
 108/108 [=====] - 17s 160ms/step - loss: 0.0170 - accuracy: 0.9339 - val_loss: 0.2414 - val_accuracy: 0.7804

Epoch 00011: val_loss did not improve from 0.19741
 Epoch 00011: early stopping
 time: 3
 Model: "model_7"

Layer (type)	Output Shape	Param #	Connected to
input_8 (InputLayer)	[(None, 128, 128, 8) 0		
conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_8[0][0]
max_pooling2d_21 (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]
conv2 (Conv2D)	(None, 64, 64, 64) 18496		max_pooling2d_21[0][0]
max_pooling2d_22 (MaxPooling2D)	(None, 32, 32, 64) 0		conv2[0][0]
conv3 (Conv2D)	(None, 32, 32, 128) 73856		max_pooling2d_22[0][0]
max_pooling2d_23 (MaxPooling2D)	(None, 16, 16, 128) 0		conv3[0][0]

conv4 (Conv2D)	(None, 16, 16, 128)	147584	max_pooling2d_23[0][0]
conv5 (Conv2D)	(None, 16, 16, 128)	147584	conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128)	147584	conv5[0][0]
up_sampling2d_21 (UpSampling2D)	(None, 32, 32, 128)	0	conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128)	147584	up_sampling2d_21[0][0]
concatenate3 (Concatenate)	(None, 32, 32, 256)	0	conv3[0][0] upsampling3[0][0]
up_sampling2d_22 (UpSampling2D)	(None, 64, 64, 256)	0	concatenate3[0][0]
upsampling2 (Conv2D)	(None, 64, 64, 64)	147520	up_sampling2d_22[0][0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_23 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D)	(None, 128, 128, 32)	36896	up_sampling2d_23[0][0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d_8 (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 [=====] - 18s 159ms/step - loss: 0.0145 - accuracy: 0.9427 - val_loss: 0.2176 - val_accuracy: 0.7829

Epoch 00001: val_loss improved from inf to 0.21760, saving model to imgs/experiment s/exp1/models\unet_3.h5

Epoch 2/100

108/108 [=====] - 17s 159ms/step - loss: 0.0141 - accuracy: 0.9447 - val_loss: 0.2358 - val_accuracy: 0.7821

Epoch 00002: val_loss did not improve from 0.21760

Epoch 3/100

108/108 [=====] - 17s 157ms/step - loss: 0.0139 - accuracy: 0.9444 - val_loss: 0.2713 - val_accuracy: 0.7740

Epoch 00003: val_loss did not improve from 0.21760

Epoch 4/100

108/108 [=====] - 17s 160ms/step - loss: 0.0137 - accuracy: 0.9452 - val_loss: 0.2757 - val_accuracy: 0.7692

Epoch 00004: val_loss did not improve from 0.21760

Epoch 5/100

108/108 [=====] - 17s 157ms/step - loss: 0.0137 - accuracy: 0.9451 - val_loss: 0.2651 - val_accuracy: 0.7829

Epoch 00005: val_loss did not improve from 0.21760

Epoch 6/100

108/108 [=====] - 18s 164ms/step - loss: 0.0147 - accuracy: 0.9418 - val_loss: 0.2751 - val_accuracy: 0.7823

Epoch 00006: val_loss did not improve from 0.21760

Epoch 7/100

108/108 [=====] - 17s 163ms/step - loss: 0.0128 - accuracy: 0.9494 - val_loss: 0.2878 - val_accuracy: 0.7739

Epoch 00007: val_loss did not improve from 0.21760

Epoch 8/100

108/108 [=====] - 17s 159ms/step - loss: 0.0131 - accuracy: 0.9475 - val_loss: 0.2755 - val_accuracy: 0.7828

Epoch 00008: val_loss did not improve from 0.21760

Epoch 9/100

108/108 [=====] - 17s 160ms/step - loss: 0.0128 - accuracy: 0.9492 - val_loss: 0.2735 - val_accuracy: 0.7805

Epoch 00009: val_loss did not improve from 0.21760

Epoch 10/100

108/108 [=====] - 17s 160ms/step - loss: 0.0126 - accuracy: 0.9501 - val_loss: 0.2779 - val_accuracy: 0.7847

Epoch 00010: val_loss did not improve from 0.21760

Epoch 11/100

108/108 [=====] - 18s 165ms/step - loss: 0.0127 - accuracy: 0.9493 - val_loss: 0.2624 - val_accuracy: 0.7824

Epoch 00011: val_loss did not improve from 0.21760

Epoch 00011: early stopping

time: 4

Model: "model_7"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_8 (InputLayer)	[(None, 128, 128, 8) 0		

conv1 (Conv2D)	(None, 128, 128, 32) 2336		input_8[0][0]

max_pooling2d_21 (MaxPooling2D)	(None, 64, 64, 32) 0		conv1[0][0]

conv2 (Conv2D)	(None, 64, 64, 64) 18496		max_pooling2d_21[0][0]

max_pooling2d_22 (MaxPooling2D)	(None, 32, 32, 64)	0	conv2[0][0]
conv3 (Conv2D)	(None, 32, 32, 128)	73856	max_pooling2d_22[0][0]
max_pooling2d_23 (MaxPooling2D)	(None, 16, 16, 128)	0	conv3[0][0]
conv4 (Conv2D)	(None, 16, 16, 128)	147584	max_pooling2d_23[0][0]
conv5 (Conv2D)	(None, 16, 16, 128)	147584	conv4[0][0]
conv6 (Conv2D)	(None, 16, 16, 128)	147584	conv5[0][0]
up_sampling2d_21 (UpSampling2D)	(None, 32, 32, 128)	0	conv6[0][0]
upsampling3 (Conv2D)	(None, 32, 32, 128)	147584	up_sampling2d_21[0][0]
concatenate3 (Concatenate)	(None, 32, 32, 256)	0	conv3[0][0] upsampling3[0][0]
up_sampling2d_22 (UpSampling2D)	(None, 64, 64, 256)	0	concatenate3[0][0]
upsampling2 (Conv2D)	(None, 64, 64, 64)	147520	up_sampling2d_22[0][0]
concatenate2 (Concatenate)	(None, 64, 64, 128)	0	conv2[0][0] upsampling2[0][0]
up_sampling2d_23 (UpSampling2D)	(None, 128, 128, 128)	0	concatenate2[0][0]
upsampling1 (Conv2D)	(None, 128, 128, 32)	36896	up_sampling2d_23[0][0]
concatenate1 (Concatenate)	(None, 128, 128, 64)	0	conv1[0][0] upsampling1[0][0]
conv2d_8 (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 [=====] - 18s 163ms/step - loss: 0.0122 - accuracy: 0.9512 - val_loss: 0.2368 - val_accuracy: 0.7839

```

Epoch 00001: val_loss improved from inf to 0.23680, saving model to imgs/experiment
s/exp1/models\unet_4.h5
Epoch 2/100
108/108 [=====] - 17s 159ms/step - loss: 0.0131 - accuracy:
0.9487 - val_loss: 0.2457 - val_accuracy: 0.7797

Epoch 00002: val_loss did not improve from 0.23680
Epoch 3/100
108/108 [=====] - 17s 161ms/step - loss: 0.0124 - accuracy:
0.9509 - val_loss: 0.2908 - val_accuracy: 0.7739

Epoch 00003: val_loss did not improve from 0.23680
Epoch 4/100
108/108 [=====] - 17s 158ms/step - loss: 0.0116 - accuracy:
0.9538 - val_loss: 0.2862 - val_accuracy: 0.7789

Epoch 00004: val_loss did not improve from 0.23680
Epoch 5/100
108/108 [=====] - 17s 158ms/step - loss: 0.0128 - accuracy:
0.9503 - val_loss: 0.2470 - val_accuracy: 0.7675

Epoch 00005: val_loss did not improve from 0.23680
Epoch 6/100
108/108 [=====] - 17s 161ms/step - loss: 0.0194 - accuracy:
0.9300 - val_loss: 0.2517 - val_accuracy: 0.7813

Epoch 00006: val_loss did not improve from 0.23680
Epoch 7/100
108/108 [=====] - 17s 159ms/step - loss: 0.0138 - accuracy:
0.9470 - val_loss: 0.2723 - val_accuracy: 0.7813

Epoch 00007: val_loss did not improve from 0.23680
Epoch 8/100
108/108 [=====] - 17s 161ms/step - loss: 0.0118 - accuracy:
0.9530 - val_loss: 0.2801 - val_accuracy: 0.7727

Epoch 00008: val_loss did not improve from 0.23680
Epoch 9/100
108/108 [=====] - 17s 160ms/step - loss: 0.0111 - accuracy:
0.9556 - val_loss: 0.2817 - val_accuracy: 0.7762

Epoch 00009: val_loss did not improve from 0.23680
Epoch 10/100
108/108 [=====] - 17s 160ms/step - loss: 0.0109 - accuracy:
0.9565 - val_loss: 0.2831 - val_accuracy: 0.7786

Epoch 00010: val_loss did not improve from 0.23680
Epoch 11/100
108/108 [=====] - 17s 160ms/step - loss: 0.0110 - accuracy:
0.9564 - val_loss: 0.2730 - val_accuracy: 0.7794

Epoch 00011: val_loss did not improve from 0.23680
Epoch 00011: early stopping

```

In [35]:

```

# 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)

#new_model = Model_3(nb_filters, number_class)
#new_model.build((None, 128,128,8))
#new_model.compile(optimizer=adam, loss=loss, metrics=['accuracy'])

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())
    #new_model.load_weights(path_models+ '/' + method + '_' +str(tm)+'.h5')

    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, patches_pred
    time_ts_array = np.asarray(time_ts)
    del new_model
    # 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 [36]:

```

# 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 [37]:

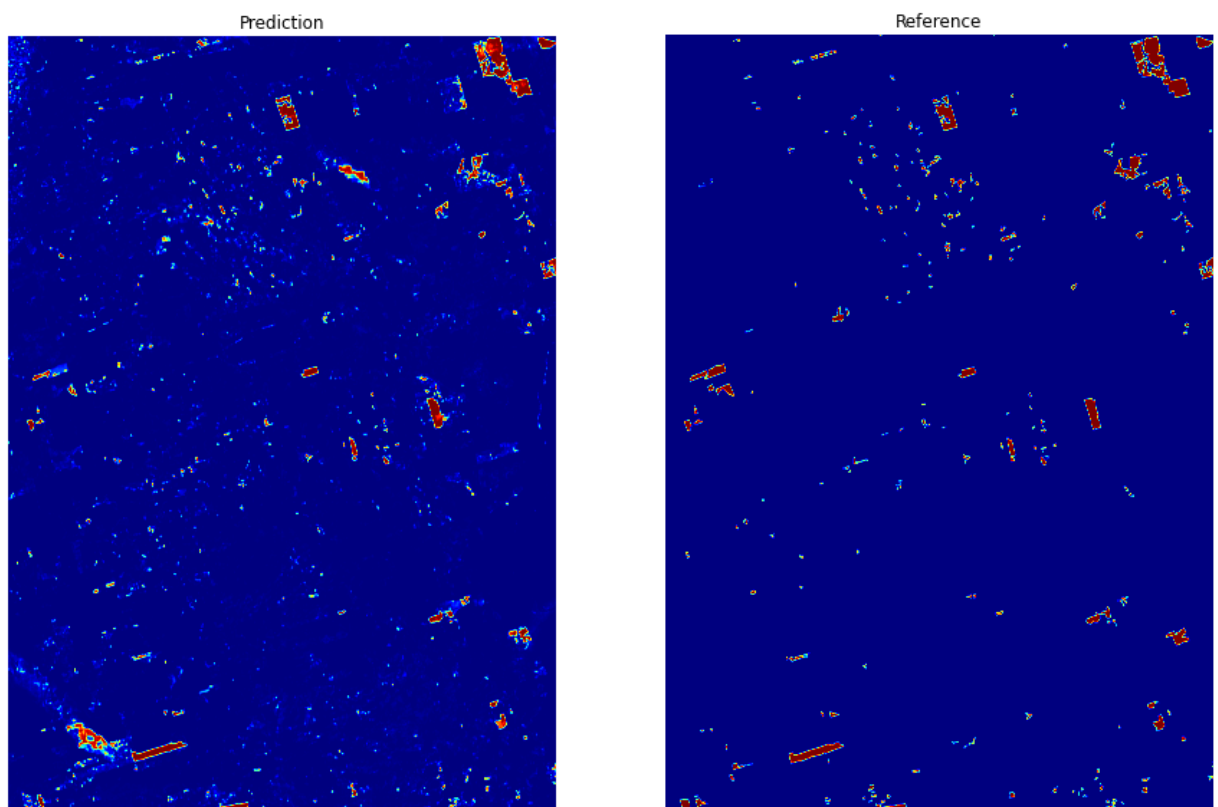
```

ref = final_mask1
ref[ref==0]=0
ref[ref==2]=0
# 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, cmap = 'jet')
ax2.axis('off')

```

Out[37]: (-0.5, 6999.5, 9999.5, -0.5)



In [38]:

```

# 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_)

```

```
0.9997152328491211
```

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

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

```
0.9793128811583227
```

```
0.9589105294675243
```

```
0.9385081777767259
```

```
0.9181058260859276
```

```
0.8977034743951292
```

```
0.8773011227043308
```

```
0.8568987710135324
```

```
0.836496419322734
```

```
0.8160940676319356
```

```
0.7956917159411372
```

```
0.7752893642503389
```

```
0.7548870125595404
```

```
0.7344846608687421
```

```
0.7140823091779437
```

```
0.6936799574871453
```

```
0.6732776057963469
```

```
0.6528752541055485
```

```
0.6324729024147501
```

```
0.6120705507239517
```

```
0.5916681990331534
```

```
0.5712658473423549
```

```
0.5508634956515566
```

```
0.5304611439607582
```

```
0.5100587922699598
```

```
0.48965644057916136
```

```
0.46925408888836295
```

```
0.44885173719756455
```

```
0.42844938550676626
```

```
0.40804703381596785
```

```
0.38764468212516945
```

```
0.36724233043437104
```

```
0.34683997874357264
```

```
0.32643762705277424
```

```
0.30603527536197583
```

```
0.28563292367117743
```

```
0.265230571980379
```

```
0.24482822028958073
```

```
0.22442586859878233
```

```
0.20402351690798393
```

```
0.18362116521718552
```

```
0.16321881352638712
```

```
0.14281646183558871
```

```
0.12241411014479031
```

```
0.10201175845399202
```

```
0.08160940676319361
```

```
0.06120705507239521
```

```
0.04080470338159681
```

```
0.020402351690798404
```

```
0.0
```

In [39]:

```

# Complete NaN values
metrics_copy = metrics_.copy()
metrics_copy = complete_nan_values(metrics_copy)

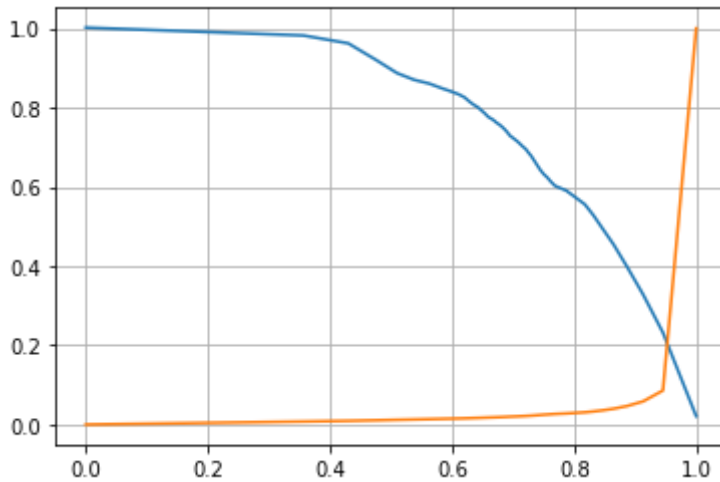
```

```
In [40]: # 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 0.8055881170596597



In []: