

```
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

```

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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]:

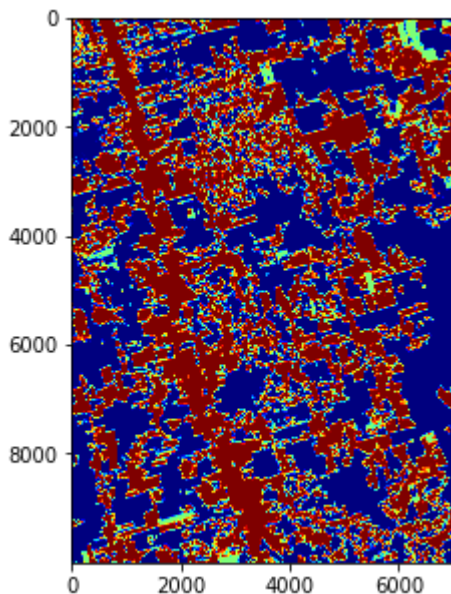
```

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 [41]:

```

# 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 [42]:

```

# 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 [43]:

```

time_tr = []
times = 5
for tm in range(0,times):
    print('time: ', tm)
    model = Model_3(nb_filters, number_class)
    model.build((None, 128,128,8))
    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', moni
    lr_reduce = ReduceLROnPlateau(factor=0.9, min_delta=0.0001, patience=5, verbose=

```

```

callbacks_list = [earlystop, 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_3_2"

Layer (type)	Output Shape	Param #
conv1 (Conv2D)	multiple	2336
conv2 (Conv2D)	multiple	18496
conv3 (Conv2D)	multiple	73856
maxPool1 (MaxPooling2D)	multiple	0
maxPool2 (MaxPooling2D)	multiple	0
maxPool3 (MaxPooling2D)	multiple	0
conv4 (Conv2D)	multiple	147584
conv5 (Conv2D)	multiple	147584
conv6 (Conv2D)	multiple	147584
conv7 (Conv2D)	multiple	147584
conv8 (Conv2D)	multiple	147520
conv9 (Conv2D)	multiple	36896
upSamp1 (UpSampling2D)	multiple	0
upSamp2 (UpSampling2D)	multiple	0
upSamp3 (UpSampling2D)	multiple	0
conv2d_12 (Conv2D)	multiple	195

Total params: 869,635

Trainable params: 869,635

Non-trainable params: 0

C:\Users\selferrari\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 "

Epoch 1/100

108/108 [=====] - 18s 163ms/step - loss: 0.0929 - accuracy: 0.7678 - val_loss: 0.1035 - val_accuracy: 0.7718

Epoch 00001: val_loss improved from inf to 0.10347, saving model to imgs/experiment
s/exp1/models\unet_0.h5
Epoch 2/100
108/108 [=====] - 17s 159ms/step - loss: 0.0642 - accuracy:
0.8275 - val_loss: 0.0977 - val_accuracy: 0.7896

Epoch 00002: val_loss improved from 0.10347 to 0.09775, saving model to imgs/experim
ents/exp1/models\unet_0.h5
Epoch 3/100
108/108 [=====] - 17s 163ms/step - loss: 0.0594 - accuracy:
0.8390 - val_loss: 0.1186 - val_accuracy: 0.7669

Epoch 00003: val_loss did not improve from 0.09775
Epoch 4/100
108/108 [=====] - 17s 160ms/step - loss: 0.0586 - accuracy:
0.8396 - val_loss: 0.1251 - val_accuracy: 0.7853

Epoch 00004: val_loss did not improve from 0.09775
Epoch 5/100
108/108 [=====] - 17s 160ms/step - loss: 0.0550 - accuracy:
0.8463 - val_loss: 0.1375 - val_accuracy: 0.7911

Epoch 00005: val_loss did not improve from 0.09775
Epoch 6/100
108/108 [=====] - 17s 157ms/step - loss: 0.0527 - accuracy:
0.8520 - val_loss: 0.1224 - val_accuracy: 0.7862

Epoch 00006: val_loss did not improve from 0.09775
Epoch 7/100
108/108 [=====] - 17s 157ms/step - loss: 0.0477 - accuracy:
0.8606 - val_loss: 0.1757 - val_accuracy: 0.7914

Epoch 00007: val_loss did not improve from 0.09775
Epoch 8/100
108/108 [=====] - 17s 160ms/step - loss: 0.0433 - accuracy:
0.8682 - val_loss: 0.1680 - val_accuracy: 0.7907

Epoch 00008: val_loss did not improve from 0.09775
Epoch 9/100
108/108 [=====] - 17s 159ms/step - loss: 0.0399 - accuracy:
0.8748 - val_loss: 0.1935 - val_accuracy: 0.7830

Epoch 00009: val_loss did not improve from 0.09775
Epoch 10/100
108/108 [=====] - 17s 158ms/step - loss: 0.0380 - accuracy:
0.8777 - val_loss: 0.1846 - val_accuracy: 0.7922

Epoch 00010: val_loss did not improve from 0.09775
Epoch 11/100
108/108 [=====] - 17s 159ms/step - loss: 0.0347 - accuracy:
0.8824 - val_loss: 0.1681 - val_accuracy: 0.7829

Epoch 00011: val_loss did not improve from 0.09775
Epoch 12/100
108/108 [=====] - 17s 162ms/step - loss: 0.0322 - accuracy:
0.8895 - val_loss: 0.1657 - val_accuracy: 0.7883

Epoch 00012: val_loss did not improve from 0.09775
Epoch 00012: early stopping
time: 1
Model: "model_3_3"

Layer (type)	Output Shape	Param #
=====		

conv1 (Conv2D)	multiple	2336
conv2 (Conv2D)	multiple	18496
conv3 (Conv2D)	multiple	73856
maxPool1 (MaxPooling2D)	multiple	0
maxPool2 (MaxPooling2D)	multiple	0
maxPool3 (MaxPooling2D)	multiple	0
conv4 (Conv2D)	multiple	147584
conv5 (Conv2D)	multiple	147584
conv6 (Conv2D)	multiple	147584
conv7 (Conv2D)	multiple	147584
conv8 (Conv2D)	multiple	147520
conv9 (Conv2D)	multiple	36896
upSamp1 (UpSampling2D)	multiple	0
upSamp2 (UpSampling2D)	multiple	0
upSamp3 (UpSampling2D)	multiple	0
conv2d_13 (Conv2D)	multiple	195
=====		
Total params: 869,635		
Trainable params: 869,635		
Non-trainable params: 0		

Epoch 1/100

108/108 [=====] - 18s 158ms/step - loss: 0.0986 - accuracy: 0.7458 - val_loss: 0.0961 - val_accuracy: 0.7815

Epoch 00001: val_loss improved from inf to 0.09608, saving model to imgs/experiments/exp1/models/unet_1.h5

Epoch 2/100

108/108 [=====] - 17s 159ms/step - loss: 0.0661 - accuracy: 0.8222 - val_loss: 0.1043 - val_accuracy: 0.7750

Epoch 00002: val_loss did not improve from 0.09608

Epoch 3/100

108/108 [=====] - 17s 159ms/step - loss: 0.0631 - accuracy: 0.8292 - val_loss: 0.1040 - val_accuracy: 0.7826

Epoch 00003: val_loss did not improve from 0.09608

Epoch 4/100

108/108 [=====] - 17s 156ms/step - loss: 0.0601 - accuracy: 0.8345 - val_loss: 0.0978 - val_accuracy: 0.7951

Epoch 00004: val_loss did not improve from 0.09608

Epoch 5/100

108/108 [=====] - 17s 158ms/step - loss: 0.0577 - accuracy: 0.8399 - val_loss: 0.1082 - val_accuracy: 0.7911

Epoch 00005: val_loss did not improve from 0.09608

Epoch 6/100

108/108 [=====] - 18s 165ms/step - loss: 0.0558 - accuracy: 0.8443 - val_loss: 0.1106 - val_accuracy: 0.7779

Epoch 00006: val_loss did not improve from 0.09608
 Epoch 7/100
 108/108 [=====] - 17s 160ms/step - loss: 0.0527 - accuracy: 0.8506 - val_loss: 0.1036 - val_accuracy: 0.7944

Epoch 00007: val_loss did not improve from 0.09608
 Epoch 8/100
 108/108 [=====] - 17s 160ms/step - loss: 0.0500 - accuracy: 0.8552 - val_loss: 0.1105 - val_accuracy: 0.7943

Epoch 00008: val_loss did not improve from 0.09608
 Epoch 9/100
 108/108 [=====] - 17s 157ms/step - loss: 0.0479 - accuracy: 0.8593 - val_loss: 0.0977 - val_accuracy: 0.7970

Epoch 00009: val_loss did not improve from 0.09608
 Epoch 10/100
 108/108 [=====] - 17s 159ms/step - loss: 0.0464 - accuracy: 0.8603 - val_loss: 0.1091 - val_accuracy: 0.8004

Epoch 00010: val_loss did not improve from 0.09608
 Epoch 11/100
 108/108 [=====] - 17s 157ms/step - loss: 0.0432 - accuracy: 0.8670 - val_loss: 0.1056 - val_accuracy: 0.7898

Epoch 00011: val_loss did not improve from 0.09608
 Epoch 00011: early stopping
 time: 2
 Model: "model_3_4"

Layer (type)	Output Shape	Param #
conv1 (Conv2D)	multiple	2336
conv2 (Conv2D)	multiple	18496
conv3 (Conv2D)	multiple	73856
maxPool1 (MaxPooling2D)	multiple	0
maxPool2 (MaxPooling2D)	multiple	0
maxPool3 (MaxPooling2D)	multiple	0
conv4 (Conv2D)	multiple	147584
conv5 (Conv2D)	multiple	147584
conv6 (Conv2D)	multiple	147584
conv7 (Conv2D)	multiple	147584
conv8 (Conv2D)	multiple	147520
conv9 (Conv2D)	multiple	36896
upSamp1 (UpSampling2D)	multiple	0
upSamp2 (UpSampling2D)	multiple	0
upSamp3 (UpSampling2D)	multiple	0
conv2d_14 (Conv2D)	multiple	195

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

Epoch 1/100

108/108 [=====] - 23s 207ms/step - loss: 0.1219 - accuracy: 0.7283 - val_loss: 0.0905 - val_accuracy: 0.7596

Epoch 00001: val_loss improved from inf to 0.09046, saving model to imgs/experiment s/exp1/models\unet_2.h5

Epoch 2/100

108/108 [=====] - 18s 167ms/step - loss: 0.0672 - accuracy: 0.8191 - val_loss: 0.1032 - val_accuracy: 0.7693

Epoch 00002: val_loss did not improve from 0.09046

Epoch 3/100

108/108 [=====] - 18s 167ms/step - loss: 0.0635 - accuracy: 0.8261 - val_loss: 0.1003 - val_accuracy: 0.7776

Epoch 00003: val_loss did not improve from 0.09046

Epoch 4/100

108/108 [=====] - 18s 164ms/step - loss: 0.0602 - accuracy: 0.8335 - val_loss: 0.1023 - val_accuracy: 0.7698

Epoch 00004: val_loss did not improve from 0.09046

Epoch 5/100

108/108 [=====] - 18s 166ms/step - loss: 0.0583 - accuracy: 0.8374 - val_loss: 0.1016 - val_accuracy: 0.7716

Epoch 00005: val_loss did not improve from 0.09046

Epoch 6/100

108/108 [=====] - 18s 170ms/step - loss: 0.0576 - accuracy: 0.8379 - val_loss: 0.1132 - val_accuracy: 0.7664

Epoch 00006: val_loss did not improve from 0.09046

Epoch 7/100

108/108 [=====] - 18s 168ms/step - loss: 0.0557 - accuracy: 0.8415 - val_loss: 0.1043 - val_accuracy: 0.7933

Epoch 00007: val_loss did not improve from 0.09046

Epoch 8/100

108/108 [=====] - 18s 169ms/step - loss: 0.0540 - accuracy: 0.8443 - val_loss: 0.1085 - val_accuracy: 0.7830

Epoch 00008: val_loss did not improve from 0.09046

Epoch 9/100

108/108 [=====] - 18s 165ms/step - loss: 0.0512 - accuracy: 0.8490 - val_loss: 0.1081 - val_accuracy: 0.7866

Epoch 00009: val_loss did not improve from 0.09046

Epoch 10/100

108/108 [=====] - 18s 166ms/step - loss: 0.0509 - accuracy: 0.8512 - val_loss: 0.1267 - val_accuracy: 0.7976

Epoch 00010: val_loss did not improve from 0.09046

Epoch 11/100

108/108 [=====] - 18s 166ms/step - loss: 0.0487 - accuracy: 0.8544 - val_loss: 0.1024 - val_accuracy: 0.7869

Epoch 00011: val_loss did not improve from 0.09046

Epoch 00011: early stopping

time: 3

Model: "model_3_5"

Layer (type)	Output Shape	Param #
--------------	--------------	---------

=====		
conv1 (Conv2D)	multiple	2336
conv2 (Conv2D)	multiple	18496
conv3 (Conv2D)	multiple	73856
maxPool1 (MaxPooling2D)	multiple	0
maxPool2 (MaxPooling2D)	multiple	0
maxPool3 (MaxPooling2D)	multiple	0
conv4 (Conv2D)	multiple	147584
conv5 (Conv2D)	multiple	147584
conv6 (Conv2D)	multiple	147584
conv7 (Conv2D)	multiple	147584
conv8 (Conv2D)	multiple	147520
conv9 (Conv2D)	multiple	36896
upSamp1 (UpSampling2D)	multiple	0
upSamp2 (UpSampling2D)	multiple	0
upSamp3 (UpSampling2D)	multiple	0
conv2d_15 (Conv2D)	multiple	195
=====		
Total params: 869,635		
Trainable params: 869,635		
Non-trainable params: 0		

Epoch 1/100

108/108 [=====] - 19s 168ms/step - loss: 0.1198 - accuracy: 0.7419 - val_loss: 0.1020 - val_accuracy: 0.7645

Epoch 00001: val_loss improved from inf to 0.10196, saving model to imgs/experiments/exp1/models/unet_3.h5

Epoch 2/100

108/108 [=====] - 18s 166ms/step - loss: 0.0716 - accuracy: 0.8129 - val_loss: 0.1063 - val_accuracy: 0.7652

Epoch 00002: val_loss did not improve from 0.10196

Epoch 3/100

108/108 [=====] - 18s 166ms/step - loss: 0.0673 - accuracy: 0.8224 - val_loss: 0.1160 - val_accuracy: 0.7472

Epoch 00003: val_loss did not improve from 0.10196

Epoch 4/100

108/108 [=====] - 18s 167ms/step - loss: 0.0638 - accuracy: 0.8276 - val_loss: 0.1125 - val_accuracy: 0.7743

Epoch 00004: val_loss did not improve from 0.10196

Epoch 5/100

108/108 [=====] - 18s 170ms/step - loss: 0.0624 - accuracy: 0.8280 - val_loss: 0.1079 - val_accuracy: 0.7795

Epoch 00005: val_loss did not improve from 0.10196

Epoch 6/100

108/108 [=====] - 18s 171ms/step - loss: 0.0591 - accuracy:

0.8359 - val_loss: 0.0948 - val_accuracy: 0.7862

Epoch 00006: val_loss improved from 0.10196 to 0.09477, saving model to imgs/experiments/exp1/models\unet_3.h5

Epoch 7/100

108/108 [=====] - 18s 167ms/step - loss: 0.0592 - accuracy: 0.8347 - val_loss: 0.0890 - val_accuracy: 0.7874

Epoch 00007: val_loss improved from 0.09477 to 0.08896, saving model to imgs/experiments/exp1/models\unet_3.h5

Epoch 8/100

108/108 [=====] - 19s 178ms/step - loss: 0.0567 - accuracy: 0.8403 - val_loss: 0.1221 - val_accuracy: 0.7707

Epoch 00008: val_loss did not improve from 0.08896

Epoch 9/100

108/108 [=====] - 19s 175ms/step - loss: 0.0571 - accuracy: 0.8413 - val_loss: 0.1106 - val_accuracy: 0.7790

Epoch 00009: val_loss did not improve from 0.08896

Epoch 10/100

108/108 [=====] - 19s 176ms/step - loss: 0.0542 - accuracy: 0.8456 - val_loss: 0.0928 - val_accuracy: 0.7916

Epoch 00010: val_loss did not improve from 0.08896

Epoch 11/100

108/108 [=====] - 18s 172ms/step - loss: 0.0535 - accuracy: 0.8478 - val_loss: 0.1024 - val_accuracy: 0.7916

Epoch 00011: val_loss did not improve from 0.08896

Epoch 12/100

108/108 [=====] - 18s 169ms/step - loss: 0.0507 - accuracy: 0.8516 - val_loss: 0.0952 - val_accuracy: 0.7918

Epoch 00012: val_loss did not improve from 0.08896

Epoch 13/100

108/108 [=====] - 18s 167ms/step - loss: 0.0501 - accuracy: 0.8546 - val_loss: 0.0978 - val_accuracy: 0.7993

Epoch 00013: val_loss did not improve from 0.08896

Epoch 14/100

108/108 [=====] - 18s 169ms/step - loss: 0.0490 - accuracy: 0.8533 - val_loss: 0.1275 - val_accuracy: 0.7869

Epoch 00014: val_loss did not improve from 0.08896

Epoch 15/100

108/108 [=====] - 18s 172ms/step - loss: 0.0471 - accuracy: 0.8592 - val_loss: 0.1350 - val_accuracy: 0.7934

Epoch 00015: val_loss did not improve from 0.08896

Epoch 16/100

108/108 [=====] - 19s 173ms/step - loss: 0.0454 - accuracy: 0.8624 - val_loss: 0.1133 - val_accuracy: 0.7916

Epoch 00016: val_loss did not improve from 0.08896

Epoch 17/100

108/108 [=====] - 18s 172ms/step - loss: 0.0448 - accuracy: 0.8623 - val_loss: 0.1378 - val_accuracy: 0.7951

Epoch 00017: val_loss did not improve from 0.08896

Epoch 00017: early stopping

time: 4

Model: "model_3_6"

Layer (type)	Output Shape	Param #
--------------	--------------	---------

=====		
conv1 (Conv2D)	multiple	2336
<hr/>		
conv2 (Conv2D)	multiple	18496
<hr/>		
conv3 (Conv2D)	multiple	73856
<hr/>		
maxPool1 (MaxPooling2D)	multiple	0
<hr/>		
maxPool2 (MaxPooling2D)	multiple	0
<hr/>		
maxPool3 (MaxPooling2D)	multiple	0
<hr/>		
conv4 (Conv2D)	multiple	147584
<hr/>		
conv5 (Conv2D)	multiple	147584
<hr/>		
conv6 (Conv2D)	multiple	147584
<hr/>		
conv7 (Conv2D)	multiple	147584
<hr/>		
conv8 (Conv2D)	multiple	147520
<hr/>		
conv9 (Conv2D)	multiple	36896
<hr/>		
upSamp1 (UpSampling2D)	multiple	0
<hr/>		
upSamp2 (UpSampling2D)	multiple	0
<hr/>		
upSamp3 (UpSampling2D)	multiple	0
<hr/>		
conv2d_16 (Conv2D)	multiple	195
<hr/>		
=====		
Total params: 869,635		
Trainable params: 869,635		
Non-trainable params: 0		
<hr/>		

Epoch 1/100

108/108 [=====] - 19s 172ms/step - loss: 0.1157 - accuracy: 0.7222 - val_loss: 0.1044 - val_accuracy: 0.7686

Epoch 00001: val_loss improved from inf to 0.10442, saving model to imgs/experiments/exp1/models/unet_4.h5

Epoch 2/100

108/108 [=====] - 18s 171ms/step - loss: 0.0694 - accuracy: 0.8182 - val_loss: 0.1037 - val_accuracy: 0.7665

Epoch 00002: val_loss improved from 0.10442 to 0.10369, saving model to imgs/experiments/exp1/models/unet_4.h5

Epoch 3/100

108/108 [=====] - 18s 169ms/step - loss: 0.0665 - accuracy: 0.8257 - val_loss: 0.1035 - val_accuracy: 0.7729

Epoch 00003: val_loss improved from 0.10369 to 0.10349, saving model to imgs/experiments/exp1/models/unet_4.h5

Epoch 4/100

108/108 [=====] - 18s 170ms/step - loss: 0.0619 - accuracy: 0.8336 - val_loss: 0.1064 - val_accuracy: 0.7839

Epoch 00004: val_loss did not improve from 0.10349

Epoch 5/100

108/108 [=====] - 18s 168ms/step - loss: 0.0596 - accuracy: 0.8372 - val_loss: 0.0893 - val_accuracy: 0.7767

Epoch 00005: val_loss improved from 0.10349 to 0.08931, saving model to imgs/experiments/exp1/models/unet_4.h5

ents/exp1/models\unet_4.h5

Epoch 6/100

108/108 [=====] - 19s 174ms/step - loss: 0.0578 - accuracy: 0.8384 - val_loss: 0.0991 - val_accuracy: 0.7837

Epoch 00006: val_loss did not improve from 0.08931

Epoch 7/100

108/108 [=====] - 19s 175ms/step - loss: 0.0550 - accuracy: 0.8450 - val_loss: 0.1142 - val_accuracy: 0.7639

Epoch 00007: val_loss did not improve from 0.08931

Epoch 8/100

108/108 [=====] - 19s 173ms/step - loss: 0.0544 - accuracy: 0.8446 - val_loss: 0.1147 - val_accuracy: 0.7855

Epoch 00008: val_loss did not improve from 0.08931

Epoch 9/100

108/108 [=====] - 18s 170ms/step - loss: 0.0512 - accuracy: 0.8528 - val_loss: 0.1339 - val_accuracy: 0.7773

Epoch 00009: val_loss did not improve from 0.08931

Epoch 10/100

108/108 [=====] - 19s 174ms/step - loss: 0.0500 - accuracy: 0.8553 - val_loss: 0.1154 - val_accuracy: 0.7760

Epoch 00010: val_loss did not improve from 0.08931

Epoch 11/100

108/108 [=====] - 18s 170ms/step - loss: 0.0493 - accuracy: 0.8559 - val_loss: 0.1419 - val_accuracy: 0.7919

Epoch 00011: val_loss did not improve from 0.08931

Epoch 12/100

108/108 [=====] - 19s 174ms/step - loss: 0.0483 - accuracy: 0.8572 - val_loss: 0.1410 - val_accuracy: 0.7829

Epoch 00012: val_loss did not improve from 0.08931

Epoch 13/100

108/108 [=====] - 18s 172ms/step - loss: 0.0466 - accuracy: 0.8619 - val_loss: 0.1522 - val_accuracy: 0.7706

Epoch 00013: val_loss did not improve from 0.08931

Epoch 14/100

108/108 [=====] - 18s 172ms/step - loss: 0.0441 - accuracy: 0.8655 - val_loss: 0.1422 - val_accuracy: 0.7754

Epoch 00014: val_loss did not improve from 0.08931

Epoch 15/100

108/108 [=====] - 18s 168ms/step - loss: 0.0442 - accuracy: 0.8660 - val_loss: 0.1507 - val_accuracy: 0.7925

Epoch 00015: val_loss did not improve from 0.08931

Epoch 00015: early stopping

In [44]:

```
# 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 [45]:

```

# 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)
```

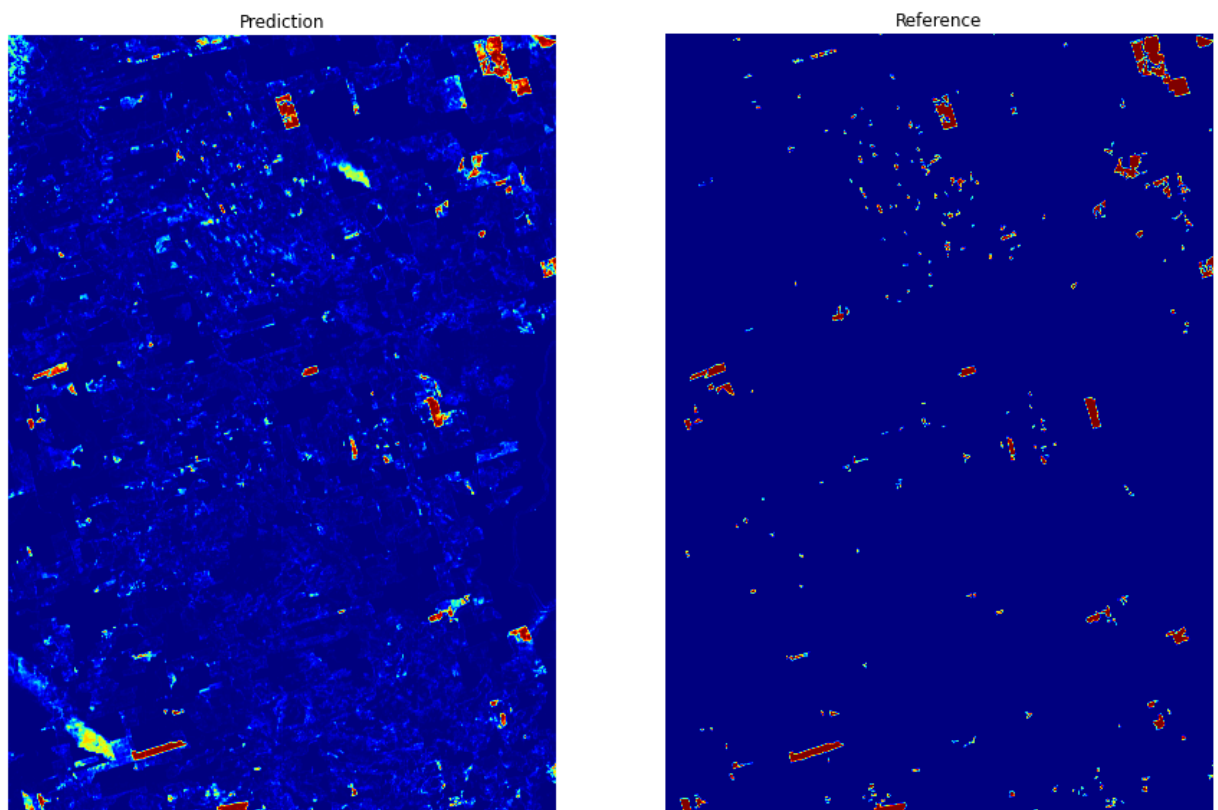
0
1
2
3
4

In [46]:

```
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[46]: (-0.5, 6999.5, 9999.5, -0.5)



In [47]:

```
# 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_)

```

```
0.996409285068512
```

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

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

```
0.9760744016997669
```

```
0.9557395183310218
```

```
0.9354046349622765
```

```
0.9150697515935314
```

```
0.8947348682247863
```

```
0.8743999848560411
```

```
0.854065101487296
```

```
0.8337302181185509
```

```
0.8133953347498057
```

```
0.7930604513810606
```

```
0.7727255680123154
```

```
0.7523906846435703
```

```
0.7320558012748252
```

```
0.7117209179060799
```

```
0.6913860345373348
```

```
0.6710511511685897
```

```
0.6507162677998446
```

```
0.6303813844310995
```

```
0.6100465010623543
```

```
0.5897116176936091
```

```
0.569376734324864
```

```
0.5490418509561188
```

```
0.5287069675873737
```

```
0.5083720842186286
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```
0.48803720084988345
```

```
0.46770231748113833
```

```
0.4473674341123931
```

```
0.427032550743648
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0.40669766737490287
```

```
0.38636278400615764
```

```
0.36602790063741253
```

```
0.3456930172686674
```

```
0.3253581338999223
```

```
0.3050232505311772
```

```
0.28468836716243195
```

```
0.26435348379368684
```

```
0.24401860042494172
```

```
0.2236837170561965
```

```
0.20334883368745138
```

```
0.18301395031870626
```

```
0.16267906694996115
```

```
0.14234418358121603
```

```
0.1220093002124708
```

```
0.10167441684372569
```

```
0.08133953347498057
```

```
0.06100465010623535
```

```
0.04066976673749023
```

```
0.020334883368745116
```

```
0.0
```

In [48]:

```

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

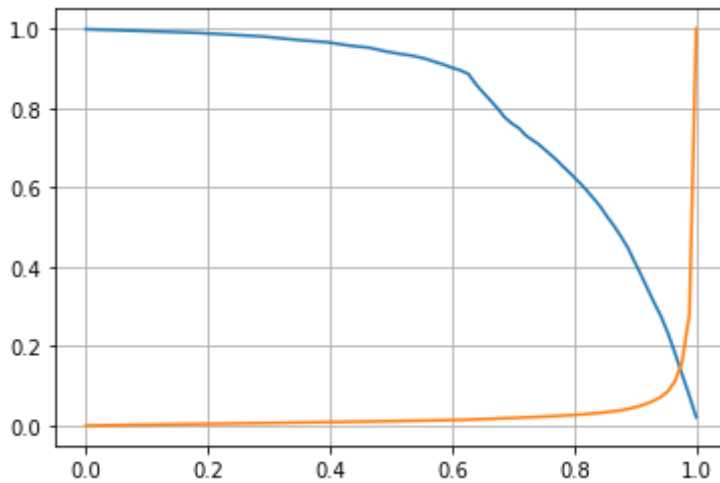
```

```
In [49]: # 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 0.8192160883357321



In []: