TEAM NAME - _BRUTEFORCE_

PS ID - SIH1518

TEAM ID - 43084

PS TITLE - CHANGE DETECTION DUE TO HUMAN ACTIVITY

INSTITUE NAME - IIIIT BANGALORE

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ABOUT THE DATASET

- We have used sentinel-2 dataset as mentioned in our problem statement.
- The sentinel-2 dataset consists of 13 bands of different wavelengths. 4 bands of 10m and rest mix of 20m and 60m
- The resolution of sentitnel-2 is 10m

DATA EXTRACTION

APPROACH 1

- We used an online software called **dataspace.copernicus.eu** to download sentinel data of desired time and location.
- We also used **QGIS** software to clip the raster and classify data as forest, built up, water body, etc.
- The mask generated from these data was used as ground truth for our base model.

APPROACH 2

- We used **LULC** data(Bhuvan Panchayat) which act as ground truth for our model.
- Then we clipped the sentinel data to match with the LULC.
- We made shape file for each class.
- We took the attributes from the LULC to train and classify the sentinel data.

METHODS

- **METHOD 1**

  BINARY SEGMENTATION

- **METHOD 2**

  MULTICLASS SEGMENTATION

METHOD 1 : BINARY SEGMENTATION

POINT 1

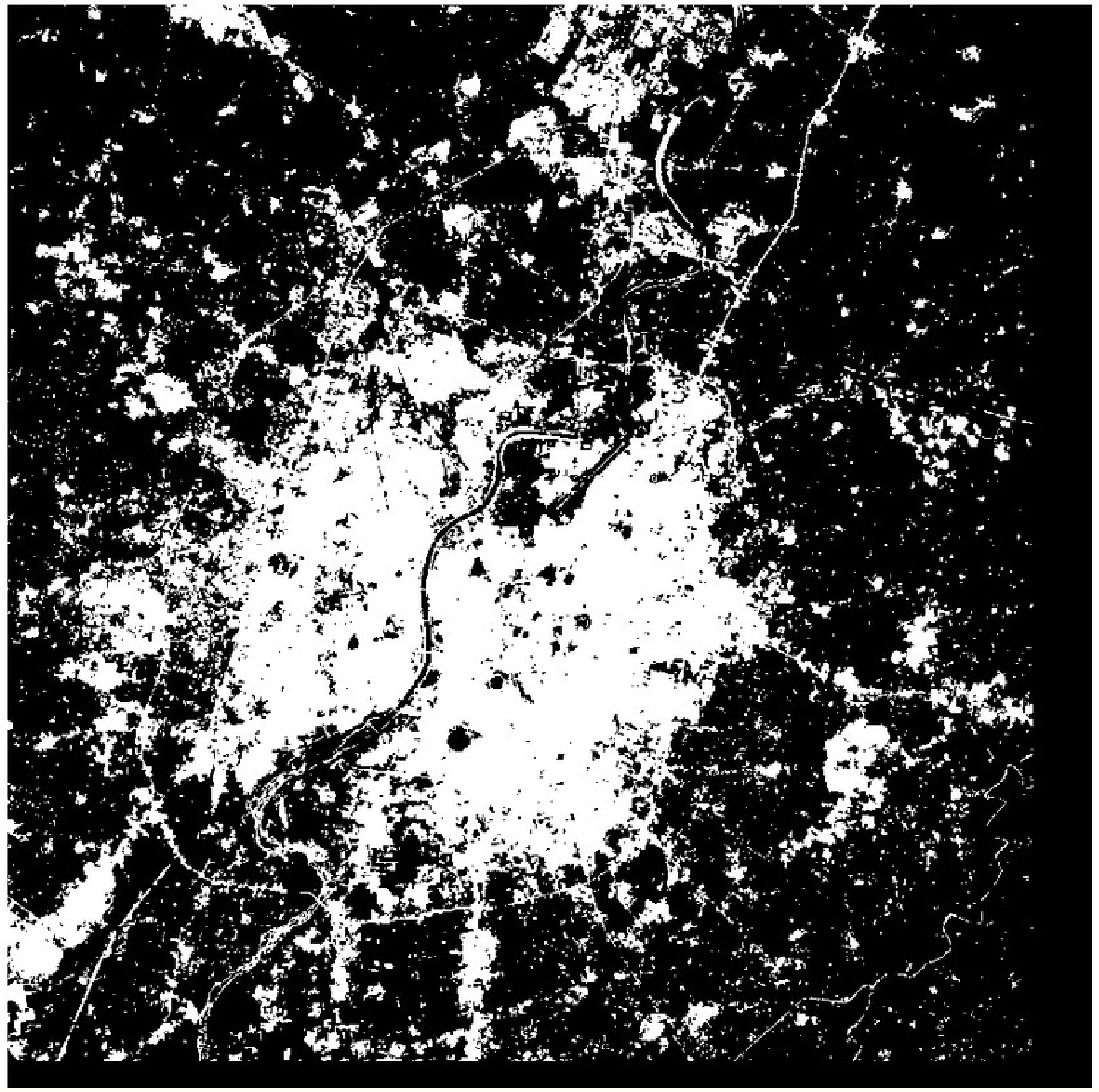
The first approach was to predict the urban land cover as one class and the other as the other class.

POINT 2

This was a binary segmentation task. So we used **Unet, Unet++, DeepLabv3 and Unet with attention layers.**

AHMEDABAD CITY

0riginal (RGB)



Binary mask

CHOOSING THE BEST PERFORMED MODEL

- Here the accuracy is not a good metric to judge a model as, if the model predicts all the pixels belonging to same class even then the accuracy of the model will be around **80% to 85%**

- Hence we used the dice coefficient as the metric to choose the best model.

- We tried different loss functions which can solve the problem of misclassification of the urban land cover task and take both the classes into account in place of binary entropy like **Tsky Loss, Dice Loss, Focal Loss.**

- Unet ++ and Unet attention were overfitting, so we reduced the number of encoder and decoders. **Unet** performed the best for binary segmentation.

METHOD 2 : MULTI-CLASS SEGMENTATION

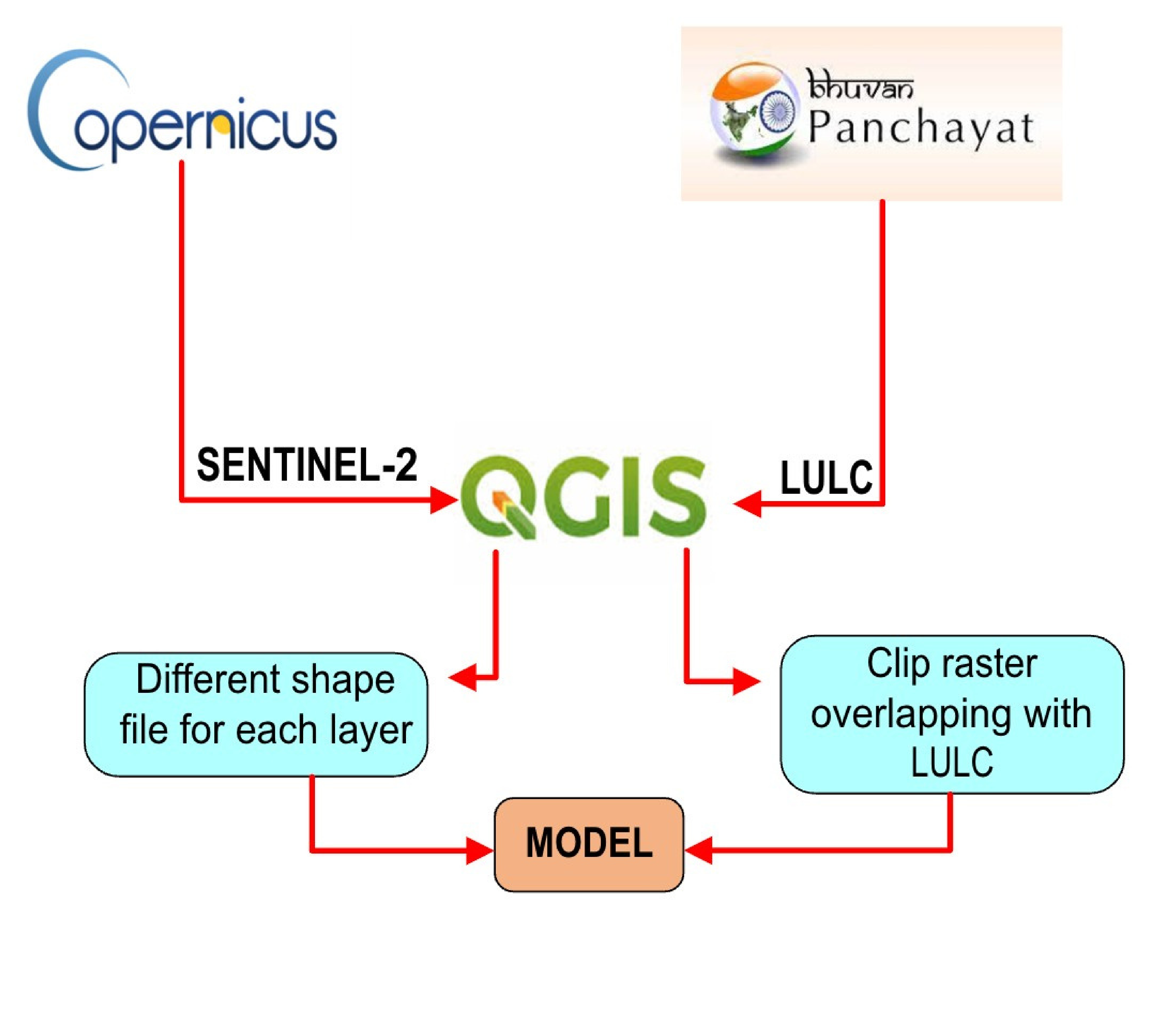
The different classes we are trying to classify are :

BARREN LAND	FOREST	FOREST PLANTATION (RESERVED FOREST AND ETC)
WATER BODY (RIVERS, LAKES, RESERVOIRS)	TRANSPORTATION (HIGHWAY)	RURAL + URBAN (BUILT UP)

DATA PREPROCESS

- We are using four bands of 10m resolution: B2, B3, B4, B8
- We did the same preprocess as approach 2 for all the classes from the LULC data set (Level - 2)
- We did the geo referencing of the vector to raster using a sentinal-2 bands.
- We prepared the dataset, which consists of images(128,128) or (256,256) based on the choice of model.

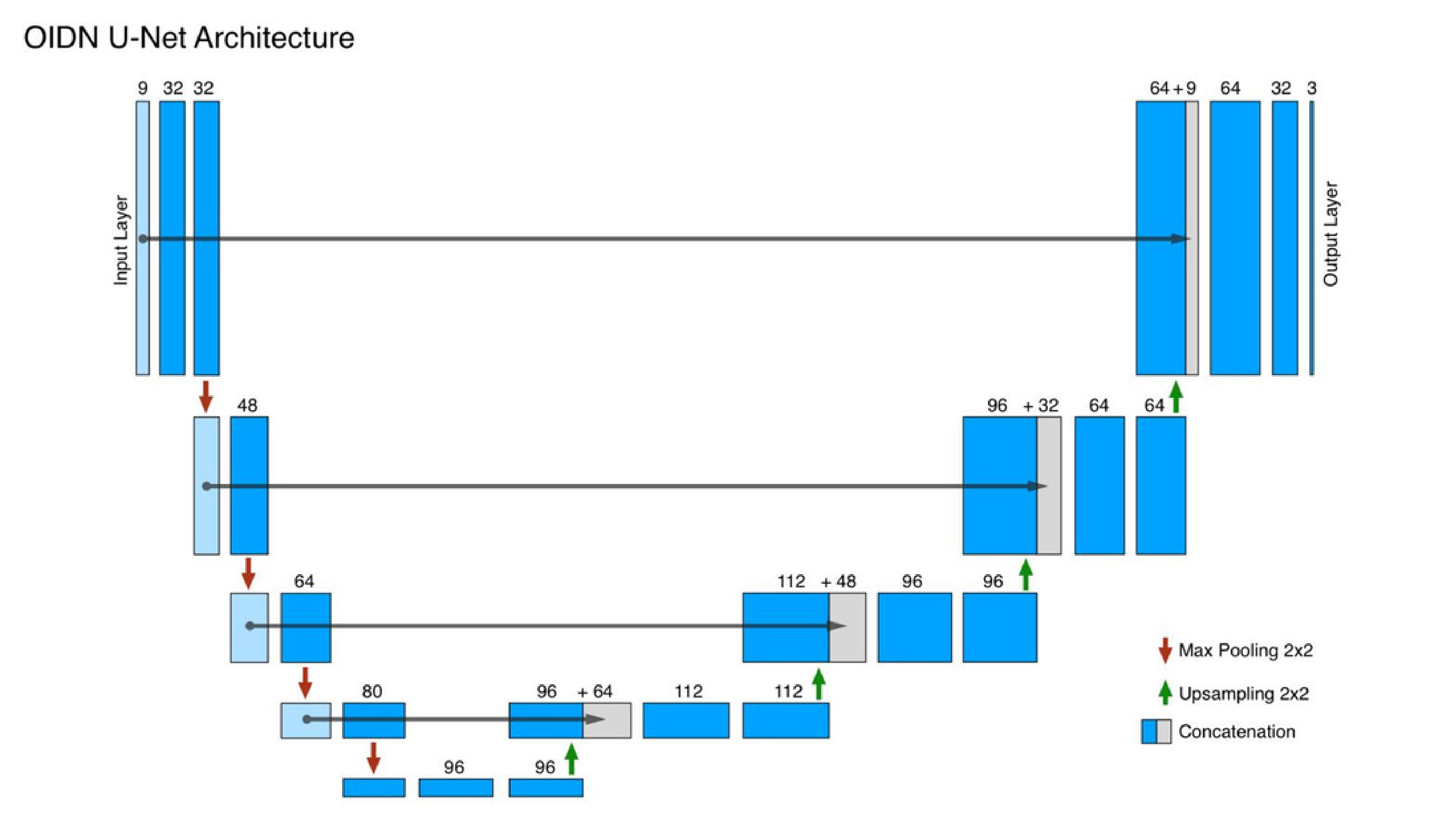
PRE PROCCESSING



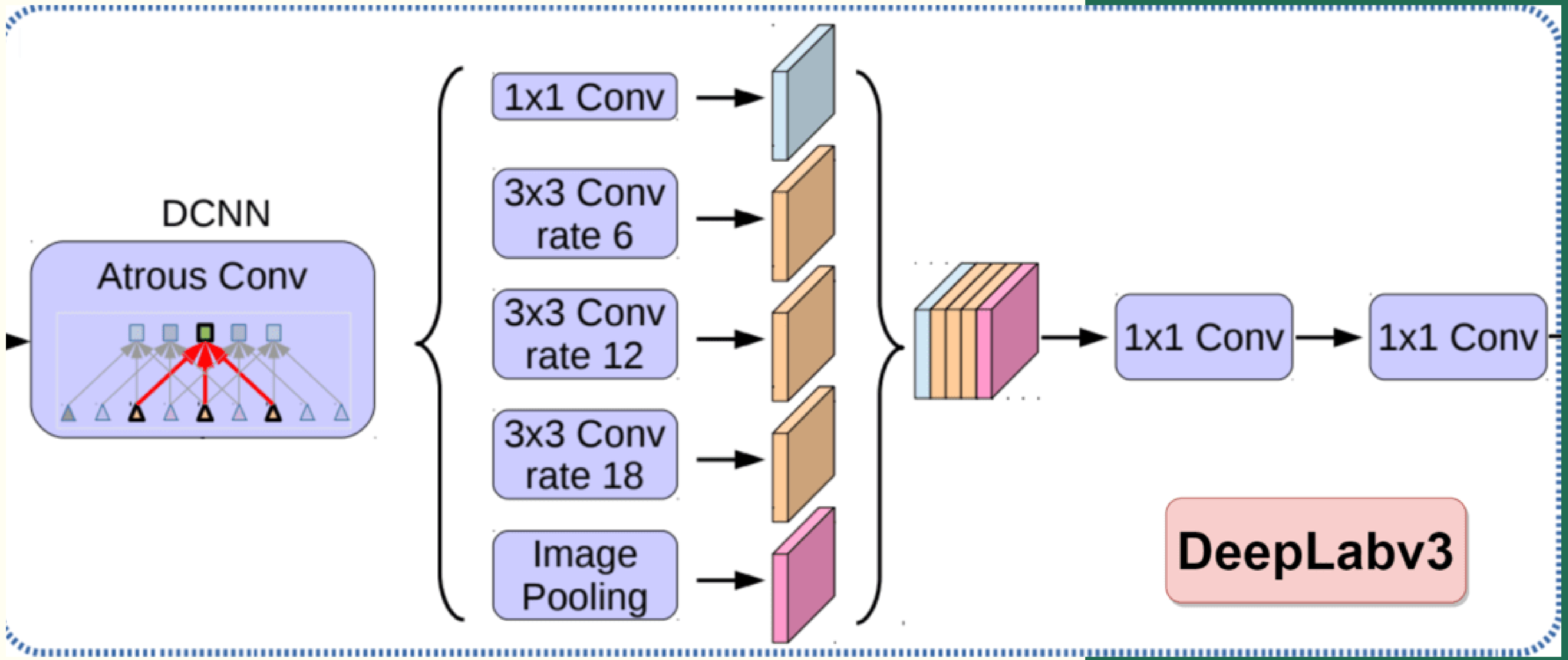
MODELS USED

UNET

Unet gave good accuracy of 80 - 85% but as it was unable to take all the attributes from the data due to large size of the data. As a result output was not accurate. Thus, we need to look for higher complex models.



DEEPLABV3



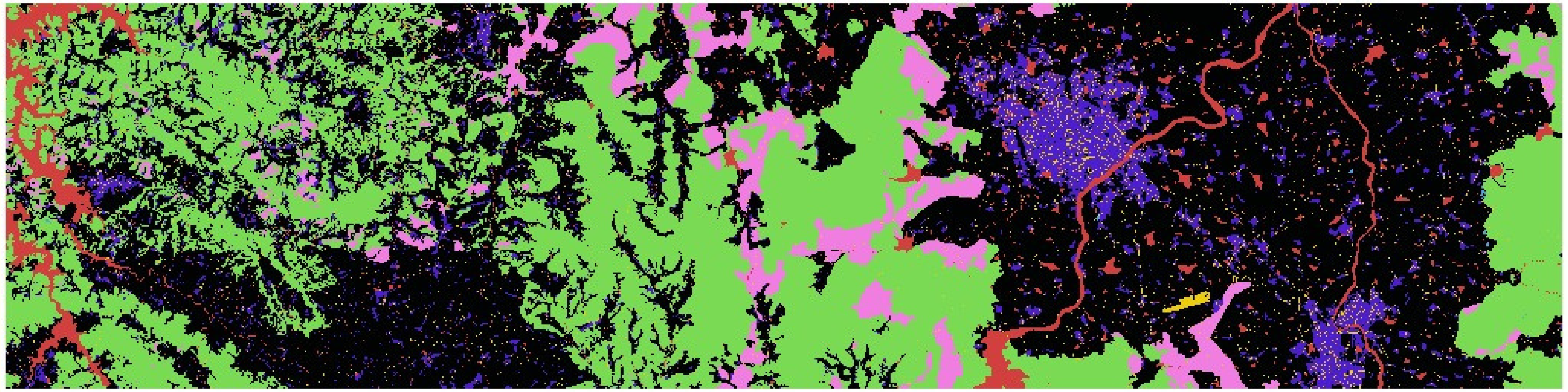
- Deeplabv3 with loss function as categorical loss was not giving accurate results.
- As the data contained large percentage of forest and relatively lower of rest five classes. Due to forest class imbalance, other classes were also getting classified into forest class.
- So we created our own loss function named Weighted focal category loss taking consideration of focal loss.
- In this loss function due to forest class imbalance we increased the weight for other classes and gave more penalty for misclasifying these classes.

SHIVAMOGGA

satellite image

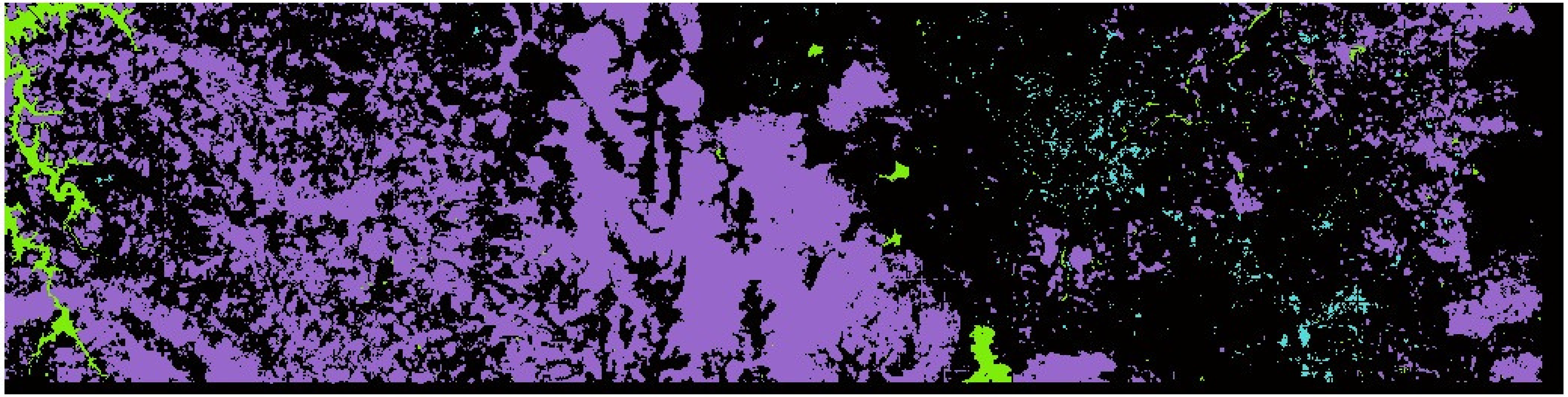
Mask generated by LULC

Pink - Forest plantation
Green - Forest
Red - water bodies
Purple - settlement

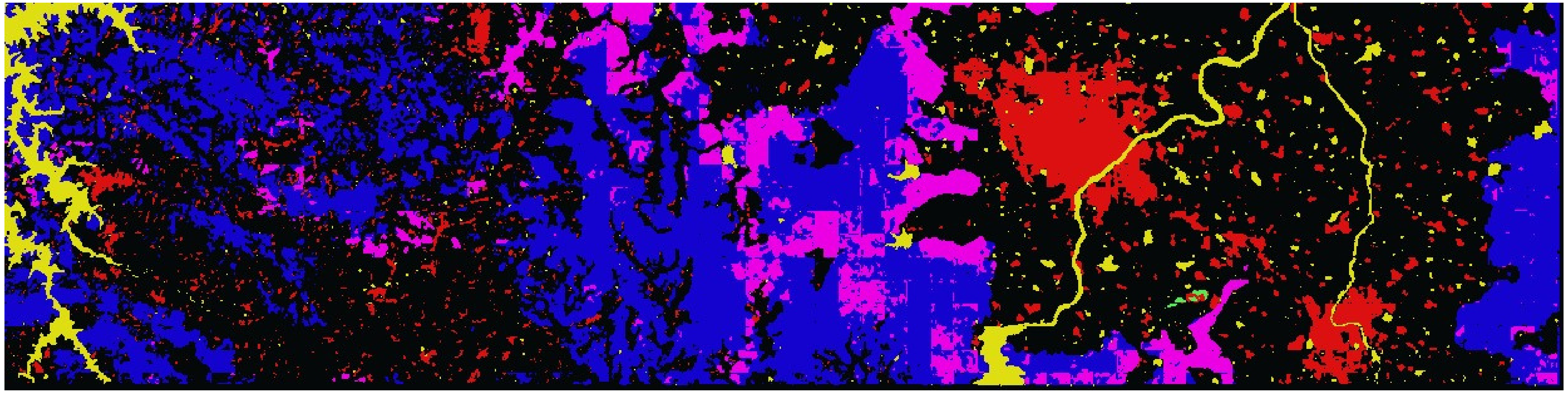


SHIVAMOGGA

Unet output ~ 80%



Deeplabv3 output ~ 85%



Purple - Forest
Green - Water bodies

Yellow - Water bodies
Red - Settelement
Blue - Forest
Purple - Forest Plantation
Green - Transport

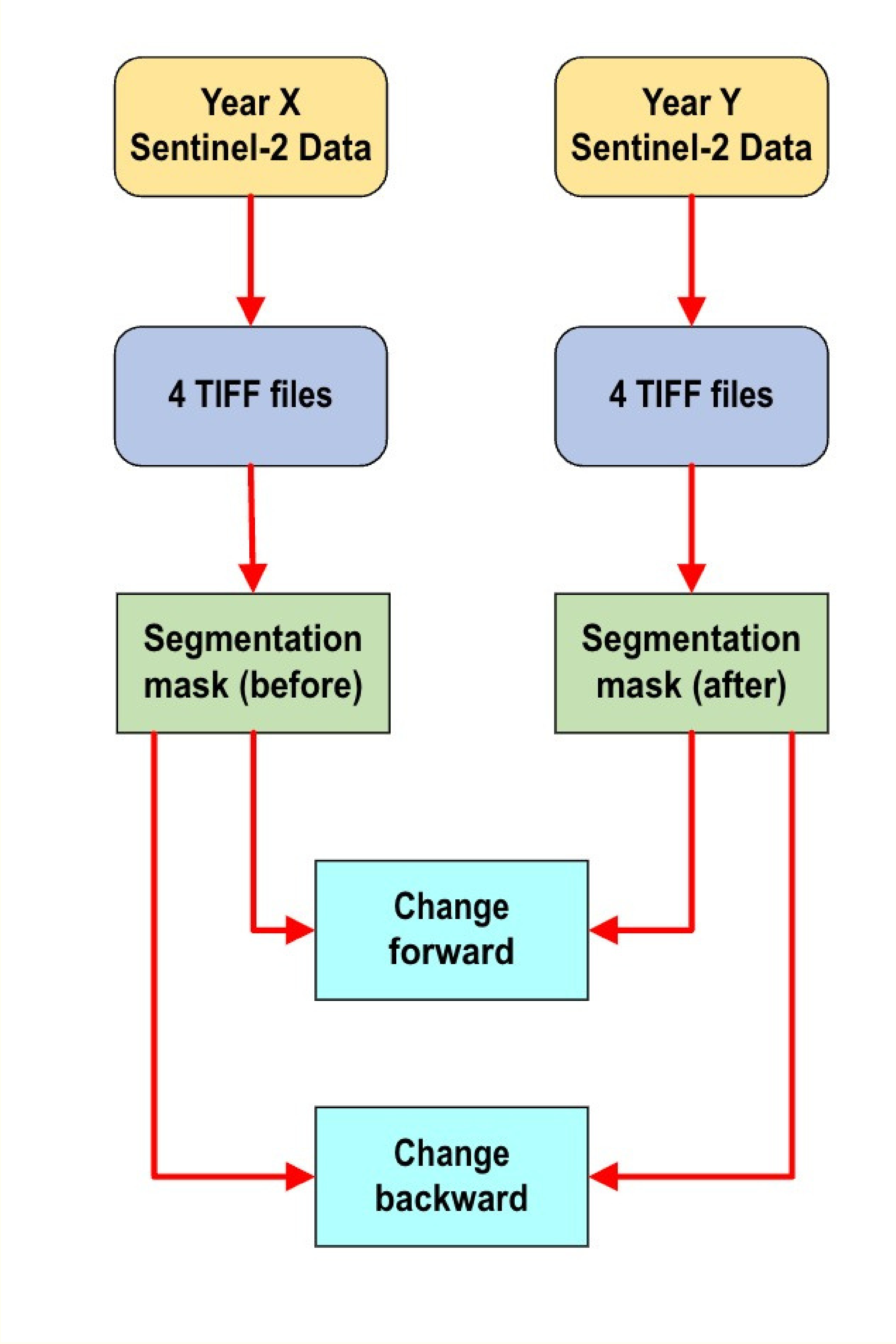
CHANGE DETECTION

We did change detection in two ways:
1. Forward
2. Backward

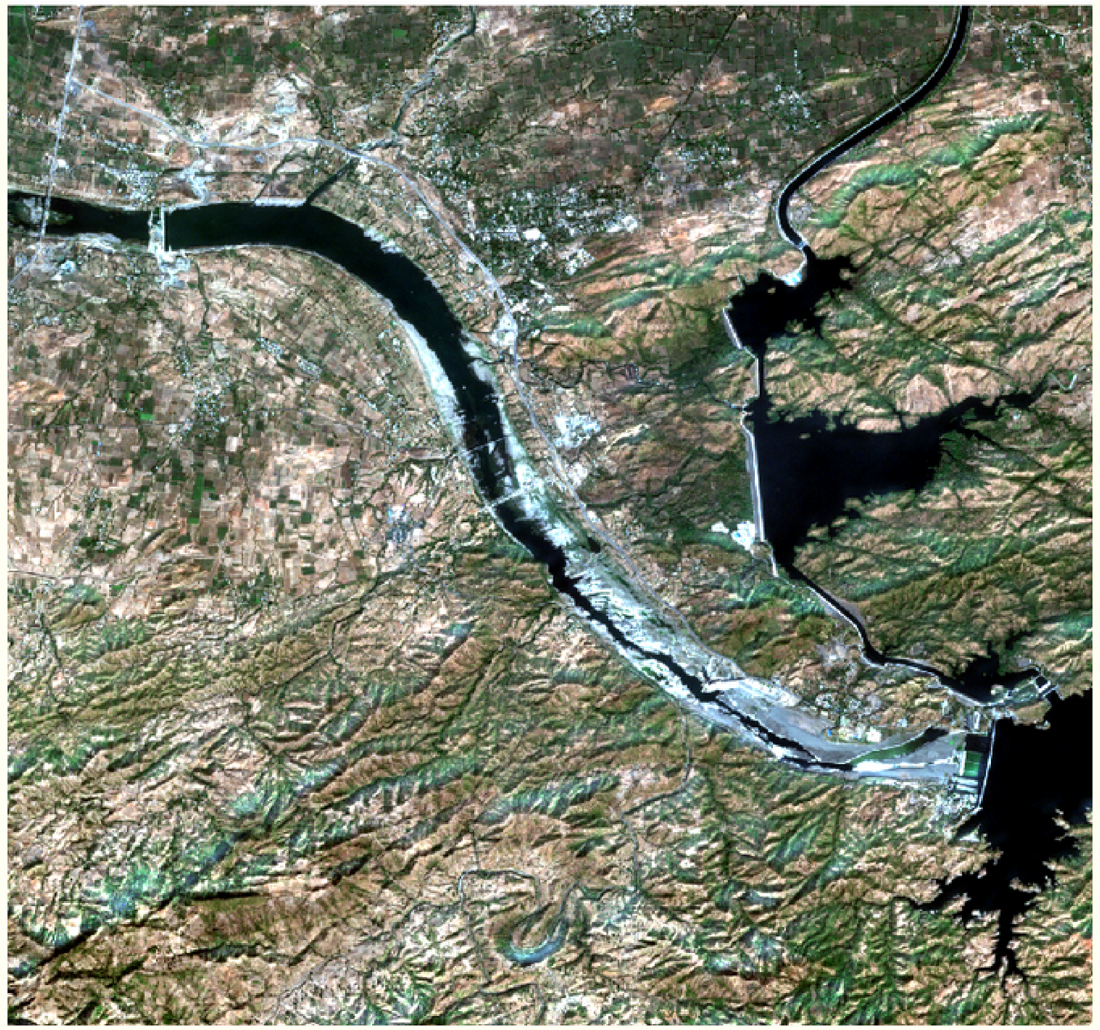
Forward/Augmented:
If class X in year A has changed to class Y in year B then in change detection mapping we replaced X by Y where they are overlapping and for no change leave it blank.

Backward/Depletion:
If class X in year A has changed to class Y in year B then in change detection mapping we replaced Y by X where they are overlapping and for no change leave it blank.

MODEL WORKFLOW



STATUE OF UNITY

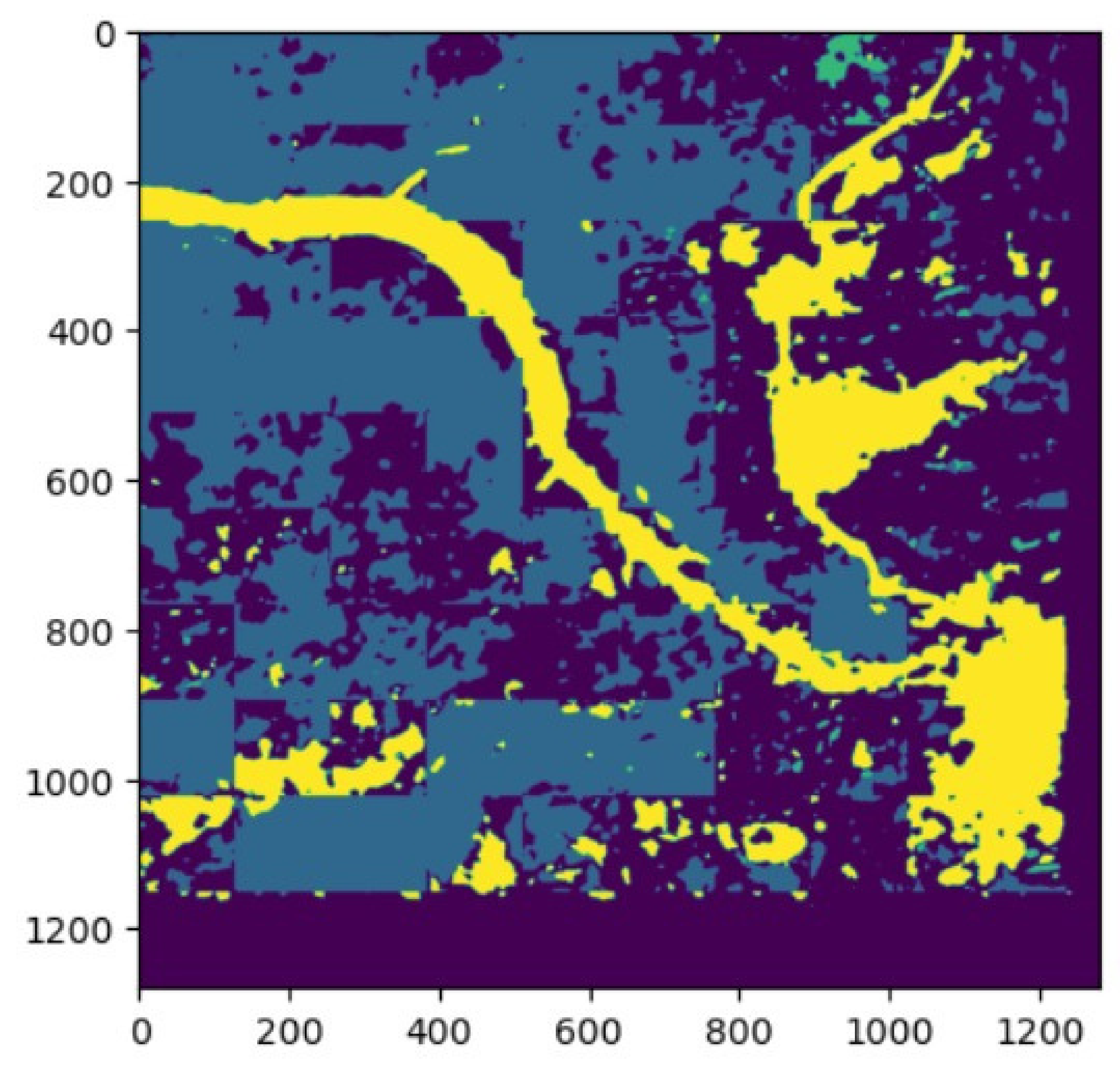


2018

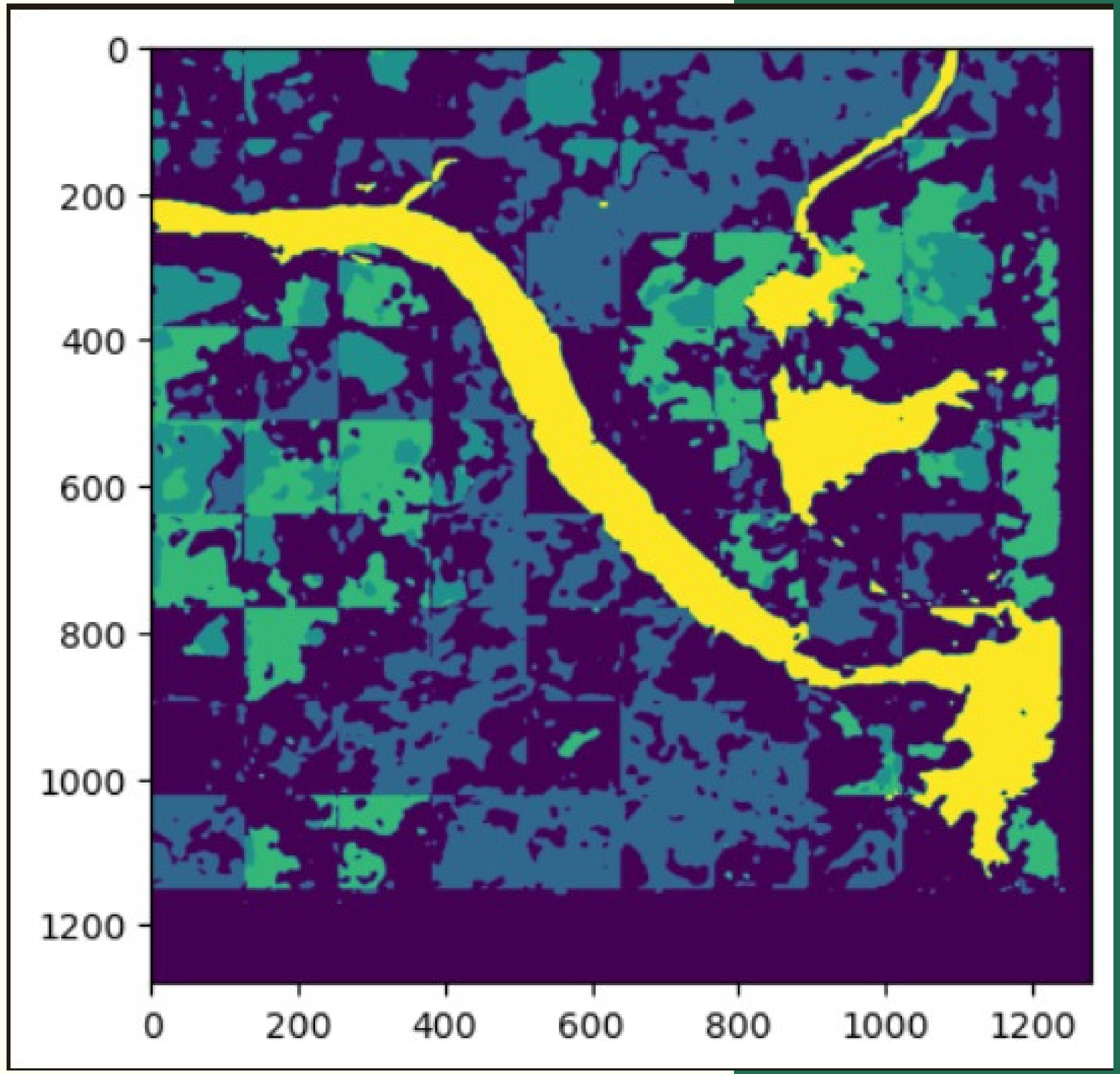
2023

STATUE OF UNITY

Green - Built up
Blue - Forest
Yellow - Water boy

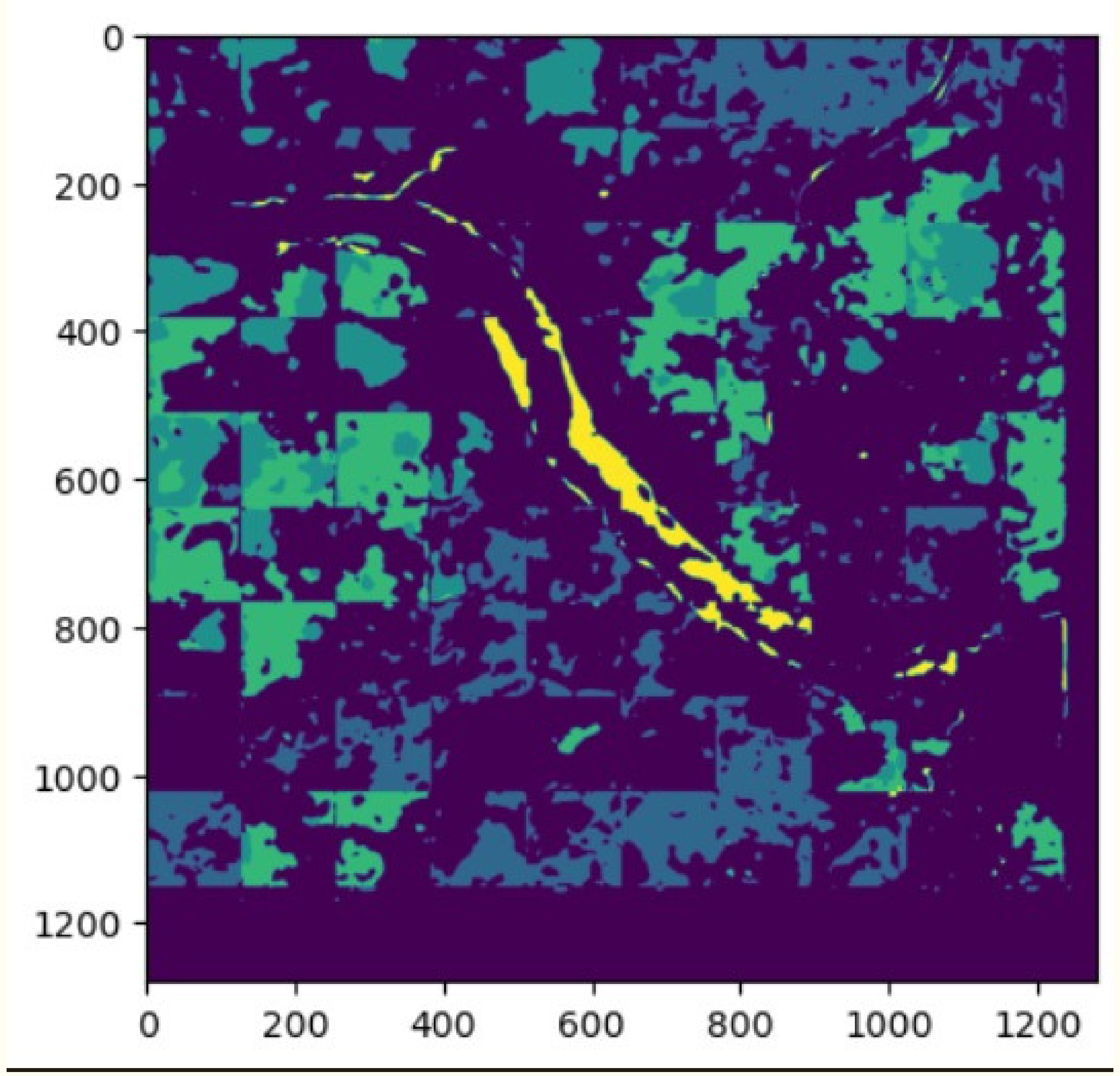


2018

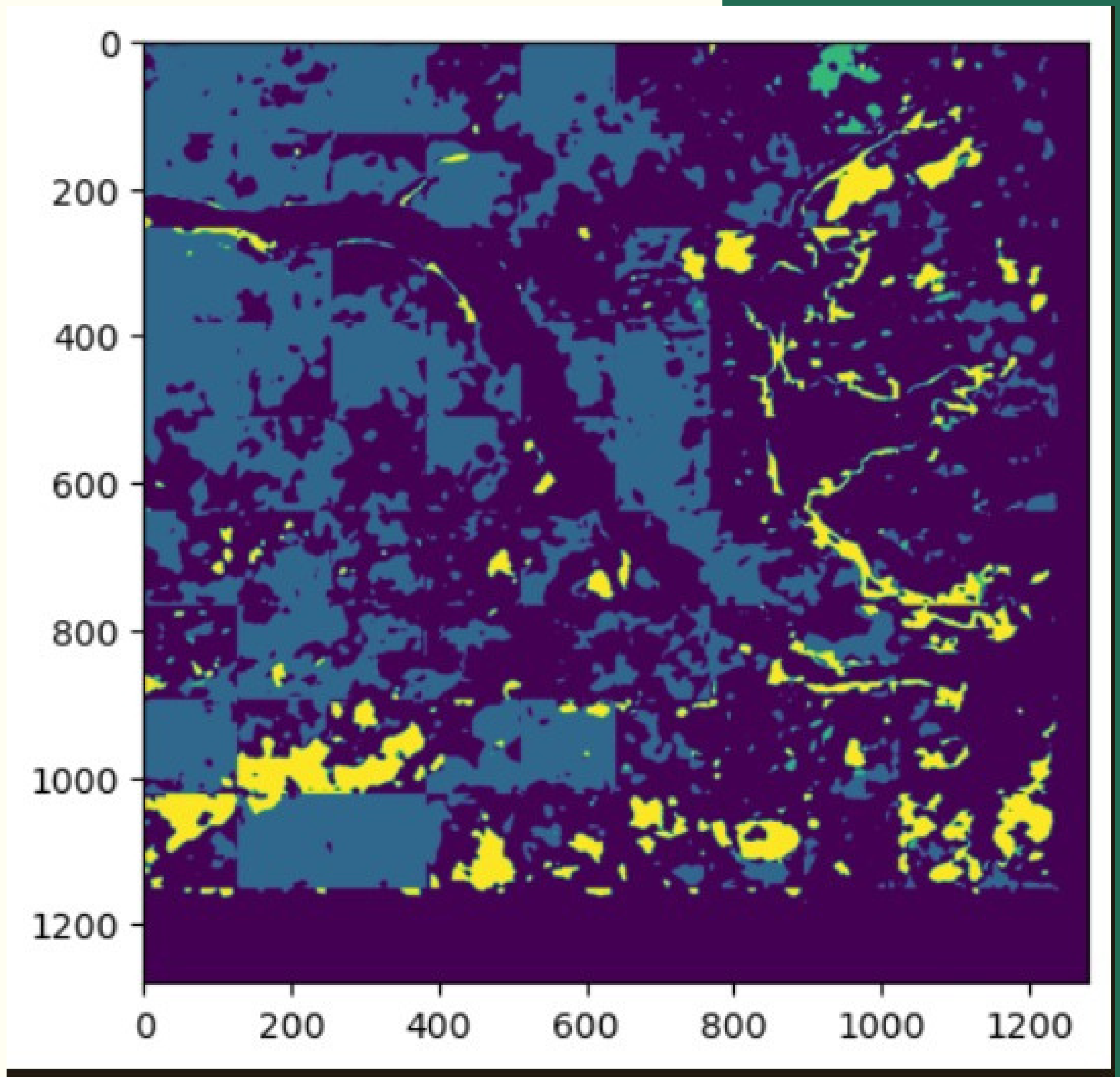


2023

Green - Built up
Blue - Forest
Yellow - Water boy



Forward



Backward

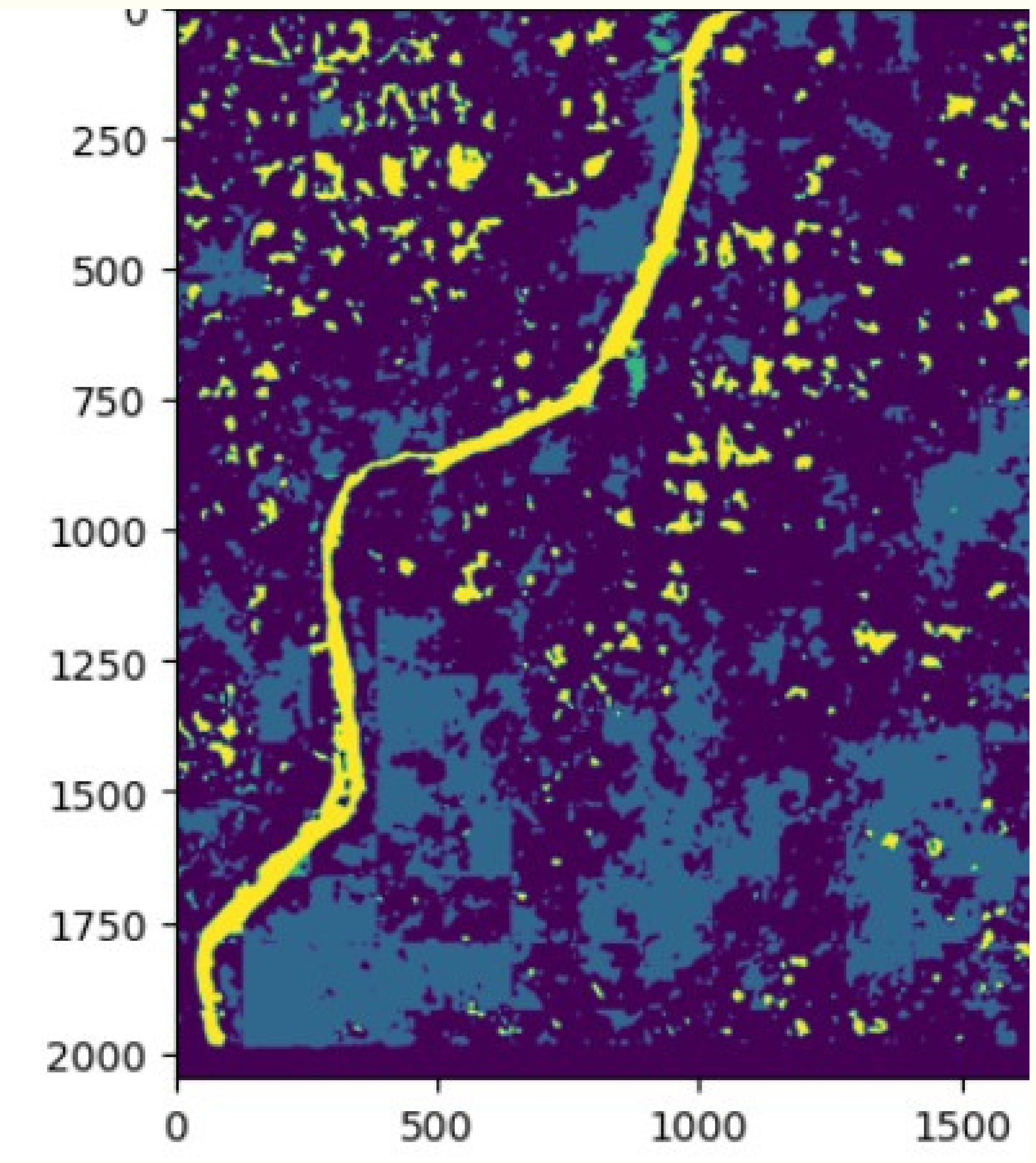
BARODA

2018

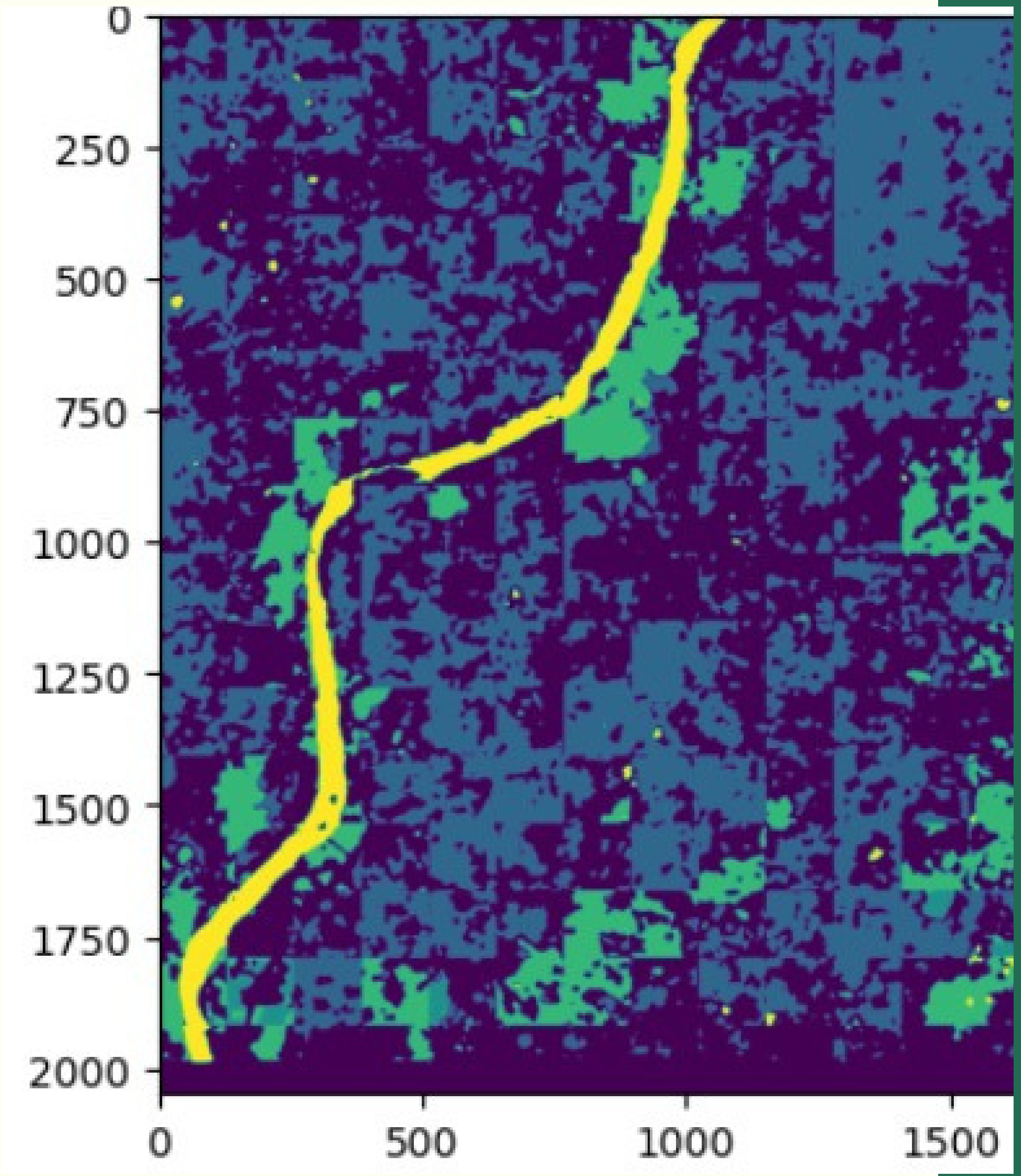
2023

BARODA

Green - Forest
Blue - Built up
Yellow - Water body

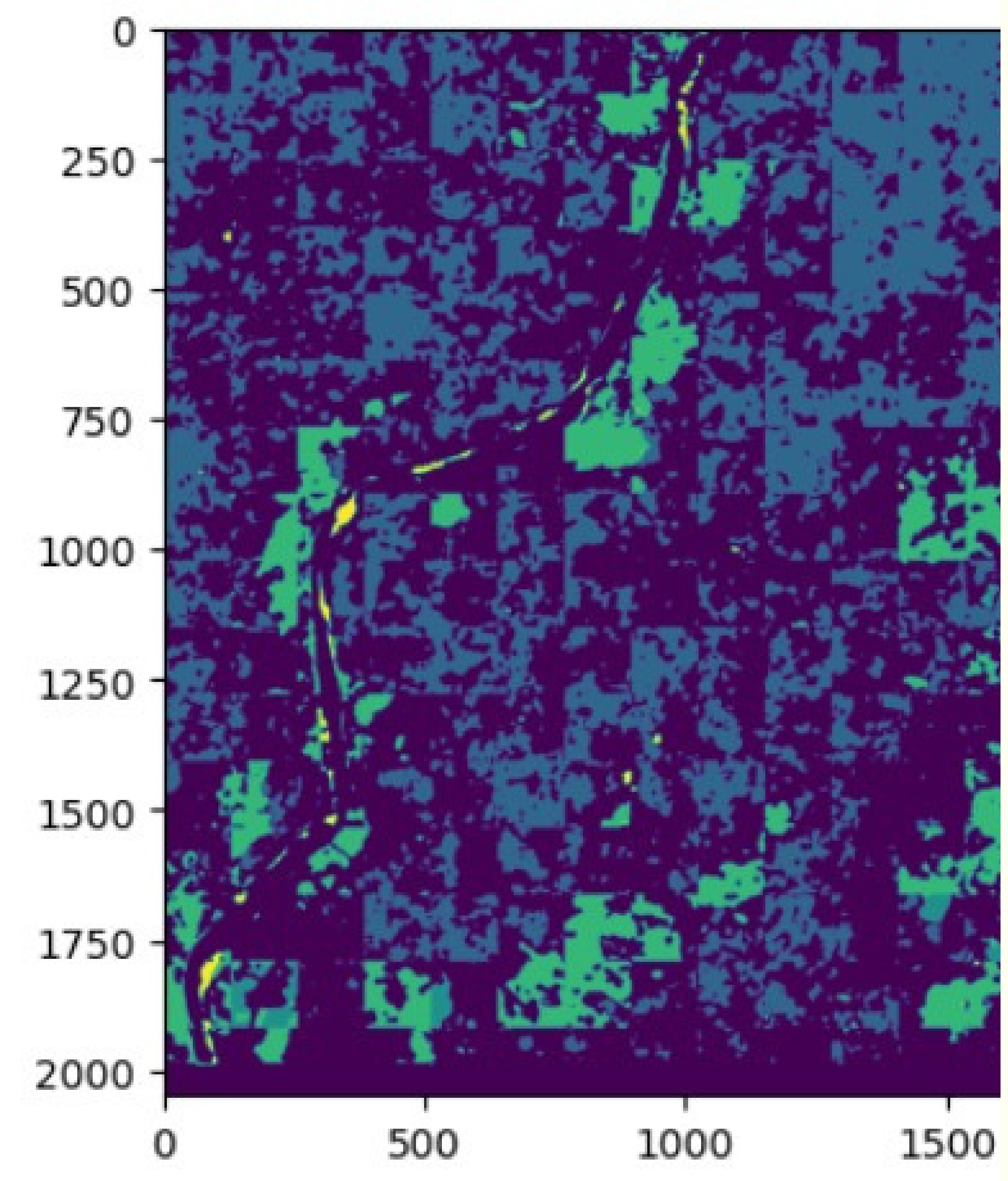


2018

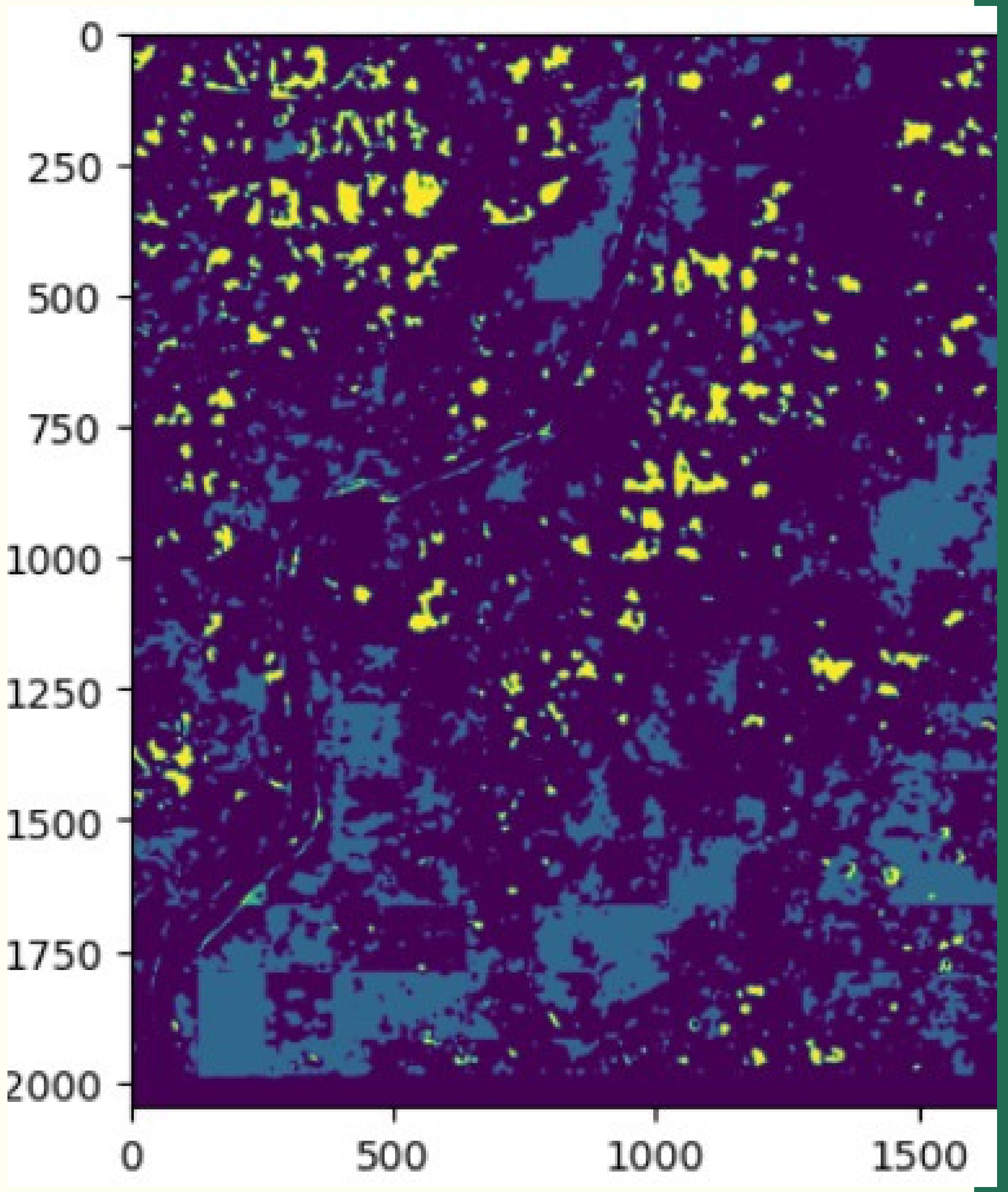


2023

Green - Forest
Blue - Built up
Yellow - Water body

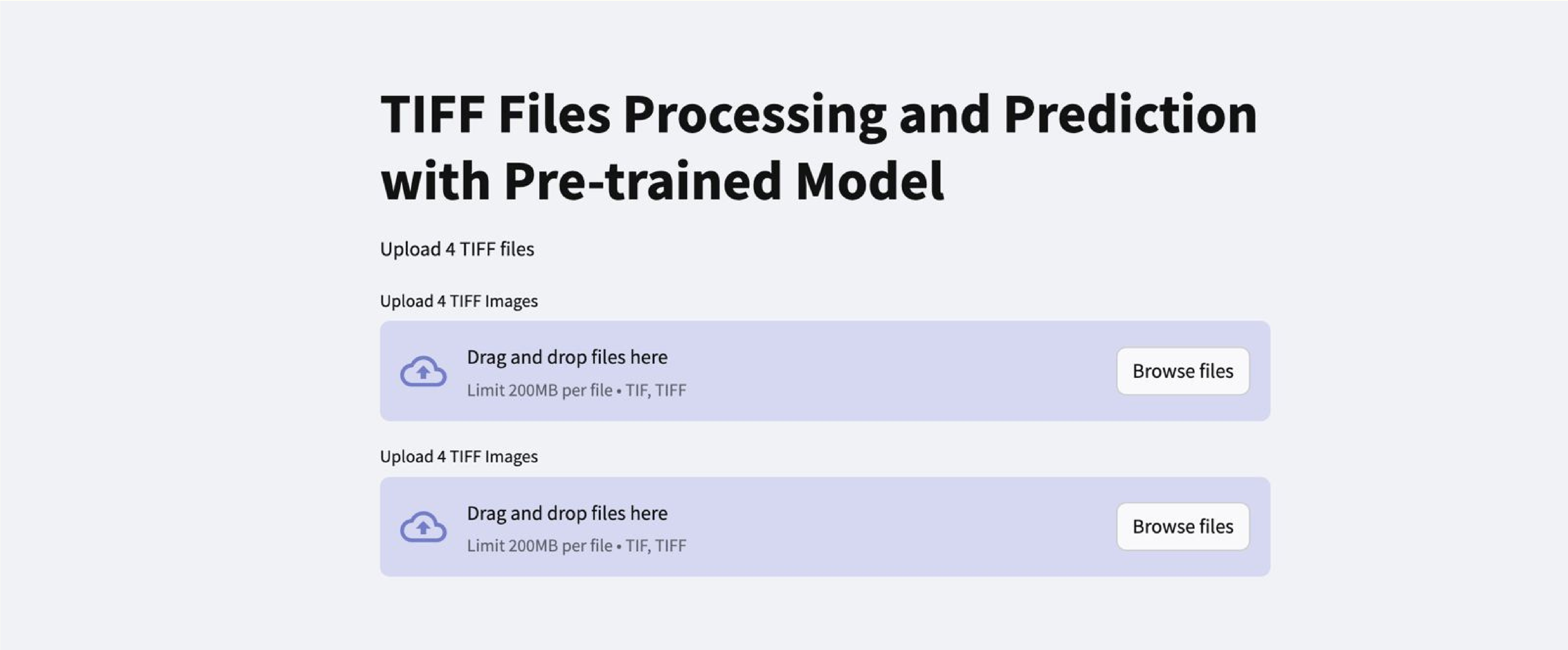


Forward



Backward

UI


TIFF Files Processing and Prediction with Pre-trained Model
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Browse files

TECH STACK USED

TensorFlow

NumPy

Keras

Streamlit

SOFTWARE USED

bhuvan Panchayat

QGIS

Bhoonidhi

opernicus

Thank You