

An academic insight on the functioning of fAlr

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SoTM EU 2025 - Dundee, November 13



Aerial satellite view of a settlement with numerous small houses and dirt roads. A white hand cursor is positioned over one of the buildings in the center-left area.

RUN PREDICTION

Current Zoom: 19
Predicted on: 20 Zoom
Response: 6 sec

Config

Use JOSM Q: Confidence: Vectorization Config :
Tolerance Area

Feedback

Initial Predictions: 27
Total feedbacks count: 0

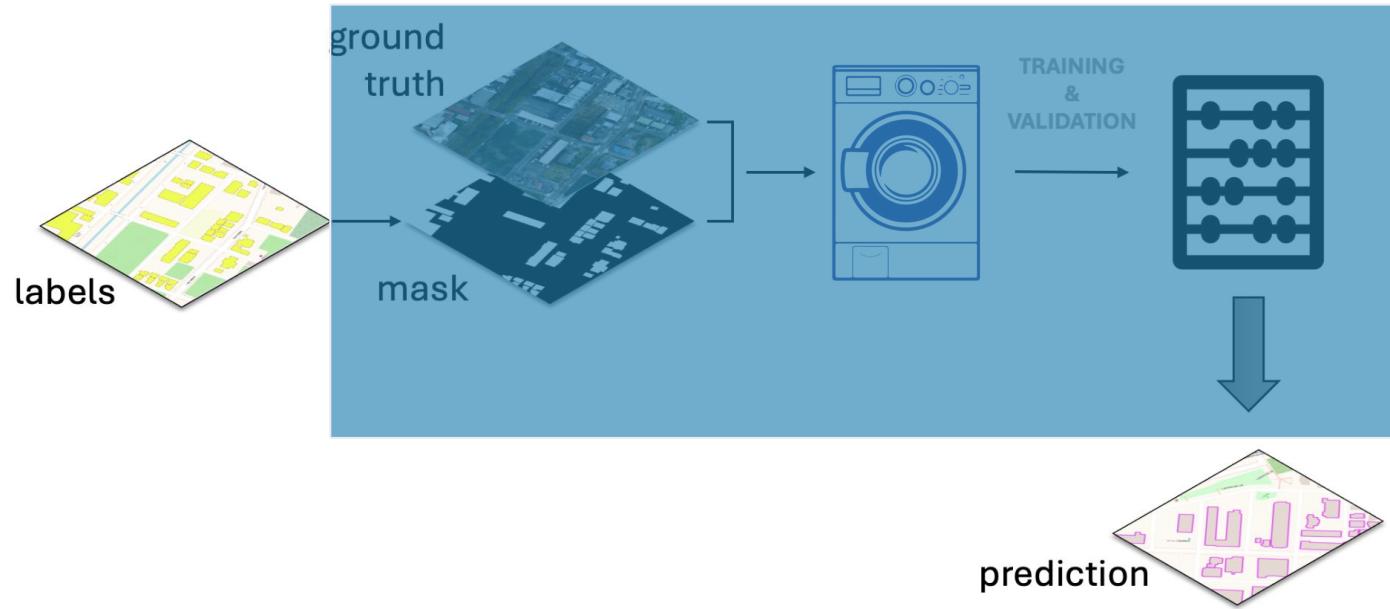
Loaded Model

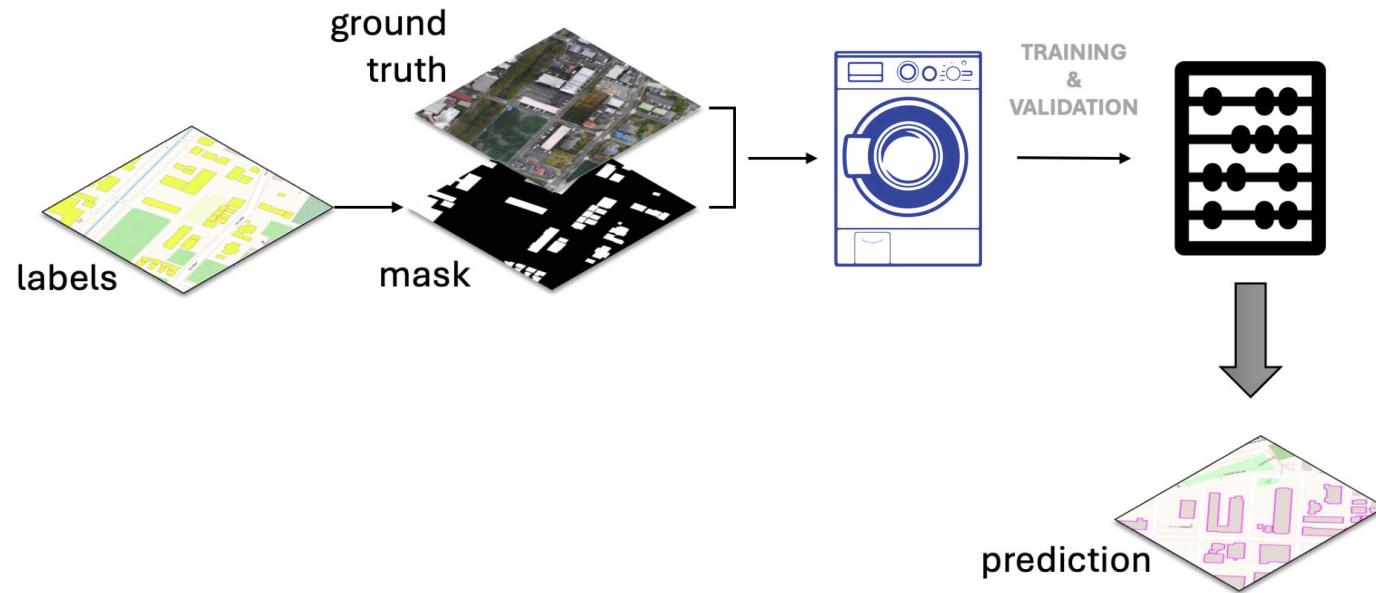
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Name: Kakuma Buildings Model
Last Modified: 4/29/2024, 3:54:46 PM

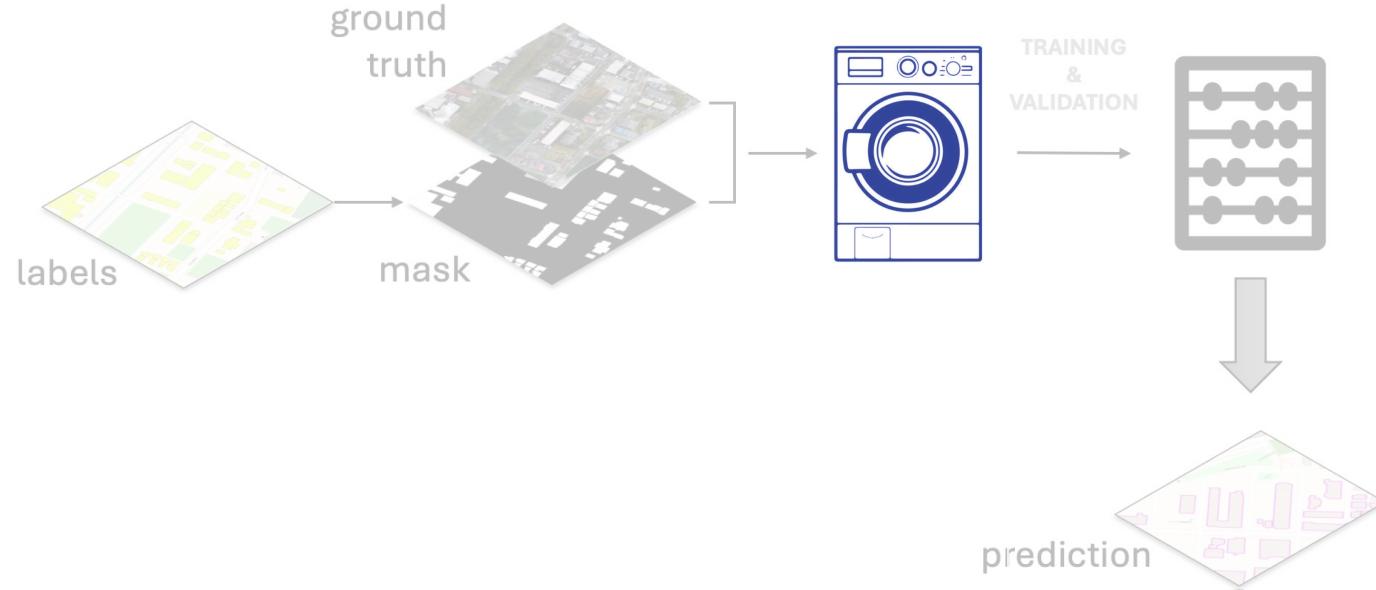
Published Training

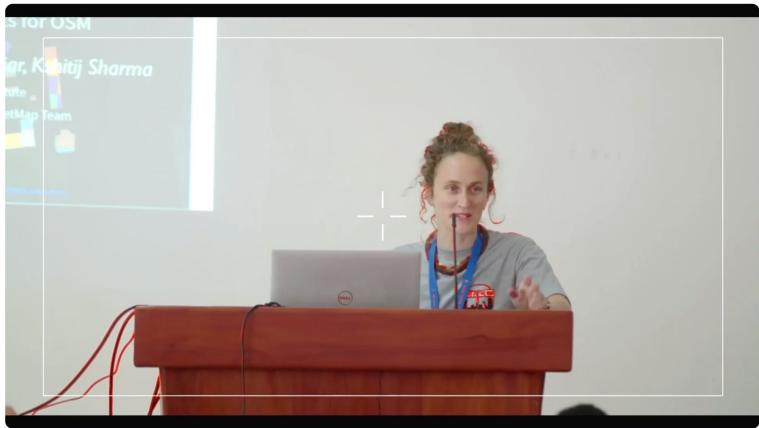
ID: 17
Description:
Zoom Level: 19, 20, 21
Accuracy: 99.30 %
Model Size: 124.11 MB

<https://www.hotosm.org/tech-suite/fair/>









STATE OF THE MAP 2025
October 3-5, 2025 | Manila, Philippines
2025.stateofthemap.org

Research topic

- Masaryk University
- Missing Maps Czechia and Slovakia
- Humanitarian mapping in Brno

Contact with fAir developers from HOT:

- Omran Najjar, Kshitij Sharma, Anna Zanchetta
- User study of fAir

Research goal:

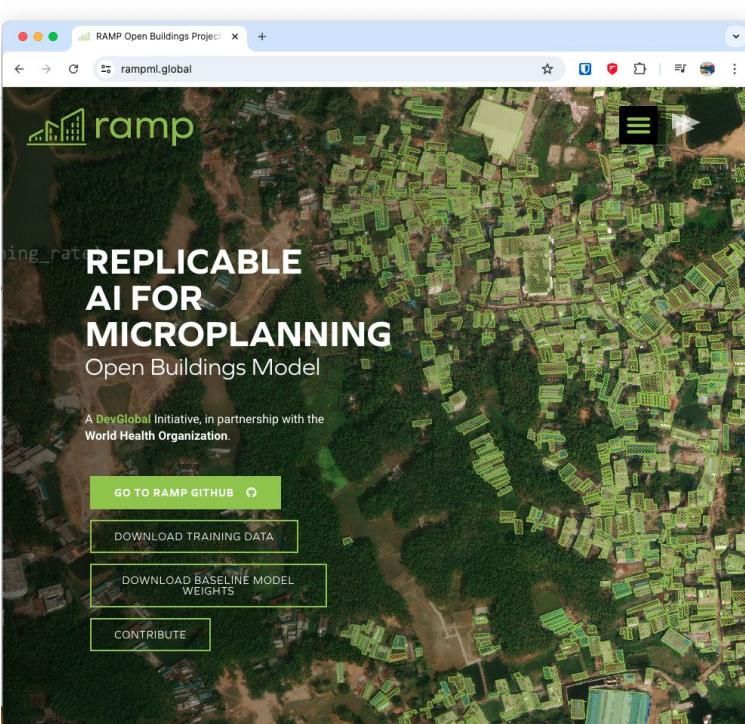
- Compare AI-assisted mapping of buildings with the fAir tool and manual mapping of buildings without AI assistance
- JOSM editor with plugins for mapping of buildings

— October – December 2024

STATE OF THE MAP 2025

OpenStreetMap
MissingMaps2025

RAMP



vs

YOLO



You Only Look Once

Article Talk

From Wikipedia, the free encyclopedia

You Only Look Once (YOLO) is a series of real-time [object detection](#) systems based on [convolutional neural networks](#). First introduced by Joseph Redmon et al. in 2015,^[1] YOLO has undergone several iterations and improvements, becoming one of the most popular object detection frameworks.^[2]

The name "You Only Look Once" refers to the fact that the algorithm requires only one forward propagation pass through the neural network to make predictions, unlike previous region proposal-based techniques like [R-CNN](#) that require thousands for a single image.

Overview [edit]

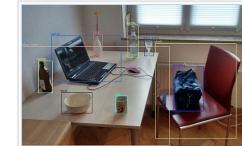
Compared to previous methods like [R-CNN](#) and [OverFeat](#),^[3] instead of applying the model to an image at multiple locations and scales, YOLO applies a single neural network to the full image. This network divides the image into regions and predicts bounding boxes and probabilities for each region. These bounding boxes are weighted by the predicted probabilities.

OverFeat [edit]

OverFeat was an early influential model for simultaneous object classification and localization.^{[3][4]} Its architecture is as follows:

- Train a neural network for image classification only ("classification-trained

You Only Look Once	
Original authors	Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi
Initial release	2015
Stable release	YOLOv12 / 2025-02-20
Written in	Python
Type	Object detection Convolutional neural network Computer vision
Website	pjreddie.com/darknet/yolo/



Objects detected with OpenCV's Deep Neural Network module by using a YOLOv3 model trained on [COCO](#) dataset capable to detect objects of 80 common classes

Dataset

25



21



3

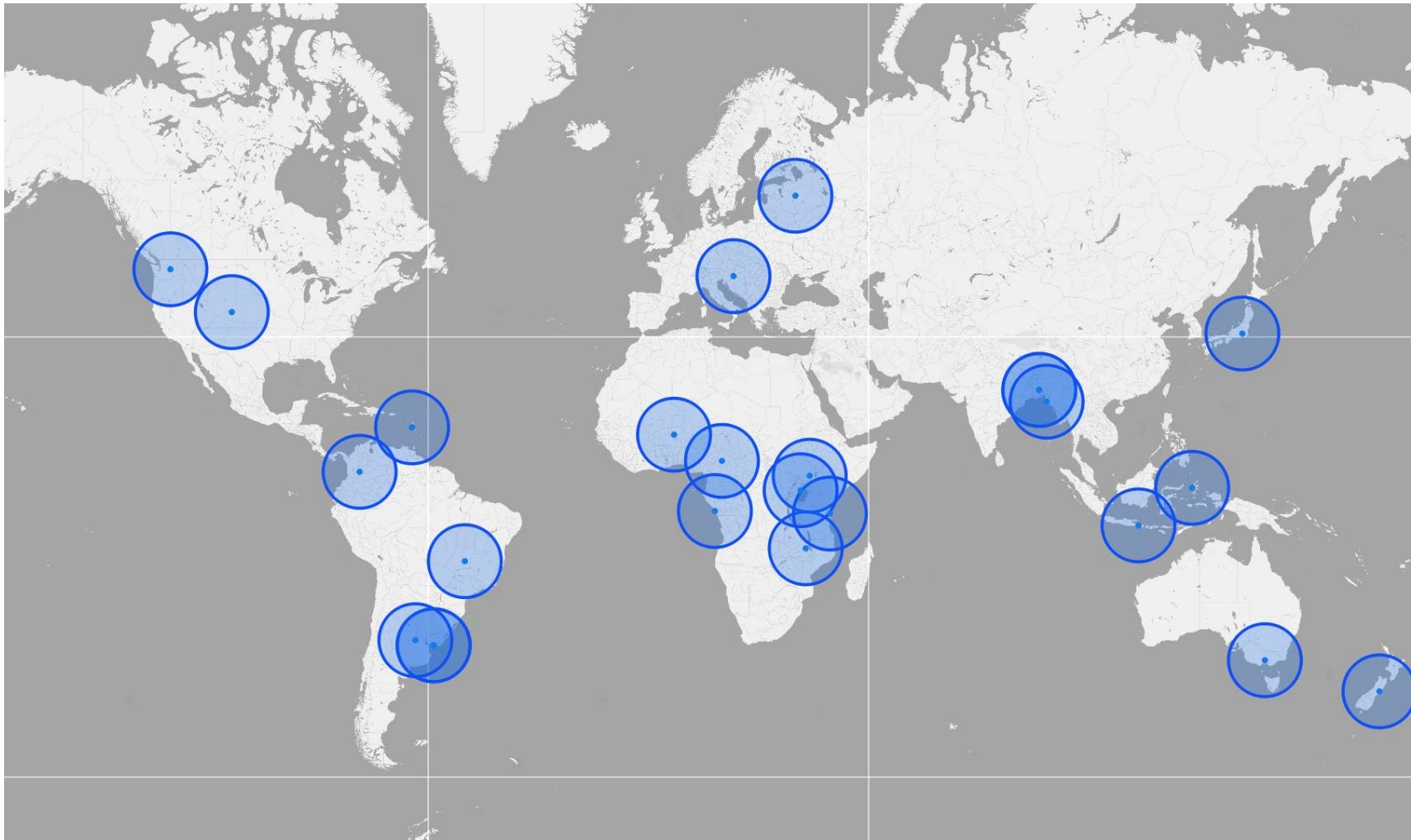


8400



256
x
256





Urbanity



Roof cover

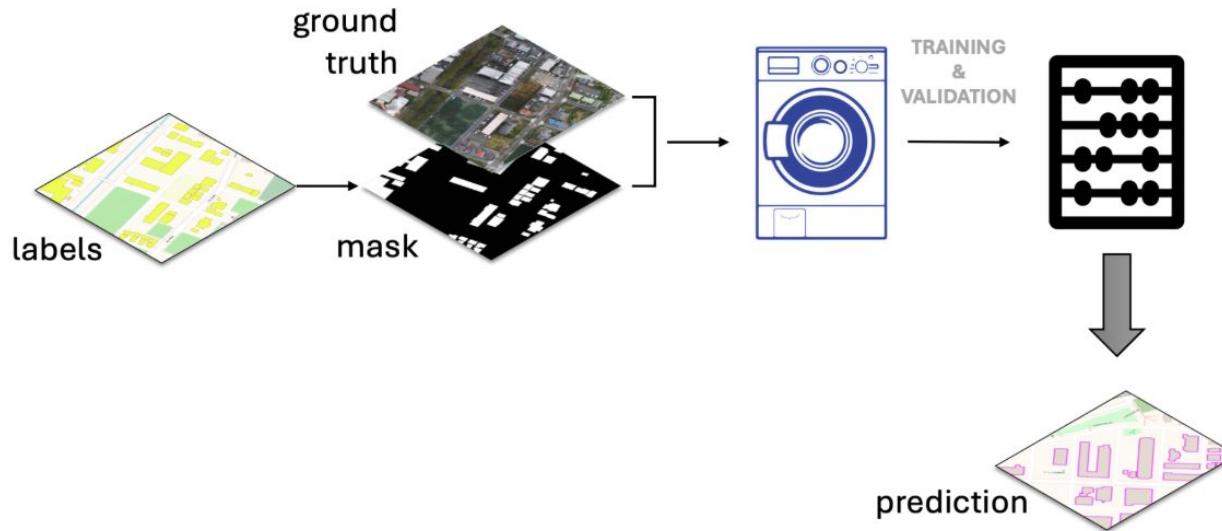


Density

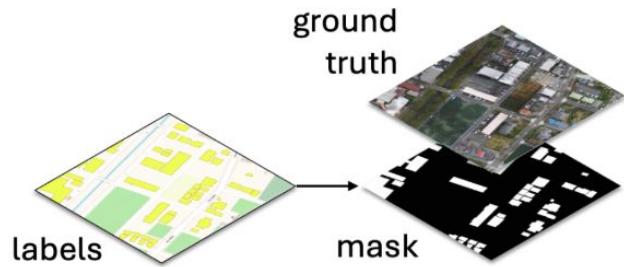


RAMP vs YOLO

RAMP vs YOLO



RAMP vs YOLO

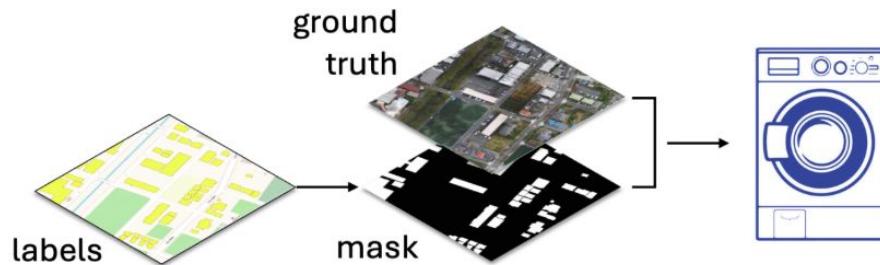


0

train /val / test

70	15	15
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RAMP vs YOLO



0

1

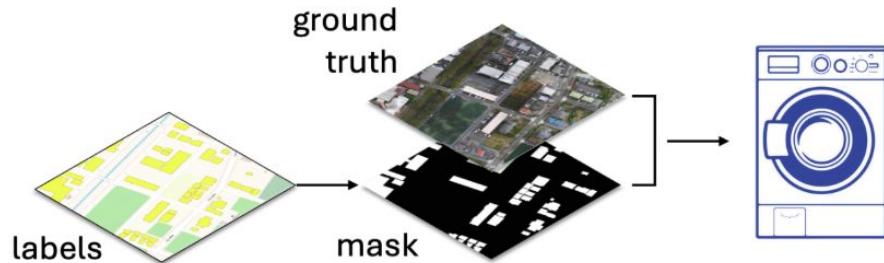
train /val / test

70 15 15

x 5 50 epochs

(K-fold cross validation)

RAMP vs YOLO



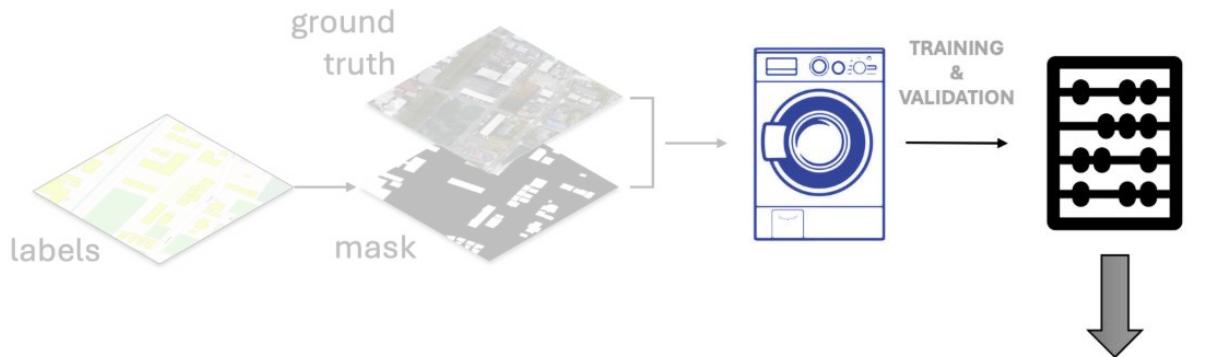
train /val / test



2



RAMP vs YOLO



0

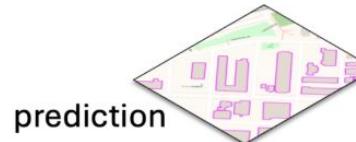
train /val / test

70 15 15

x 5 50 epochs

(K-fold cross validation)

1



prediction

2

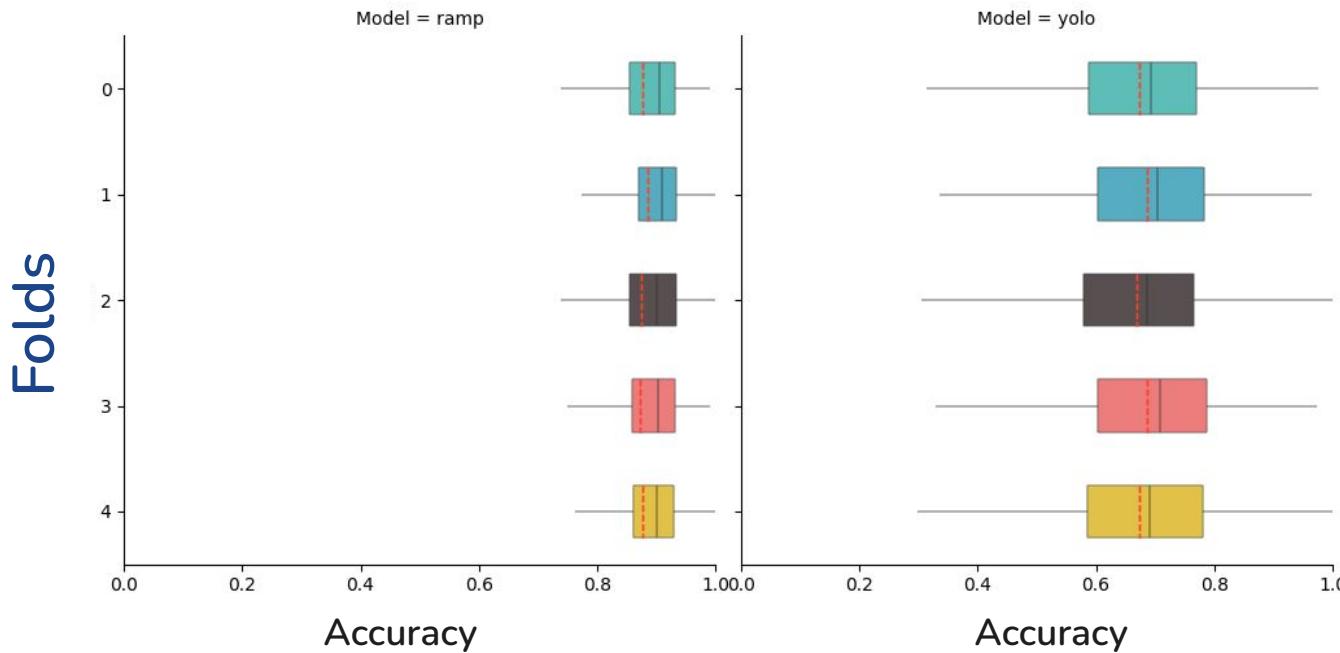


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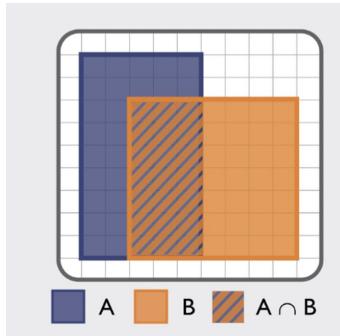


1

RAMP vs YOLO



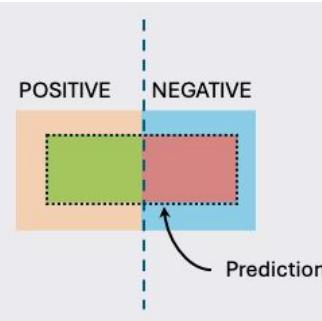
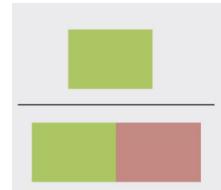
RAMP vs YOLO



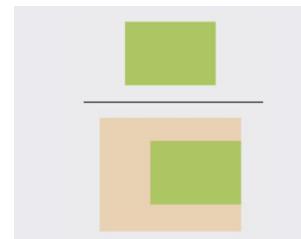
IoU

$$\frac{\text{A} \cap \text{B}}{\text{A} + \text{B} - \text{A} \cap \text{B}}$$

Precision



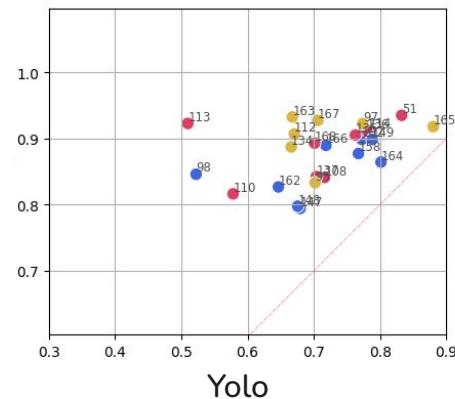
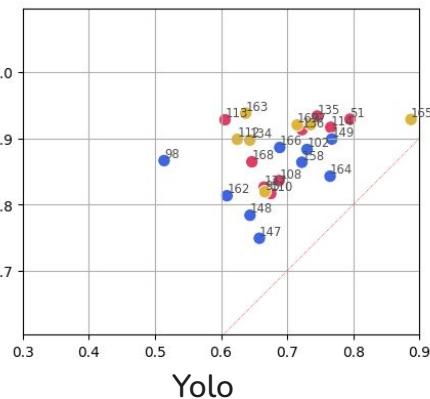
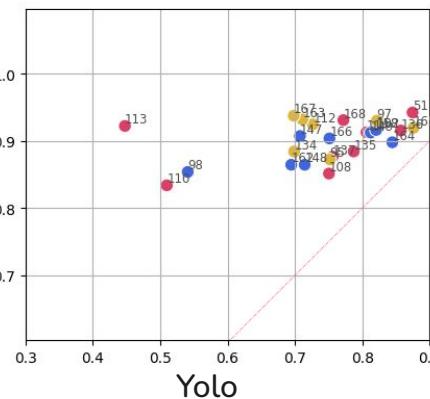
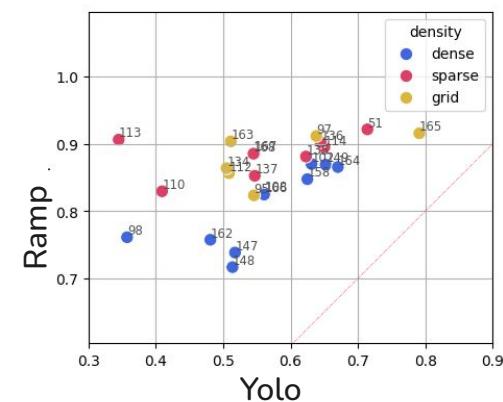
Recall



F1 score

 \sum

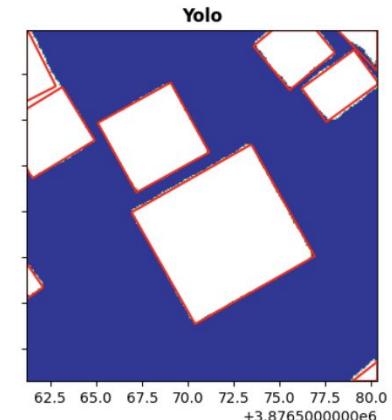
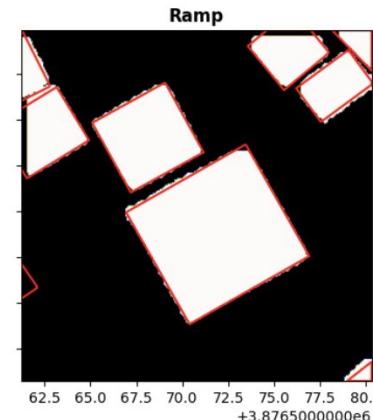
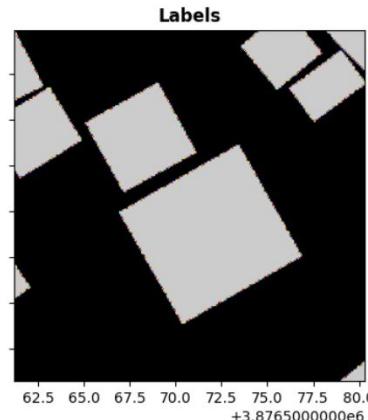
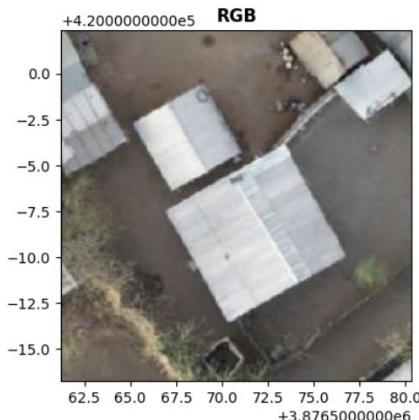
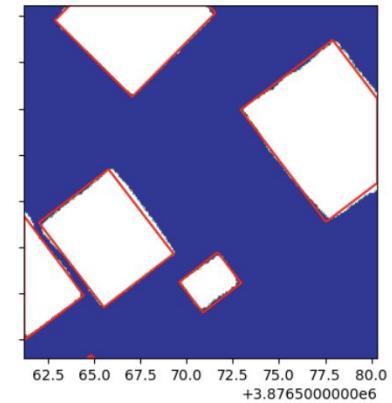
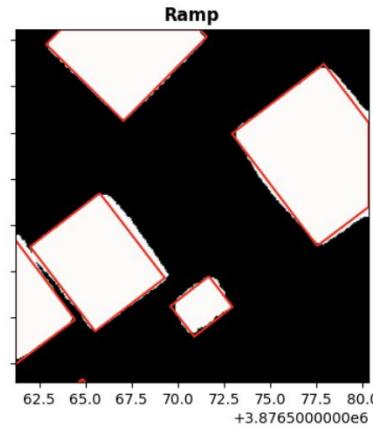
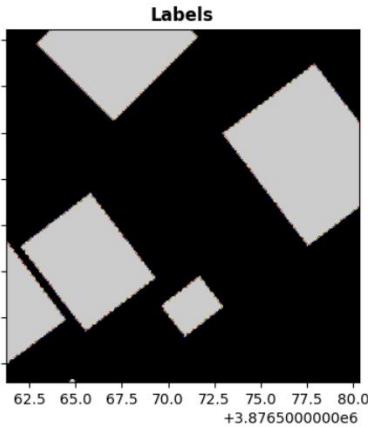
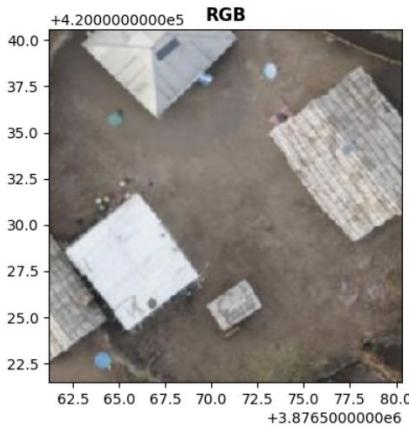
RAMP vs YOLO

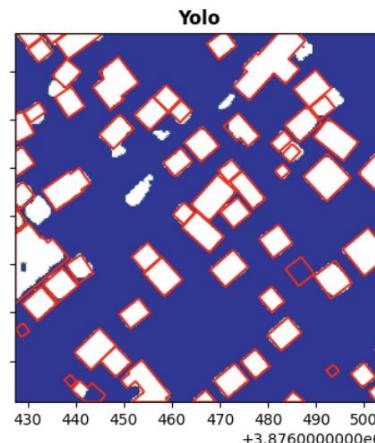
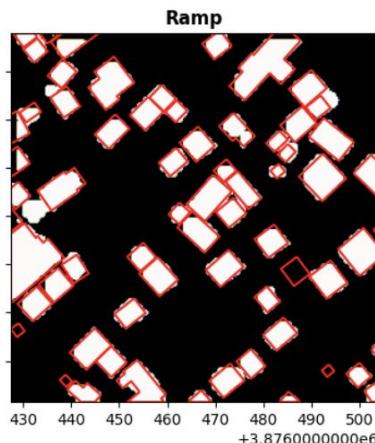
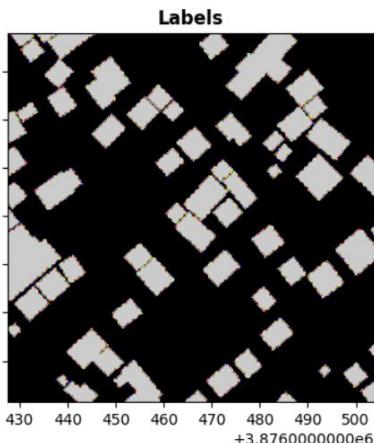
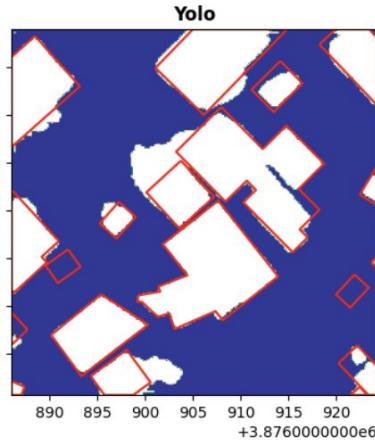
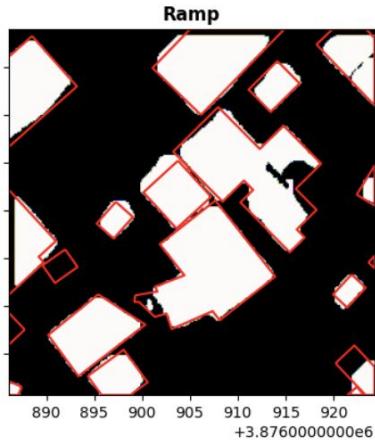
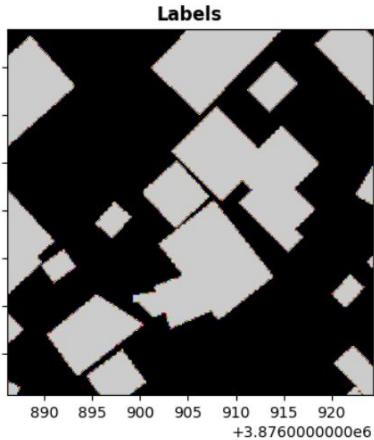


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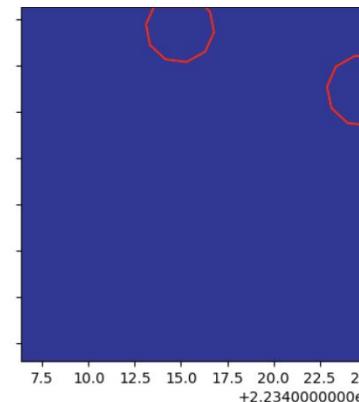
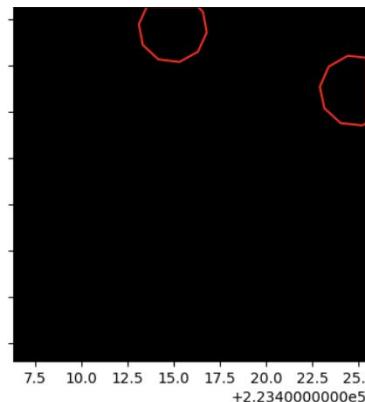
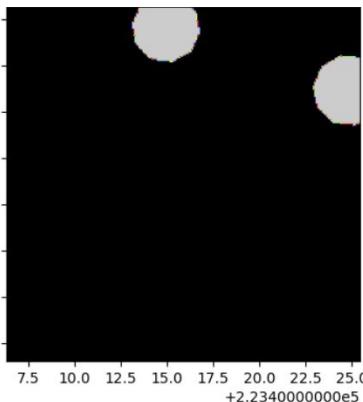
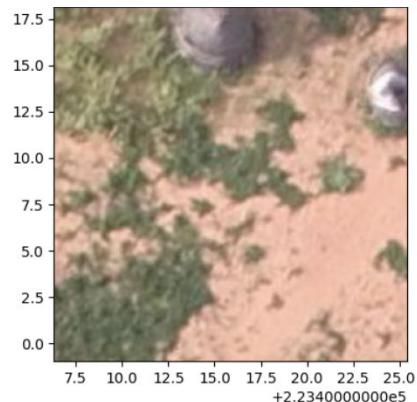
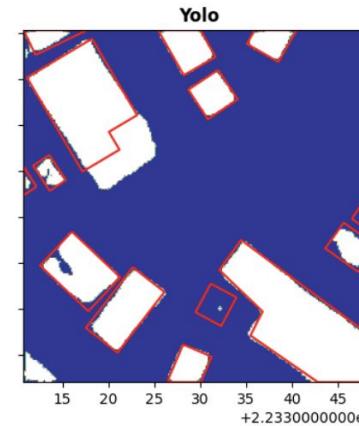
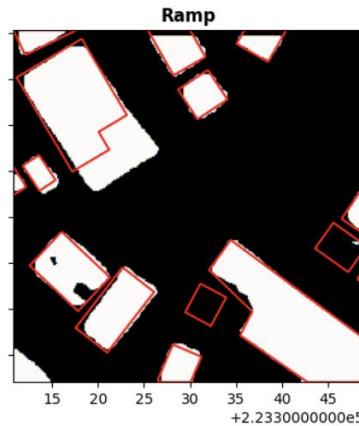
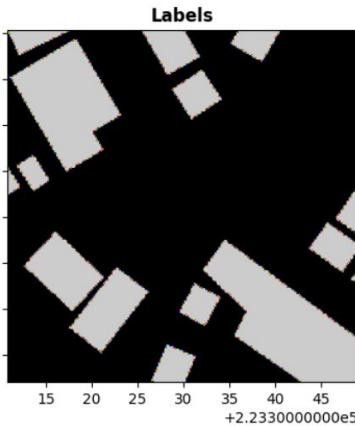
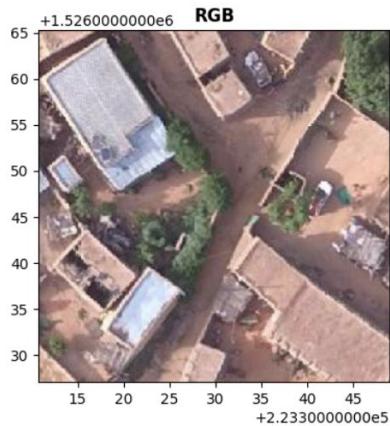
RAMP vs YOLO

51 (sparse)

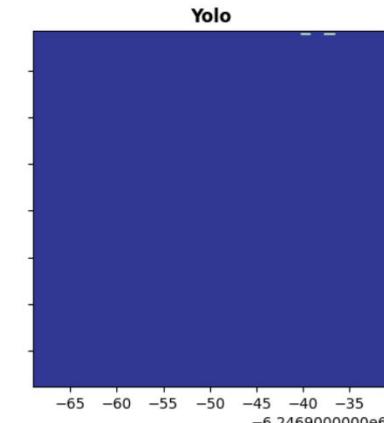
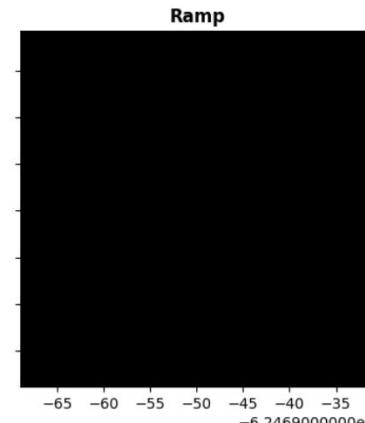
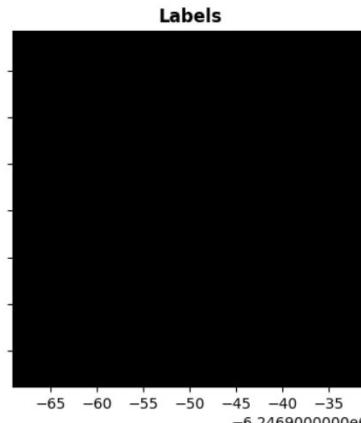
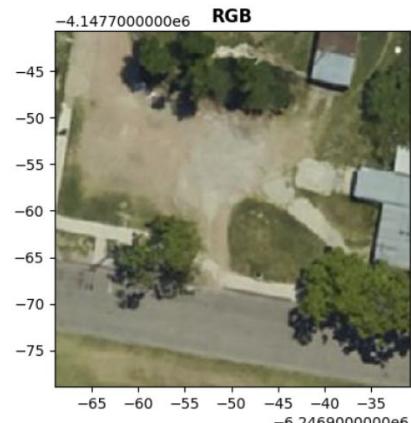
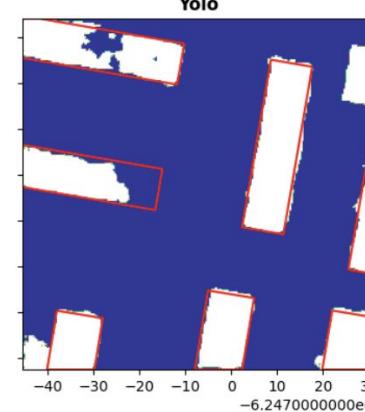
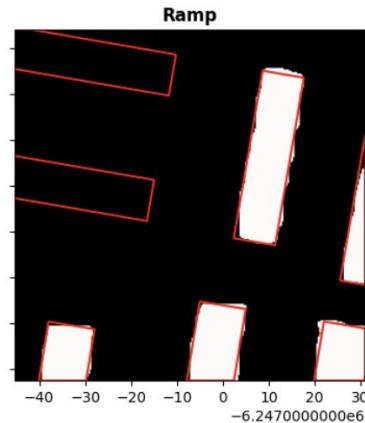
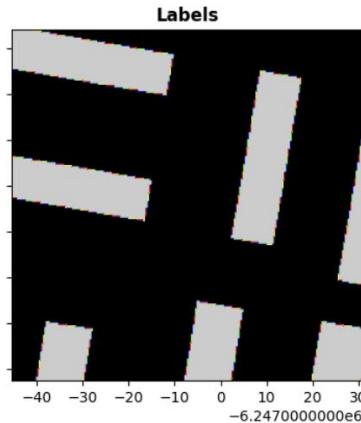
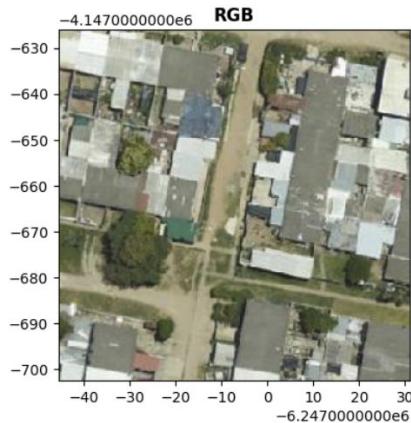


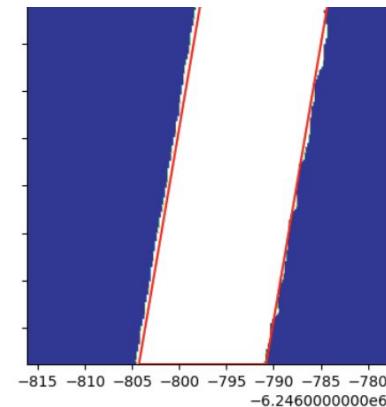
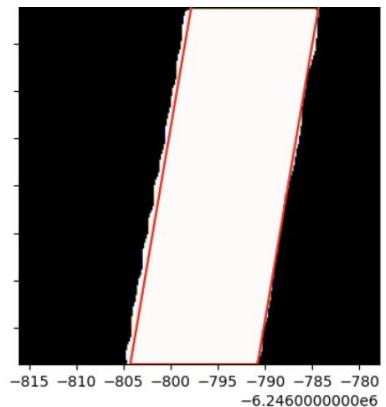
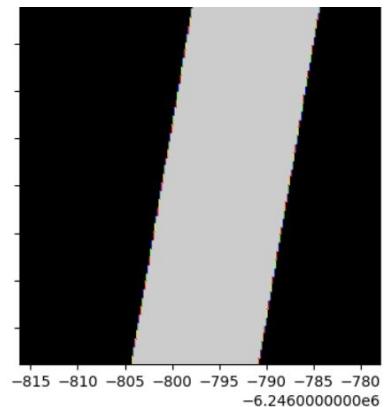
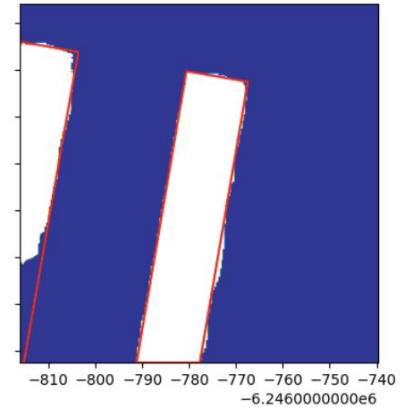
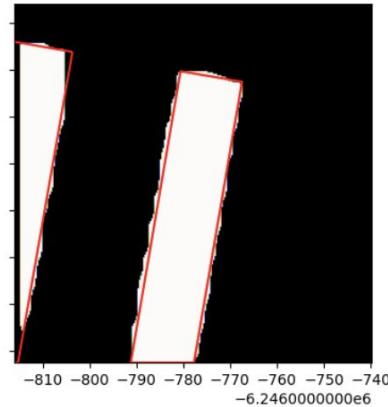
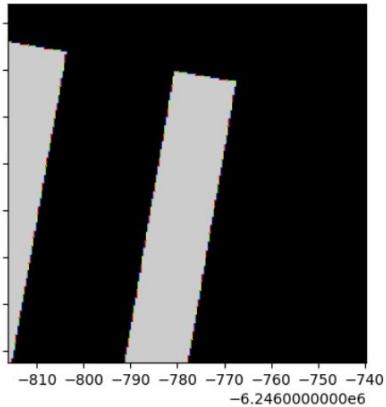


164 (dense)



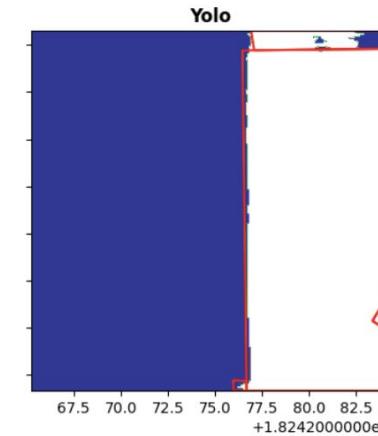
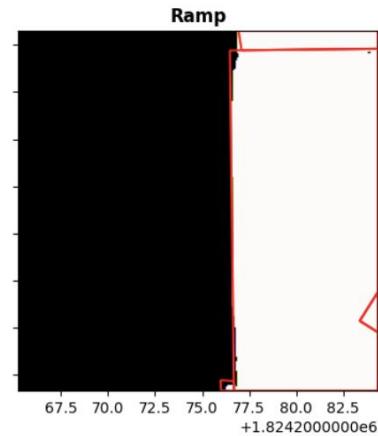
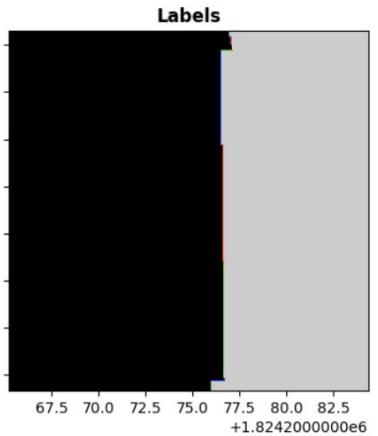
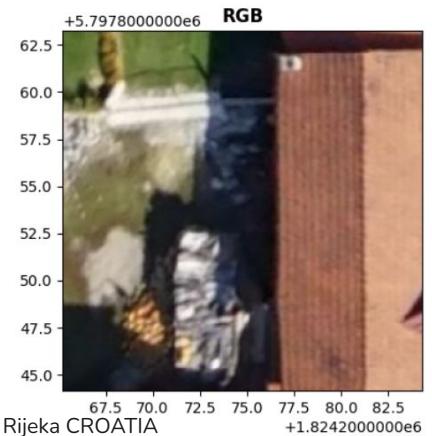
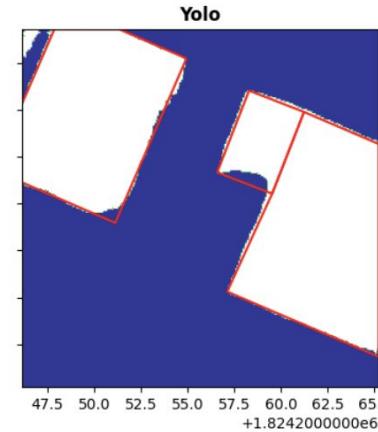
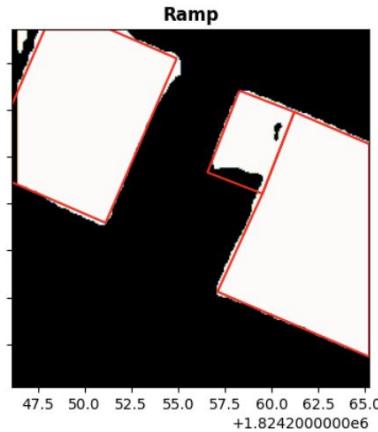
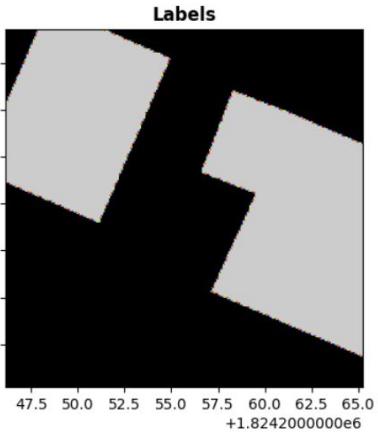
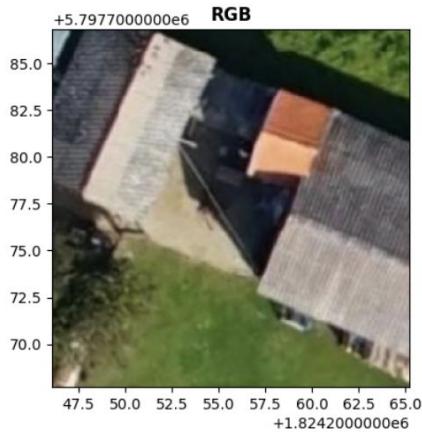
97 (grid)



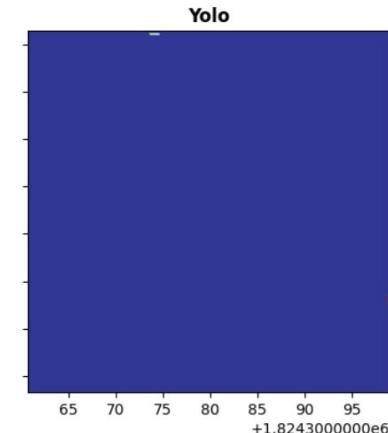
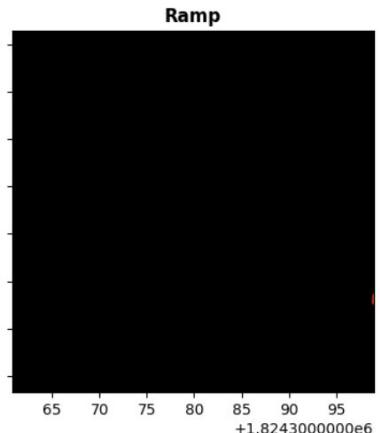
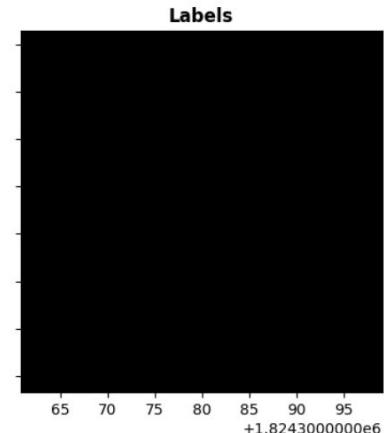
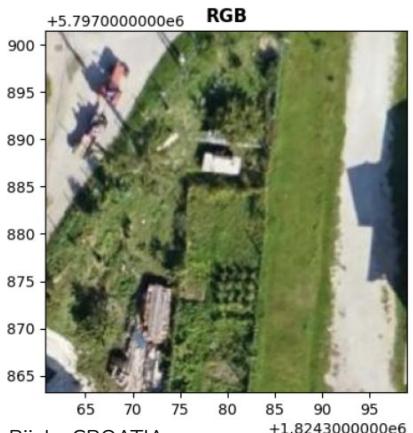
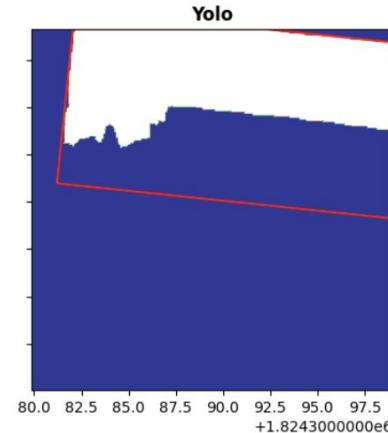
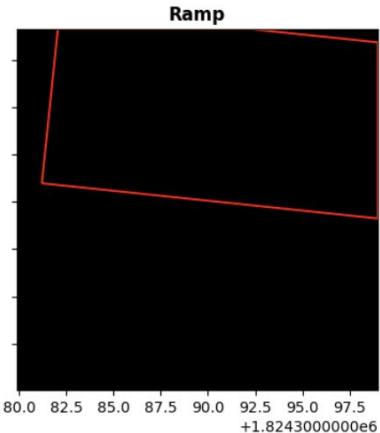
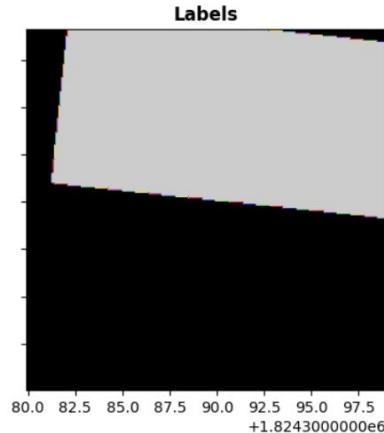
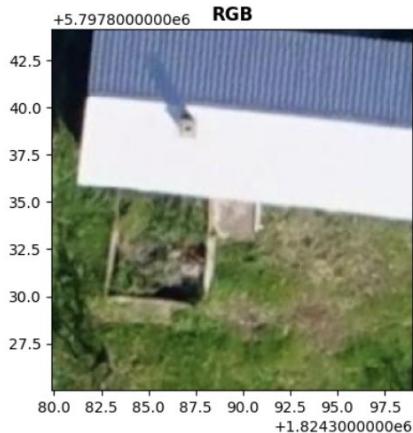


Montevideo URUGUAY

110 (sparse)

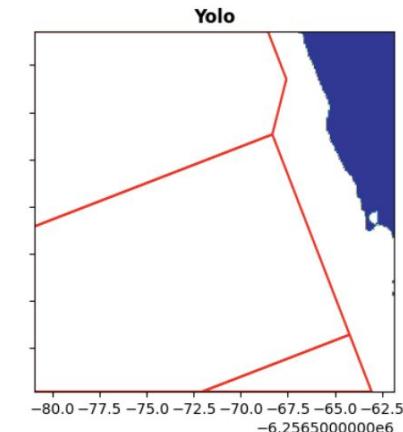
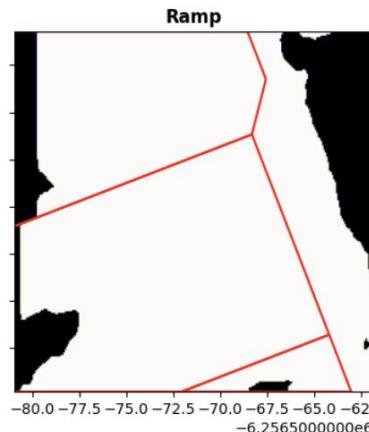
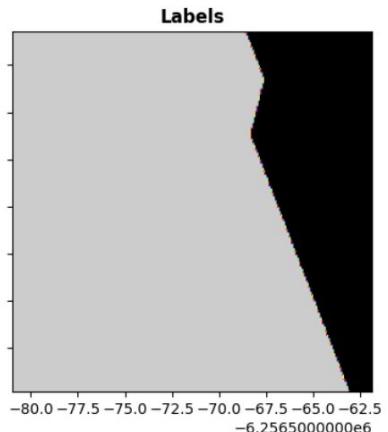
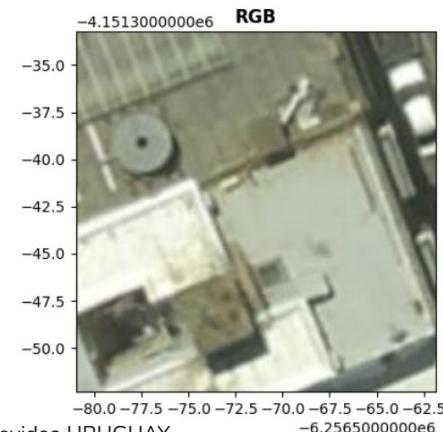
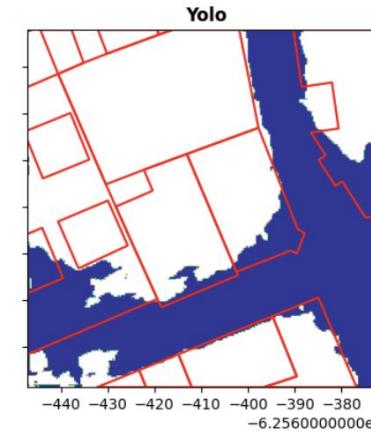
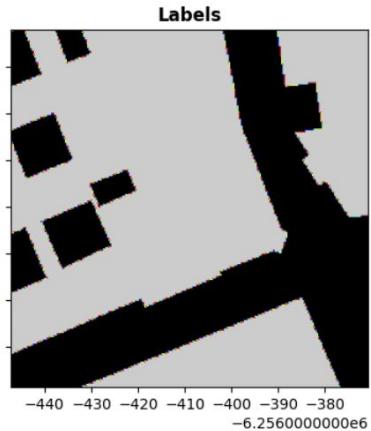
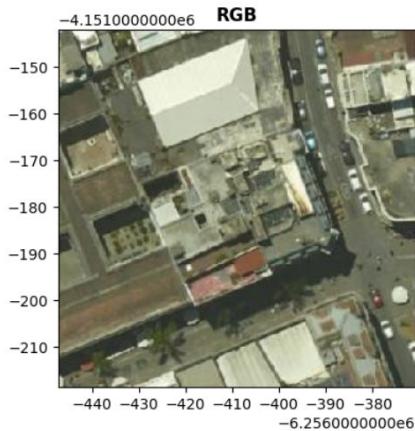


Gornja Rijeka CROATIA



Gornja Rijeka CROATIA

98 (dense)

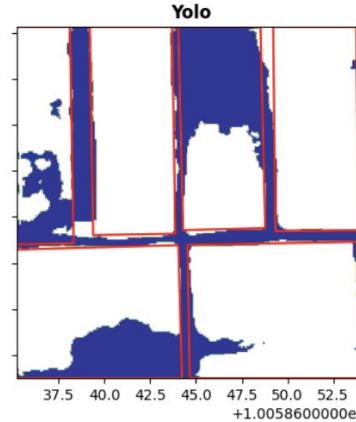
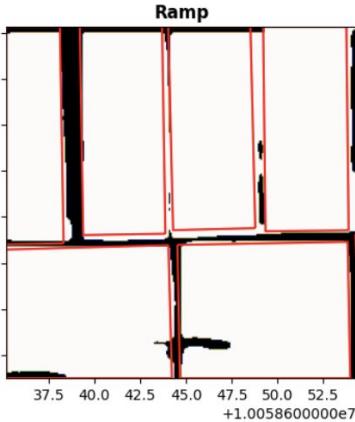
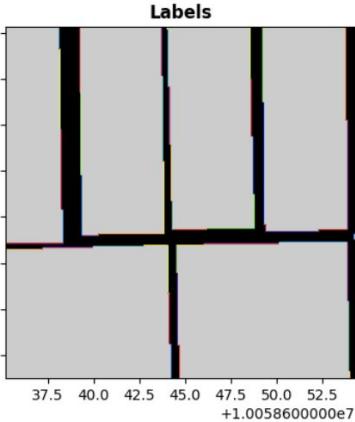
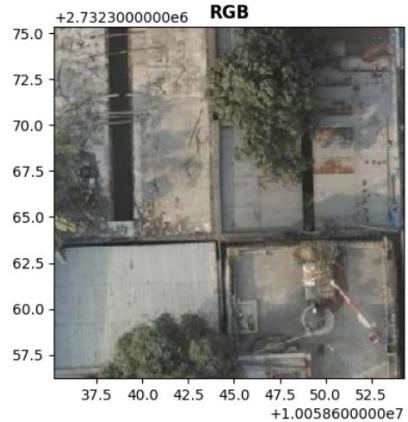
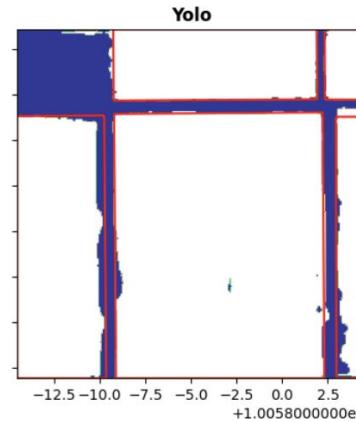
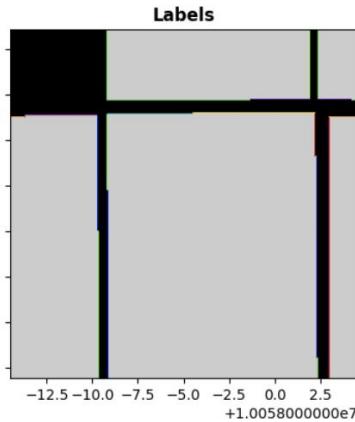
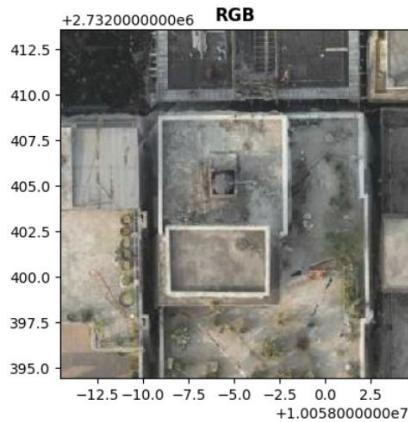


Montevideo URUGUAY

147 (dense)

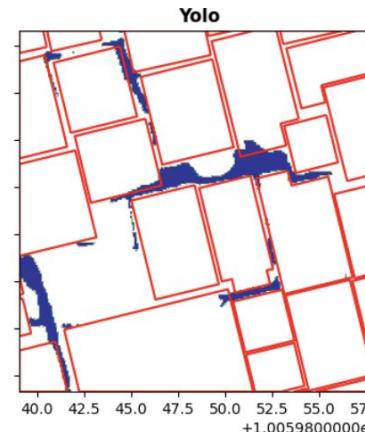
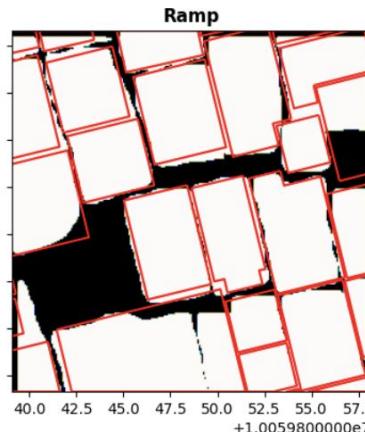
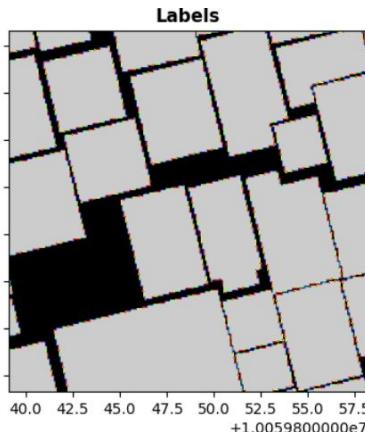
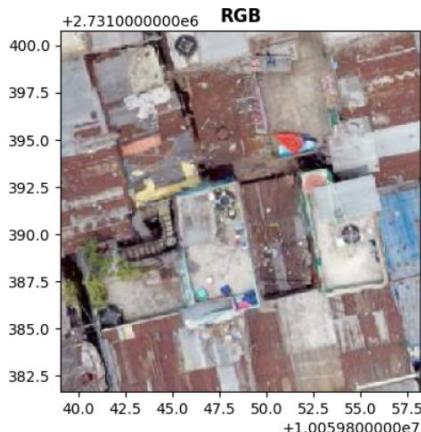
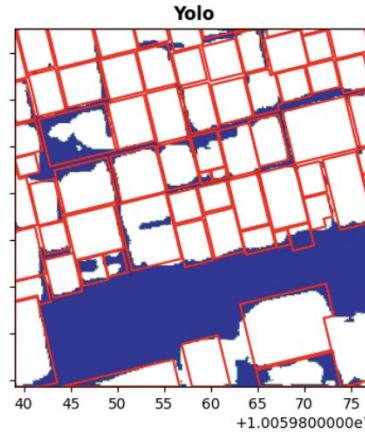
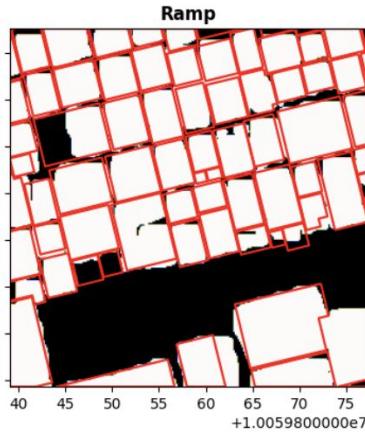
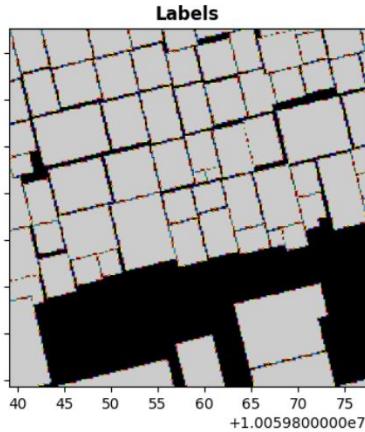
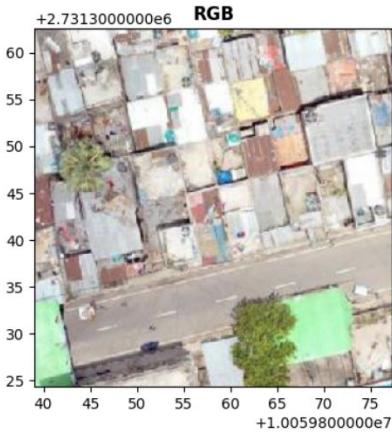


IoU, recall



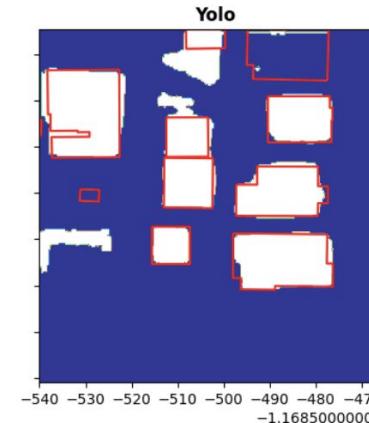
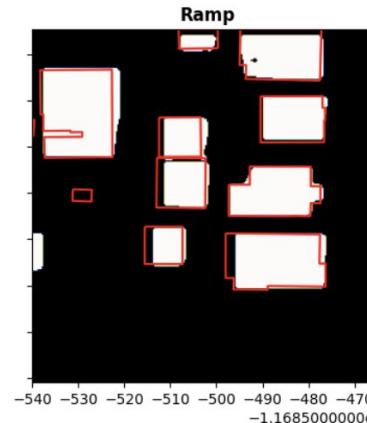
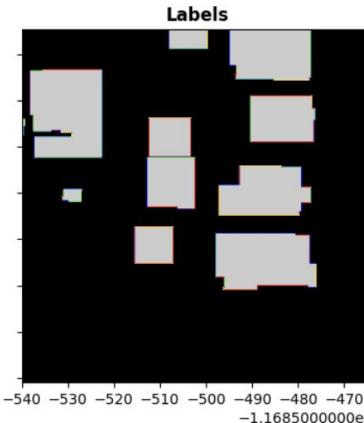
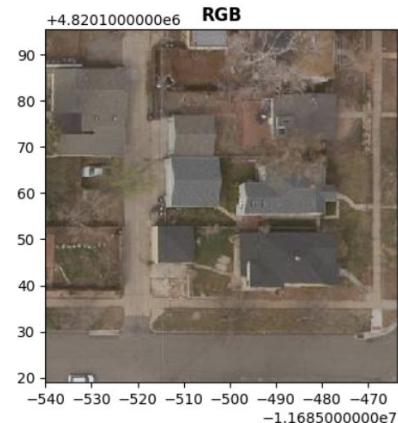
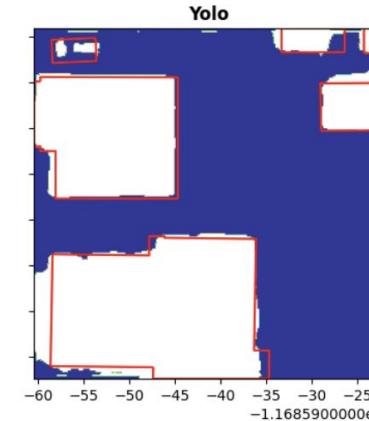
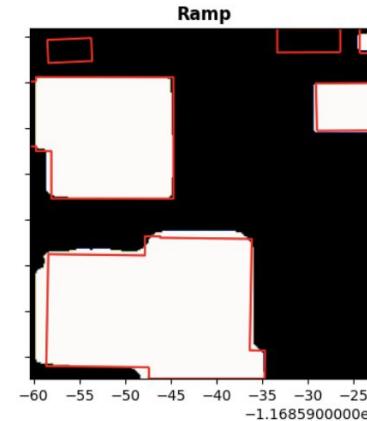
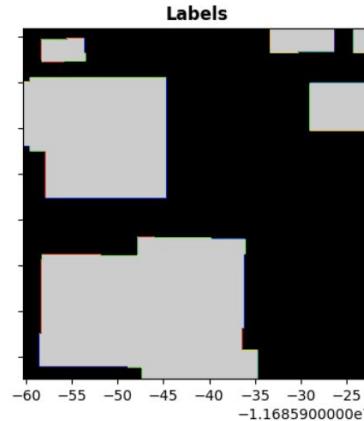
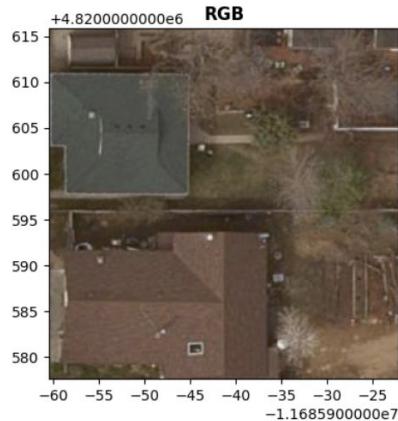


IoU, recall

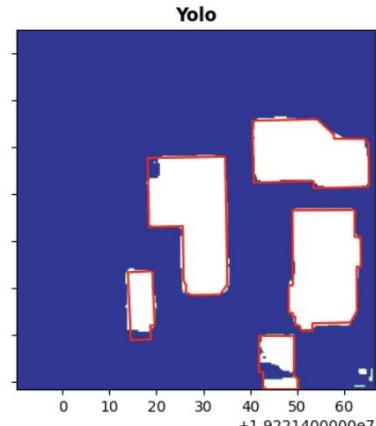
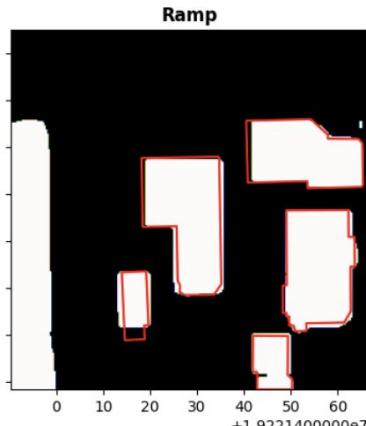
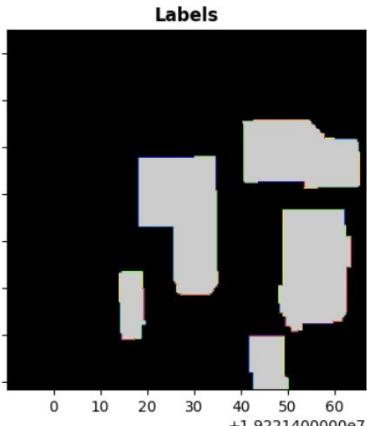
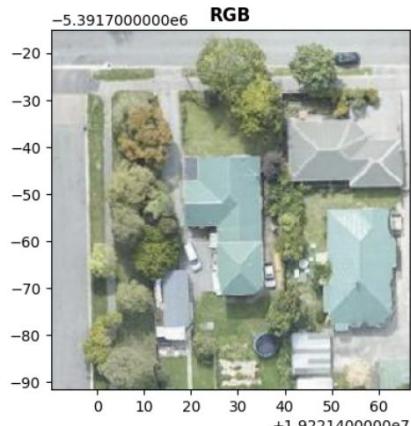
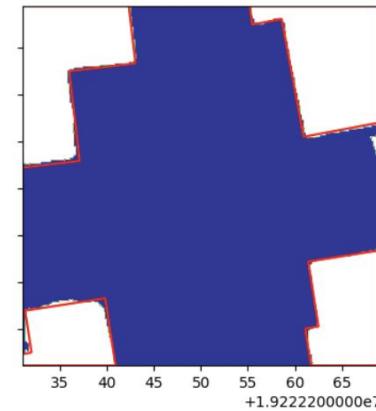
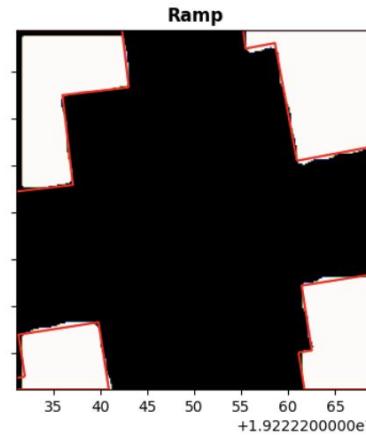
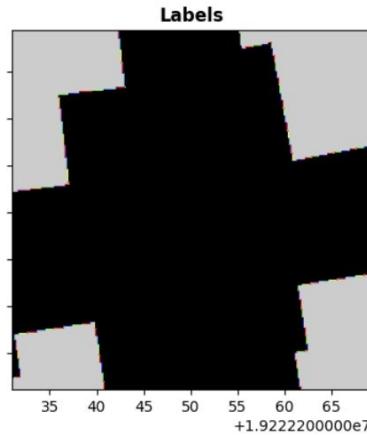
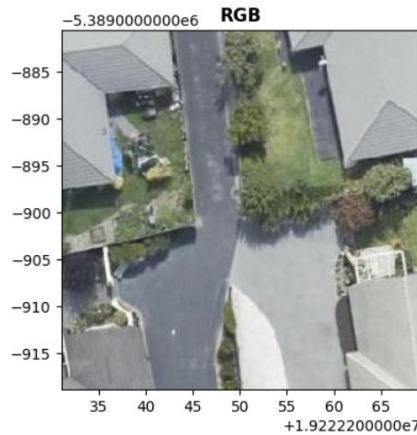


Dhaka BANGLADESH

95 (grid)

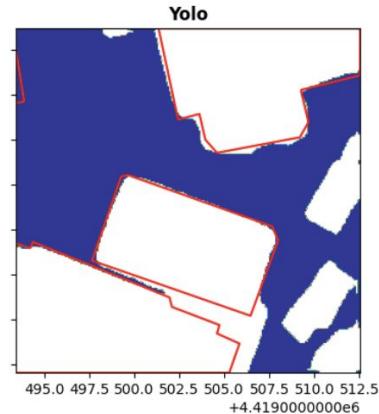
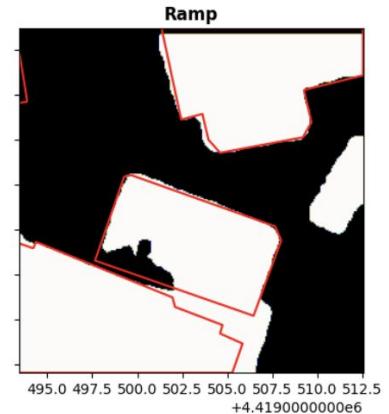
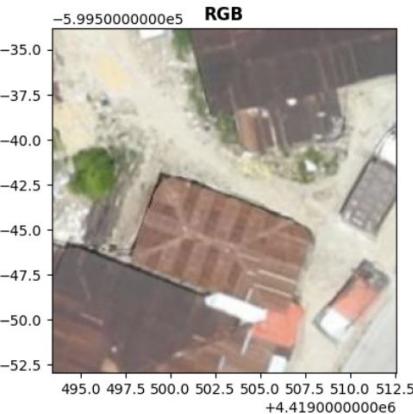
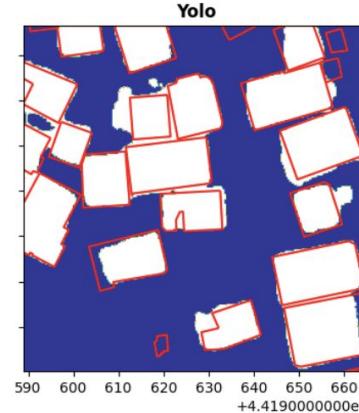
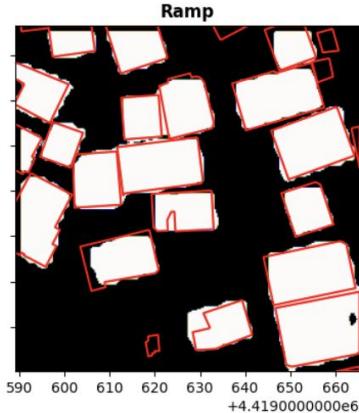
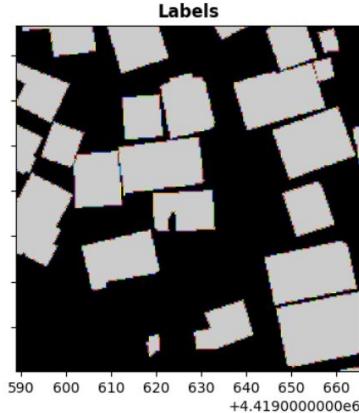
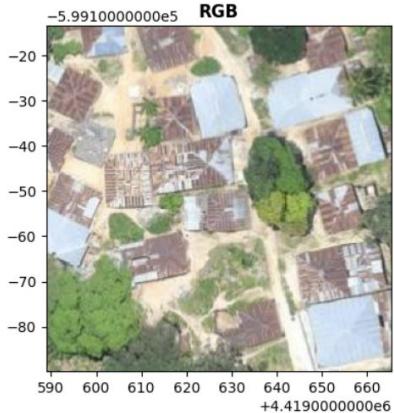


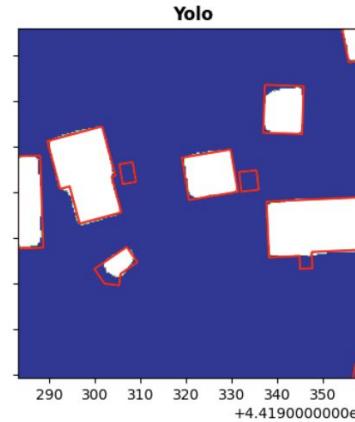
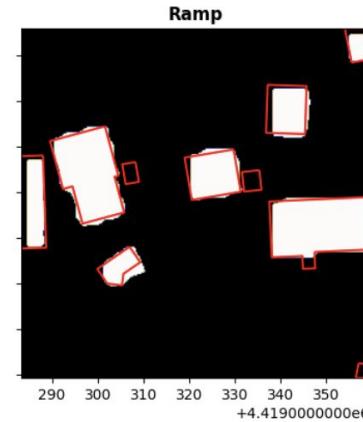
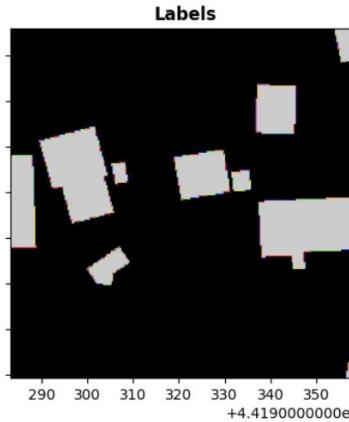
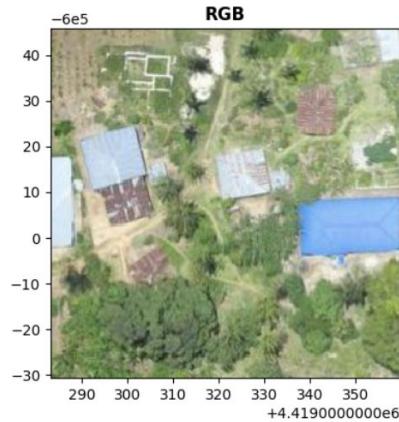
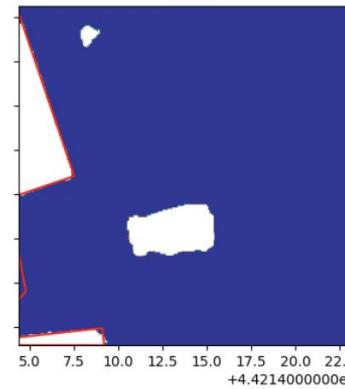
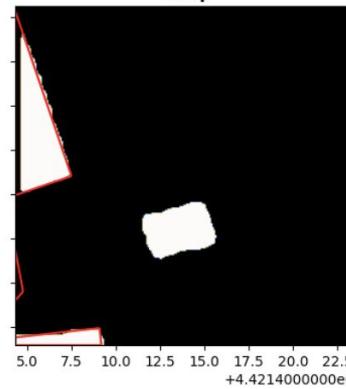
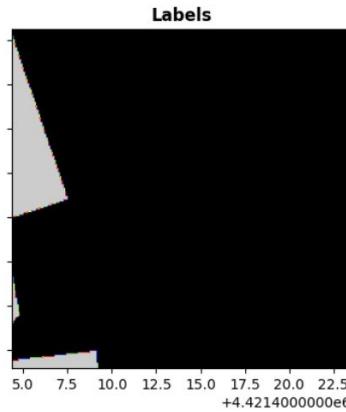
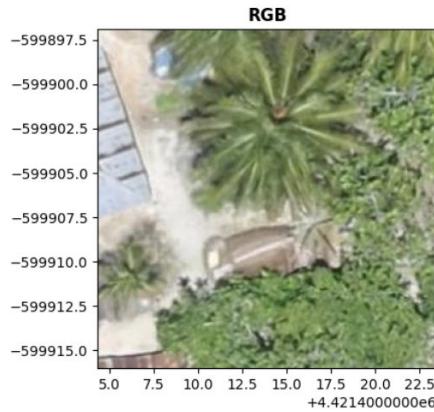
114 (sparse)



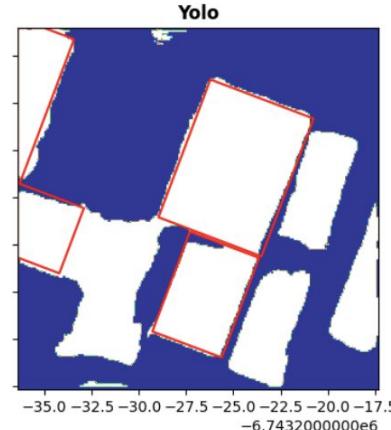
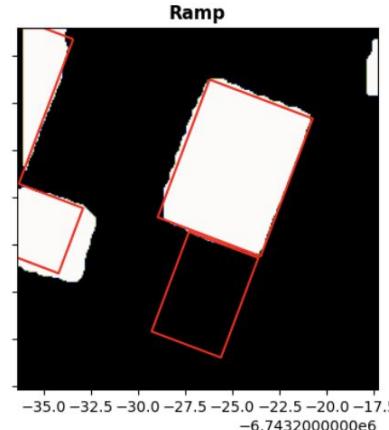
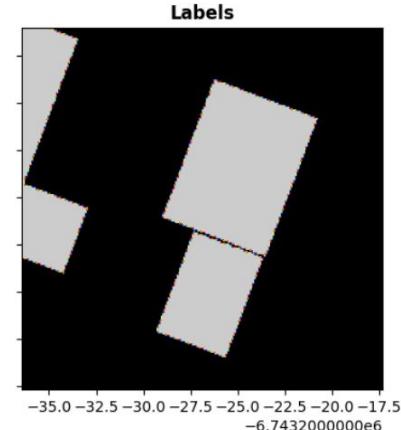
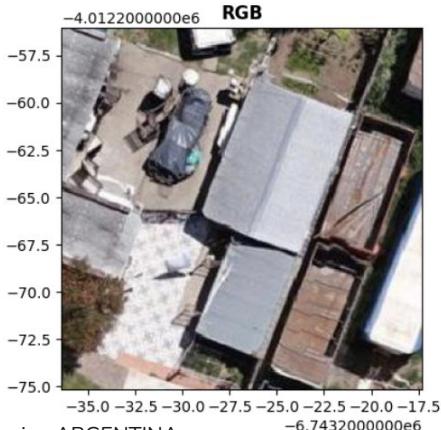
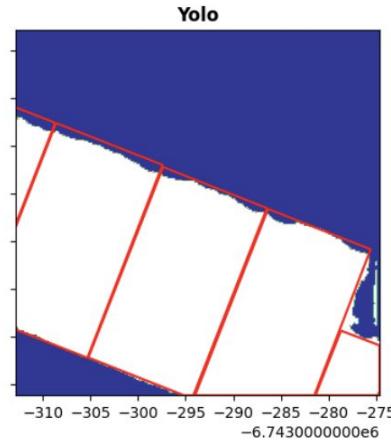
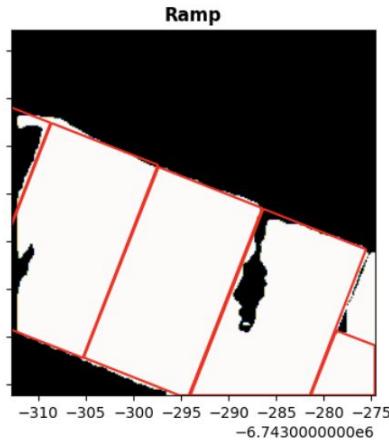
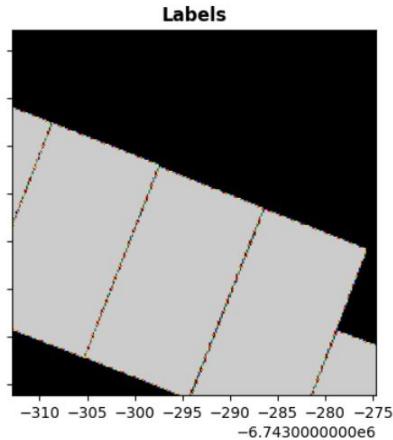
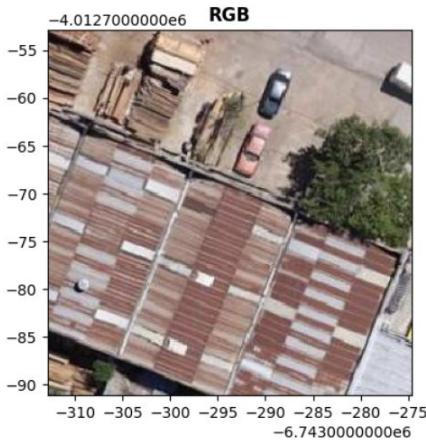
Christchurch NEW ZEALAND

113 (sparse)

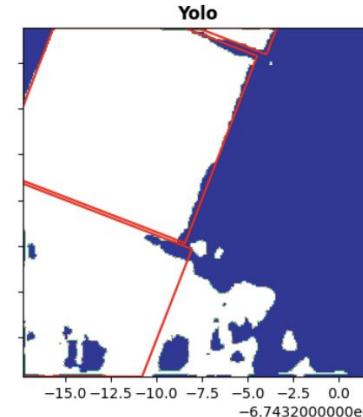
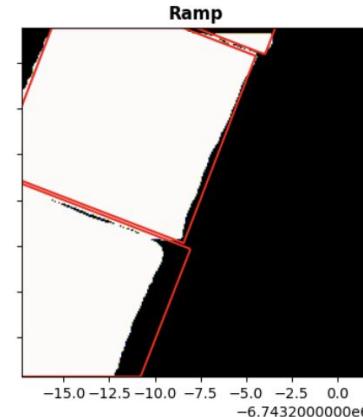
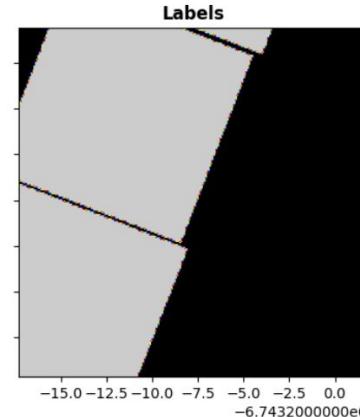
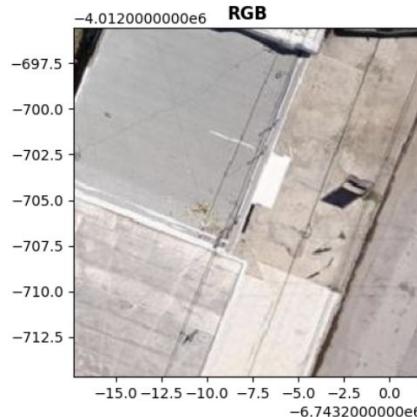
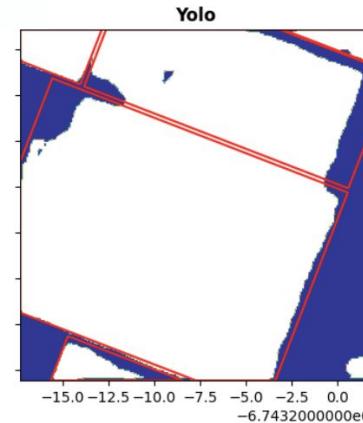
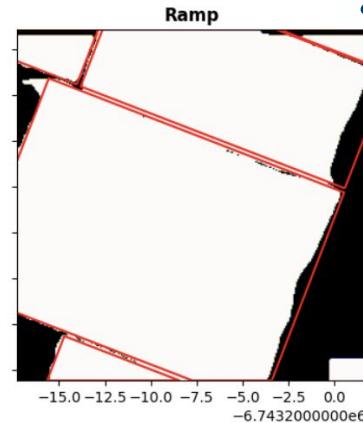
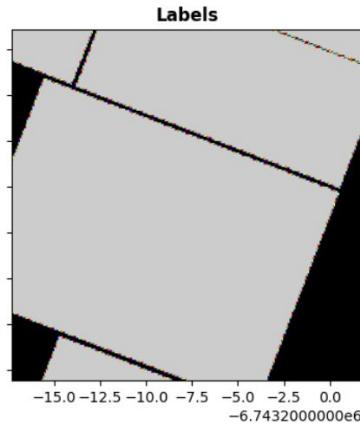
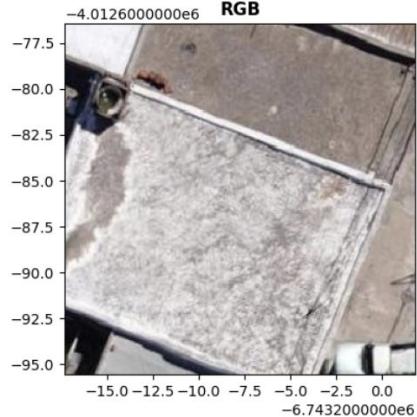




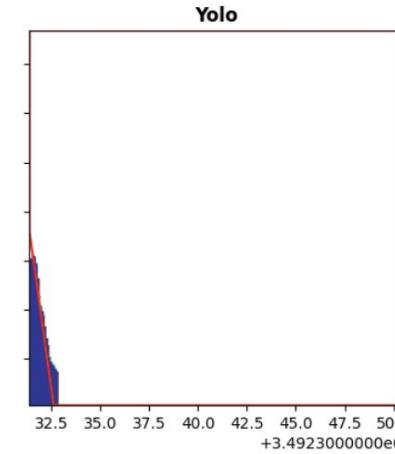
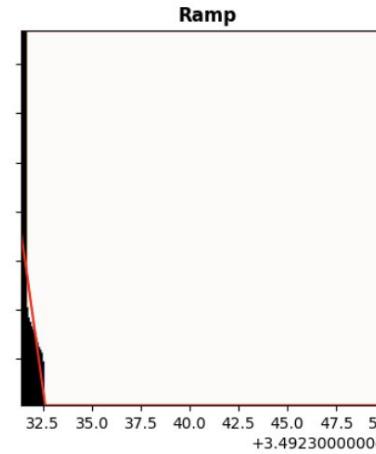
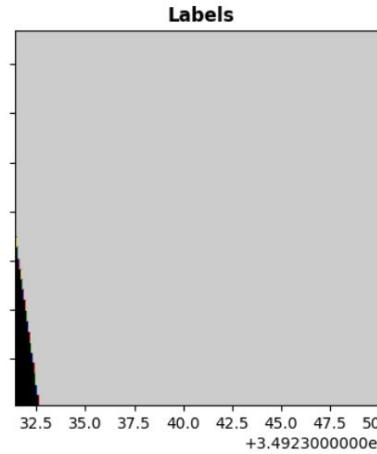
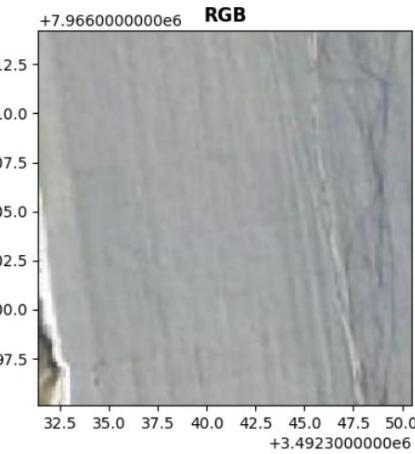
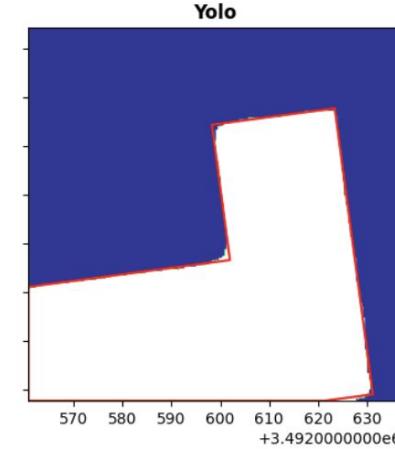
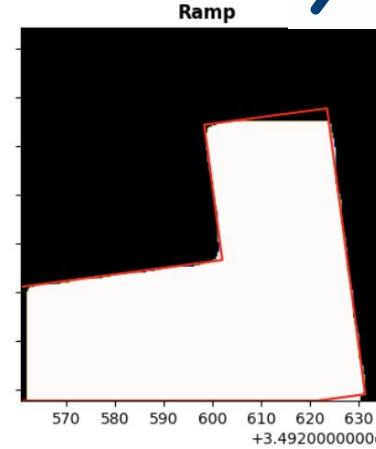
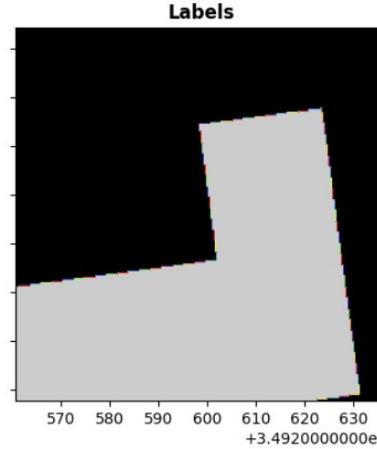
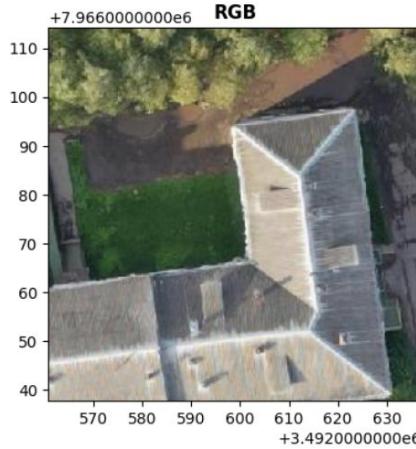
134 (grid)



Pergamino ARGENTINA

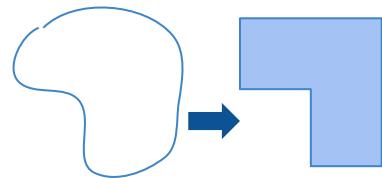
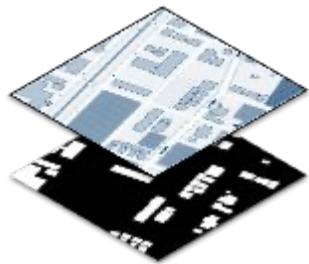


168 (sparse)











YOLO

RAMP



YOLO

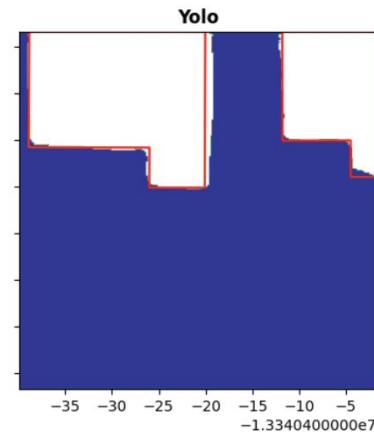
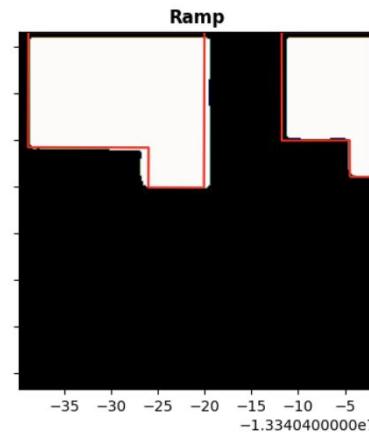
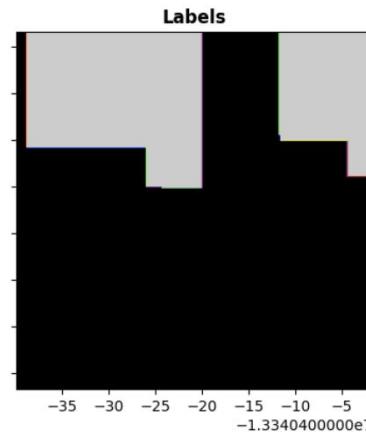
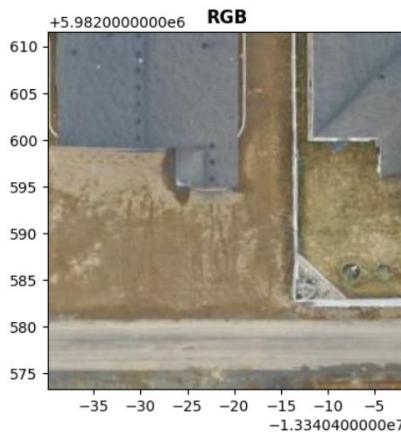
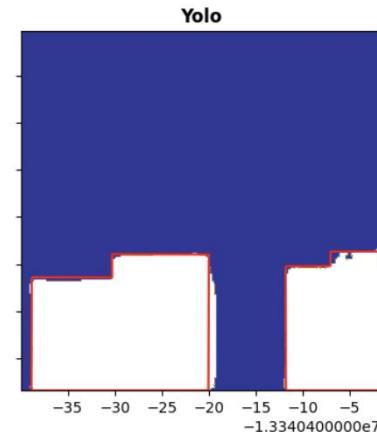
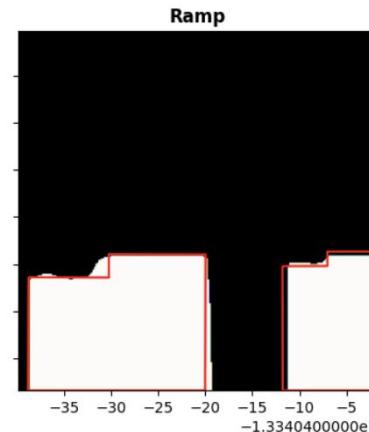
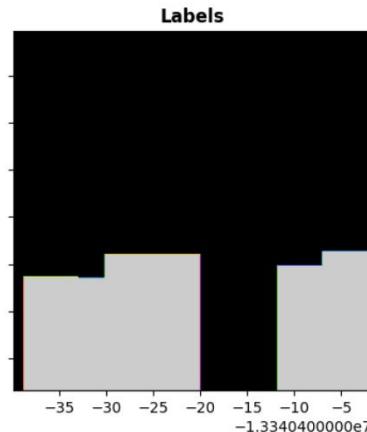
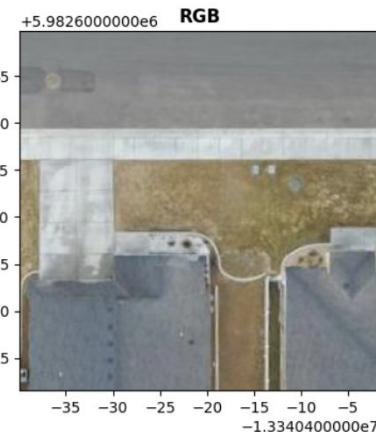
RAMP



RAMP

YOLO

Would you use these to map in OSM? And for disaster mapping?





<https://fair.hotosm.org/>



https://gitlab.heigit.org/azanchetta/fair_research



<en.osm.town/@ciupava>

The
Alan Turing
Institute

