A knowledge transfer approach for water body segmentation using PeruSAT-1 satellite's images.

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Importance of detecting water bodies

2017

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Importance of detecting water bodies

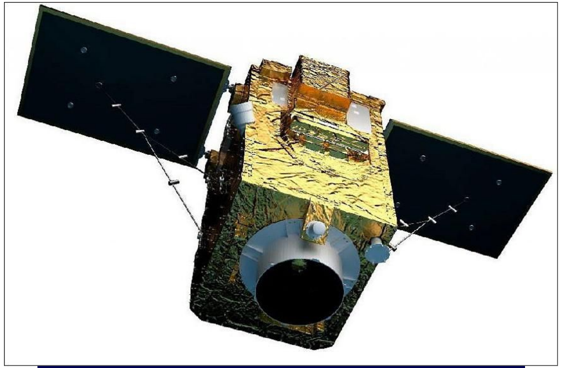
We focus our attention on the analysis of water-bodies (e.g. rivers, lakes, ponds) from the coast of Peru to assess the affected regions by the Niño costero phenomenon, which is a recurrent natural phenomenon in Peru and has a large impact on agricultural production, social services, and infrastructure.

Objective

In this work, we present a new approach for segmenting water surfaces from satellite images based on the application of convolutional neural networks. First, we explore the application of a U-Net model and then a transfer knowledge-based model. Our results show that both approaches are comparable when trained using an 680-labelled satellite image dataset; however, as the number of training samples is reduced, the performance of the transfer knowledge-based model, which combines high and very high image resolution characteristics, is improved.

VHR dataset: PeruSat-1

- Operating since september 2016
- Resolution 2.8 m/pixel
- 4 bands R,G,B, NIR
- Panchromatic Image 0.7m/pixel



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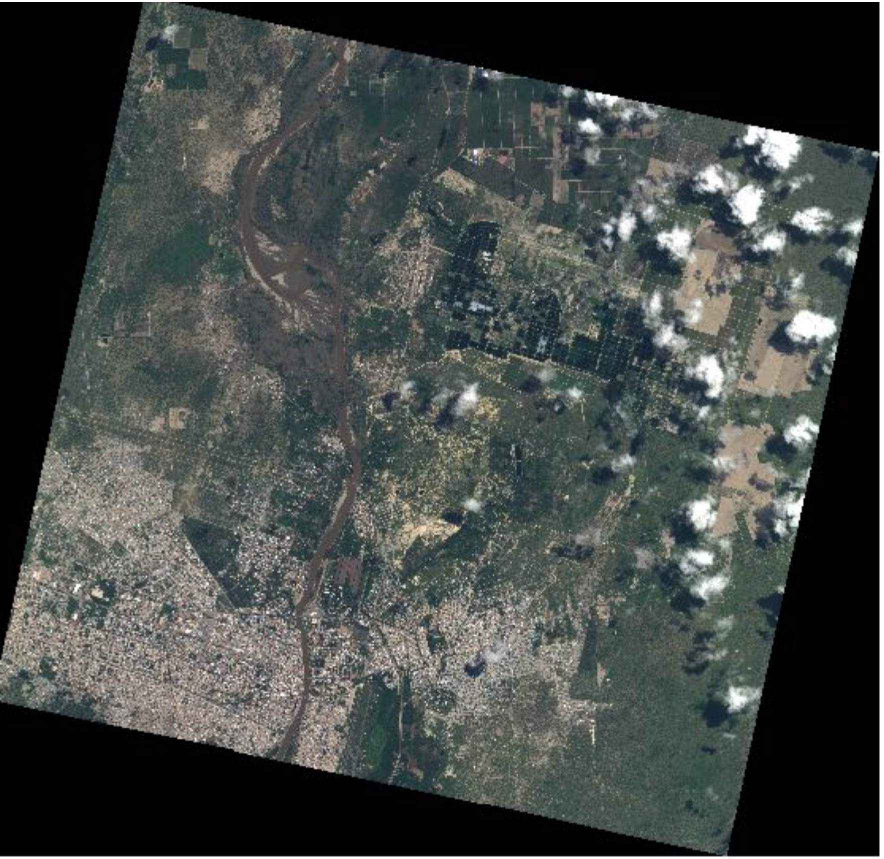
DEL PERU CONIDA

6040 rows x 6222 columns



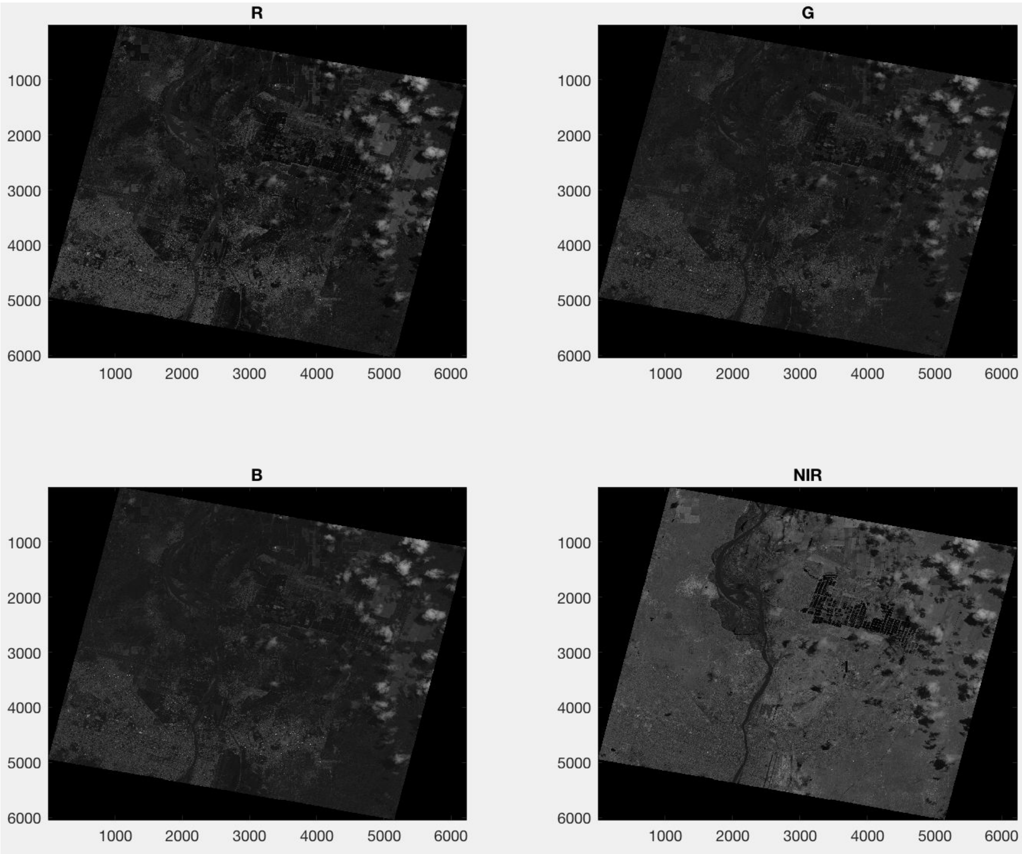


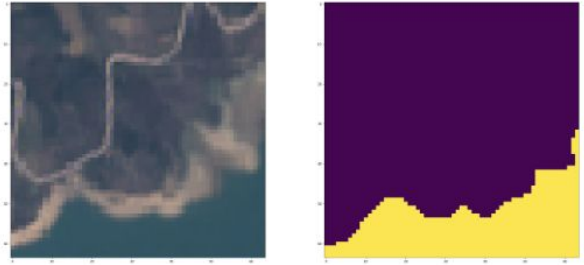
*Imagen de Perú-Sat 1

HR dataset: Sentinel

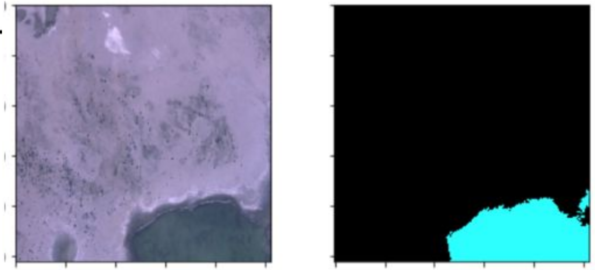
- Sentinel-2 is a European wide-swath, high resolution, multi-spectral imaging mission.
- 13 bands.
- In our study, we use 4 bands from this satellite (red, green, blue, and NIR), each of 10m per pixel resolution, to match the same characteristics of the PeruSAT-1 satellite.

Datasets

	Perusat-1	Sentinel_D1
Quantity	945	7670
Size	512x512	64x64
Resolution	2.8m/pixel	10m/pixel



Sentinel



Perusat-1

Perusat - Histogram

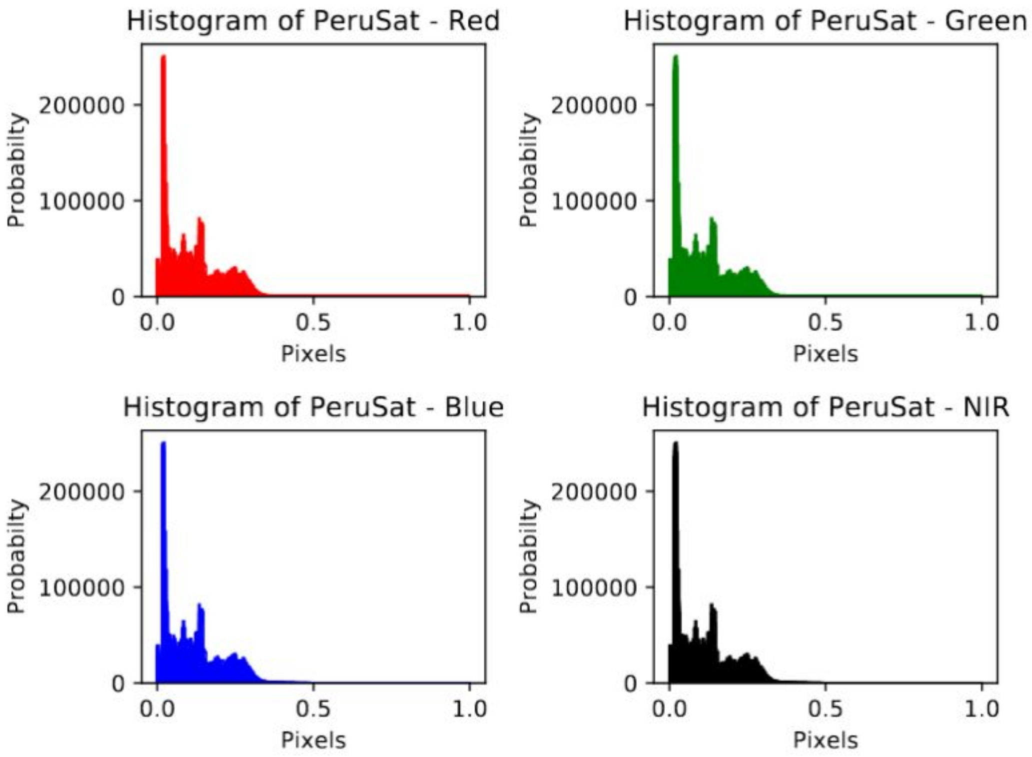


Fig.1 Histogram of all the dataset

Sentinel - Histogram

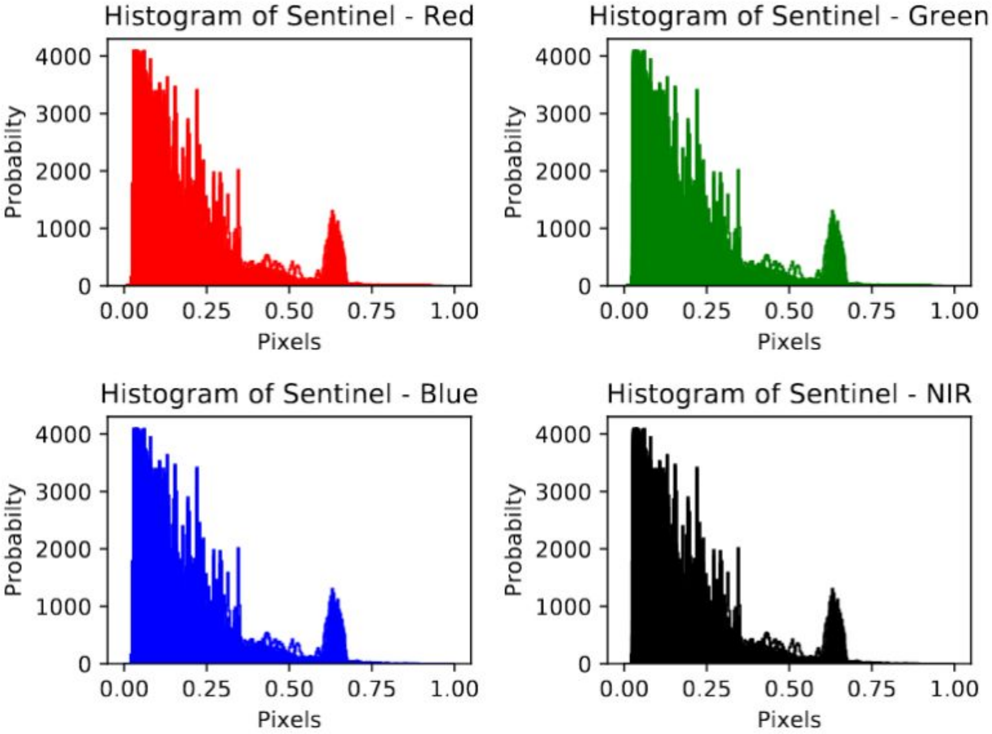


Fig.1 Histogram of all the dataset

Problem Description

01 **Distillation approach**

- How much online data are available? Are they sufficient?
- How low the low resolution actually is?

Model 1:

To train this model, we used images from the VHR dataset. The neural network architecture was based on a variation of the U-Net called TernausNet.

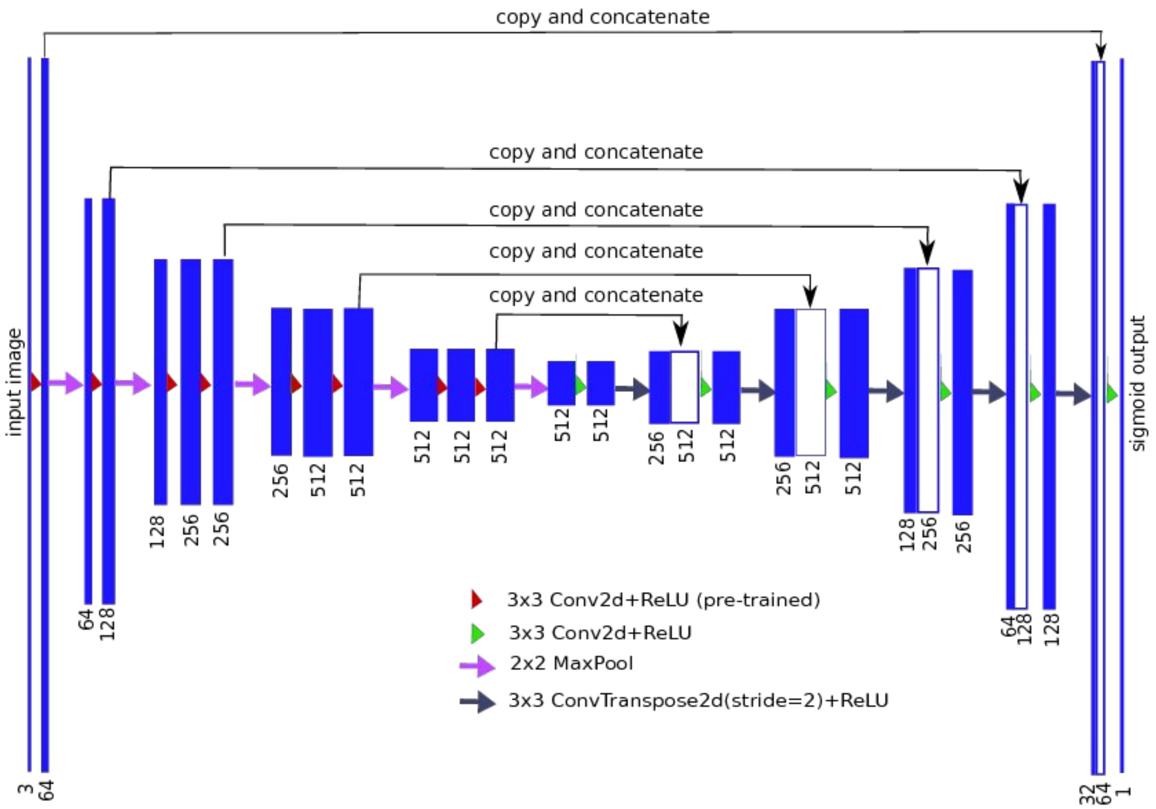


Fig.1. TernausNet:Unet + VGG11 encoder (Iglovikov, Shvets, 2018).

Model 2 (Parallel):

This architecture has two U-Nets, one working on high-resolution (HR) images, and the other working on very high-resolution (VHR) images, and both networks designed for performing the semantic segmentation, trained at once.

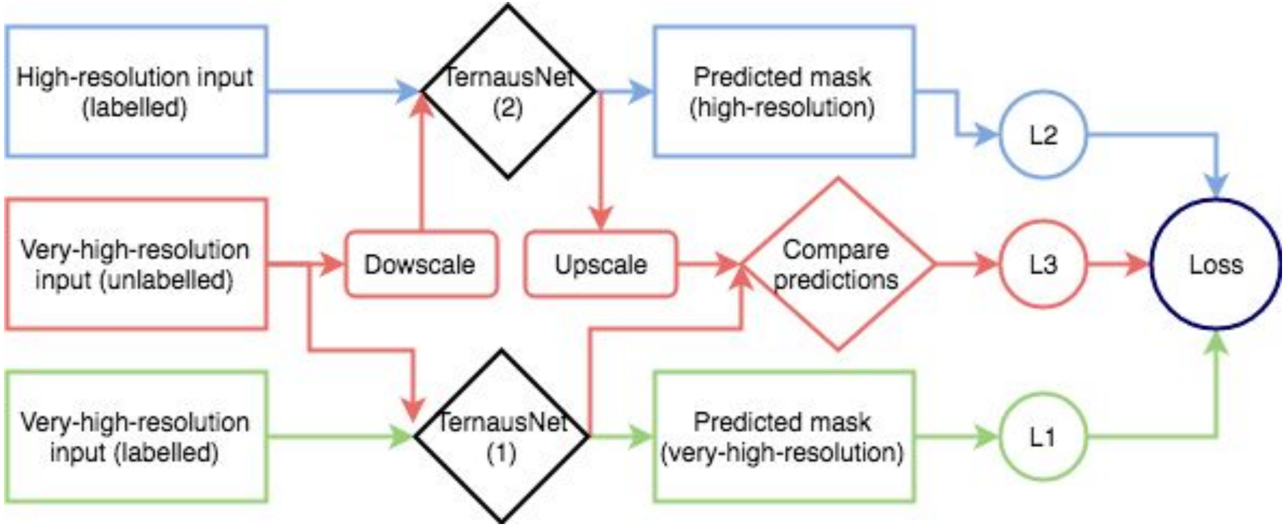


Fig.1. Knowledge transfer-based combined model that uses mapping information from high resolution images to improve the segmentation capability of the very high-resolution images.

Model 3 (Sequential):

Unlike the previous model the loss of the VHR_model is not affected only by the loss of the HR.

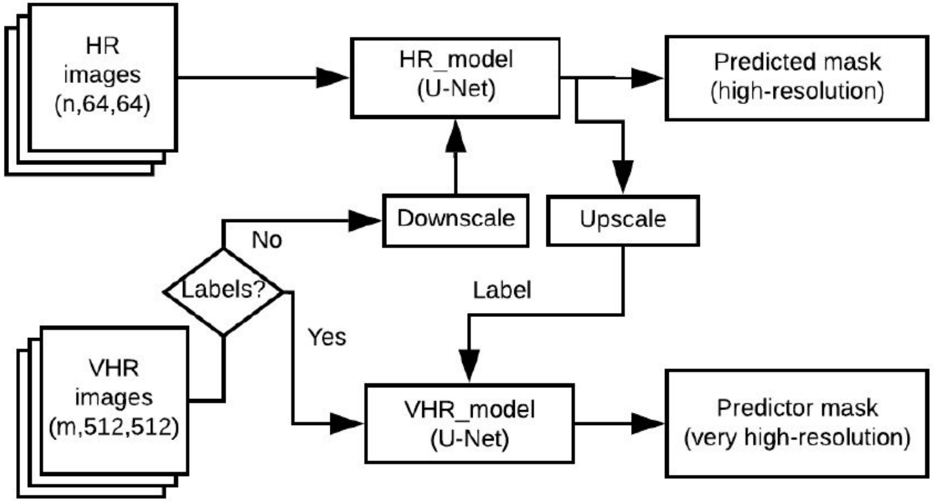


Fig. 1. Knowledge transfer based on two models, which uses mapping information from lesser resolution images to improve the segmentation capability of the very high-resolution images

Experiments And Results

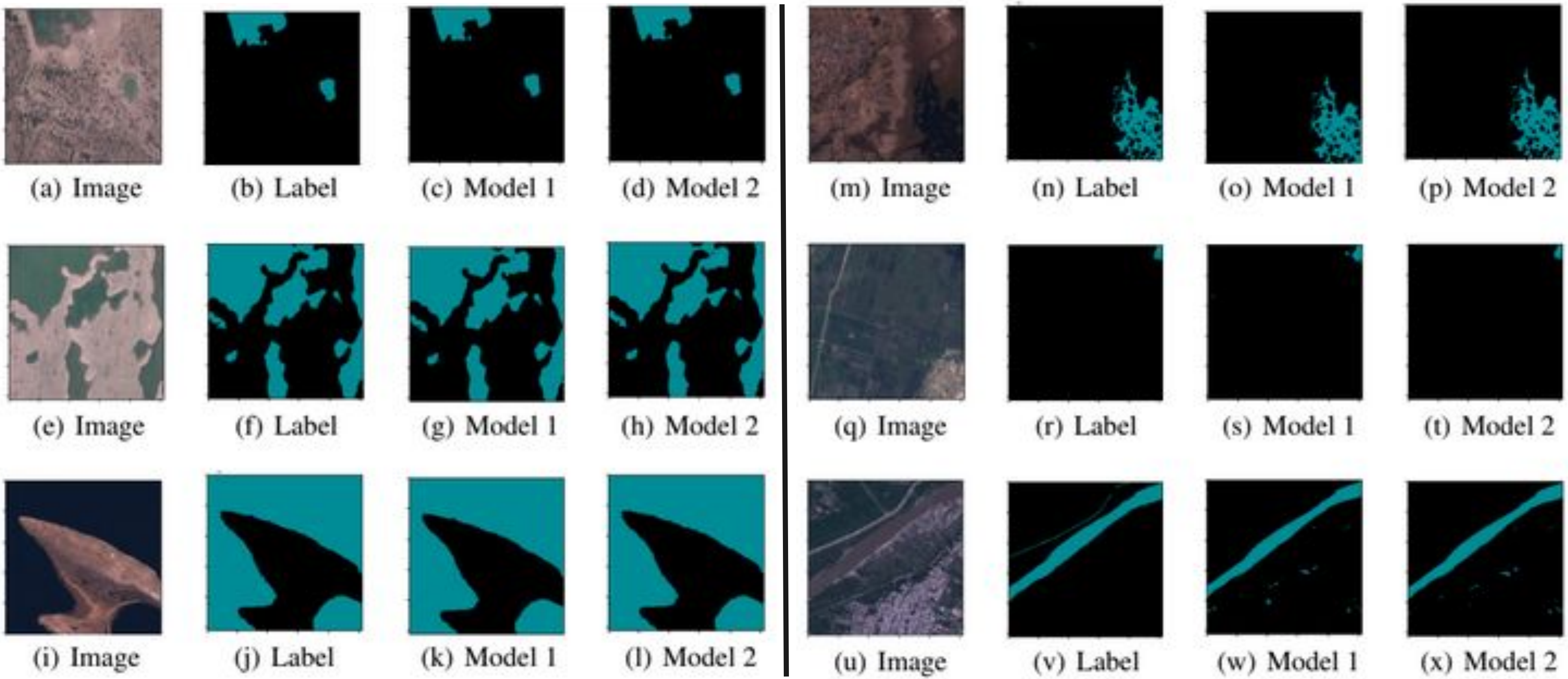
The HR-dataset was divided into:

- HR_dataset (Sentinel): 7671 Training(80%), and validation(20%) and test (10%)
- For the labelled VHR-dataset, we used 680, 170 and 95 samples for the training, validation, and testing dataset; and regarding the unlabelled data, we used 131, and 37, for the training, and validation.

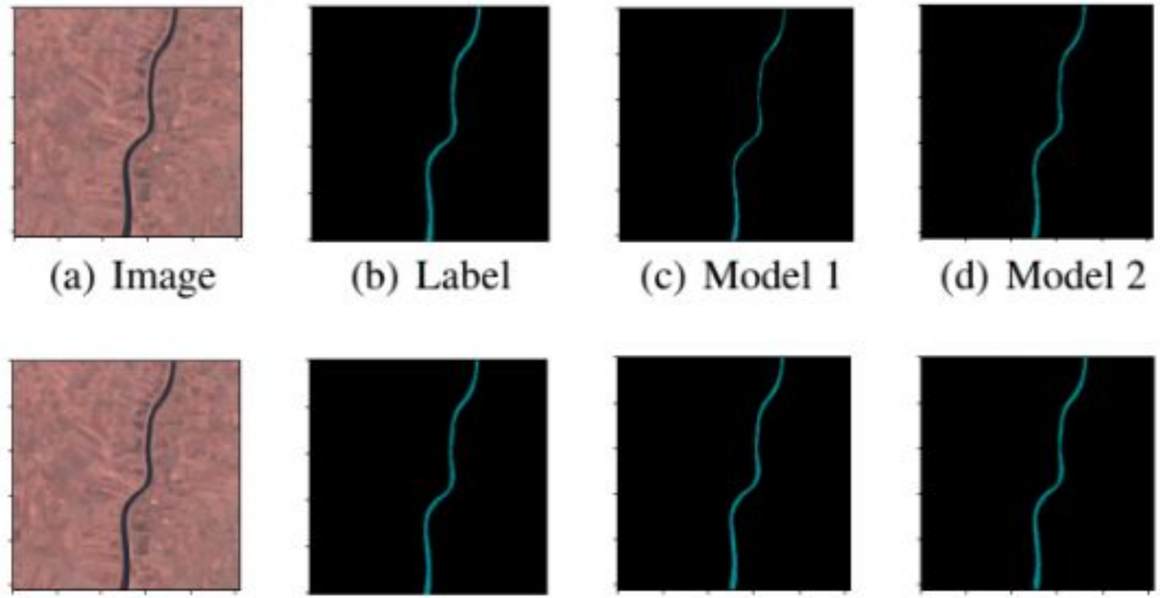
Experiments And Results

- All the experiments used the same VHR labelled testing dataset.
- Model 1 used all the labelled VHR data.
- Model 2 used the HR-dataset, and both, labelled and unlabelled VHR-dataset.

Results (680 training samples)



Results



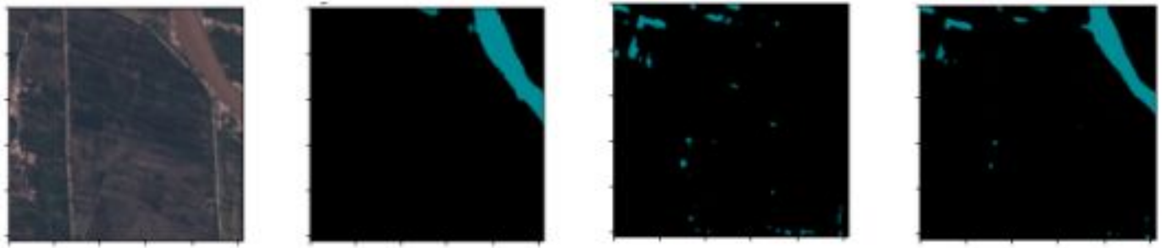
(a) Image (b) Label (c) Model 1 (d) Model 2

(e) Image (f) Label (g) Model 1 (h) Model 2

	Model 1		Model 2	
Training samples	Dice %	IoU %	Dice %	IoU %
68	78.43	64.62	88.40	79.61
680	97.63	95.36	95.78	92.14

This behaviour may suggest that model 2 takes advantage of different resolution in the training dataset to make the segmentation process more robust in the presence of complex cases.

Results

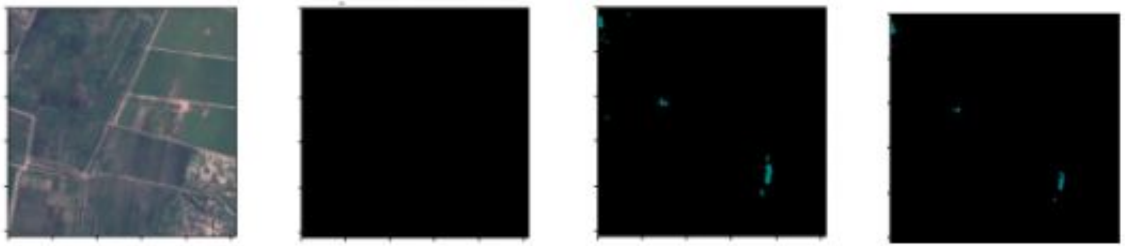


(i) Image (j) Label (k) Model 1 (l) Model 2

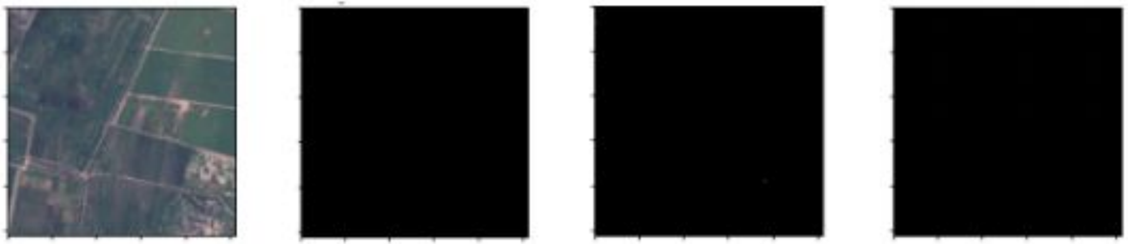
(m) Image (n) Label (o) Model 1 (p) Model 2

	Model 1		Model 2	
Training samples	Dice %	IoU %	Dice %	IoU %
68	21.79	18.22	77.64	66.57
680	87.15	77.56	84.53	74.14

Results



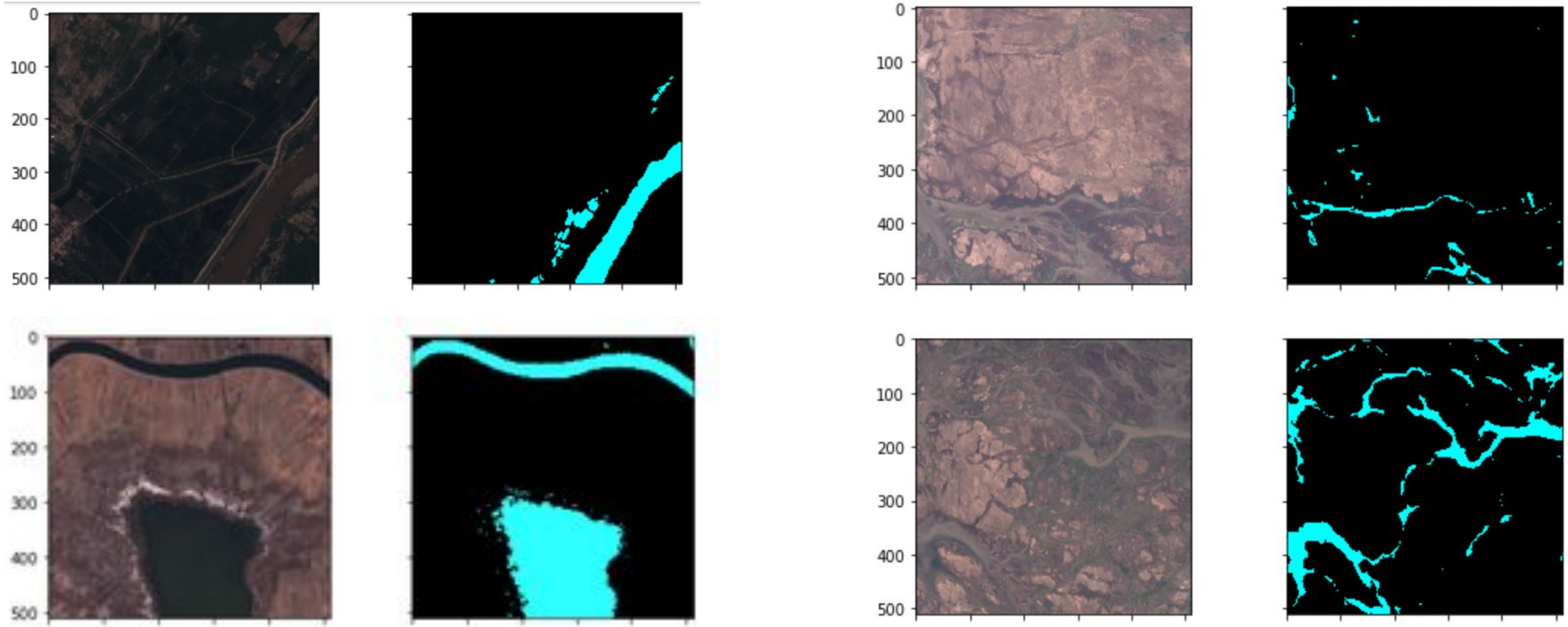
(q) Image (r) Label (s) Model 1 (t) Model 2



(u) Image (v) Label (w) Model 1 (x) Model 2

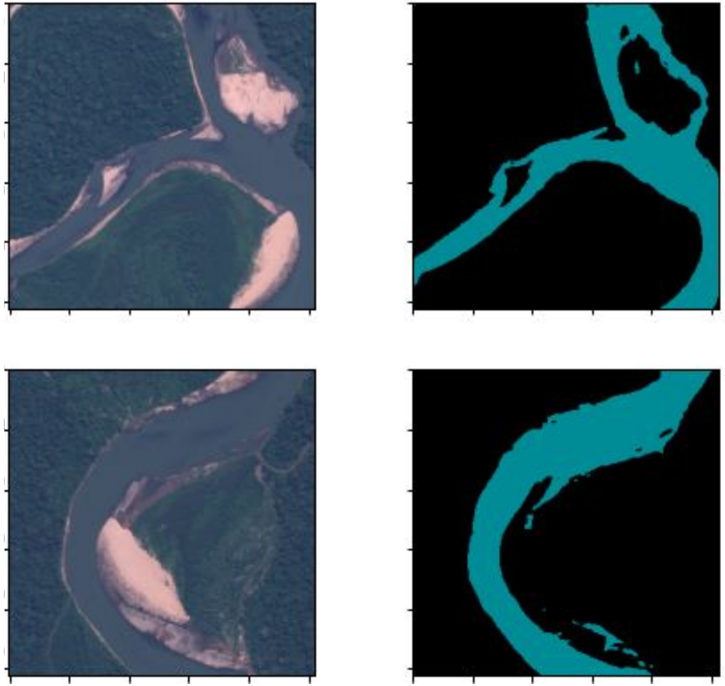
	Model 1		Model 2	
Training samples	Dice %	IoU %	Dice %	IoU %
68	0.08	0.00	0.13	0.00
680	21.71	20.00	20.49	20.00

Predictions in the coast

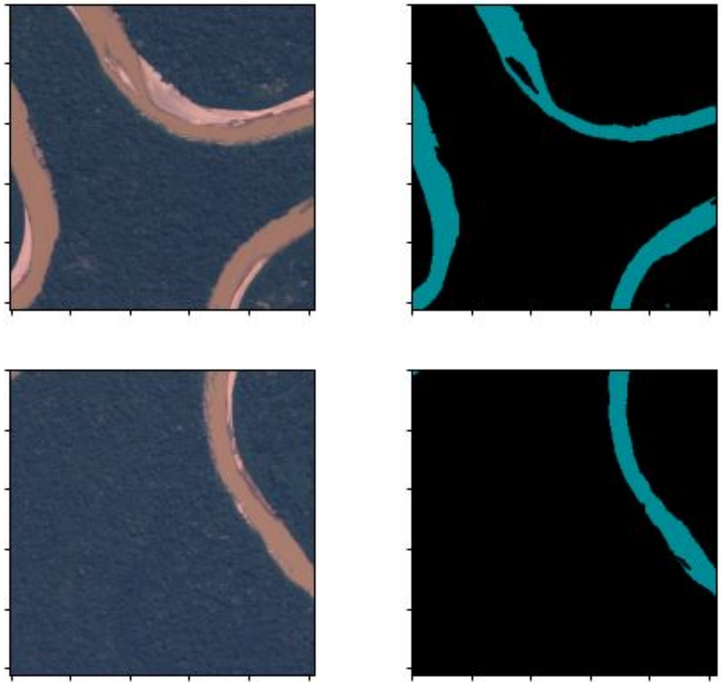


a) Imagen b) Prediction a) Imagen b) Prediction

Predictions in the jungle

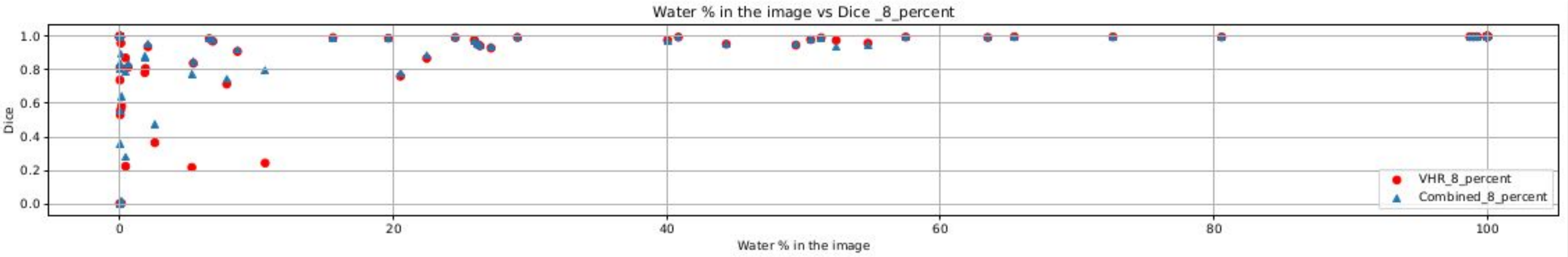


a) Imagen b) Prediction

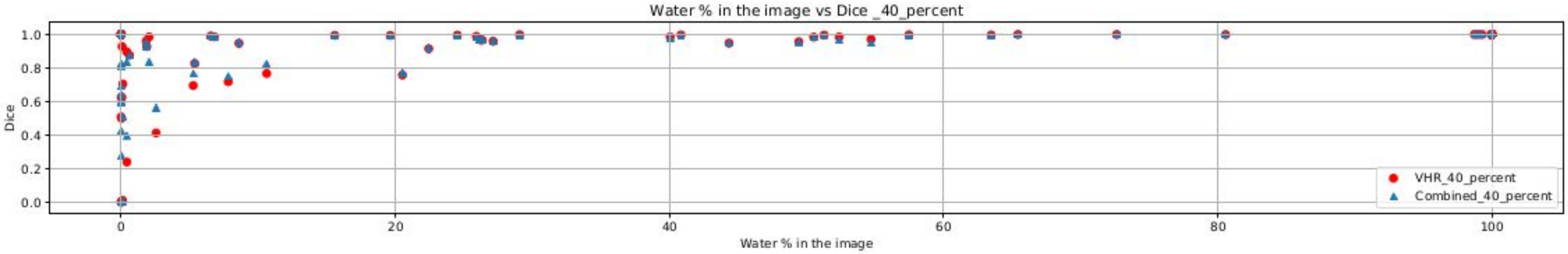


a) Imagen b) Prediction

Water vs Dice (68 training samples of VHR)



Water vs Dice (170 training samples of VHR)



Water vs Dice (680 training samples of VHR)