

DETECTION OF HOUSING AND AGRICULTURE AREAS ON DRY-RIVERBEDS FOR THE EVALUATION OF RISK BY LANDSLIDES USING LOW-RESOLUTION SATELLITE IMAGERY BASED ON DEEP LEARNING. STUDY ZONE: LIMA, PERU

Brian Cerron, Cristopher Bazan & Alberto Coronado

National University of Engineering

Lima 15333, Peru

{bcerronr, cristopher.bazan}@uni.pe, macoronado@uni.edu.pe

ABSTRACT

The expansion of human settlements in Peru has caused risk exposure to landslides. However, this risk could increase because the intensity of the El Niño phenomenon will be greater in the coming years, increasing rainfall on the Peruvian coast. In this paper, we present a novel methodology for detecting housing areas and agricultural lands in low-resolution satellite imagery in order to analyze potential risk in case of unexpected landslides. It was developed by creating two datasets from Lima Metropolitana in Peru, one of which is for detecting dry riverbeds and agriculture lands, and the other for classifying housing areas. We applied data augmentation based on geometrical methods and trained architectures based on U-net methods separately and then, overlap the results for risk assessment. We found that there are areas with significant potential risk that have been classified by the Peruvian government as medium or low risk areas. On this basis, it is recommended obtain a dataset with better resolution that can identify how many housing areas will be affected and take the appropriate prevention measures. Further research in post-processing is needed for suppress noise in our results.

1 INTRODUCTION

The detection of landslides in satellite images has received great attention in recent years, due to its relationship with urban planning and land use. Based on the research of Wang et al [1], El Niño phenomenon will have greater intensity in the coming years, whose effects will generate landslides and floods in the South American Pacific coastal area, but it is in Peru where the effects of this phenomenon have a greater socioeconomic impact due to its geographical location, poor urban planning and the activation of dry riverbeds¹ that had remained passive for years, as observed in 2017, when there was at least three hundred and seventy two thousand damaged homes, according to statistics from INDECI [2].

One of the ways to analyze this problem is to have information about the landslide susceptibility which it has received extensive research. Moayedi et al.[3] developed a hybrid model called PSO-ANN to create landslide susceptibility maps over the city of Kermanshah, Iran, and more recently Ghorbanzadeh et al [4] showed that convolutional neural networks of deep learning have better performance than traditional machine learning methods that use 4-band images from Nepal and China. In addition, there are datasets that contain land cover classification and building footprint detection such as DeepGlove [5], EuroSat [6] and SpaceNet [7] that have promoted the development of different investigations related to semantic segmentation approach [8, 9, 10].

¹Dry riverbed is a type of landslide which course is channeled, as shown in Figure 2, and in Peru it is common to find constructions in the course of dry riverbeds as shown in Figure 3

Although there are numerous approaches to the detection of landslides and buildings separately, none analyzes the direct relationship between floods or landslides in populated and agricultural areas. In addition, there is no dataset available focused on Peruvian geography. So this is the main reason a novel approach is developed whose methodology consists in: (1) obtaining two corresponding novel datasets, the first has dry riverbeds, risk areas and agriculture, while the second one has residential, human settlement and industrial areas; (2) the increase of the dataset that performs geometric operations, as well as its preprocessing; (3) The selection of the appropriate deep learning method that can classify pixels; and (4) Fusion of results for risk analysis. Finally, discussion and future work that will be developed for this approach.

2 DATASET AND EVALUATION METRIC

The low resolution satellite imagery used for both tasks were collected by RapidEye satellite provided by Planet Labs through its imagery exploration toolkit. This satellite imagery has 3-band natural color (red, green, blue) and a 5m pixel resolution. For the purpose of this research, the full dataset covers a total of 450 km^2 of our study zone: Lima, Peru. Each image has been labelled manually using LabelMe software [11] as the selected annotation toolkit. Each image is paired with a ground truth mask², samples are shown in Figure 4 and Figure 5. The masks are images with a total of 3 different classes and depend on the task. Task 1 is for detecting mainly dry riverbeds and agriculture lands and Task 2 for detecting types of housing areas, the descriptions of each class are shown in Table 1 and Table 2.

We carefully annotated our dataset to avoid overlapping in the annotations and they do not always have all of the classes in one image. The annotations are not perfect due to the fact that many areas can be not seen easily to determine for which class belongs.

Table 1: Description of classes for task 1

Value	Class	RGB	Description
1	Dry riverbed	(1,0,0)	channel where used to flow a river
2	Inhabited land	(0,1,0)	any kind of building
3	Agriculture land	(1,1,0)	croplands, farms
0	Background	(0,0,0)	others

Table 2: Description of classes for task 2

Value	Class	RGB	Description
1	Residential	(0,1,0)	area where housing predominates
2	Human settlement	(1,0,0)	areas in initial process of colonization
3	Industrial	(1,1,0)	industrial plant, farm, warehouse
0	Background	(0,0,0)	others

We used the mean overlap or dice coefficient(F1 score) as evaluation metric:

$$Dice - Coefficient = \frac{1}{n} \sum_{i=1}^{c=n} S, S = \frac{2TP_c}{2TP_c + FP_c + FN_c}$$

where TP_c stands for true positive pixel in class c applied to the full output of the model in evaluation; FP_c , false positive pixels in class c and FN_c , false negative pixels in class c . Then the average is computed over all the different classes that we selected depending on the task.

²RGB color code for visualization

3 METHODS

In order to do an evaluation of risk areas, we split the workflow in two tasks, following the flowchart shown in Figure 6. Both tasks are designed like a segmentation-based approach. The first task aims to identify mainly dry riverbeds and agriculture lands, and the second task aims to identify different types of housing areas in satellite imagery. The main reason is to overlap the results from both tasks and find the housing areas over dry riverbeds, which implies the housing areas are in potential risk in case of unexpected landslide.

3.1 DATA AUGMENTATION

On small-scale dataset, data augmentation has been playing a significant role for deep learning models, since this technique tackles potential problems(i.e. overfitting), improves the distribution of the dataset and the generalization ability of the deep learning model[12]. Since we have a small number of training samples in both tasks, we used data augmentation with different methods which include rescaling, flipping, cropping, rotation and canal shuffling. The data collection for each task described in section 2 has been preprocessed for each semantic segmentation model. For the first task, a large satellite image has been sliced in 100 chips with a size of 590x590 pixels with overlapping, and for the second task the selected size was 512x512 pixels. For both tasks we only considered chips as inputs if they had annotations.

3.2 MODEL ARCHITECTURES

Since this is a semantic segmentation approach for multi-class segmentation, three architectures have been implemented and compare each other using the evaluation metric mentioned in section 2. U-Net architecture [13] was initially used for biomedical image segmentation, but it has been proved that it has awesome performance in satellite imagery tasks [14, 15] with small quantities of data. This architecture has two main sequential sides: The first side of the model, known as down-sampling, extracts feature maps by applying 3x3 convolutions using rectified linear unit (ReLU) as activation function, then 2x2 max pooling operation with a stride value of 2. The second side consists in upsampling the feature maps, generated by the downsampling side, then operates with a 2x2 convolution, this will expand it to the original input size. Deep Residual Unet architecture [16] was proposed for road extraction task, this model is based on the combination of the U-Net architecture and residual neural network. The residual unit tackles the degradation problem, so information propagation through the network will not face this issue. Finally, Deep UNet architecture [17], which is also based on U-Net but it uses down-sampling blocks in the downsampling side and up-sampling blocks in the upsampling side. Each model outputs a 2-D matrix, which each pixel is assigned to its corresponding predicted class value.

3.3 IMPLEMENTATION DETAILS

The mentioned models were implemented on Tensorflow and have been trained in the cross-entropy loss function. We made comparisons using different optimizers such as SGD, RMS prop, Adam with different learning rate(0.01, 0.001, 0.0005), Nadam and Adadelata. A Nvidia GeForce GTX 1080 was used to train our networks, each of them with 300 epochs and a batch size of 4 images and masks.

4 RESULTS

The results of our experiments are based on the validation set. We evaluated the performance of different optimizers mentioned in 3.3 with the architectures and experimental results, based on Figure 1, shows the Adadelata, NAdam and Adam with learning rate of 0.0005 have slightly better performance. Then we computed the evaluation metric of each class, since it is more indicative for the performance of the selected architectures and optimizers.

The results and comparison are shown in Table 3 and Table 4 for each task. The columns shows the best performer architecture with different optimizers and F1 score separated into the classes, then the average with background and without background. For the first task, Unet with Adadelata optimizer

generated the best performance and for the second task, Residual Unet with Adadelata optimizer, as well. Samples of the original input image, ground truth and prediction mask from each task are shown Figure 7 and Figure 8.

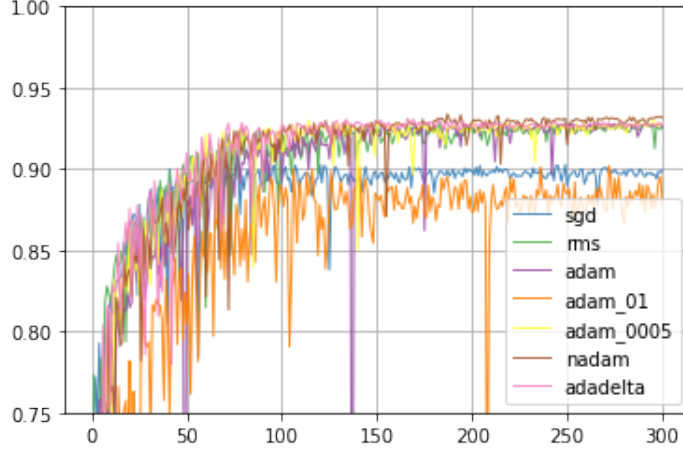


Figure 1: Performance results for the different optimizers.

Table 3: Experimental results for Task 1

Model	F1 Score					
	0	1	2	3	Avg	Avg (w/o background)
Unet + Adam	0.95	0.56	0.722	0.905	0.784	0.729
Unet + Adadelata	0.957	0.641	0.722	0.918	0.809	0.760
Unet + Adam($l_r=0.0005$)	0.953	0.593	0.72	0.913	0.795	0.742

Table 4: Experimental results for Task 2

Model	F1 Score					
	0	1	2	3	Avg	Avg (w/o background)
Residual Unet + Adadelata	0.961	0.531	0.77	0.319	0.645	0.54
Residual Unet + Adam	0.963	0.551	0.803	0.232	0.637	0.529
Residual Unet + NAdam	0.965	0.608	0.829	0.096	0.603	0.509
Residual Unet + Adam($l_r=0.0005$)	0.961	0.547	0.785	0.269	0.641	0.534

5 CONCLUSIONS AND FUTURE WORK

In this work, we have proposed a methodology for detecting housing areas in low-resolution satellite imagery in order to analyze potential risk in case of unexpected landslides. The proposed methodology verified that there is housing areas lying on dry riverbeds which implies that these areas are in significant potential risk, even though that these are considered as low susceptibility areas based on the map in Figure 9.

For future work, we will focus on post processing techniques in order to obtained better results, also it is very promising that the performance will improve with different modern semantic segmentation algorithms. It would be beneficial for monitoring the urban planning problem in real time in the Peruvian coast and other places with similar geography.

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A APPENDIX: SAMPLE OF DRY RIVERBED IN PERU

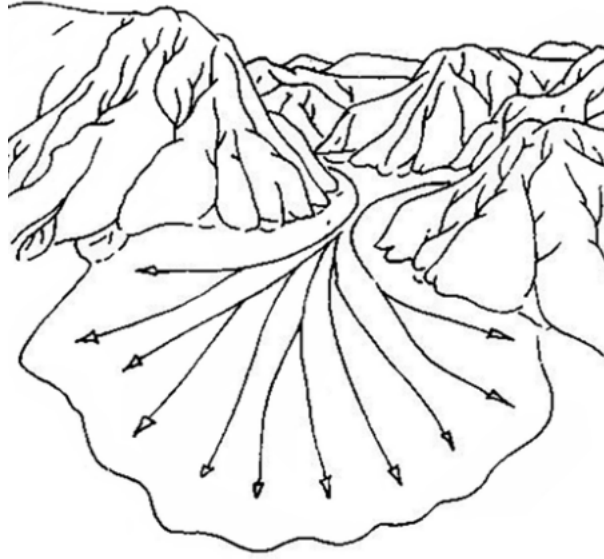


Figure 2: Idealized scheme of the operation of an alluvial fan at the exit of a dry riverbed, with indication of the flow directions. Image from Pedraza, J. Geomorfología: principios, métodos y aplicaciones(Madrid:Rueda, 1996),414



Figure 3: Huaycan - Lima, the yellow lines show the direction of debris flow, the red ones (A) indicate the houses built in the middle of dry riverbed. Image from Villacorta Chambi et al. Peligros geológicos en el área de Lima Metropolitana y la región Callao N° 59(Lima:Instituto Geológico, Minero y Metalúrgico,2015)

B APPENDIX: DATASET VISUALIZATION

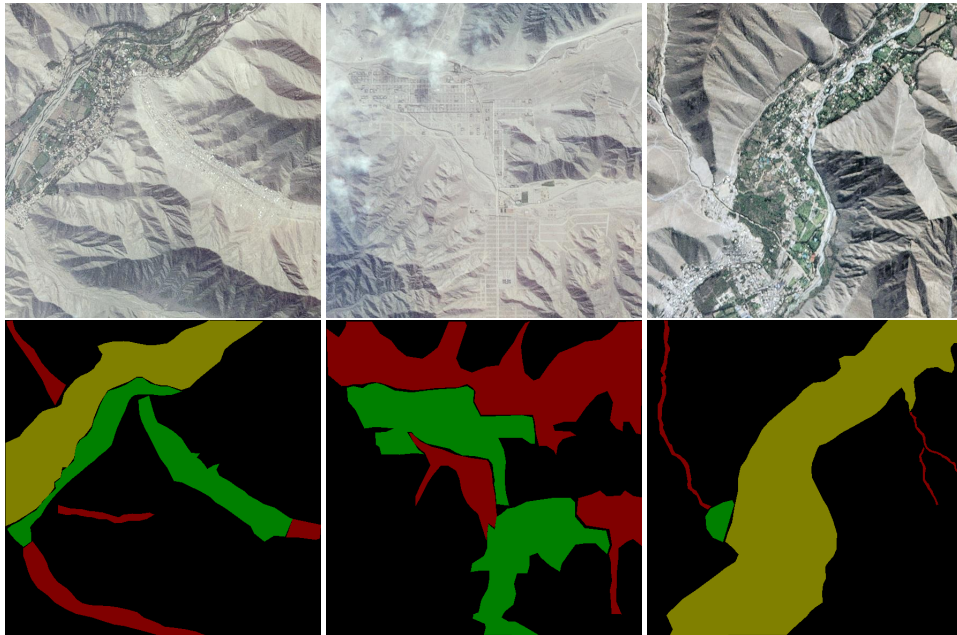


Figure 4: Samples from dataset for Task 1 with the mentioned classes in Table 1

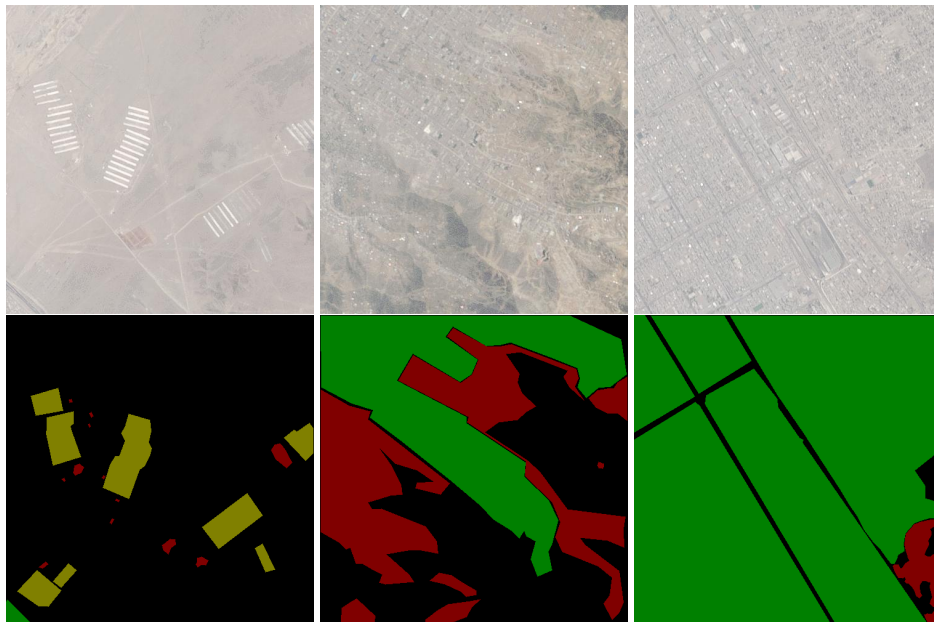


Figure 5: Samples from dataset for Task 2 with the mentioned classes in Table 2

C APPENDIX: FLOWCHART

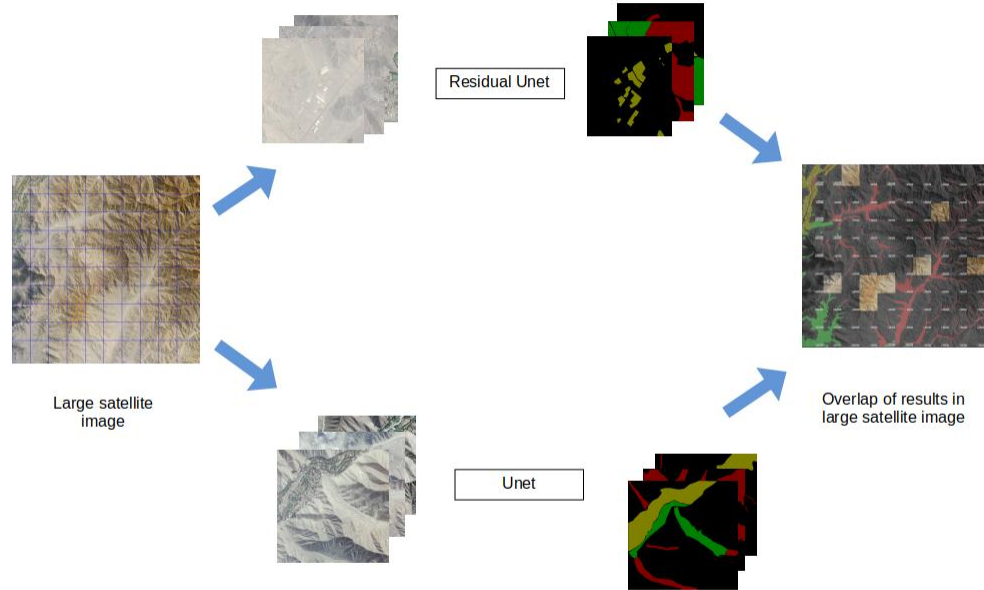


Figure 6: Flowchart of the proposed methodology.

D APPENDIX: PREDICTIONS

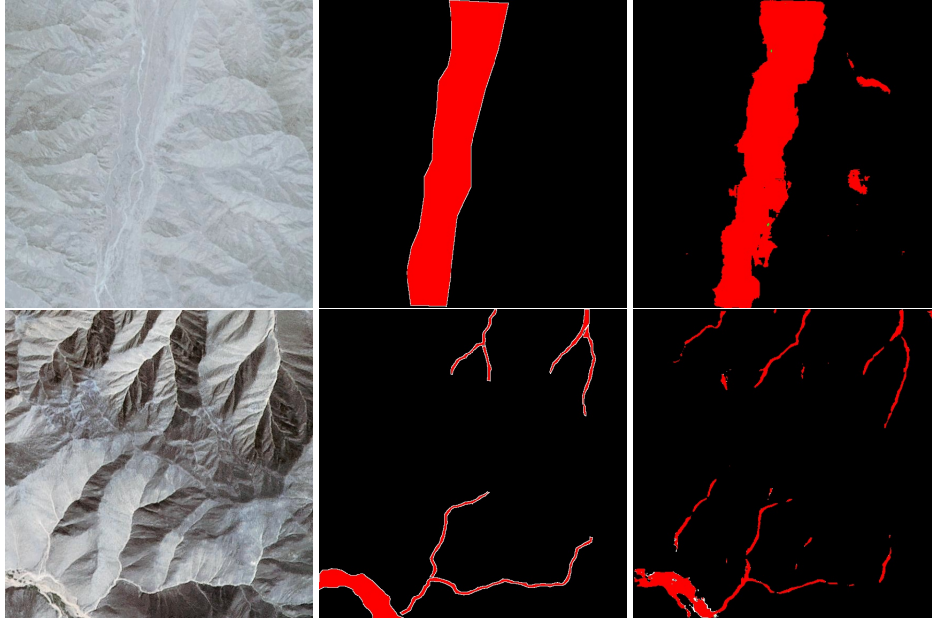


Figure 7: Samples of the results from Task 1. First column has the original images, second column has the ground truth mask an the third has the predicted mask.

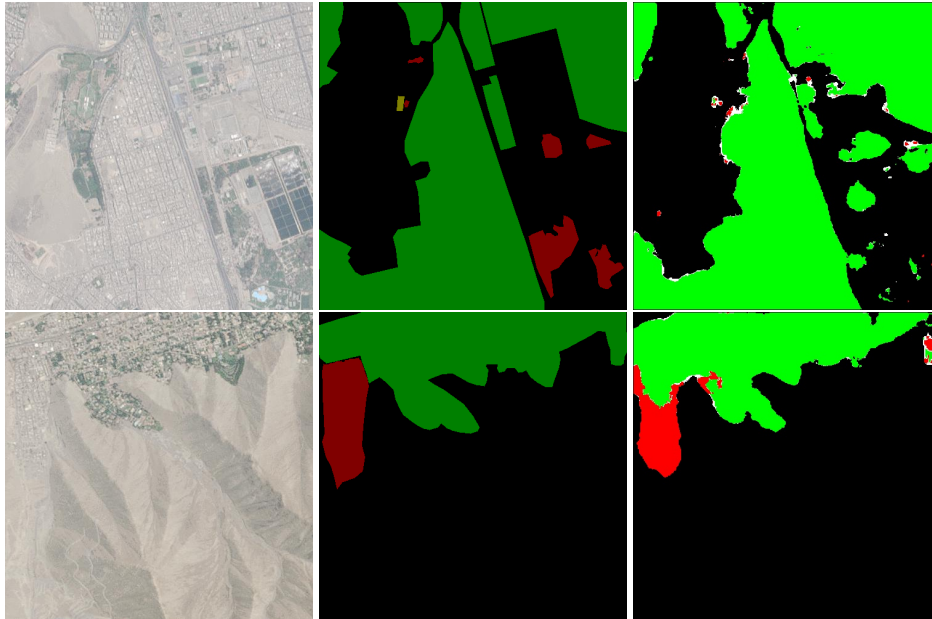


Figure 8: Samples of the results from Task 2. First column has the original images, second column has the ground truth mask an the third has the predicted mask.

E APPENDIX: FLOOD SUSCEPTIBILITY MAP



Figure 9: The flood susceptibility map provided by INGMMET. The blue circles indicate areas found by the algorithm with a high potential risk. Image from Villacorta Chambi et al. Peligros geológicos en el área de Lima Metropolitana y la región Callao N°59(Lima:Instituto Geológico, Minero y Metalúrgico,2015)