A comparison on supervised machine learning classification techniques for semantic segmentation of aerial images of rain forest regions

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Abstract: Segmentation is one of the most important operations in Computer Vision. Partition of the image in several domain-independent components is important in several practical machine learning solutions involving visual data. In the specific problem of finding anomalies in aerial images of forest regions, this can be specially important, as a multilevel classification solution can demand that each type of terrain and other components of the image are inspected by different classification algorithms or parameters. This work compares several common classification algorithms and assess their reliability on segmenting aerial images of rain forest regions as a first step into a multi-level classification solution. Finally, we draw conclusions based on the experiments using real images from a publicly available dataset, comparing the results of those classification algorithms for segmenting this kind of images.

1 INTRODUCTION

One of the most important operations in Computer Vision is segmentation. The aim of image segmentation is the domain-independent partition of the image into a set of regions which are visually distinct and uniform with respect to some property, such as grey level, texture or colour (Freixenet et al., 2002). Semantic segmentation aims at pixel-wise classification of images into high-level components and is needed in challenging tasks such as remote sensing, driving assistance systems or precise object localisation in general. The input image is divided into regions, which correspond to the high-level objects of the scene (Heitz and Koller, 2008).

The global community have spent a reasonable attention on the deforestation records of the Amazon rainforest. However, the Amazon region is threatened by agents that take advantage of its dimension (larger than most countries on earth). So far, most of the academic efforts are concentrated on statistics and modelling of the ecosystem behaviour. This work, on the other hand, is part of an effort to move from statistics into action. Our goal to equip the preservation agents and authorities with methodologies and tools that enables them to take immediate action, so that the deforestation in course can be stopped, not only measured. A critical success factor of any tool is its ability to automatic acquire and classify sensory data, specially imagery information taken from aerial aircrafts (manned or unmanned). It is important to mention that the project's final goal is not to provide a fully automatic classification of aerial forest images, but, rather, a supporting decision making tool to dramatically reduce the number of images to be analysed by any human being from thousands to a few dozen of candidate images. This work is about how the segmentation process of Amazon's rain forest aerial images could be done, before any relevant classification of anomalies on those images.

In aerial images (orthographic photos), different types of terrain have different characteristics that are not always easily separable by a single segmentation criteria. Color or multi-spectral information is very useful to the segmentation of aerial images, but most existing methods which use multi-spectral features alone tend to produce very noisy segmentation maps(Dubuisson-Jolly and Gupta, 2000). If texture features are used alone, for example, the localisation of the region boundaries is not very accurate.

This is specially true when low-resolution images are the only ones available. Many are the issues that could degenerate an aerial image quality and cause some impact on a classification algorithm performance: water bodies reflecting the sunlight can cause saturation (fig. 1) and regions shadowed by clouds can darken a region's colour (fig. 2).

Figure 1: Sun's reflex on water causing saturation (white patch in lower right)

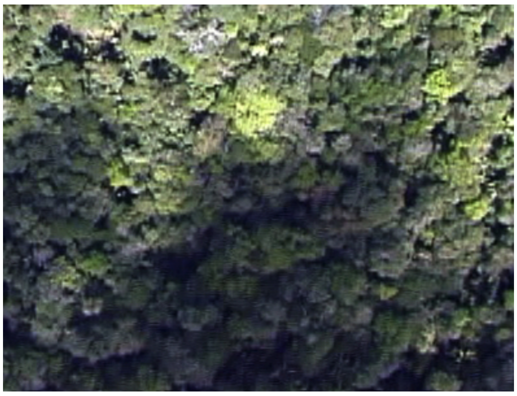


Figure 2: Clouds shadowing a patch of forest (the darker lower part), which typically causes segmentation problems

As seen in fig 3(a), a single criteria segmentation can present good results to certain images, but very bad to others. In the given example, Otsu's threshold segmentation method(Otsu, 1979) with two thresholds fails to provide the desired number of connected components (fig. 3(b)), finding too many high level components (fig. 3(c)) and compromising the classification steps afterwards. A similar problem happens when we apply Watershed segmentation which, as pointed out by (Li and Wan, 2010), often produces over-segmented regions due to image noise and detail information (fig. 3(d)).

As part of an effort to find anomalies in aerial images of rain forest regions such as human-made structures and environmental menaces, we surveyed segmentation techniques that could separate the image in its high-level components (i.e.: vegetation, water bodies, human-made objects, etc) and provided an acceptable semantical segmentation of the images. This necessity comes from the idea that everything that is not common to the region's scenery (something that is neither vegetation nor water body) is of potential interest.

We compare several machine learning techniques that use combined criteria (texture, colour, morphology, etc.) to provide a more accurate segmentation for our needs. The same set of publicly available images is used on all techniques investigated in this work, so they could be compared to each other and with an ideal segmentation that is expected by a specialist.

This work is organised as follows. Section 2 discusses related work both in single-criteria and multi-criteria techniques. Section 3 details how the dataset is organised, which features were extracted, why they matter to the problem, which classification algorithms were used and what was the overall workflow of the experiment. Section 4 discusses the results of the experiment. Finally, section 5 draw conclusions on the experiment and discusses possible future works on the subject.

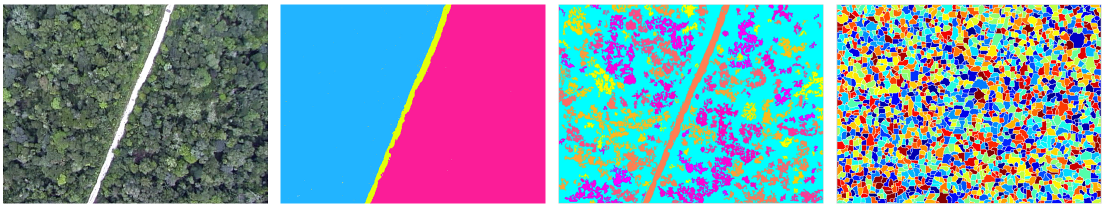
2 RELATED WORK

(Pal and Pal, 1993) do a thorough survey on single-criteria techniques for images segmentation, most of them implemented by this work with poor results due to the complexity of textures, colours and morphology on the dataset used on this our work.

In his work, Dubuisson-Jolly (Dubuisson-Jolly and Gupta, 2000) segments aerial images using multi-criteria segmentation. They create two distinct segmentations, by colour and by texture, and finally fuses both using a Maximum Likelihood algorithm. The outcome is a single segmentation for the image based on the fusion of both criteria.

(Freixenet et al., 2002) survey several methods of segmentation that integrate boundary and region information, exploring embedded integration and post-processing integration of segmentation criteria. All experiments were done in both real and synthetic images, finding very similar results. (Freixenet et al., 2002) concluded that post-processing methods have better results than embedded ones.

(Bosch et al., 2007) use Random Forest algorithm to segment images and compared it to multi-class Support Vector Machines, with comparable performance on the problem of categorising objects in scenes. The main advantage of Random forest over multi-class SVM, the authors argue, is the simplicity



(a) Original image (b) Expected segmentation (3 components) (c) Otsu's method with 2 thresholds (237 components) (d) Watershed segmentation (1,872 components)

Figure 3: Single-criteria segmentation techniques in this work's dataset

of training and test costs.

(Ghiasi and Amirfattahi, 2013) rely on colour and texture information to classify forest region images using two separate KNN classifiers. New images are broke down into super-pixels and then features are extracted. Using RGB channels and Local Binary Pattern Histogram Fourier features (LBP-HF) (T. et al., 2009), they achieved a success rate over 95% on the test dataset.

Our work combines several features extracted by the aforementioned works and experiment on several commonly used classification algorithms to find a better technique for segmenting aerial images of Amazon rain forest regions.

3 EXPERIMENTAL FRAMEWORK

Like (Heitz and Koller, 2008), we aim to classify pixels in an image to generate a segmentation map for it. Every pixel must be in one of the three classes of the problem:

- Vegetation: Grass, trees, swamped plants, etc
- Water bodies: Rivers, lakes, lagoons, swamps, waterfalls, margins, etc
- Other: Everything that does not belong to the aforementioned classes, potentially something human-made or a strange natural object

The image database comes from the GEOMA project (INPE, 2013) dataset. This dataset is composed of aerial images of the Amazonian rain forest region, taken with VGA cameras on board of manned airplanes during a number of flights between Amazon's major urban centres. The complete database has approximately 40,000 images (13 GB), from which we used a single flight outcome, comprising of 3,031 images (1.02 GB). All images use 24-bit colour space with dimensions of 640 per 480 pixels (0.3 MegaPixels). This dataset is publicly available at https://github.com/luizcavalcanti/geoma-database.

Gaussian blur is used on all images prior to any feature extraction. This was found useful because rain forest vegetation is very irregular and causes edge detector filters to produce incorrect border information (i.e. too many borders). Using a Gaussian Blur filter before edge detection aims to reduce the level of noise in the image (Deng and Cahill, 1993) and smooth borders, which improves the result of edge-detection algorithms (Shapiro and Stockman, 2001). In this work a Gaussian filter with a $5x5$ convolution matrix and $\sigma = 2$ were used.

A comparison is shown in Figure 5, where the results of a Sobel operator are presented for the same original image, with (Figure 5(c)) and without (Figure 5(b)). In this example a reduction in improper border detection can be seen.

From the whole dataset, 17 images where chosen as good representations of the overall terrain found in the remaining images. Some patches on those images were labeled by a specialist as one of the three classes of the problem and every pixel on those patches had their features extracted to compose the training dataset. A total of 4,000 pixels were used as training data, distributed among the classes as shown in table 1.

Class	Samples
Vegetation	1,200
Water body	1,600
Other	1,200
Total	4,000

Table 1: Training dataset of pixels and its distribution among the classes

For every pixel, which represents a sample in this work, we obtained a vector of features. Those features represent relevant information on colour, brightness, borders, neighbourhood and texture of the pixel or its region.

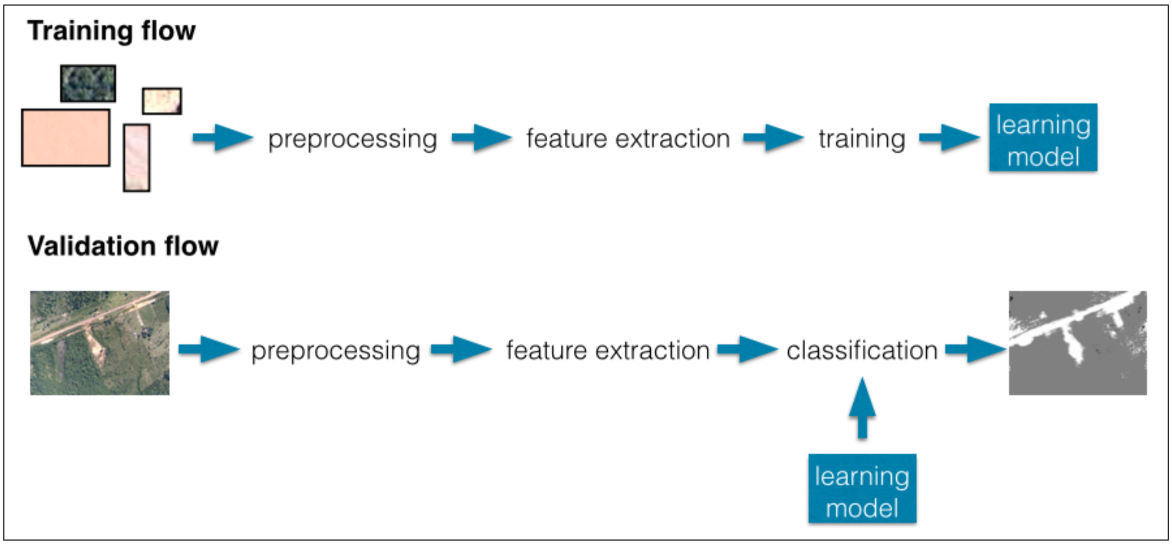


Figure 4: Overview of our approach. The training flow generates the learning models and the validation flow generates the segmentation maps for validation images

To obtain colour and brightness information we convert the RGB pixel into a HSB representation and its channels (Hue, Saturation and Brightness) compose the feature vector. For edge detection and border information, we extracted the difference of Gaussians and Sobel operator information on the neighbourhood (Nixon and Aguado, 2008).

Hessian features are also extracted to provide information on morphology and texture (Mikolajczyk and Schmid, 2002). This includes a scalar representation of the Hessian matrix, trace, determinant, first and second eigenvalues, orientation, gamma-normalized square eigenvalue difference and square of gamma-normalized eigenvalue difference.

Provided that those are relatively complex features, their representation in unidimensional variables for every pixel and its neighbours makes the feature vector grow quickly. In this work, using the aforementioned features, the features vector contains 81 discrete numeric features. This is done for the labeled pixels involved in the training phase but also for every non-labeled pixels involved in the validation/test phase, to compose the actual training and validation datasets respectively.

This data was used for training all the algorithms in this work, with the exact same attributes. A learning model was created for every algorithm using the Waikato Environment for Knowledge Analysis tool (Hall et al., 2009), also known as WEKA. The algorithms in this work are all supervised. Decision trees, KNN, Naive Bayes and Random forests were used.

For each learning algorithm, the parametrisation used in this work was decided during the training phase, using cross-validation in the training dataset as the accuracy performance criteria. For KNN, a range of $k = [1,7]$ was tested and the best results were with $k = 5$ and Euclidean distance, so that's the one used throughout the experiment. In Random forests, the maximum number of trees was 200 and the number of features per tree was 40.

From the dataset, 500 images were chosen as validation dataset. Each of their pixels had features extracted and were classified by the learning model generated on the training phase. Those same classified pixels were used to render a segmentation map for every image (Figure 6).

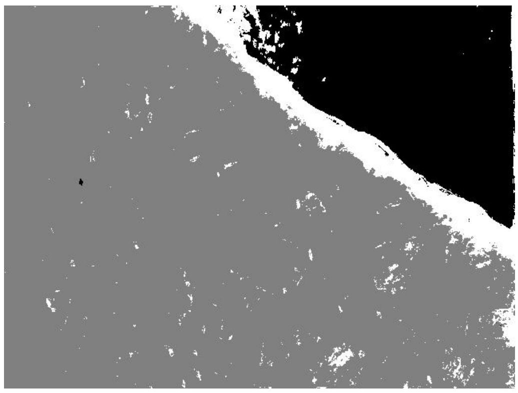
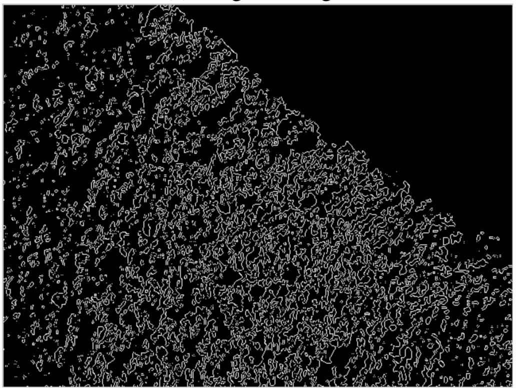


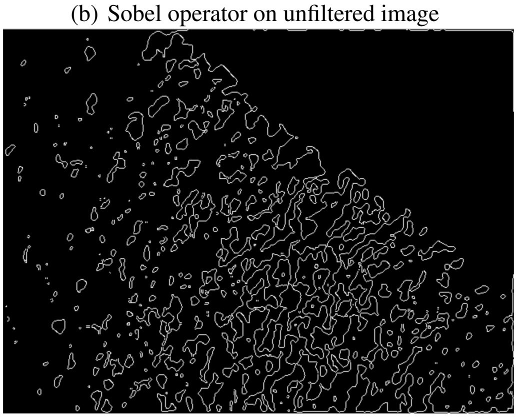
Figure 6: Example of segmentation map generated by pixel classification

Evaluating semantic segmentation is often a purely visual and subjective process, hence a specialist was responsible for analysing each one of the seg-

(a) Original image



(b) Sobel operator on unfiltered image



(c) Sobel operator on blurred image

Figure 5: A comparison between using a unfiltered and a gaussian-blurred one in edge detection (Sobel operator)

mented images for all techniques applied. For every resulting segmentation map, the specialist was responsible to classify the whole image as an ”acceptable” or ”unacceptable” semantic segmentation. The percentage of ”acceptable” segmentation composes the accuracy score of the methods in this work, and comparisons are made by this criteria (Section 4).

The specialist was instructed that ”acceptable” segmentations are comprised by well-defined and continuous segmented regions compatible with the expected semantic segmentation of the original image. Some noise, or pixels with wrong classification, is acceptable as long as it don’t form another continuous region or an expressive area inside the correct region. Were deemed ”non-acceptable” the segmentation maps that violate any of those criteria.

The overview of our approach can be seen in Figure 4.

4 RESULTS

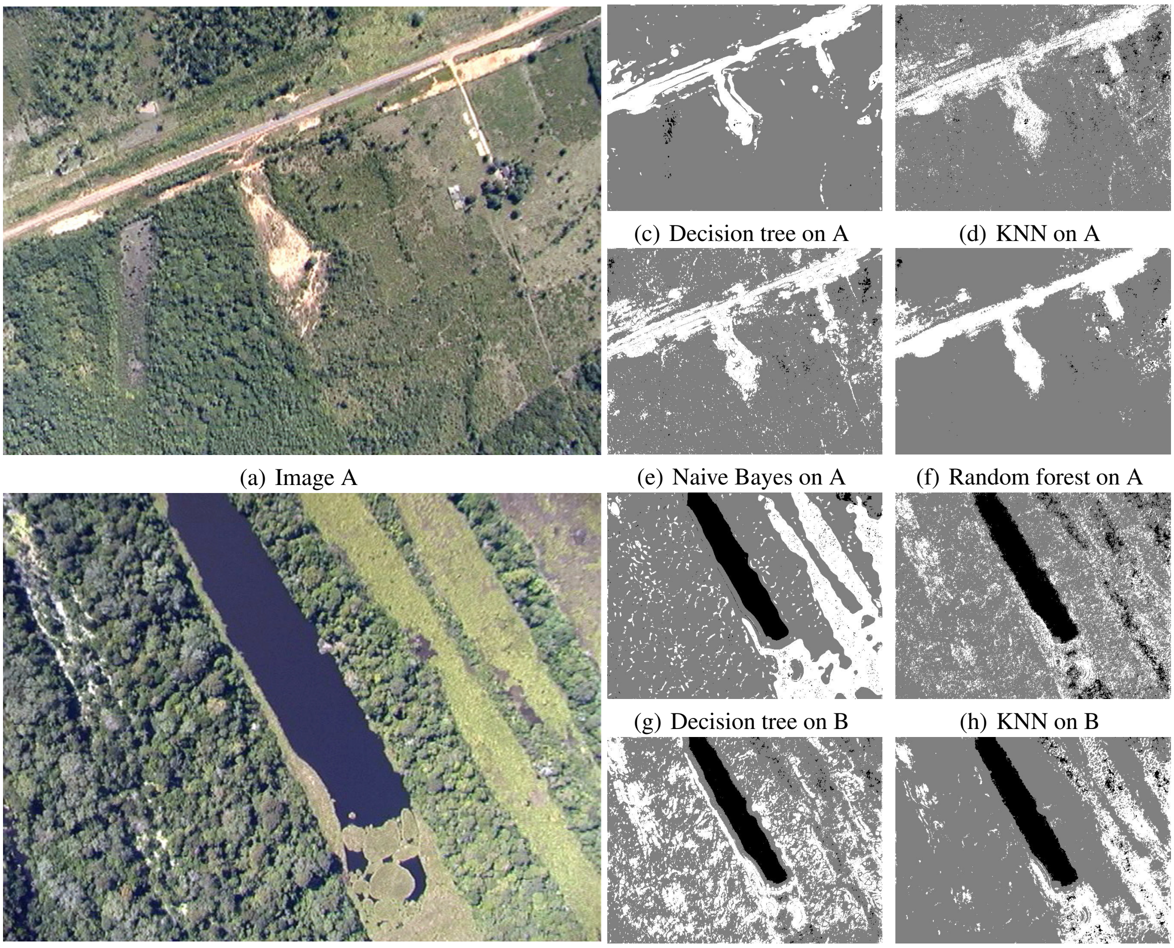
All algorithms were trained with the same training dataset and tested against the same validation dataset.

After a specialist evaluated every output for all algorithms, we came with an accuracy percentage, represented by the segmentations assigned by the specialist as ”acceptable”.

The figure 7 shows two examples of the experiment’s output: a segmentation map, for every learning algorithm used on both images. Black areas represent ”water bodies” class, grey areas represent ”vegetation” class, white areas represent ”other”. During the experiment, Random forest algorithm (Figure 7(f)) had the most problems with ”water bodies” false-positives, but had a superior semantic segmentation in images without water elements. Decision tree (Figures 7(c) and 7(g)) did not cause many false-positive problems, but usually overflowed classes’ edges in more complex images, sometimes ruining the semantic segmentation. KNN (Figures 7(d) and 7(h)) and Naive Bayes attained a good overall segmentation but had a lot of classification noise in regions that should be contiguous.

The accuracy and average execution time (per sample) for all tested algorithms are presented in table 2. The feature extraction processing time for a whole image of the dataset (307,200 pixels) took longer than expected: around 7023 milliseconds in a 2.4 GHz Intel Core i5 processor. This feature extraction time is not considered in the algorithms average execution time. Figures 8 and 9 show graphical comparisons among methods’ error rate (linear scale) and average execution time (logarithmic scale) respectively.

All algorithms, scripts and datasets used in this work are publicly available under *GNU General Public License v2 (GPLv2)* at http://github.com/luizcavalcanti/ForestClassifier and it’s free to reproduce, modify and distribute accordingly.



(a) Image A (b) Image B (c) Decision tree on A (d) KNN on A (e) Naive Bayes on A (f) Random forest on A (g) Decision tree on B (h) KNN on B (i) Naive Bayes on B (j) Random forest on B

Figure 7: Visual comparison on segmentation results

Algorithm	Accuracy	Execution time
Decision tree	82.2%	136 ms
KNN	92.6%	420,098 ms
Naive Bayes	92.8%	320 ms
Random forest	96%	3,542 ms

Table 2: Accuracy and average execution time for all algorithms tested

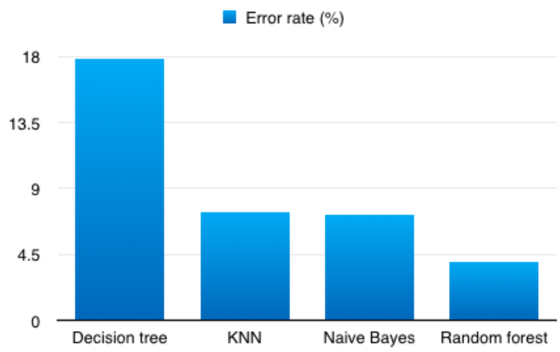


Figure 8: Comparison on error rate (linear scale)

5 CONCLUSION AND FUTURE WORKS

With over 90% of accuracy, some of the tested machine learning algorithms are good approaches to classification of aerial forest images with low resolution. Naive Bayes and KNN algorithms had a fairly good performance, but are still suffering from noise in its learning models. KNN also has a computational performance problem that needs further investigation, since it takes 3 orders of magnitude more time than Naive Bayes to classify samples. This could be related to the number of training samples that every new sample needs to be compared to, but also to the di-

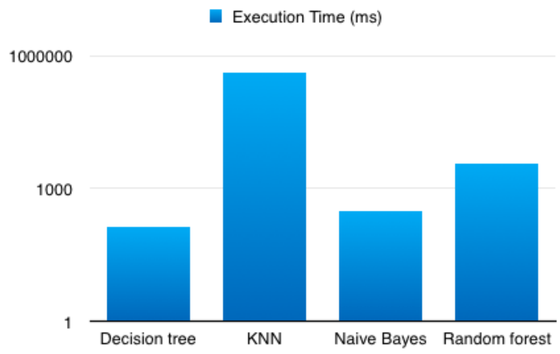


Figure 9: Comparison on execution time in milliseconds (logarithmic scale)

mensionality of the feature vector. A technique to reduce the number of comparisons should be tested.

Random forest clearly performs best in this dataset, but we must find a way to address the false-positives on water bodies, which is visibly larger than in other methods. This is definitely a theme for future works, as the overall performance of Random forest was promising.

Future works should also include a improvement on samples representation, making the feature extraction faster and reduce the feature vector dimensionality. Algorithms like KNN and SVM should benefit from those improvements, specially the later, making possible to reduce the support vector complexity and make model generalisation easier. Another area of possible improvement is in the image preprocessing, prior to the feature extraction, specially reducing noise. It is also important to test the same dataset with unsupervised machine learning techniques and compare to those in this work.

In general, the results were satisfactory in providing good directives on how to implement a efficient and robust segmentation tool for the rainforest operation scenarios. Amazon forest has been suffering from years with systematic degradation and this work is a small part of an effort to provide information and supporting actions to mitigate the deforestation activities in the region.

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