

Automatic Road Pavement Detection

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The Team



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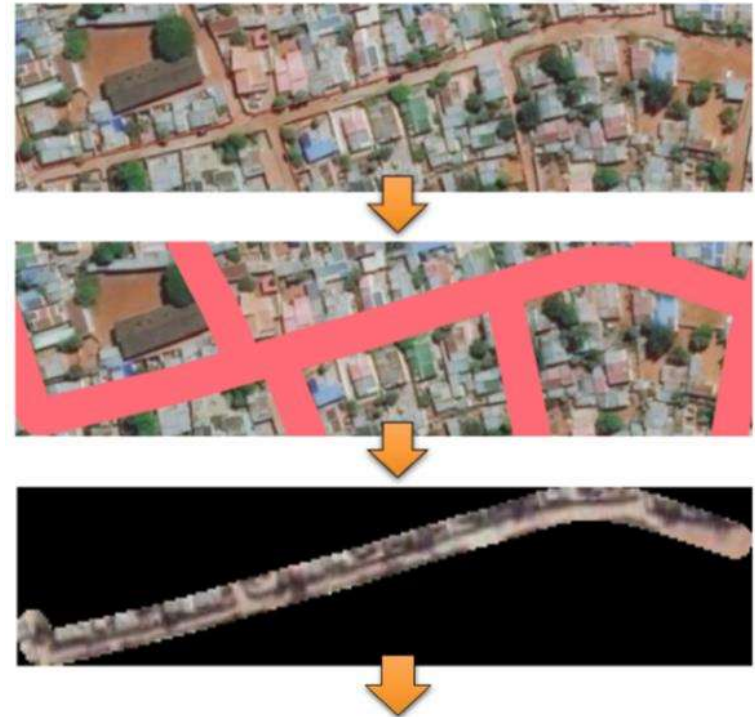
Introduction



Road Pavement Detection - Espinosa, Barbato, Frabetti, Hesse, Retif

Dataset

- **55.883** high resolution satellite **images** from Google maps (download in April 2020), TIF format
- **Resolution** (Pixel resolution is around 1.1x1.1 meters)
- Each **pixel**'s color has three numerical **RGB** components (Red, Green, Blue) which are integers in [0,255]

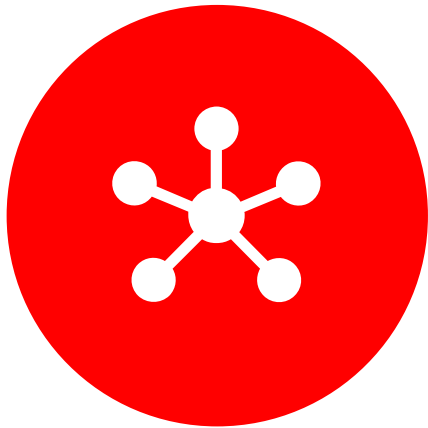


	R_band	G_band	B_band
91	127	102	97
92	124	102	96
93	137	118	111
94	114	98	90
95	80	66	58

PIXEL ANALYSIS

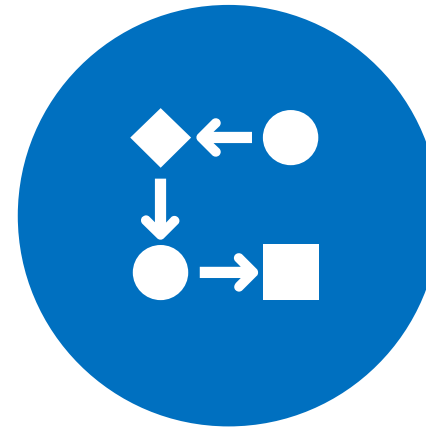
Road Pavement Detection - Espinosa, Carstho, Buben, Hesse, Retu

Clean the data – Unsupervised classification



Hierarchical Clustering

- Euclidean distance
- Average Linkage
- Cophenetic coeff. ≈ 0.7



K-means

- Lloyd's algorithm
- $k = 3$
- Random seeds

The results from Hierarchical Clustering and K-means are very similar

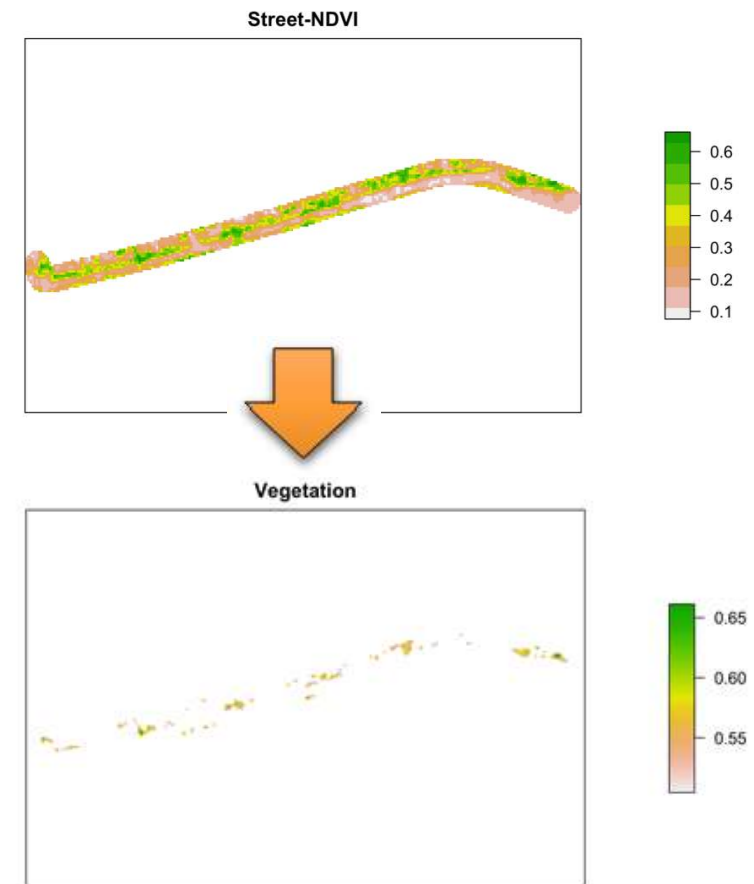
Creating the clusters and analysing them

First, we removed the pixels about the vegetation through the **NDVI** index.

We performed the hierarchical classification for **10.000** images

For each cluster we computed the following features for any of the three channels (R,G,B):

- Mean (9 features)
- Covariance matrix between the three channels (18 features)
- Quantiles for any channel (27 features)
- Minimum and maximum (18 features)
- Number of pixels (3 features)



Understand which is the right cluster



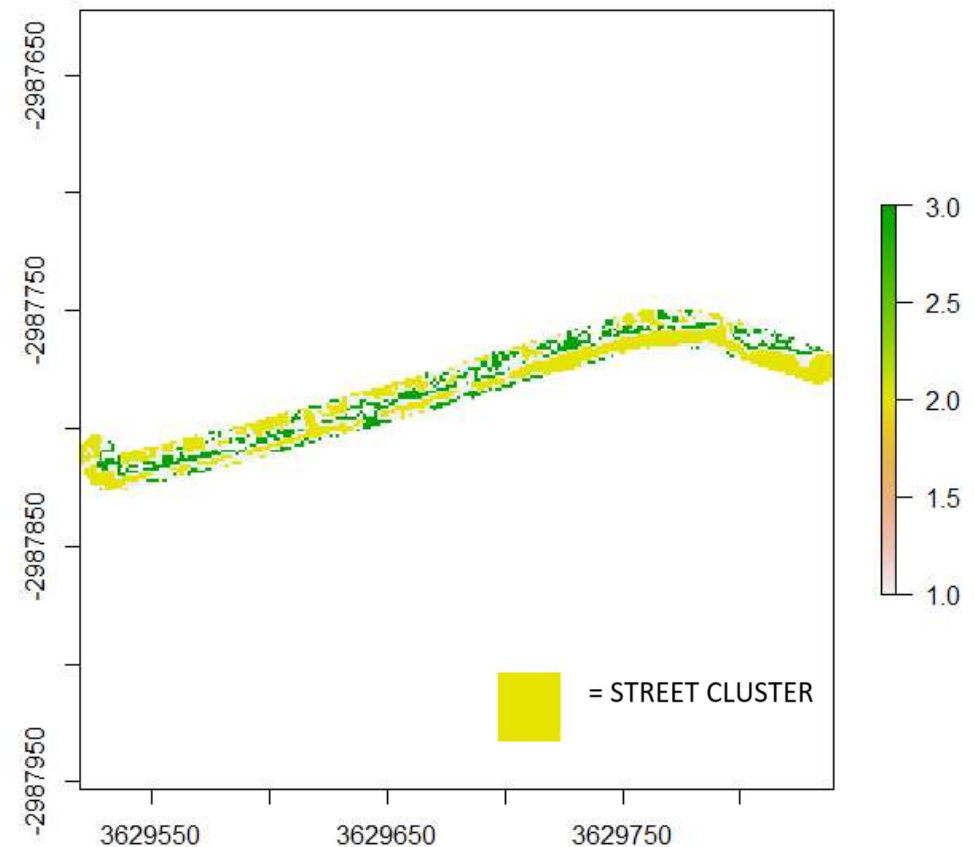
For **1000** images we visually selected the right cluster between the three comparing with the GPS photo.

For example in this image the right cluster is the yellow one.

We knew which was the right cluster only for the **10%** of them.

From this we built a **supervised classifier**.

Unsupervised classification



Selection of the right cluster with SVM, KNN and Random forest

Support Vector Machine

On the first 10 principal components of our dataset (0.92 of the total variability)

Radial kernel

Cost = 10

K-Nearest Neighbour

On the original data

$k = 7$ through 5-folds cross validation

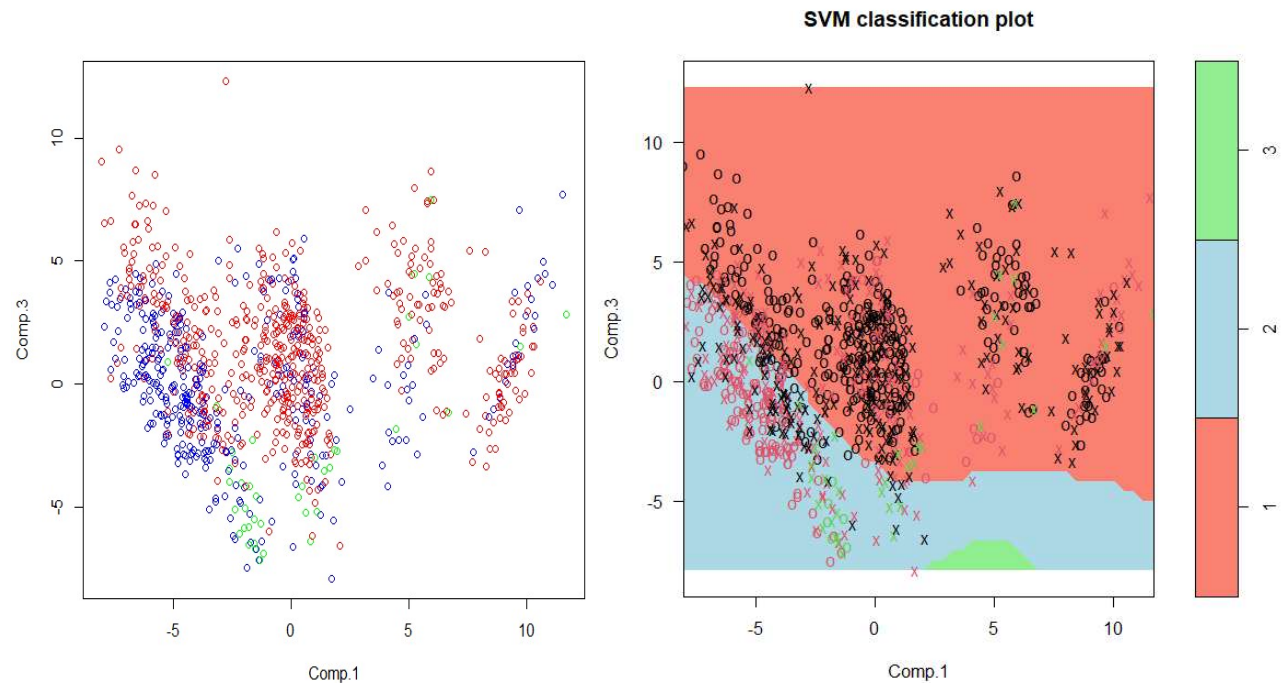
$APER \simeq 0.12$

Random Forest

On the reduced data (RGB)

$mtry = 2$, $ntree = 500$

$OOB \simeq 0.15$

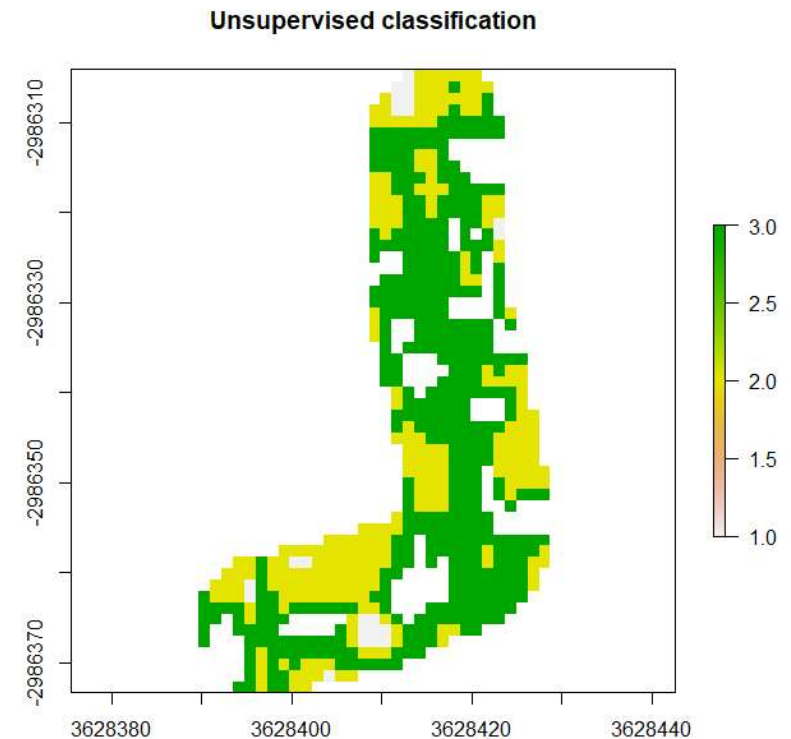
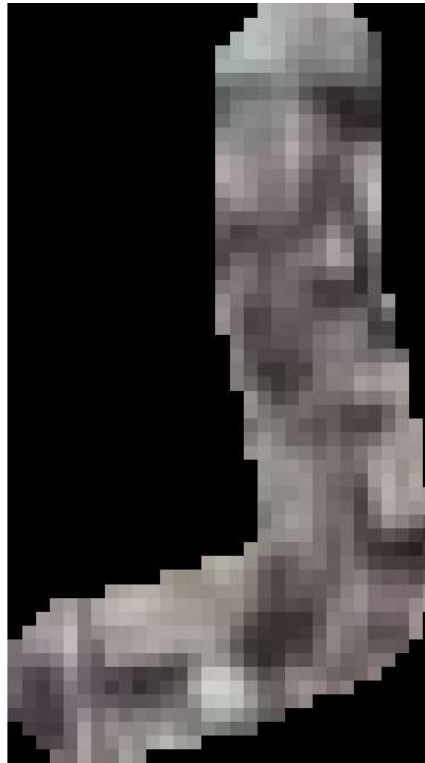


Comparison with these methods

The **differences** between the prediction of these methods affect the **20%** of the **unlabelled** data, often are for photos in which is difficult to visually "isolate" the street.

Checking 40 random photos in which the two methods give two different result it appears that **KNN** is correct the **55%** of the times.

We decided to keep in account the KNN classification.



Our final DATASET

	Length	osm_tipo	osm_surf	coord_x	coord_y	meanR	meanG	meanB	varR	varG	varB	covRG	covRB	covBG	quantR_25	quant
1	363.36502	NA	NA	32.57834	-25.97033	105.08400	96.18406	107.79615	107.05450	92.20165	86.44718	79.92725	75.16328	75.43315	98.00	
2	269.38126	NA	paved	32.58244	-25.97230	127.49674	115.61473	123.46480	583.80527	504.44965	460.55551	488.91949	459.37888	463.22811	108.00	
3	354.50837	residential	NA	32.57789	-25.97013	112.48798	102.55410	113.85574	203.63764	182.13130	172.86819	169.05204	157.86322	163.63930	102.00	
4	171.41329	residential	NA	32.58143	-25.97121	111.97481	100.61822	110.48256	209.28937	205.73771	172.72520	188.21443	163.09073	164.71205	101.00	
5	295.45597	residential	NA	32.58590	-25.97122	110.09336	101.90190	108.34028	203.46164	199.87515	183.19188	187.58953	172.78661	181.86175	99.00	
6	323.51632	NA	NA	32.58648	-25.97484	107.08663	97.89885	106.72859	327.50502	353.08896	325.00245	330.54785	314.66932	327.95850	93.00	
7	107.30680	residential	NA	32.58660	-25.97675	106.66154	96.00220	102.71868	176.68255	164.92731	161.85901	165.63290	154.25039	148.93895	96.00	
8	140.94184	residential	NA	32.59408	-25.97152	108.83977	103.25909	105.82500	311.56133	325.04997	253.62349	311.30550	269.54417	277.41627	93.75	
9	67.72668	residential	NA	32.58983	-25.97928	117.93891	111.31672	114.27170	334.65971	352.04284	303.40915	336.76334	297.73160	315.65938	104.00	
10	134.57560	residential	NA	32.58606	-25.97718	99.65542	87.98072	95.42651	57.96552	62.79673	60.17273	58.14793	50.08452	54.49858	94.00	

Once we've selected the right cluster, we keep the values of the channels only for the cluster that we want to study.

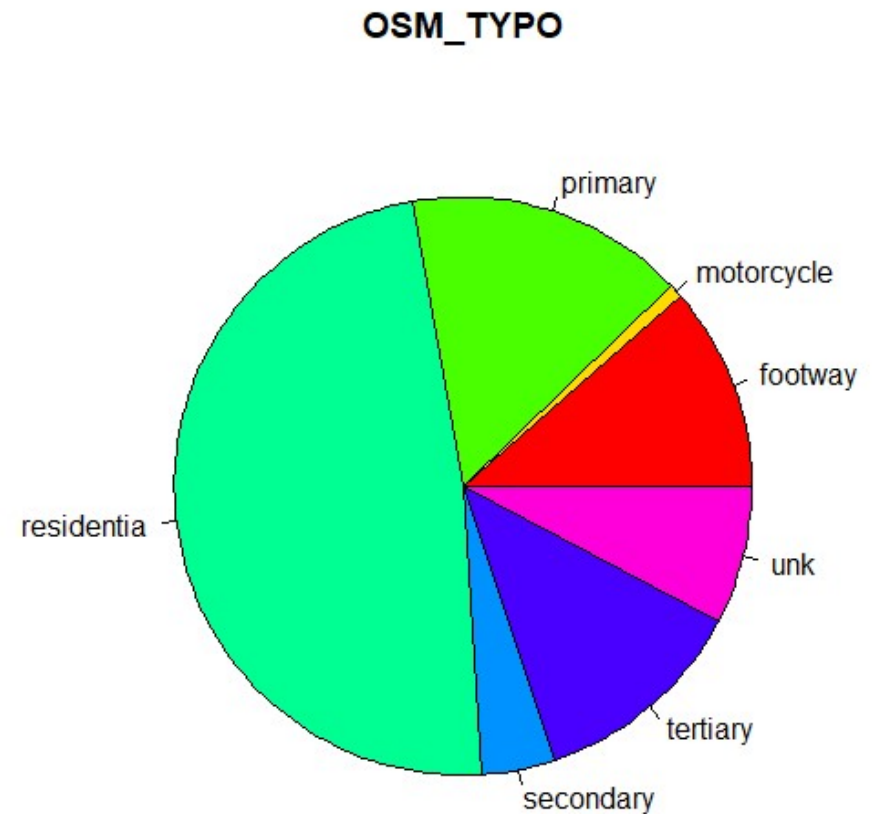
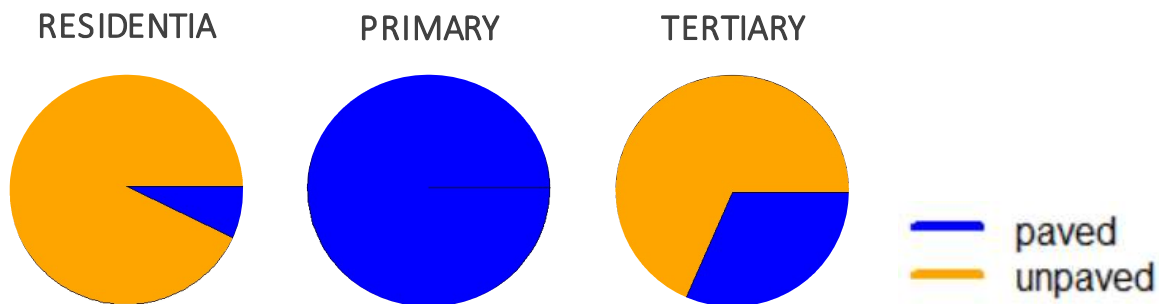


PAVEMENT ANALYSIS

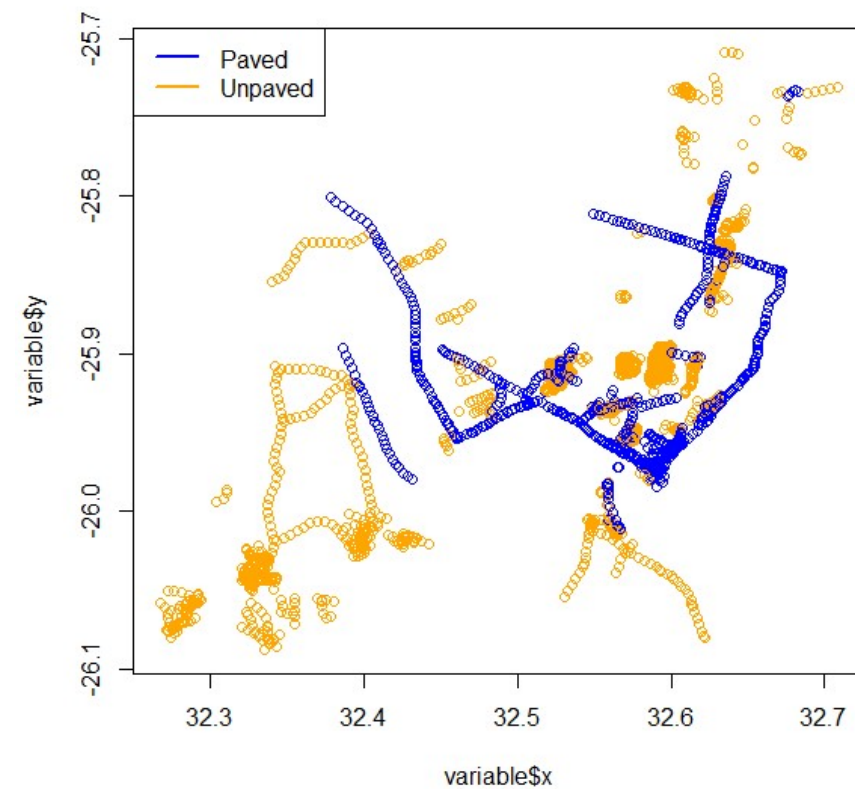
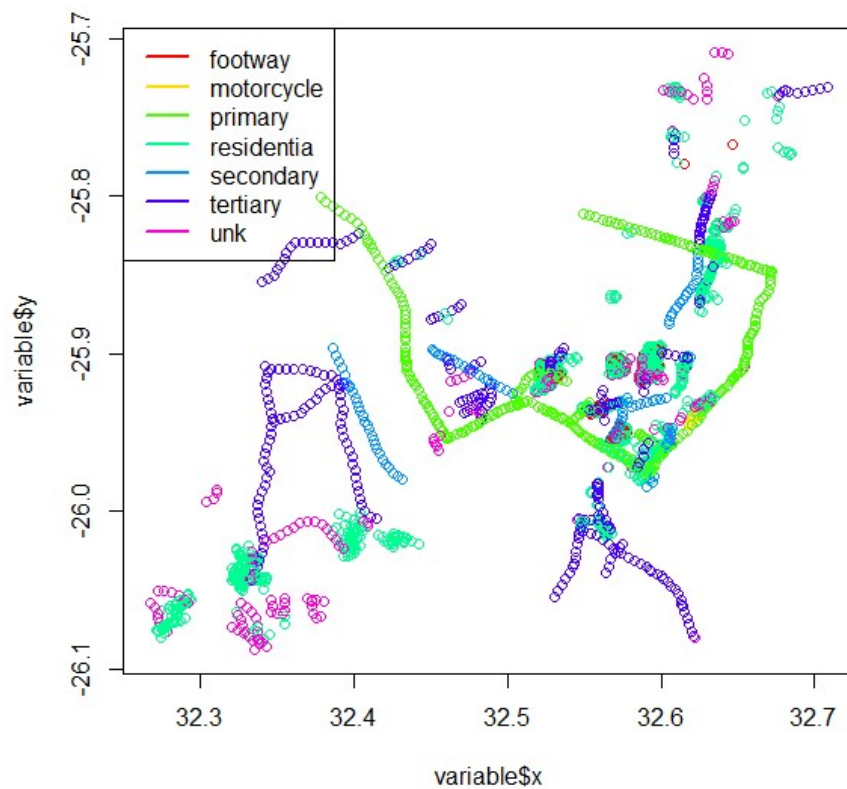
Road Pavement Detection - Virginia Beach, VA - 2011, H. H. H. H.

Data Exploration

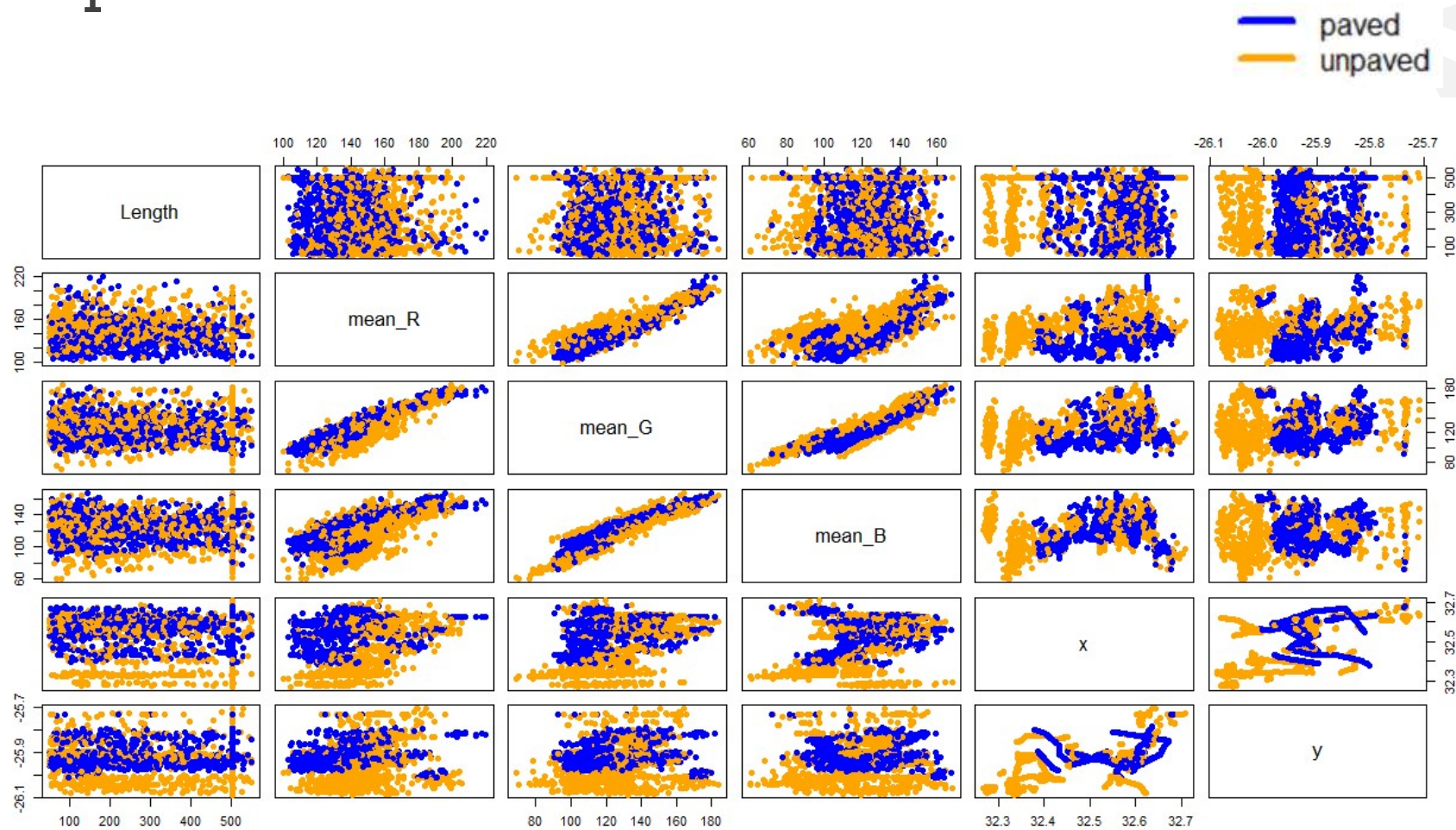
- 10.000 images
- 5% of the images are labeled – Paved/Unpaved
- 90% of the images are classified by the OSM_TYPO



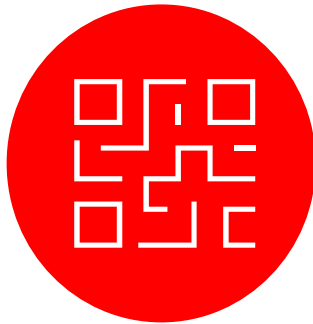
Data Exploration



Data Exploration



Pavement Detection – Supervised Classification



1. Variogram Analysis

Exploiting Spatial Data

Accuracy 😐



2. Logistic Regression

Nice to interpret!

Accuracy 😊



3. Random Forest

Difficult interpretation

Accuracy 😍

Variogram Analysis

MODEL :

D = area of Maputo

$\{s_1, s_2, \dots, s_n\}$ fixed locations in D , $n = 2321$

$\pi = \frac{1}{1+e^{-y}}$ probability to belong to the class 'paved'

$$y(s_i) = a_{0_g} + a_1 f_1(s_i) + a_2 f_2(s_i) + a_3 f_3(s_i) + \delta(s_i)$$

- f_1 = 'mean of the R band'
- f_2 = 'mean of the G band'
- f_3 = 'mean of the B band'

$g = \{ \text{'residential', 'primary', 'secondary', ...} \}$

FITTED VARIOGRAM :

Spherical model

without nugget

RESULTS ON A TEST SET :

Confusion matrix :

		PREDICTED CLASS	
		unpaved	paved
TRUE CLASS	unpaved	137	43
	paved	23	55

Accuracy : 74%

Sensitivity: 70%

Specificity: 76%

Logistic Regression

MODEL :

$\pi = \frac{1}{1+e^{-y}}$ probability to belong to class 'paved'

$$y = \beta_{0_g} + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3 + \beta_4 z_4 + \varepsilon$$

$g = \{ \text{'residential'}, \text{'primary'}, \text{'tertiary'} \}$

- z_1 = 'mean of the R band'
- z_2 = 'mean of the B band'
- z_3 = 'x coordinate'
- z_4 = 'y coordinate'

$$\beta_{0_g} = \begin{cases} -1.346, & g = \text{'residential'} \\ 1.975, & g = \text{'primary'} \\ -1.44, & g = \text{'tertiary'} \end{cases} \quad \begin{matrix} \beta_1 = -0.052 \\ \beta_2 = 0.056 \\ \beta_3 = 5.440 \\ \beta_4 = 0.650 \end{matrix}$$

MODEL SELECTION :

Akaike Information Criterion (AIC)

RESULTS ON A TEST SET :

Confusion matrix:

		PREDICTED CLASS	
		unpaved	paved
TRUE CLASS	unpaved	148	32
	paved	19	59

Accuracy: 80%

Sensitivity: 75%

Specificity: 82%

Random Forest

Confusion matrix:

TRUE CLASS	PREDICTED CLASS	
	unpaved	paved
unpaved	1692	134
paved	274	481

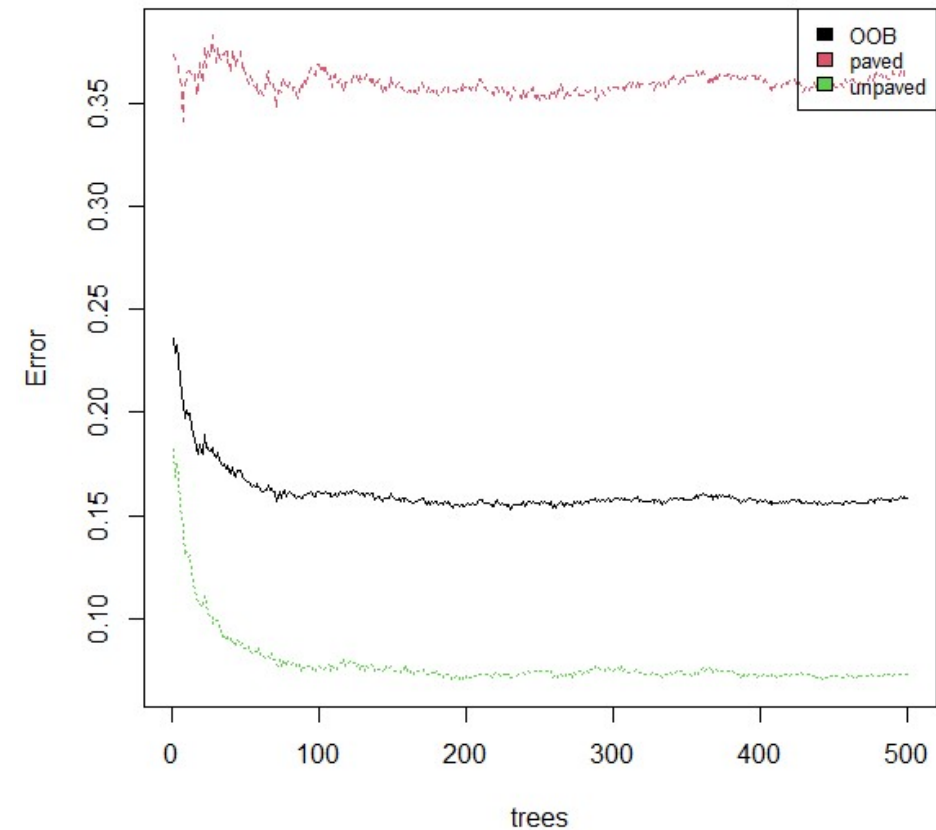
RESULTS Out-Of-Bag (OOB):

Accuracy: 84%

Sensitivity: 78%

Specificity: 86%

Road Classification Errors



Conclusion

- **Machine learning techniques** are more effective for this problem.
- We built very **simple** and **intuitive** model easy to interpret
- **Noisy images**
- Not only **Maputo...**





Thank you

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