

Automatic road extraction in small urban areas of developing countries using drone imagery and Image Translation

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August 26, 2021
Medellín, Colombia

AGENDA

- INTRODUCTION
- RELATED WORK
- USED METHOD: IMAGE TRANSLATION ON DRONE IMAGERY
- EXPERIMENTS AND RESULTS
- CONCLUSIONS
- REFERENCES

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Road layer are obtained manually from satellite imagery



Seleccionar tipo

Código: 0x0a

Código	Cate...	Descripción
0x0018	Agua	Arroyo
0x001f	Agua	Río
0x0001	Carreteras	Autopista
0x0002	Carreteras	Ruta principal
0x0003	Carreteras	Otra ruta
0x0004	Carreteras	Avenida/Ruta
0x0006	Carreteras	Calle residencial
0x0007	Carreteras	Callejón/Calle
0x000a	Carreteras	Camino sin pav
0x000c	Carreteras	Glorieta
0x0014	Carreteras	Ferrocarril
0x0000	Descono...	Tipo indeterminado
0x001c	Límites	Límite de prov

INTRODUCTION

- Tedious, prone to errors and takes long time by GIS experts
- Incomplete due to lack of up to date base imagery
- Satellite imagery is affected by shadows and clouds
- High resolution and up to date imagery is expensive

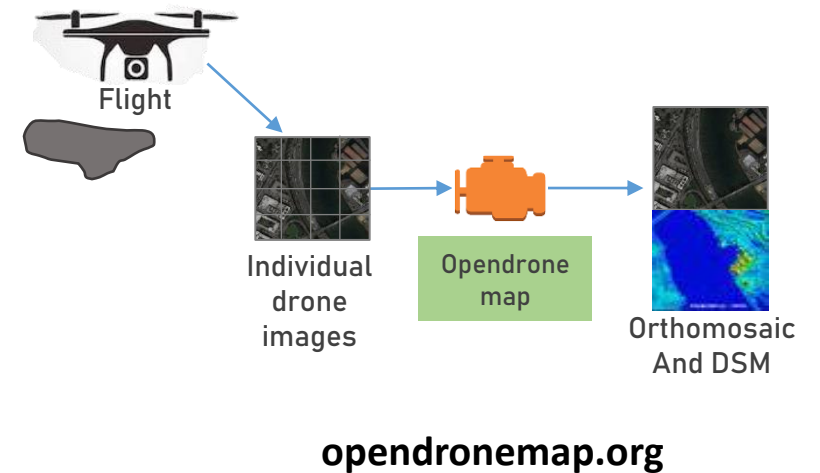
Fast road extraction is needed for:



Disaster Recovering
Urban Planing
Logistics
Mobility

Drone Imagery

- Better contrast and color
- Less image distortions becoming true orthophotos
- Since it is made on demand, it's up to date
- More objects and details per pixel
- Almost no affected by shadows-clouds and less tilted



RELATED WORK

- Occlusions by buildings and trees
- High variance of roads classes
- Similarities between object's classes:
roads-rivers and roads-buildings.

Road segmentation results by different architectures using drone imagery

Algorithm	OA-Train	OA-Val	Prec	Recall	F1	mIoU	Veg	TF	Water	Road
FC-DenseNet	0.97	0.95	0.95	0.95	0.95	0.90	0.96	0.93	0.94	0.96
U-Net	0.96	0.95	0.95	0.94	0.94	0.91	0.95	0.93	0.95	0.95
DeepLabV3+	0.94	0.93	0.91	0.90	0.90	0.89	0.94	0.88	0.87	0.89
PSPNet	0.91	0.89	0.89	0.88	0.88	0.83	0.96	0.89	0.87	0.83
MobileU-Net	0.89	0.85	0.88	0.79	0.84	0.75	0.97	0.85	0.69	0.76
SegNet	0.88	0.82	0.91	0.81	0.82	0.69	0.97	0.77	0.65	0.85

Pashaei et al, 2020

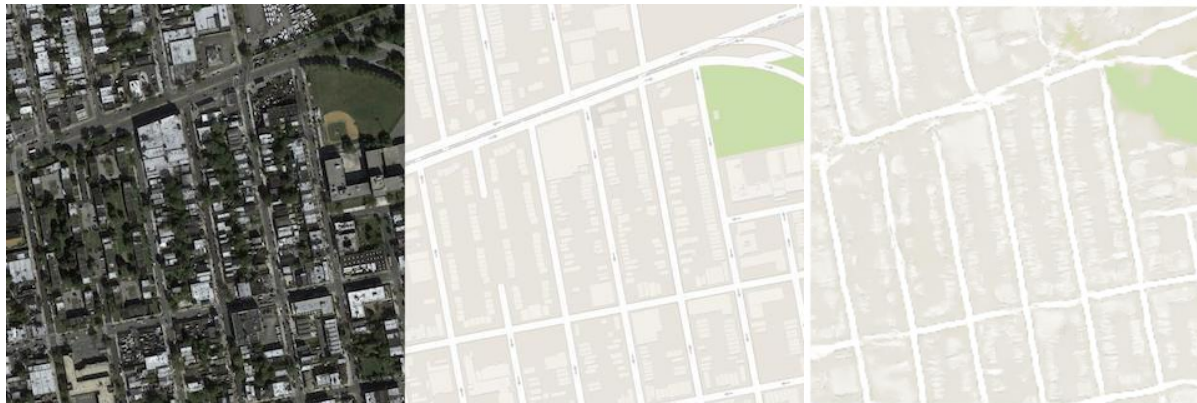


PIX2PIX FOR IMAGE TRANSLATION

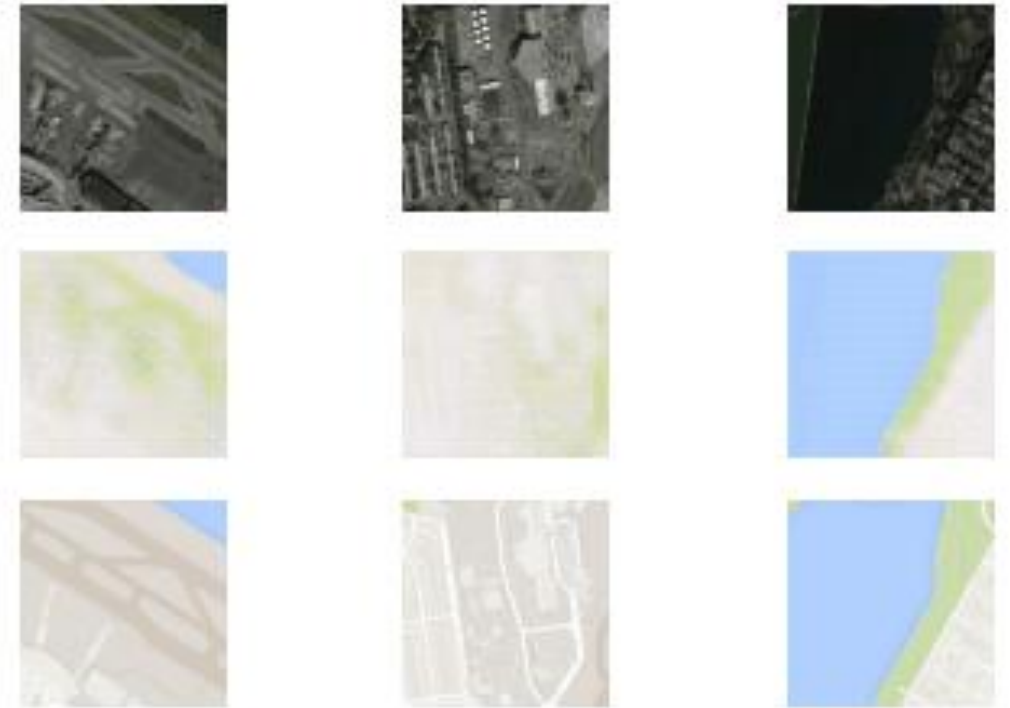
Satellite

Ground Truth Map

Predicted Map



Isola et al. 2017.



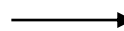
METHOD: IMAGE TRANSLATION

Pix2Pix. Generative conditional model

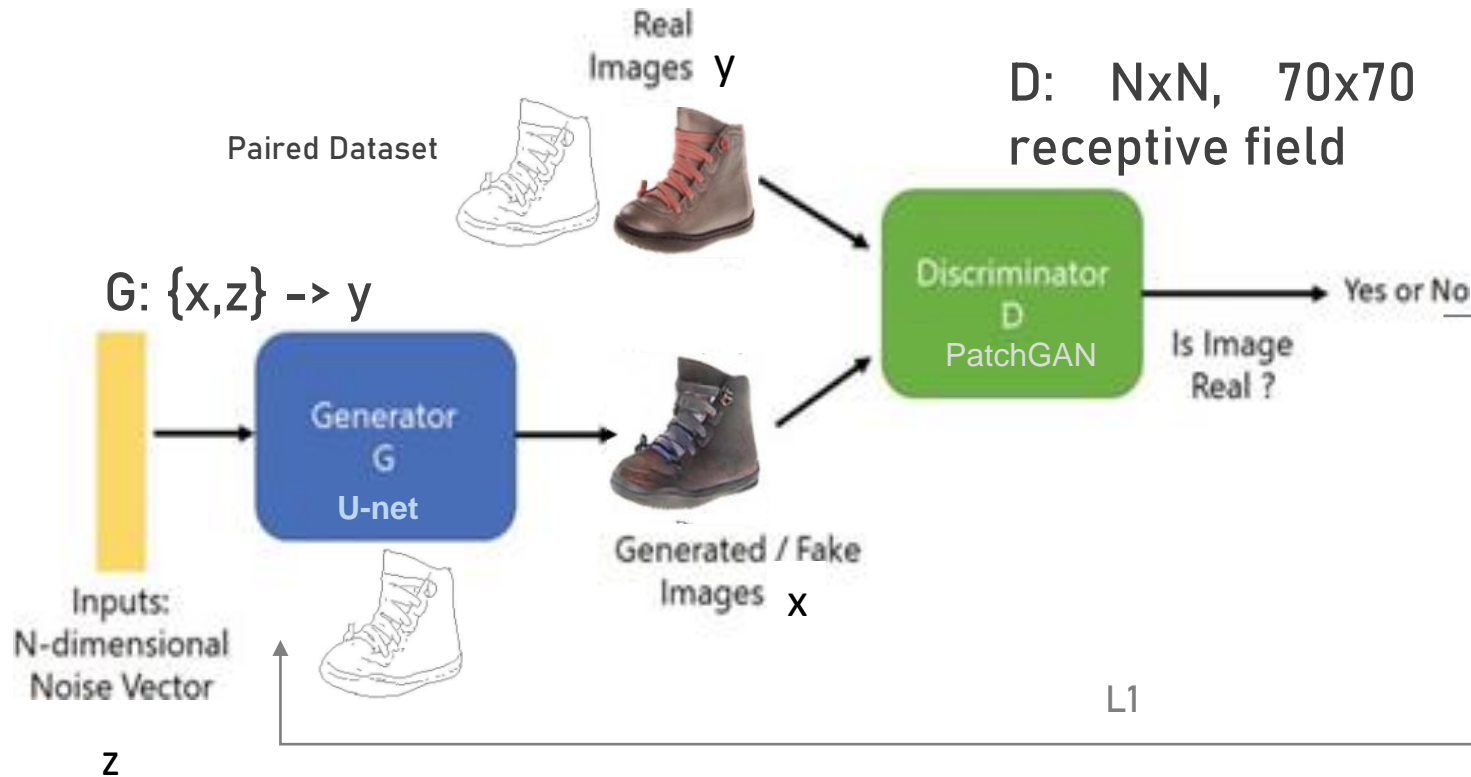


Isola et al. 2017

Latent space 1, Source
images



Latent space 2, Target
images



Isola et al. 2017

$$Loss(G, D) = E_{x,y}[\text{Log}D(x, y)] + E_{x,z}[\text{Log}(1 - D(x, G(x, z)))]$$

$$L1(G) = E_{x,y,z}[\|y - G(x, z)\|]$$

$L = Loss(G, D) + \lambda L1$, $\lambda = 100$, makes G learns faster than D

Disadvantages

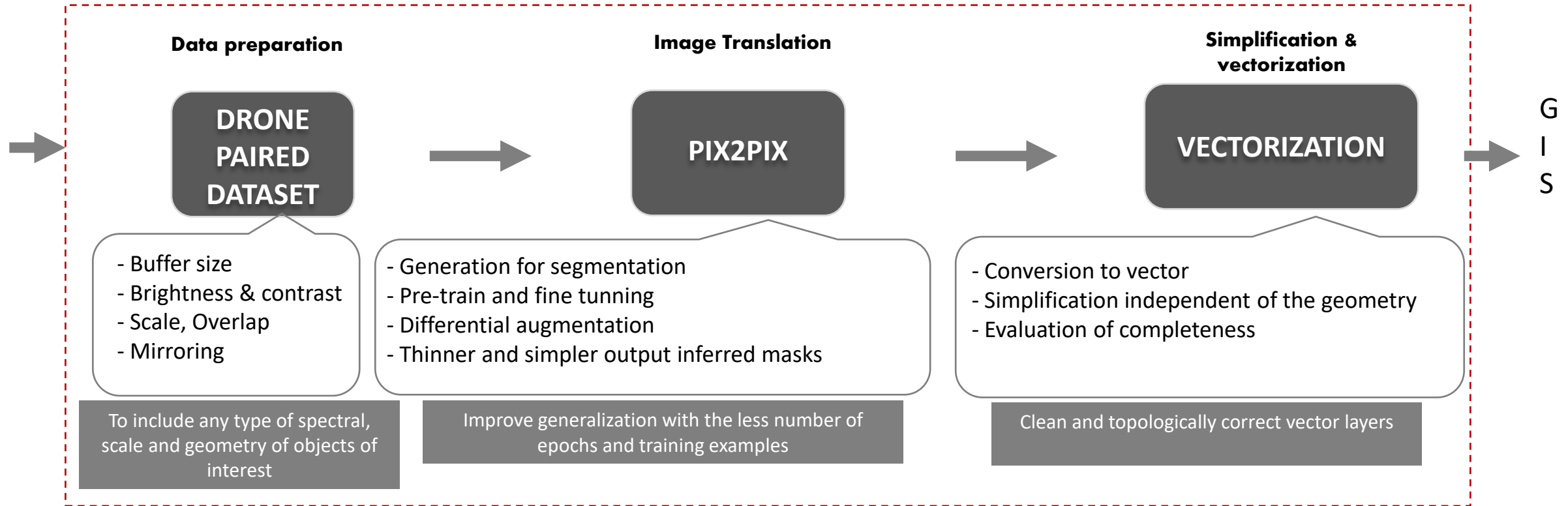
- Training paired datasets are difficult to produce
- Need of huge amounts of data. Zao et al, 2020
- GANs are complex to train.

Se han truncado las últimas 5000 líneas

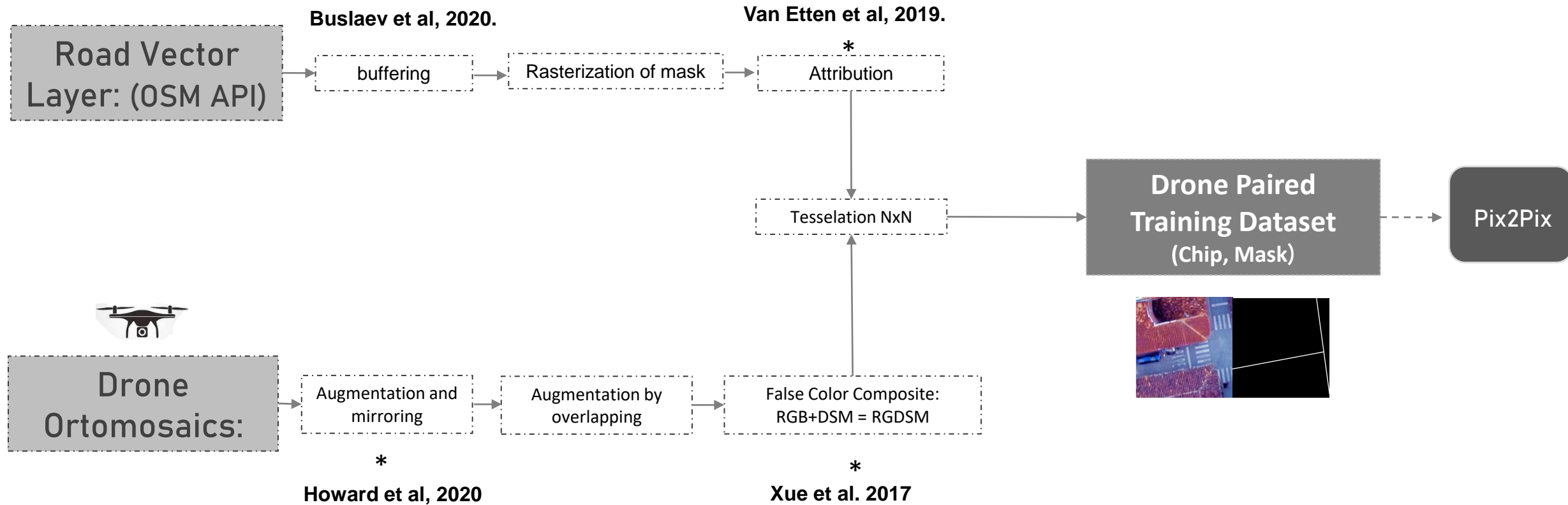
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By Authors

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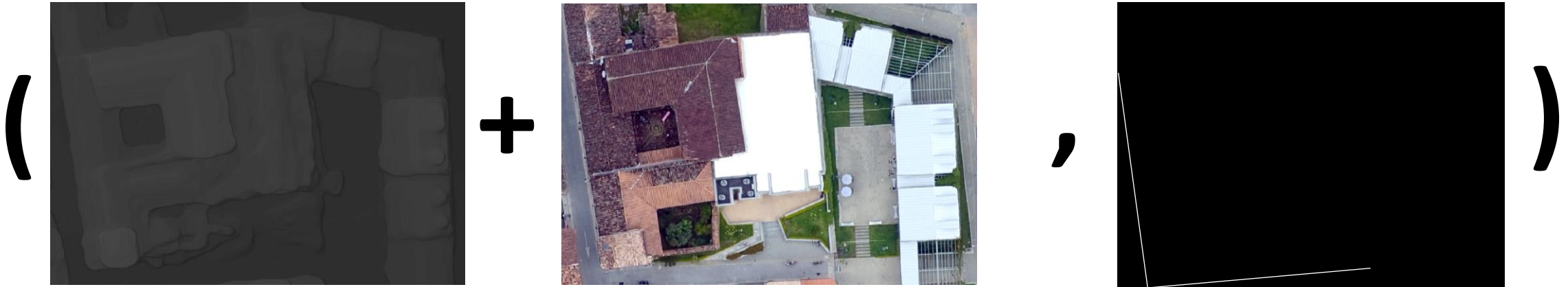


Based on **Ng and Hofmann. 2018**



Creation of an OpenSource Drone Paired Training Dataset For Roads Segmentation

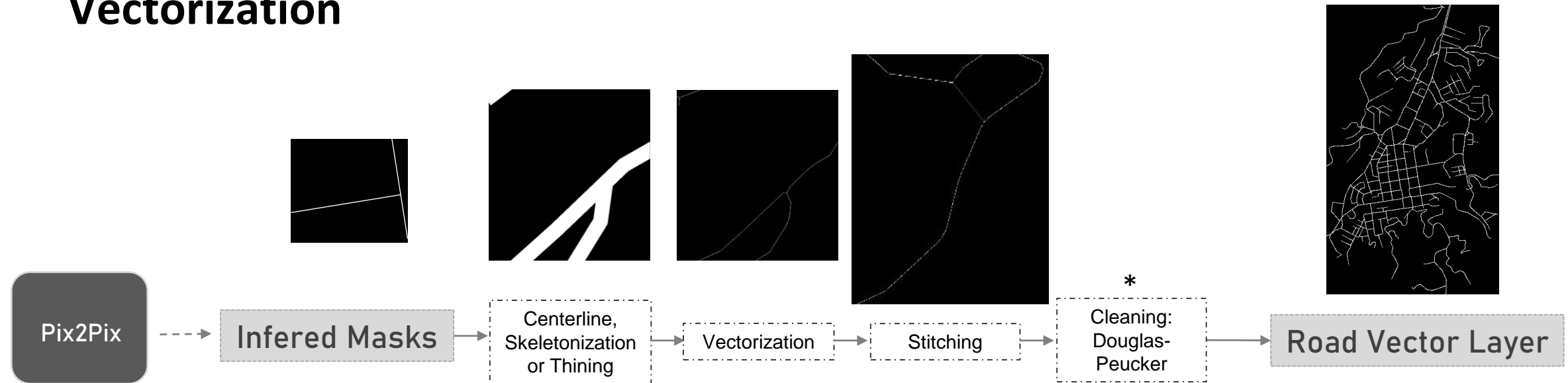
Orthomosaics + DSM of 15 small Colombian urban settlements, GSD 8cm/px Avg.



Other important objects: Buildings, Forests, Parks, Parking, Rivers, Trees, Cars, Traffic Signs (stop, zebra, no parking, arrows)

Girardota, Barbosa, El Retiro, Rionegro (incompleto), Santafe de Antioquia, San Pedro de Los Milagros, San Jerónimo, Caucasia, Andes, Urrao, Santa Barbara, Santa Rosa de Lima (Bolívar), San Juan Nepomuceno (Sucre).

Vectorization



* Optional step

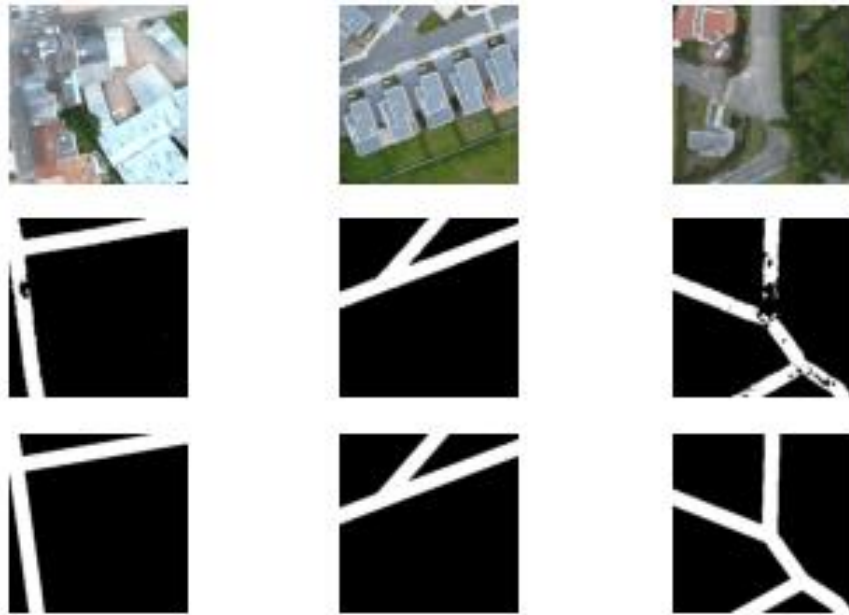
EXPERIMENTS AND RESULTS

Different models were trained and tested in Google Colab:

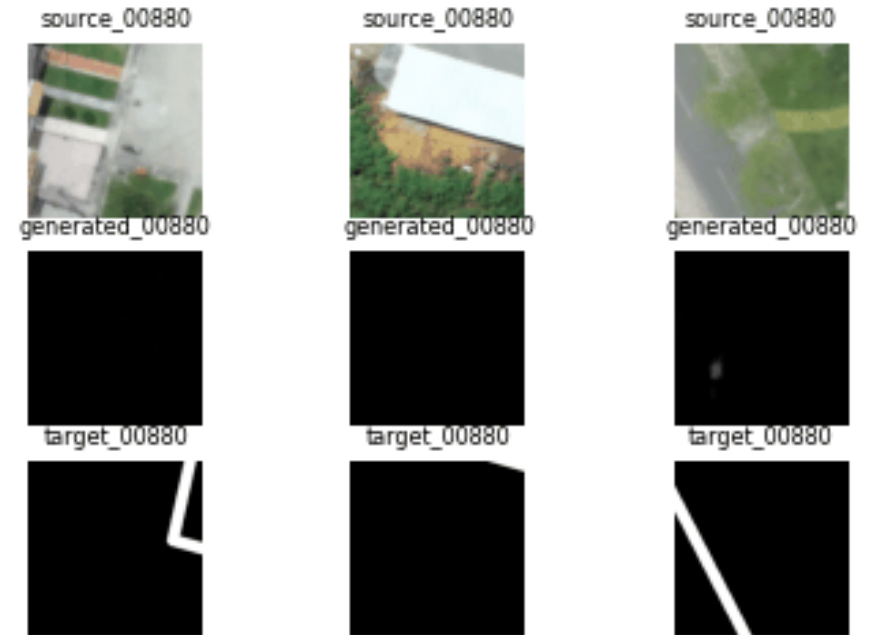
- RGB 256x256 with different road buffer size (1px ~ 10cm, 50cm, 1m, 2m), epochs and number of examples.
- RGB + DSM = RGDSM 256x256 (False Color) with different road buffer size (1px ~ 10cm, 50cm, 1m, 2m), epochs and number of examples.
- Simplification prior to vectorization: Thinning, CenterLine, Skeletonization

EXPERIMENTS AND RESULTS

RGB 1.5m road buffer mask

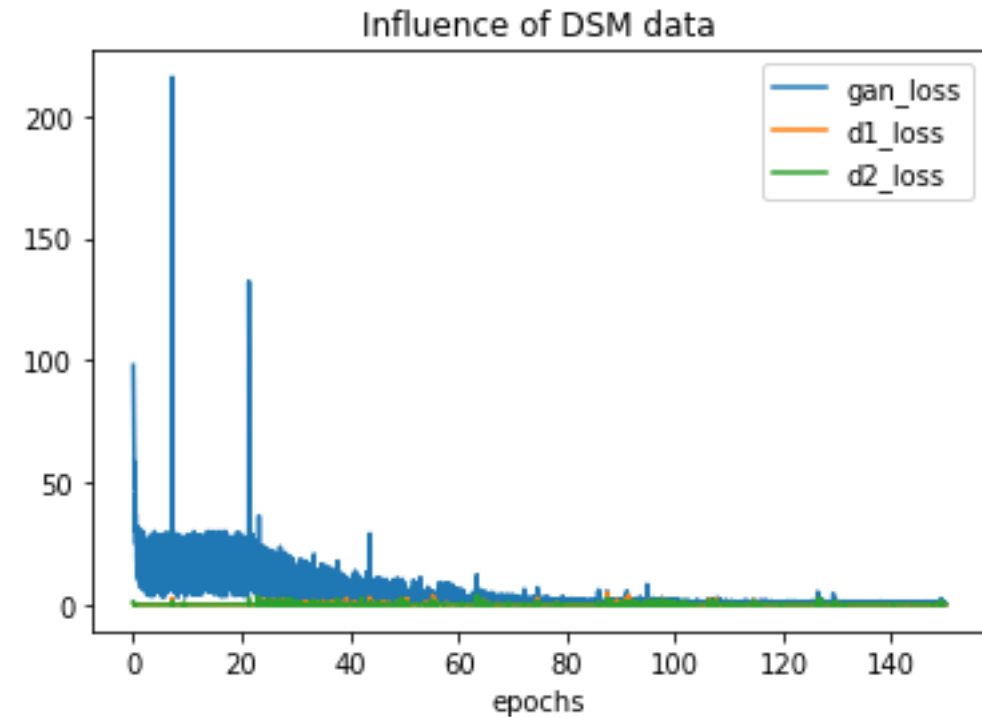
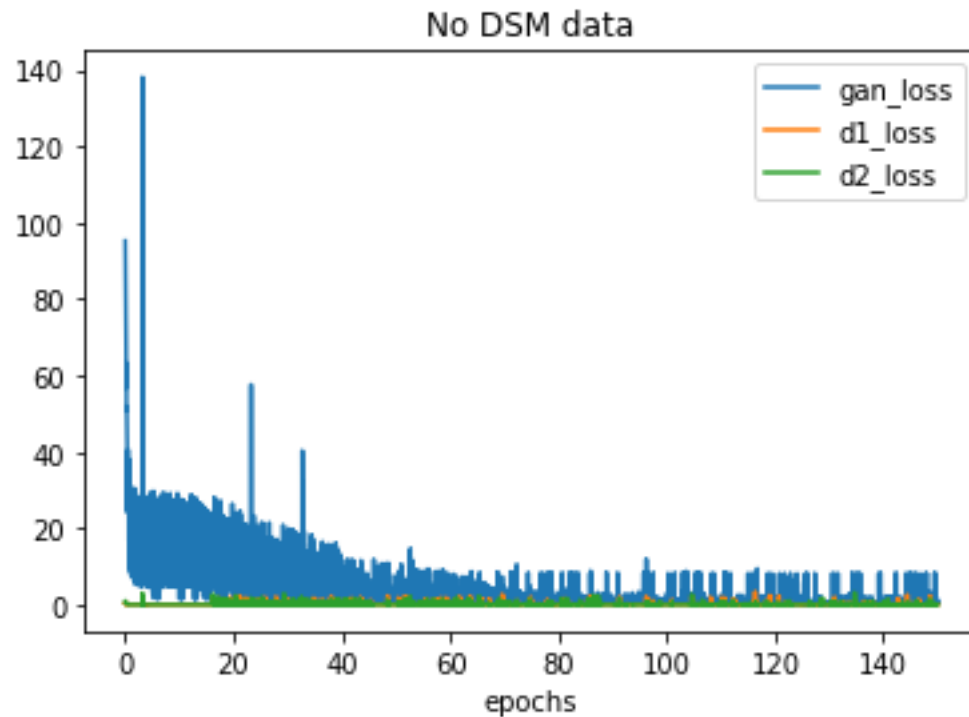


RGB 50cm road buffer mask



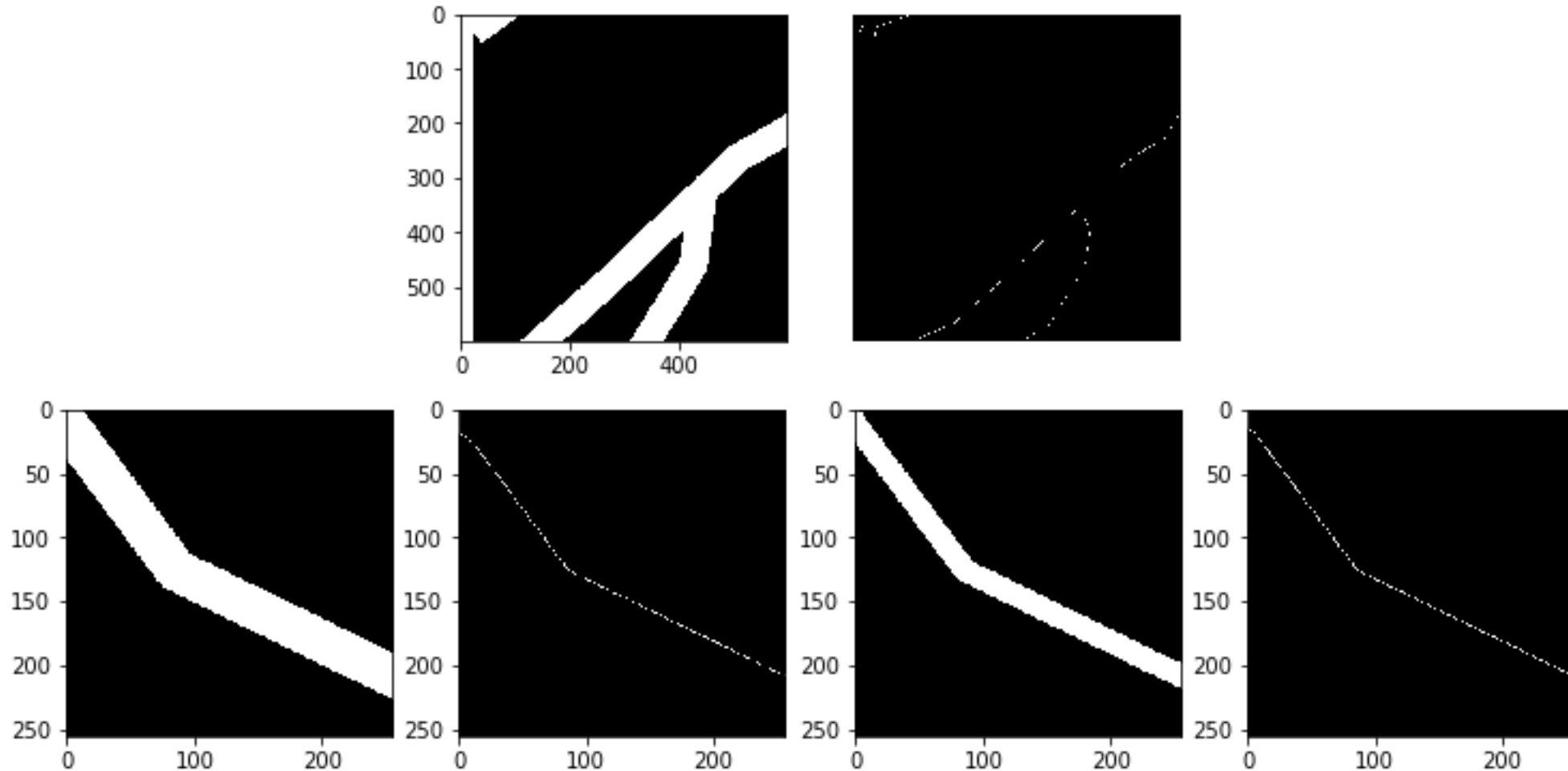
EXPERIMENTS AND RESULTS

Models trained on 50cm road buffer with 150 epochs



EXPERIMENTS AND RESULTS

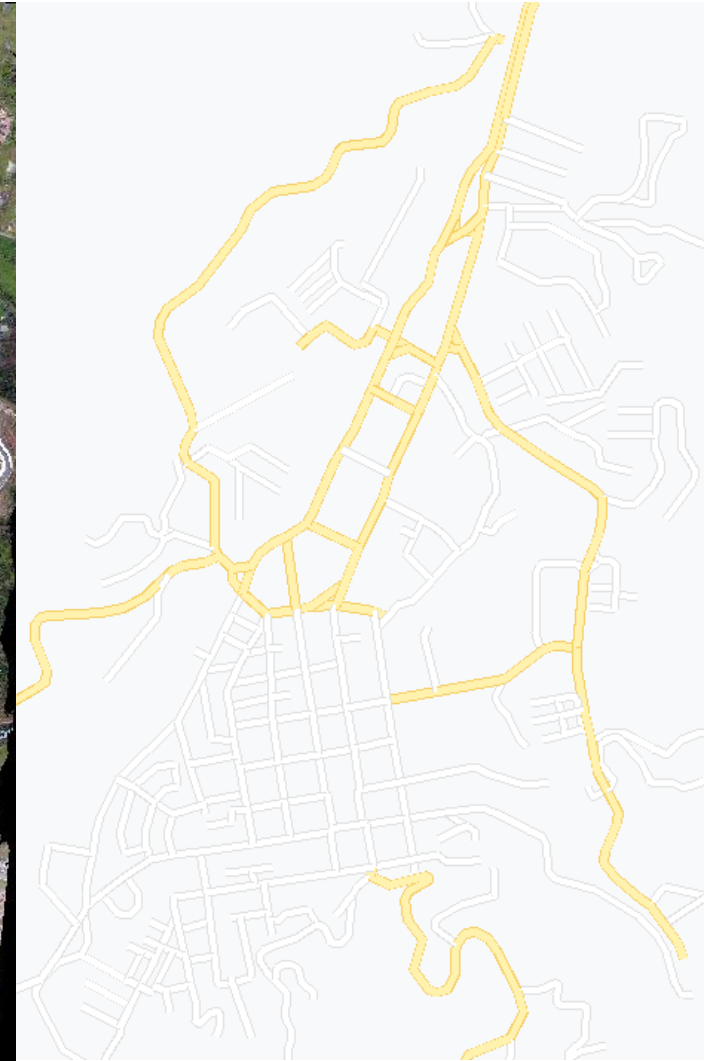
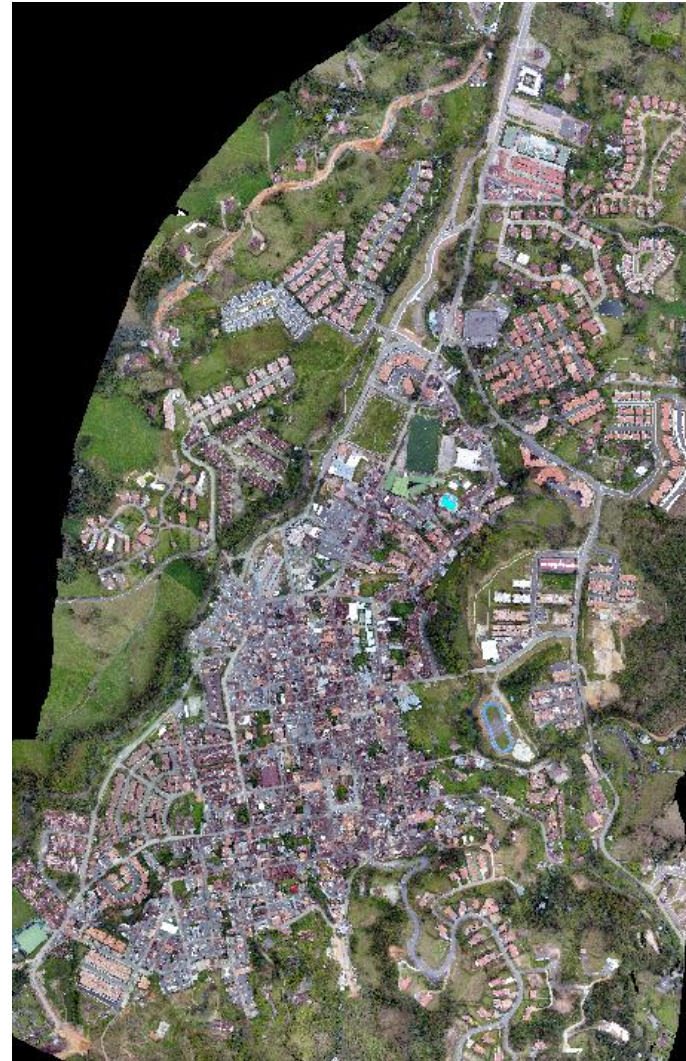
Center Line, Skeletonization or Thining?

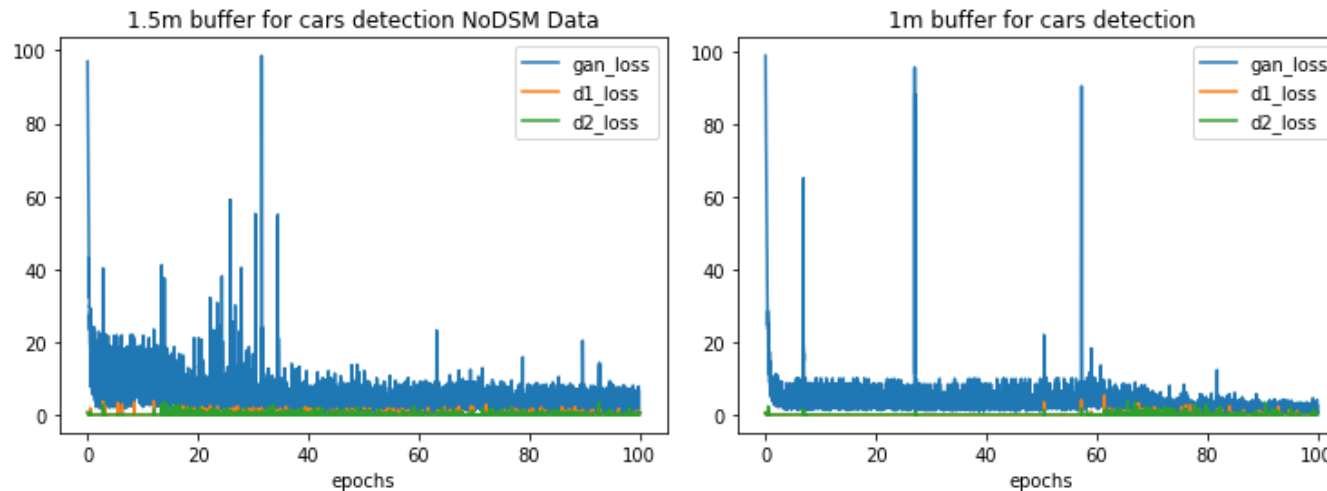
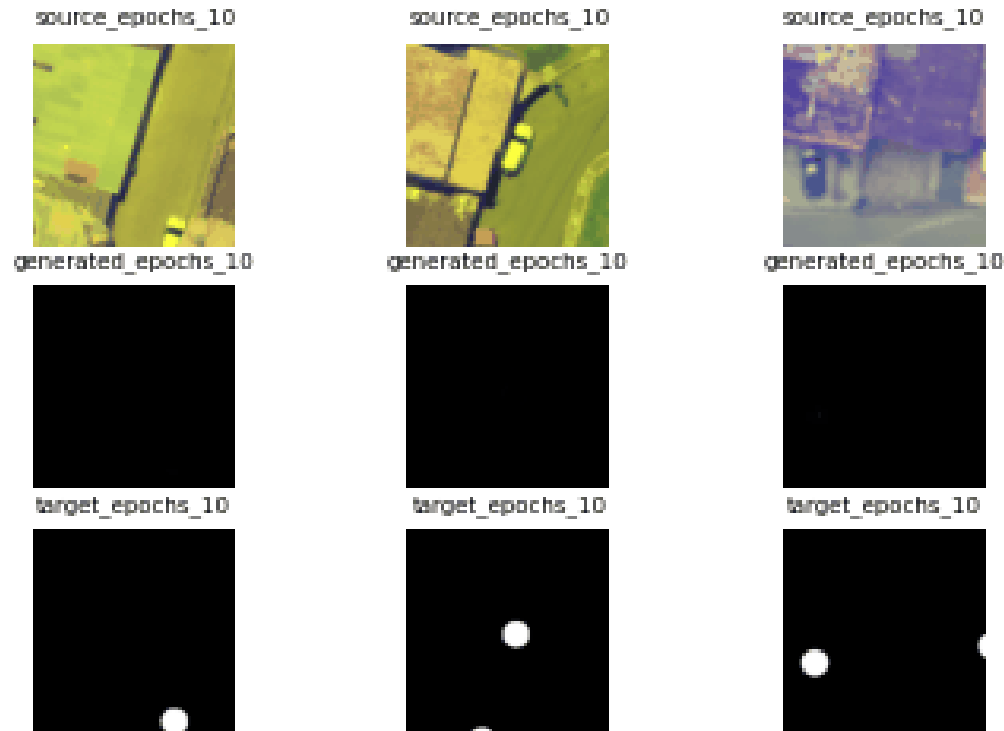


EXPERIMENTS AND RESULTS

Automatic extraction of road network of El Retiro (Ant.), a small urban settlement took 36 mins.

That work would have taken around one month by GIS specialists.





* Not reported on the paper

- Pix2Pix was able to generate missing parts of roads and solve border effects.
- Although training dataset is imbalance, model used was able to learn effectively positive class (roads).
- Model used is applicable to drone imagery even on small (less than 1000 examples) training dataset.
- Integration of DSM to RGB produced better models in terms of less variance of GAN Loss.
- The best model was obtained using 150 epochs, 1000 examples and RGDSM producing a road network of a small town in a fraction of an hour.

REFERENCES

1. Abdollahi, Abolfazl & Pradhan, Biswajeet & Shukla, Nagesh & Chakraborty, Subrata & Alamri, Abdullah. (2020). Deep Learning Approaches Applied to Remote Sensing Datasets for Road Extraction: A State-Of-The-Art Review. Remote Sensing. 12. 1444. 10.3390/rs12091444.
2. Adam Van Etten, Dave Lindenbaum, Todd Bacastow. SpaceNet: A Remote Sensing Dataset and Challenge Series. Computer Vision. 2019.
3. Alec Radford, et al. "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks". ICLR 2016.
4. Al-Najjar, H.A.H.; Kalantar, B.; Pradhan, B.; Saeidi, V.; Halin, A.A.; Ueda, N.; Mansor, S. Land Cover Classification from fused DSM and UAV Images Using Convolutional Neural Networks. Remote Sens. 2019, 11, 1461. <https://doi.org/10.3390/rs11121461>
5. Arnadi Murtiyoso, Mirza Veriandi, Deni Suwardhi, Budhy Soeksmantono and Agung Budi Harto. Automatic Workflow for Roof Extraction and Generation of 3D CityGML Models from Low-Cost UAV Image-Derived Point Clouds. International Journal of Geo-Information, 2020.
6. Batra et al. Improved Road Connectivity by Joint Learning of Orientation and Segmentation. CVPR 2019.
7. Brownlee J. www.machinelearningmastery.com (accessed on 12 March 2020).
8. Bulatov, Dimitri & Häufel, Gisela & Böge, Melanie. (2016). VECTORIZATION OF ROAD DATA EXTRACTED FROM AERIAL AND UAV IMAGERY. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. XLI-B3. 567-574. 10.5194/isprs-archives-XLI-B3-567-2016.
9. Crommelinck, Sophie & Bennett, Rohan & Gerke, Markus & Koeva, Mila & Yang, Michael Ying & Vosselman, George. (2017). SLIC Superpixels for Object Delineation from UAV Data. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences. IV-2/W3. 9-16. 10.5194/isprs-annals-IV-2-W3-9-2017.

REFERENCES

10. Crommelinck, Sophie & Bennett, Rohan & Gerke, Markus & Nex, Francesco & Yang, Michael Ying & Vosselman, George. (2016). Review of Automatic Feature Extraction from High-Resolution Optical Sensor Data for UAV-Based Cadastral Mapping. Remote Sensing. 8. 689. 10.3390/rs8080689.
11. Danyang Cao, Zhixin Chen, and Lei Gao. (2020). An improved object detection algorithm based on multi-scaled and deformable convolutional neural networks. Human Centric Computing Information Sciences. (2020). Available online: <https://doi.org/10.1186/s13673-020-00219-9>
12. Demir et al. DeepGlobe 2018: A Challenge to Parse the Earth through Satellite Images. CVPR 2018.
13. D. Marmanisa,c, K. Schindlerb , J. D. Wegnerb , S. Gallianib, M. Datcua , U. Stillac. Classification with an edge: improving semantic image segmentation with boundary detection. Elsevier, 2018.
14. Eberhard Gülch. Digital systems for automated cartographic feature extraction. Institute of Photogrammetry, University of Bonn. International Archives of Photogrammetry and Remote Sensing. 2000.
15. Fetai, Bujar & Oštir, Krištof & Fras, Mojca & Lisec, Anka. (2019). Extraction of Visible Boundaries for Cadastral Mapping Based on UAV Imagery. Remote Sensing. 11. 1510. 10.3390/rs11131510.
16. Haihong Li. Semi-automatic road extraction from satellite and aerial images. Doctoral Thesis. Swiss Federal Institute of Technology Zurich. 1997. Available online: <https://doi.org/10.3929/ethz-a-001766570>, (accessed on 21 November 2020).
17. Haowen Yan. Description Approaches and Automated Generalization Algorithms for Groups of Map Objects. ISBN 978-981-13-3678-2.

REFERENCES

18. Howard J. <https://course.fast.ai/part2> (accessed on 19 April 2021).
19. Hsiuhan Lexie Yang, Jiangye Yuan, Dalton Lunga, Melanie Laverdiere, Amy Rose, Budhendra Bhaduri. Building Extraction at Scale using Convolutional Neural Network: Mapping of the United States. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (Volume: 11, Issue: 8, Aug. 2018).
20. Hui Yang, Penghai Wu, Xuedong Yao, Yanlan Wu, Biao Wang, and Yongyang Xu. Building Extraction in Very High Resolution Imagery by Dense-Attention Networks. Remote Sensing, 2018.
21. Ian Goodfellow, Yoshua Bengio and Aaron Courville. Deep Learning. MIT Press, 2016. Available online: <http://www.deeplearningbook.org>, (accessed on 16 April 2021).
22. Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio. Generative Adversarial Networks. NIPS 2014: 2672-2680.
23. Jiangye Yuan. Learning Building Extraction in Aerial Scenes Using Convolutional Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence (Volume: 40, Issue: 11, Nov. 1 2018).
24. Jennings Anderson, Dipto Sarkar and Leysia Palen. (2019). Corporate Editors in the Evolving Landscape of OpenStreetMap. International Journal of Geo-Information. 2019.
25. Li, Zuoyue & Wegner, Jan & Lucchi, Aurelien. (2019). Topological Map Extraction From Overhead Images. 1715-1724. 10.1109/ICCV.2019.00180.

REFERENCES

26. Li, Hu, et al. Attention-Guided Multi-Scale Segmentation Neural Network for Interactive Extraction of Region Objects from High-Resolution Satellite Imagery. Remote Sensing. 2020.
27. Mathilde Caron, Hugo Touvron, Ishan Misra, Herve Jegou, Julien Mairal, Piotr Bojanowski, Armand Joulin. (2021). Emerging Properties in Self-Supervised Vision Transformers. In Press. 2021.
28. M. A. Zurbarán, P. Wightman, M. A. Brovelli. A Machine Learning Pipeline Articulating Satellite Imagery and Openstreetmap for Road Detection. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-4/W14, 2019 FOSS4G 2019 – Academic Track, 26–30 August 2019, Bucharest, Romania.
29. Mohammad Pashaei, Hamid Kamangir, Michael J. Starek and Philippe Tissot. Review and Evaluation of Deep Learning Architectures for Efficient Land Cover Mapping with UAS Hyper-Spatial Imagery: A Case Study Over a Wetland. Remote Sensing, 2020.
30. Niu, Sun et al. Hybrid Multiple Attention Network for Semantic Segmentation in Aerial Images. Computer Vision and Pattern Recognition. 2020.
31. Olaf Ronneberger, Philipp Fischer, Thomas Brox. U-Net: Convolutional Networks for Biomedical Image Segmentation. Medical Image Computing and Computer-Assisted Intervention (MICCAI), Springer, LNCS, Vol.9351: 234--241, 2015.
32. Phillip Isola, et al. "Image-to-Image Translation with Conditional Adversarial Networks" CVPR. 2017.
33. Paul Bolstad. GIS Fundamentals. A First Text on Geographic Information Systems. Third Edition. University of Minnesota. 2008.

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