

# Training semantic segmentation of aerial imagery using synthetic data

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**READAR**  
real estate radar



# Content

- Motivation
- Related Work
- Objectives
- Research Questions
- Methodology
- Conclusions
- Discussion
- Future Work

# Motivation

## Semantic segmentation and Deep Learning

- Change Detection
- Land cover
- Updating Cartography



Image taken from: <https://beyondminds.ai/blog/a-simple-guide-to-semantic-segmentation/>

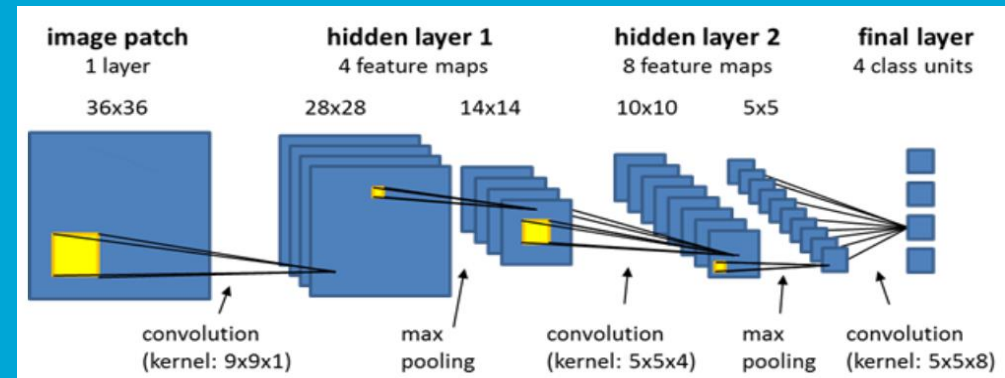


Image taken from: [https://docs.ecognition.com/eCognition\\_documentation/](https://docs.ecognition.com/eCognition_documentation/)

# Related Work

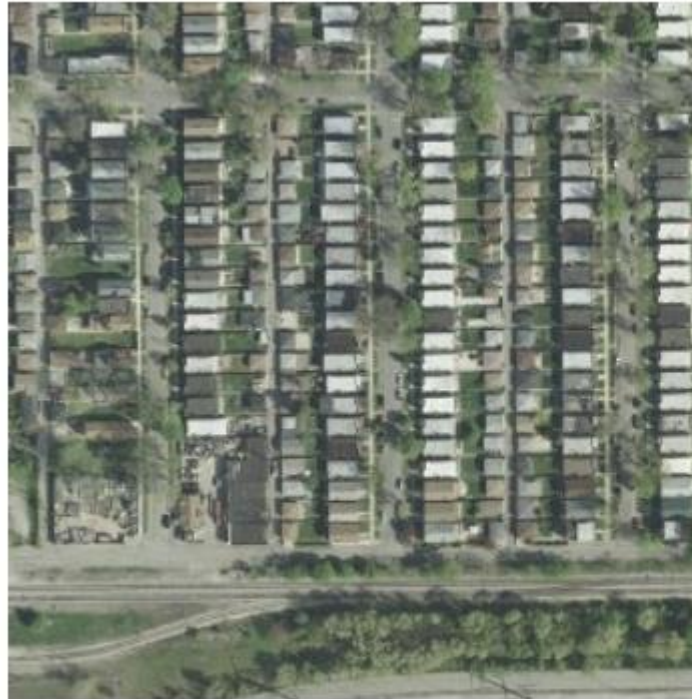
Maggioroi et. al (2017)  
Kampffmeyer et. al (2016)

## Limitations

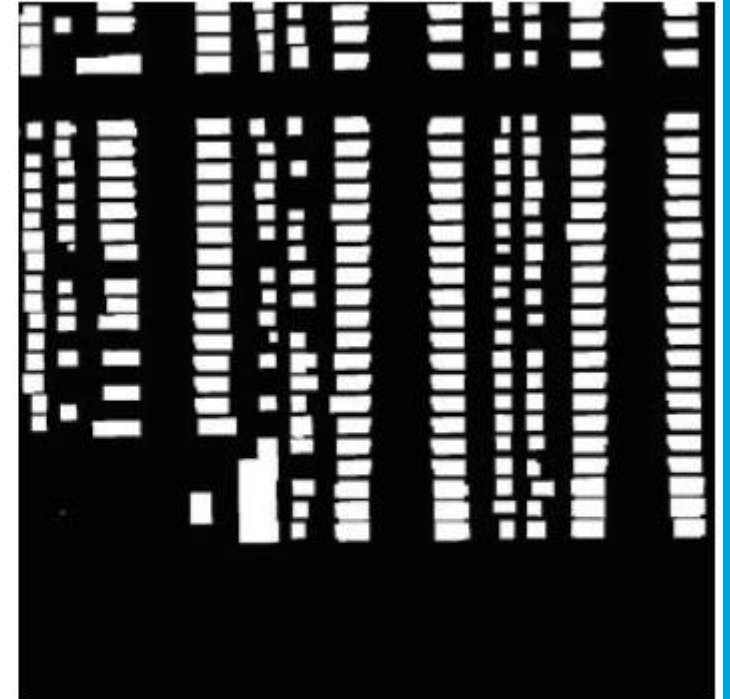
- Same training and testing area
- Do not talk about the quality of training data
- Model Oriented Focus

## Deep Learning Projects

80% time for Data Processing  
(cleaning training data)



*Chicago*



*Chicago - reference*

Image taken from: [https://docs.ecognition.com/eCognition\\_documentation/](https://docs.ecognition.com/eCognition_documentation/)

# Synthetic Data

- SYNTHIA (2018)
- SYNTHINEL (2021)

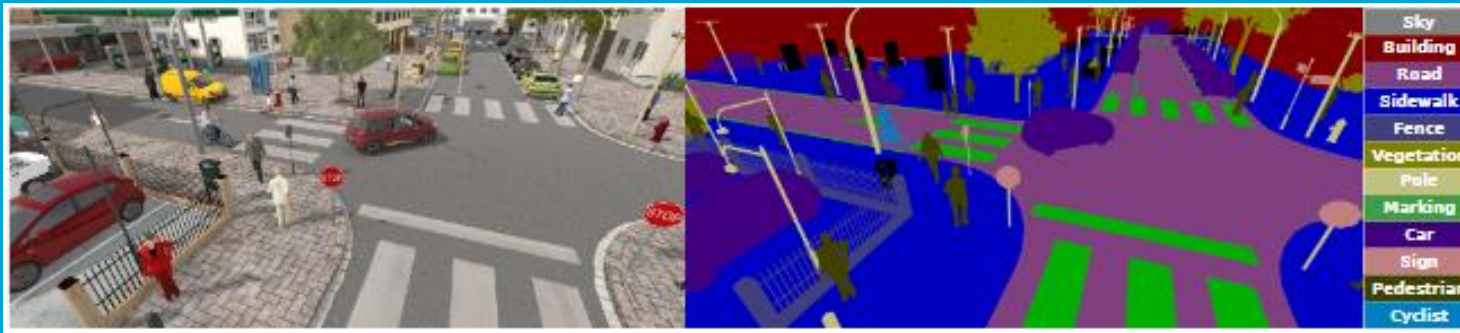


Image taken from: G. Ros, L. Sellart, J. Materzynska, D. Vazquez, and A. M. Lopez. The SYNTHIA Dataset: A Large Collection of Synthetic Images for Semantic Segmentation of Urban Scenes. Technical report, 2016.

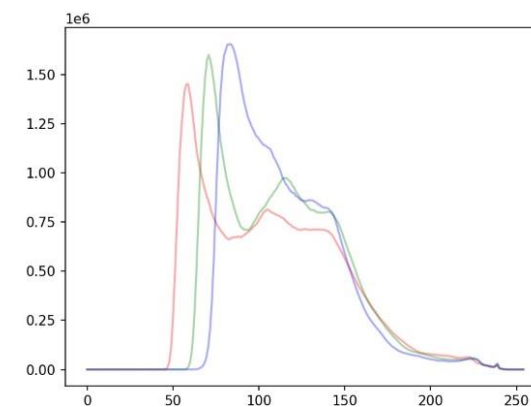
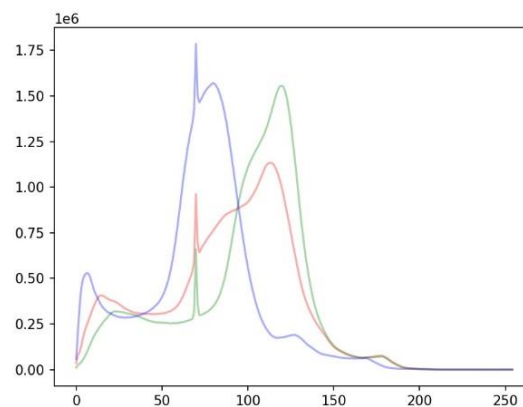
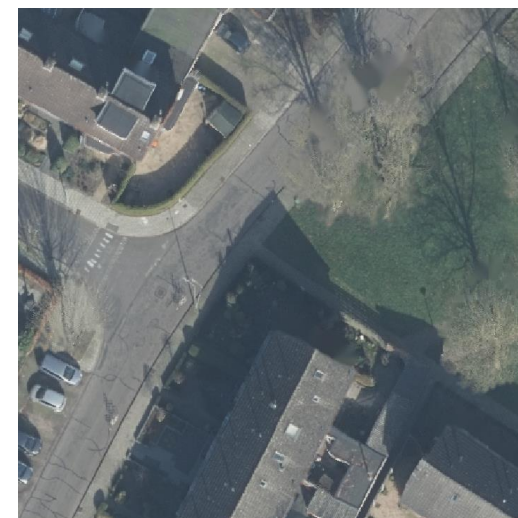


Image taken from: F. Kong, B. Huang, K. Bradbury, and J. Malof. The Synthinel-1 dataset: a collection of high resolution synthetic overhead imagery for building segmentation. 1089, 2019.

# Domain Adaptation

Transfer Learning

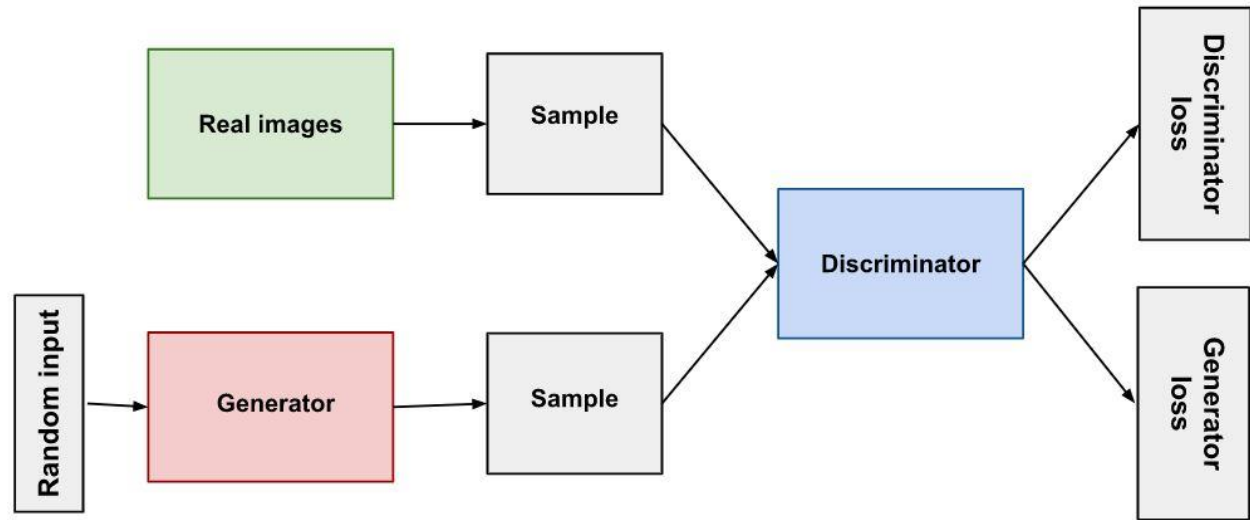
Generative Adversarial Networks



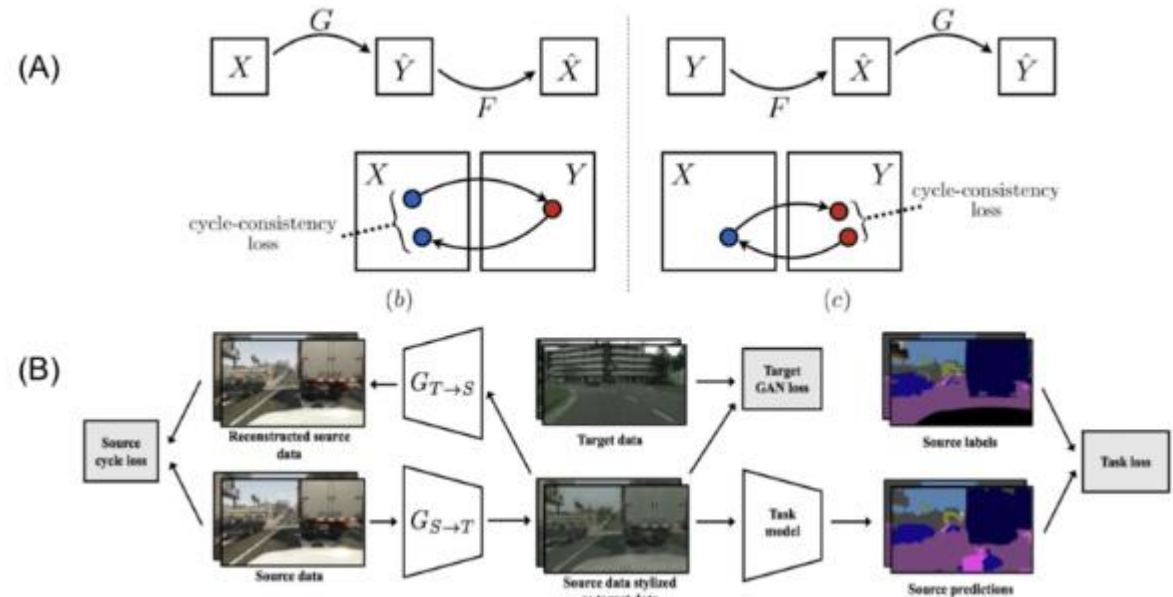
# Domain Adaptation

## CORAL

$$\min_A \|A^T C_s A - C_t\|_F^2$$



Shor, J. (2022). GANs. <https://developers.google.com/machine-learning/gan>



Deep Reinforcement Learning for Soft Robotic Applications: Brief Overview with Impending Challenges - Scientific Figure on ResearchGate. Available from: [https://www.researchgate.net/figure/A-Training-Architecture-of-CycleGAN-B-Training-Architecture-of-a-CyCADA\\_fig7\\_329368817](https://www.researchgate.net/figure/A-Training-Architecture-of-CycleGAN-B-Training-Architecture-of-a-CyCADA_fig7_329368817) [accessed 23 May, 2022]

# Objective

Evaluate the use of synthetic images for deep learning in aerial imagery

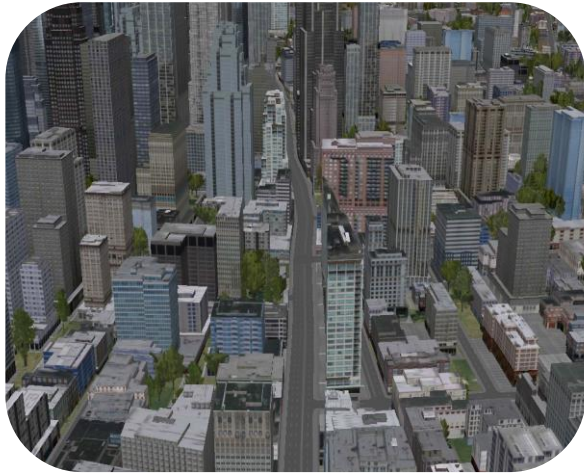




# Research Questions

To what extent can **synthetic data** improve the current **Deep Learning-based models** for automated semantic segmentation for aerial images?

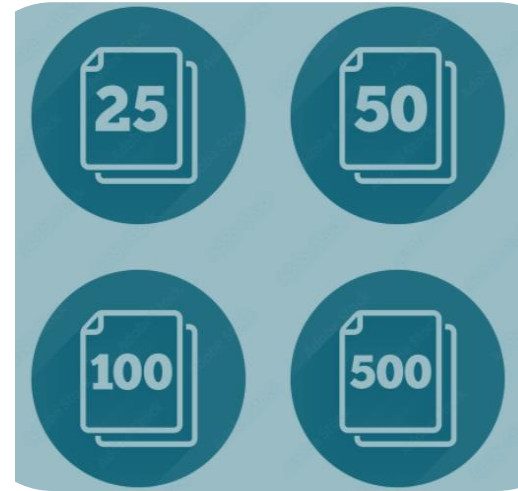
Sub-questions:



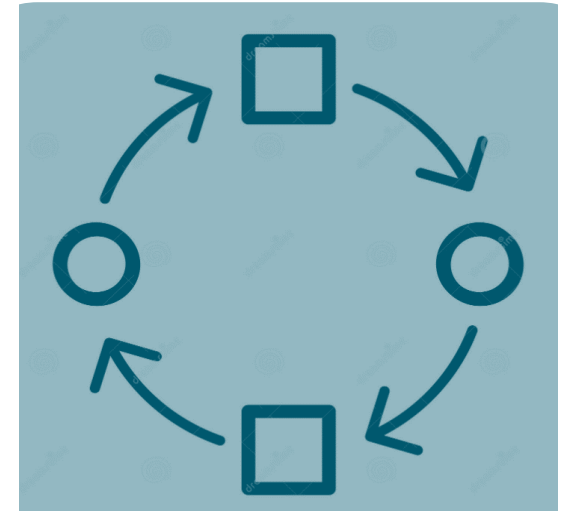
Creation of Synthetic City



3D Models

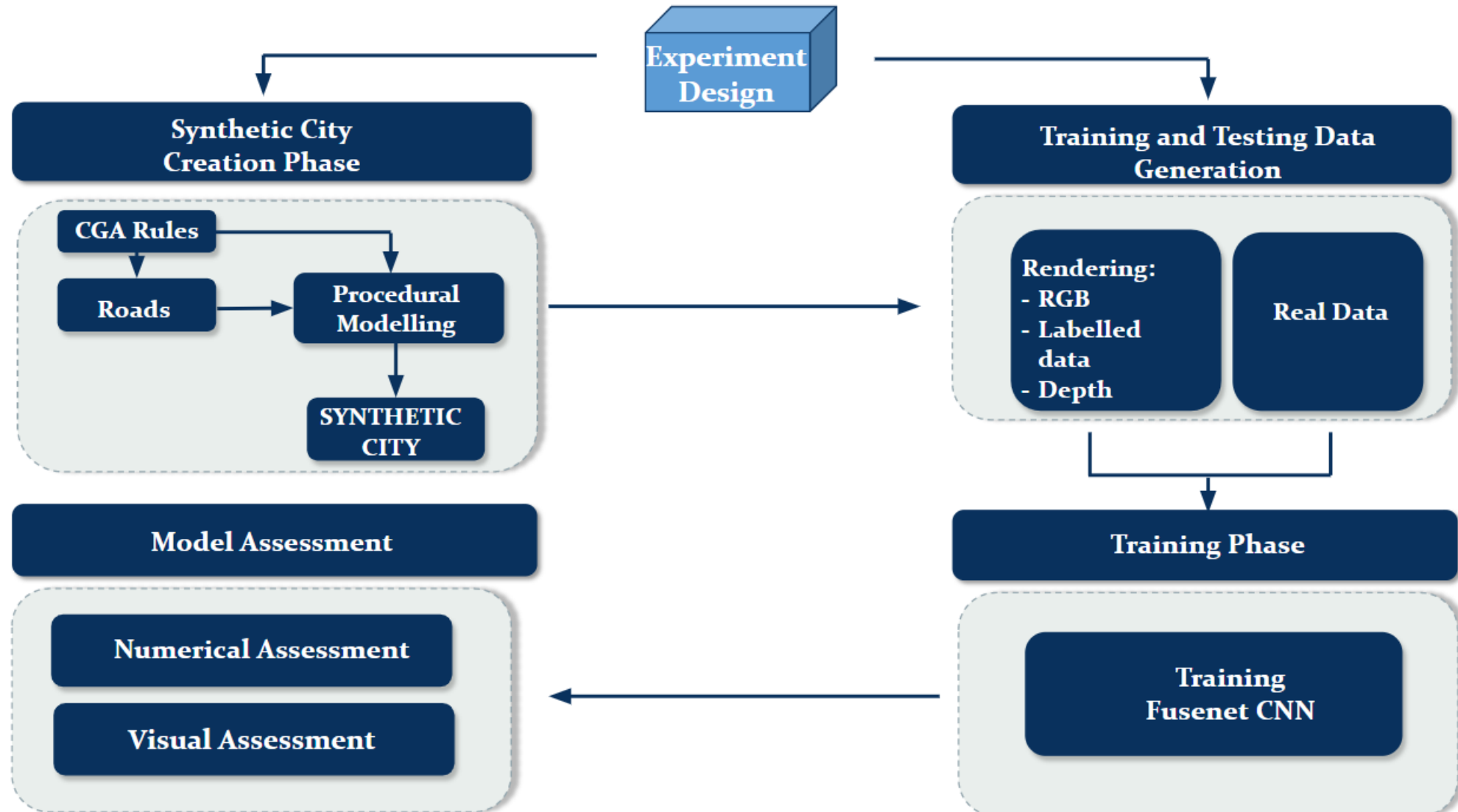


Quantity, Mix



Cross-Domain, Domain Adaptation

# Methodology



# City Engine

## Procedural Modelling

## Computed Generated Architecture Shaped Grammar

Synthetic  
City  
Creation

Datasets

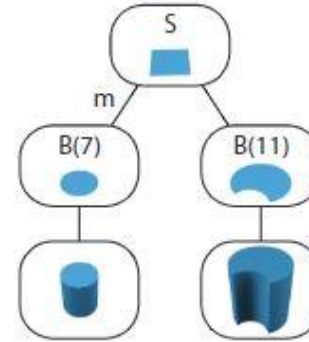
Training  
Model

Assessment



```
S --> 1("circle") m=B(7) t(3,0,0) s(10,0,10) minus(m) B(11)  
B(h) --> extrude(h)
```

(a) Grammar



(b) Shape tree



(c) Result

Image taken from: Muller, M. and Schwarz, P. (2015). Advanced Procedural Modeling of Architecture. ACM Trans. Graph, 34



# Synthetic Data Creation



Synthetic City Creation

Datasets

Training Model

Assessment

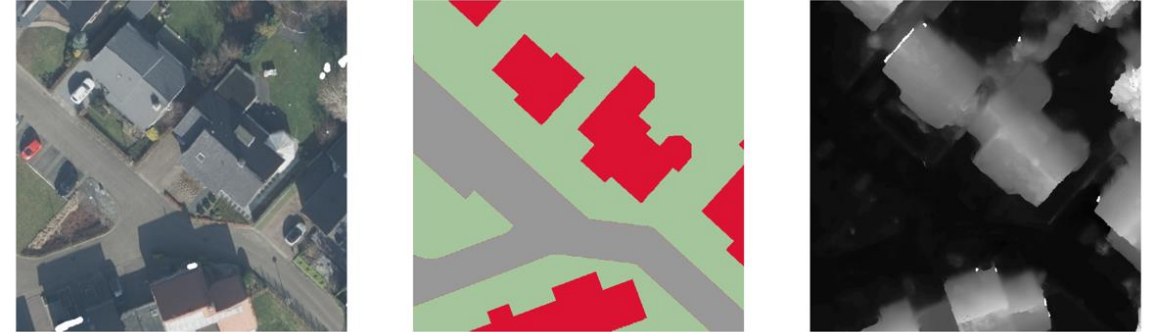
City Engine



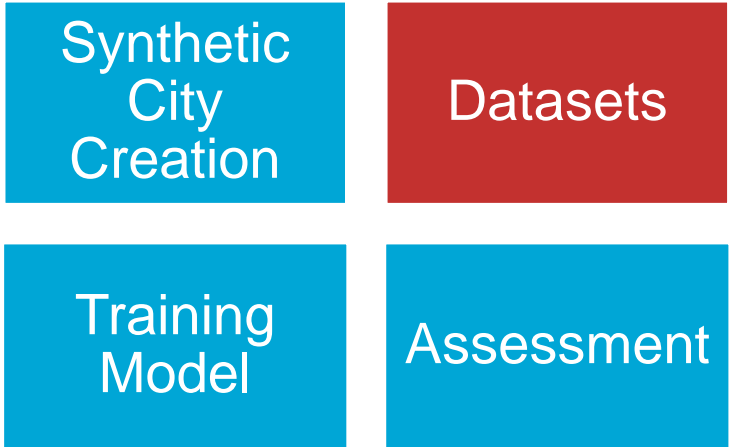
Blender



# Training and Testing Data



## Synthetic Dataset



Haaksbergen



Potsdam

## Real Dataset

Building  
Road  
Other

# Training Phase

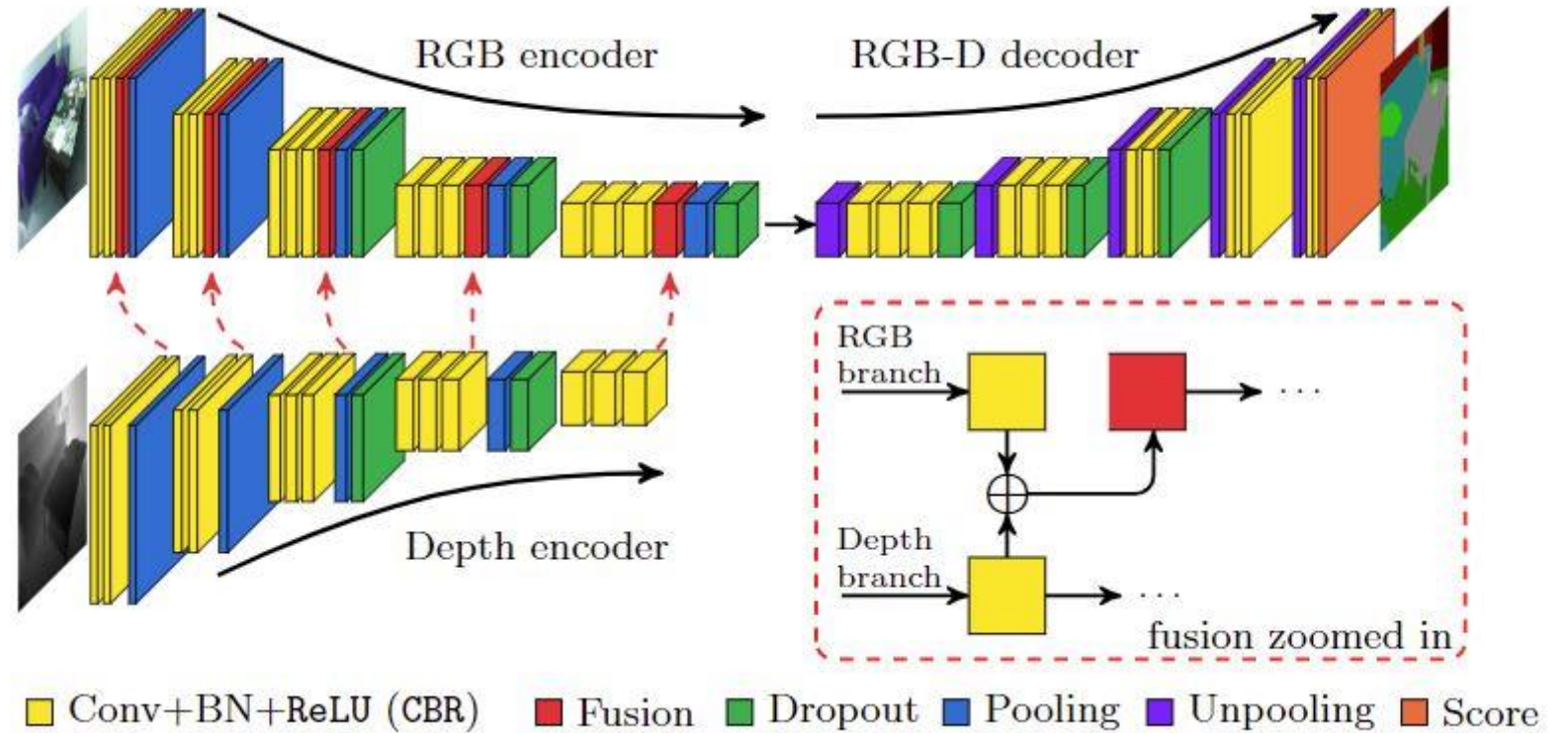
Synthetic City Creation

Datasets

Training Model

Assessment

Train to detect Buildings, Roads and Other



## FuseNet Architecture

# Assessment

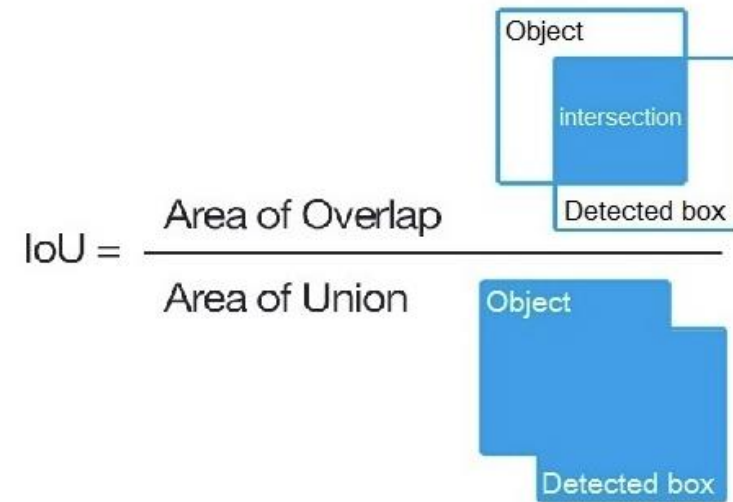
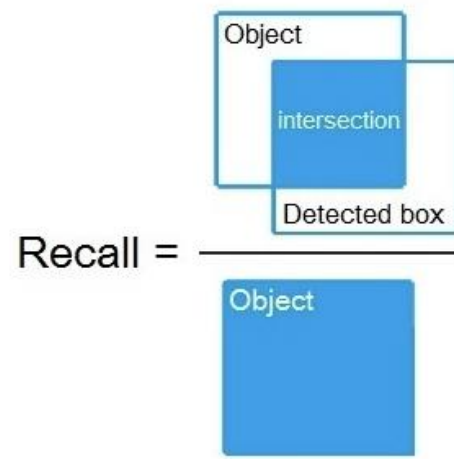
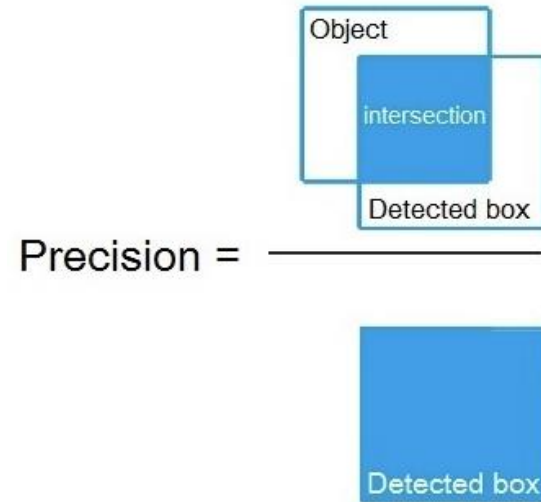
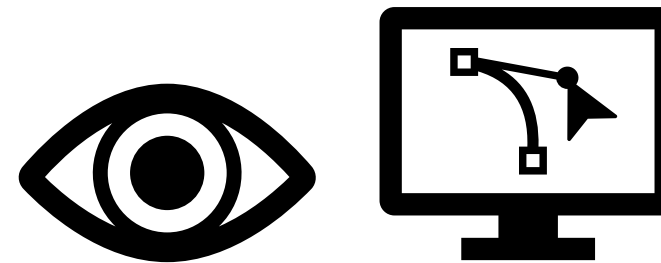
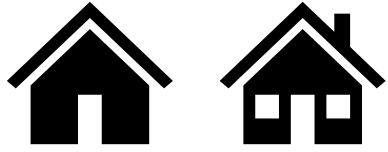


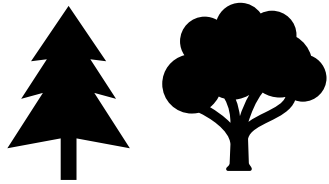
Image taken from: <http://www.gabormelli.com/>



# Experiment Design



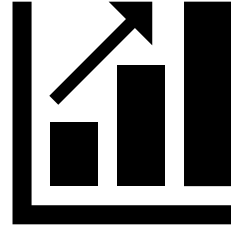
1. Building Models



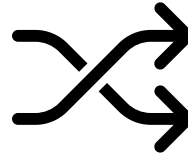
2. Tree Models



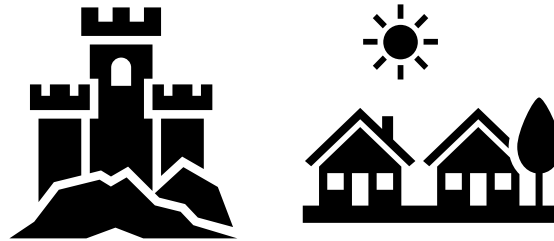
3. Road Patterns



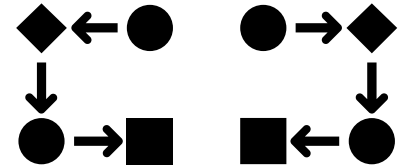
4. Quantity Images



5. Mix between real and synthetic



6. Cross-Domain



7. Domain Adaptation



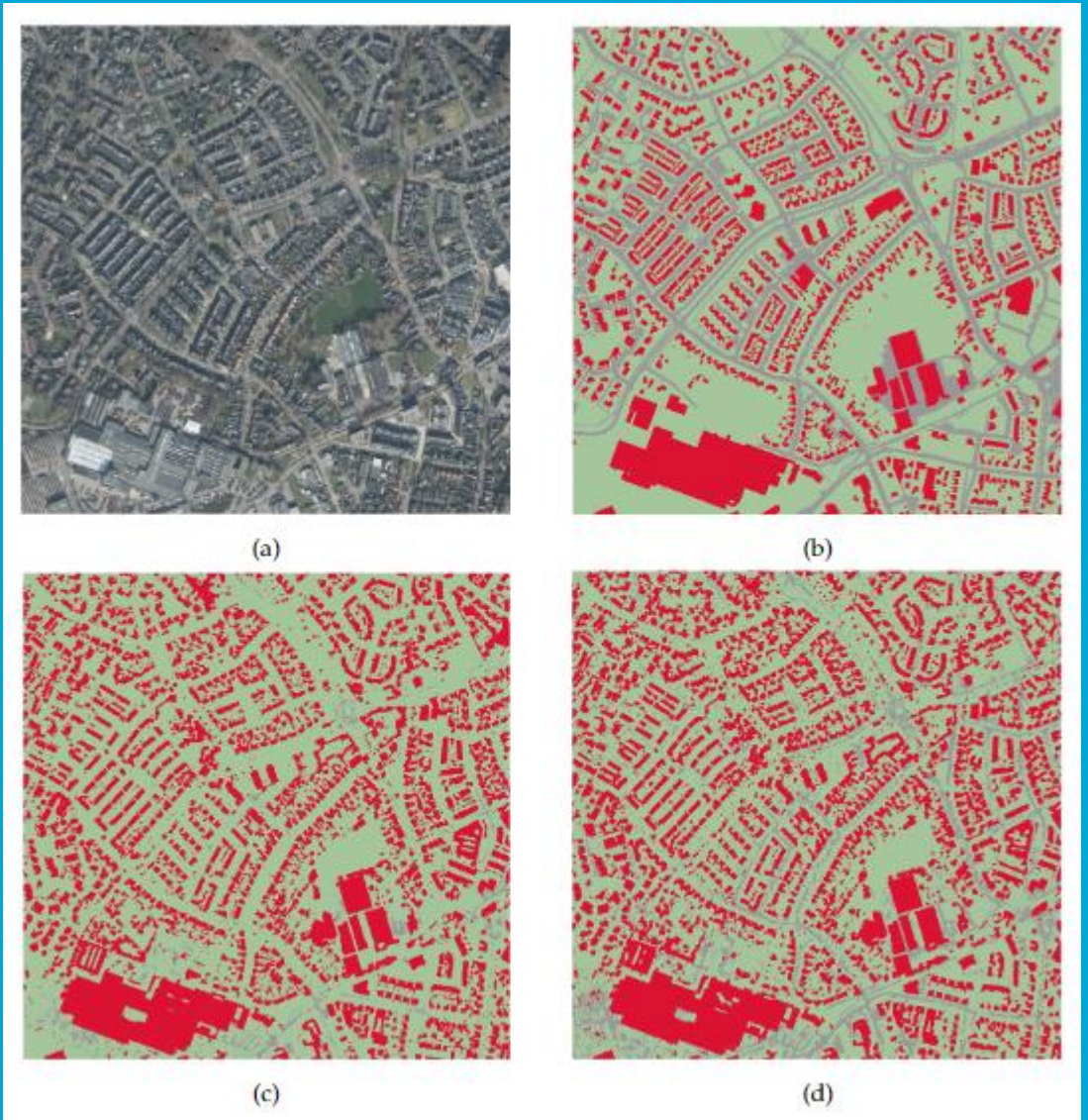
# Building Models

Model	IoU Building	IoU Road	IoU Other	mIoU
Dutch City	<b>0.58</b>	<b>0.20</b>	<b>0.59</b>	<b>0.46</b>
International City (Default)	0.57	0.04	<b>0.59</b>	0.40

Table 2. Buildings Performance



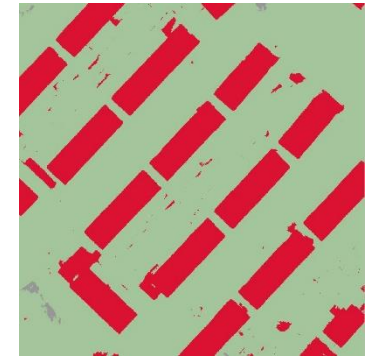
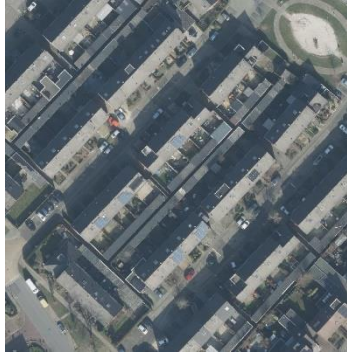
Building  
Road  
Other



(a) True Ortho  
(c) International City

(b) Ground Truth  
(d) Dutch City

# Visual Assessment



Building  
Road  
Other

True Ortho

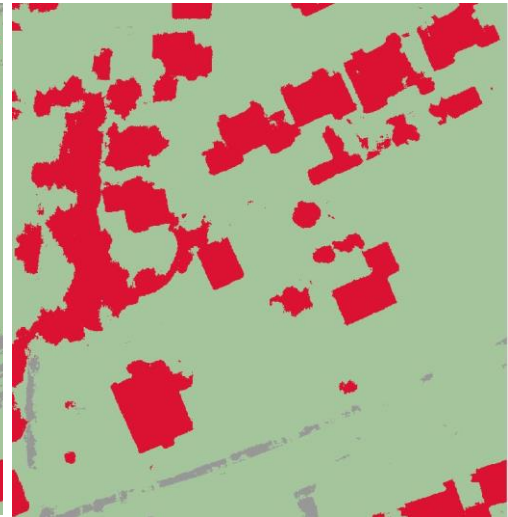
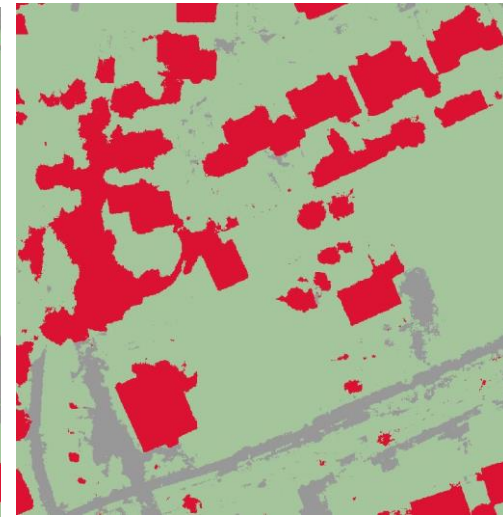
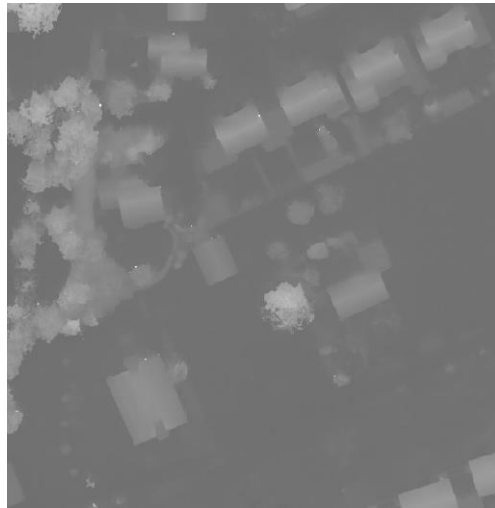
Ground Truth

Dutch City

International City

# Visual Assessment

Building  
Road  
Other



True Ortho

DSM

Ground Truth

Dutch City

International City

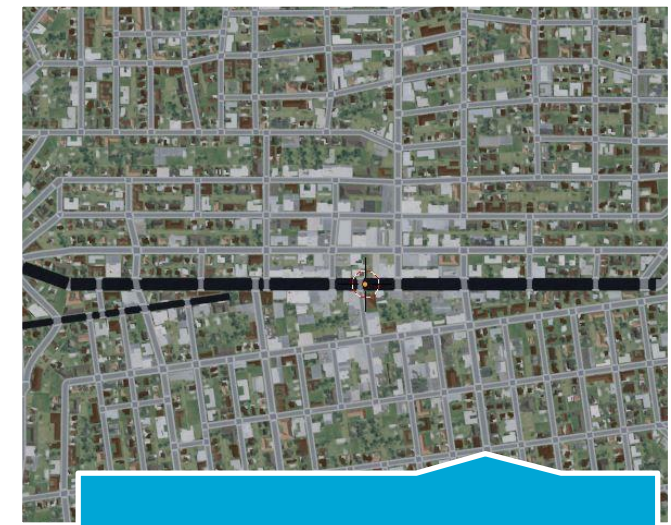
# Road Patterns

Model	IoU building	IoU roads	IoU other	mIoU
Organic	0.45	0.28	<b>0.54</b>	0.42
Raster	<b>0.49</b>	<b>0.36</b>	0.48	<b>0.44</b>
Organic - Raster	0.43	0.30	0.43	0.39
Radial	0.46	<b>0.36</b>	0.22	0.35

Table 2. Road Pattern Performance



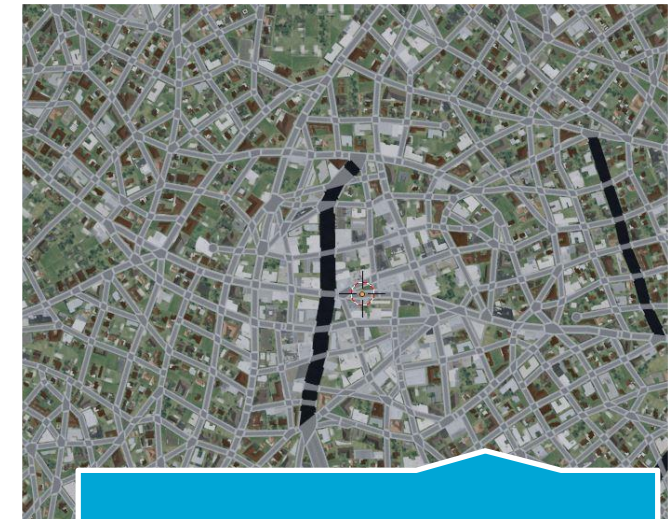
Organic Raster



Raster

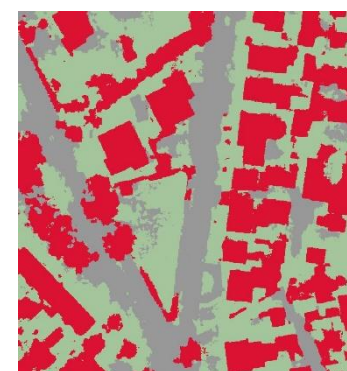
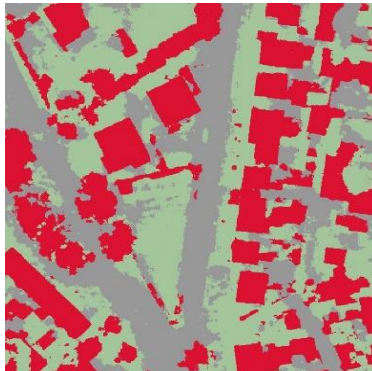
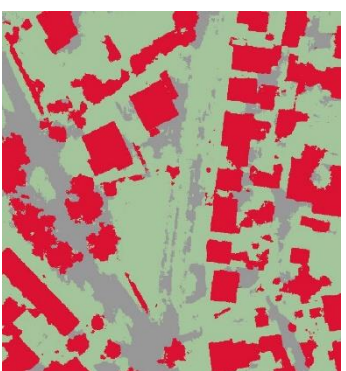
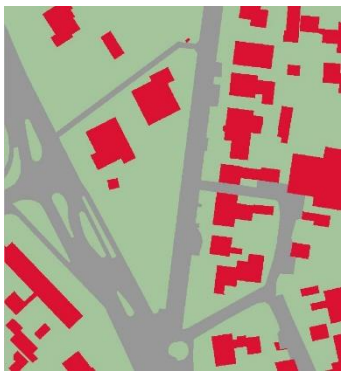
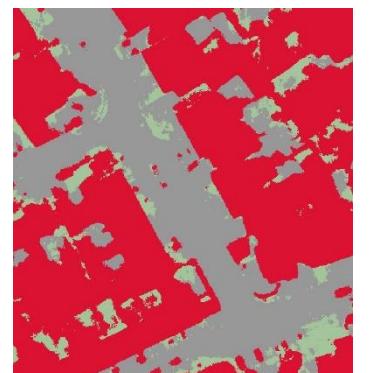
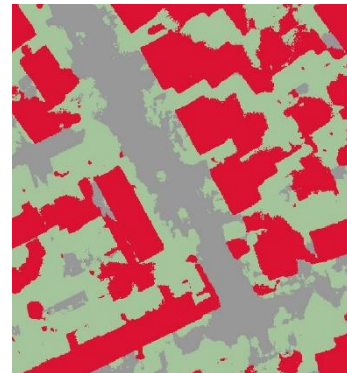
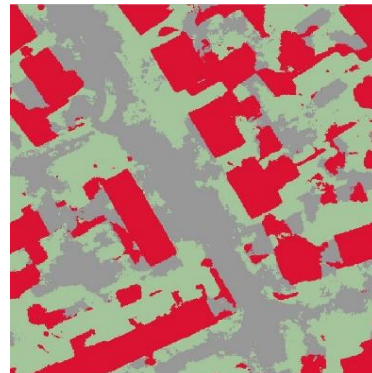


Radial



Organic

# Visual Assessment



True Ortho

Ground Truth

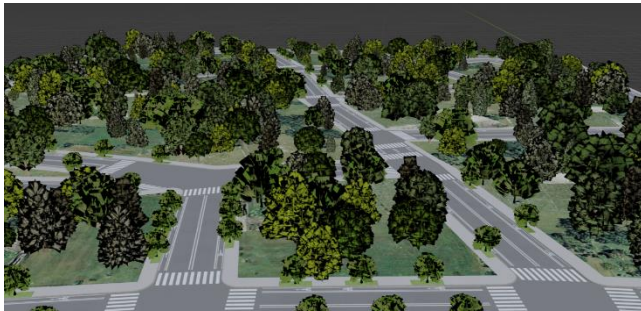
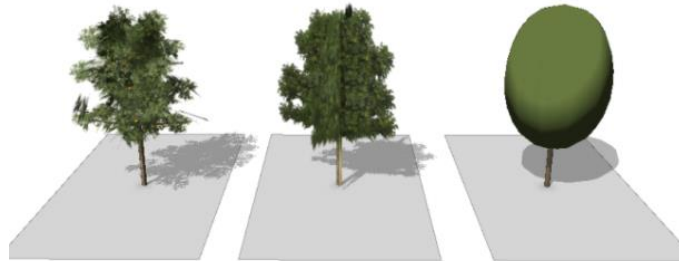
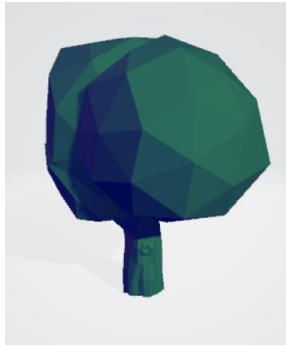
Organic

Organic - Raster

Raster

Radial

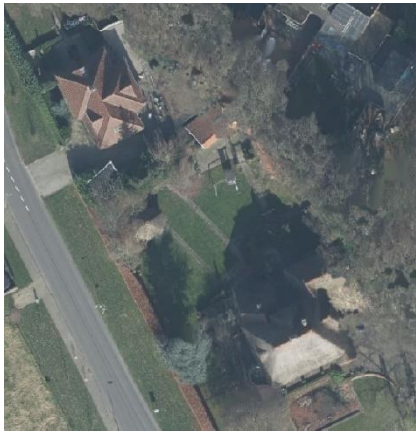
# Tree Models



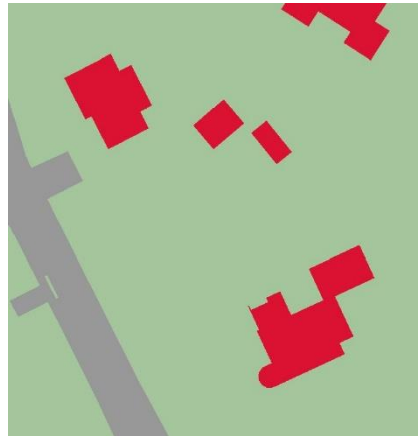
Model	IoU building	IoU roads	IoU other	mIoU
No trees	0.43	<b>0.30</b>	<b>0.43</b>	<b>0.39</b>
Poly Tree	0.43	<b>0.30</b>	0.42	<b>0.39</b>
Fan Tree	0.40	0.22	0.29	0.30
Realistic Tree	<b>0.57</b>	0.29	0.29	0.38

Table 3. Trees Performance

# Visual Assessment



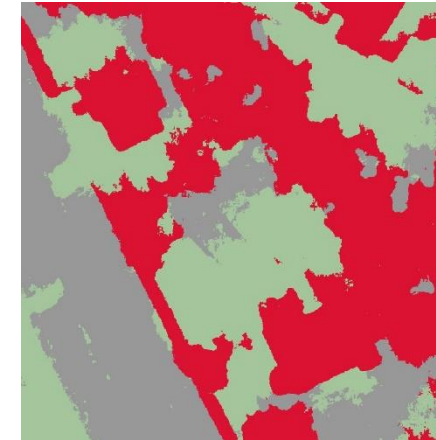
True Ortho



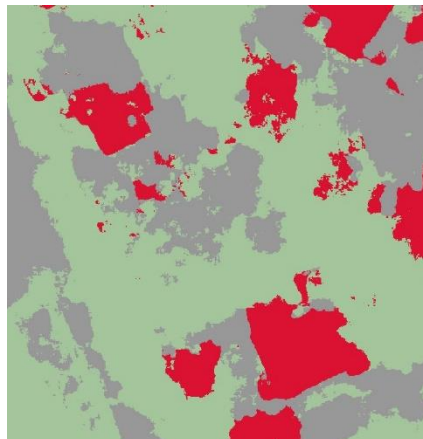
Ground Truth



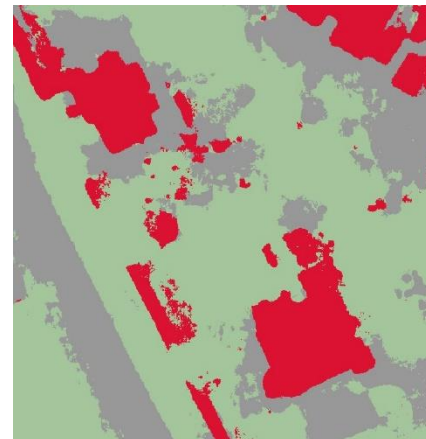
No Trees



Poly Tree



Fan Tree

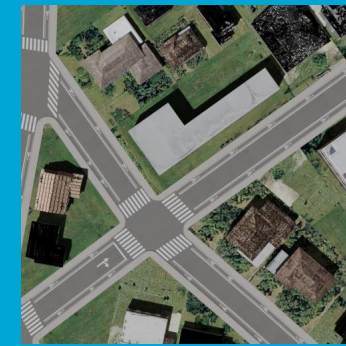


Realistic Tree

Building  
Road  
Other

# Domain Adaptation

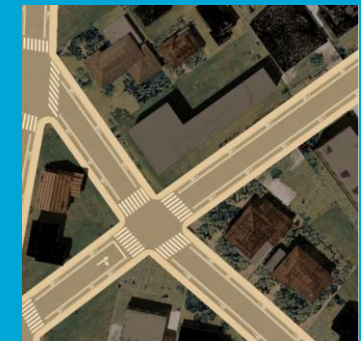
Model	IoU building	IoU roads	IoU other	mIoU
<b>Synthetic City</b>	<b>0.56</b>	0.26	0.53	0.45
<b>Coral</b>	0.46	0.05	0.58	0.36
<b>Coral by Classes</b>	0.44	0.04	<b>0.59</b>	0.36
<b>Cycle GAN</b>	0.51	<b>0.40</b>	0.55	<b>0.49</b>
<b>Cycada</b>	0.52	0.39	0.56	<b>0.49</b>



Synthetic



Coral



Coral by class



Cycle GAN



Cycada

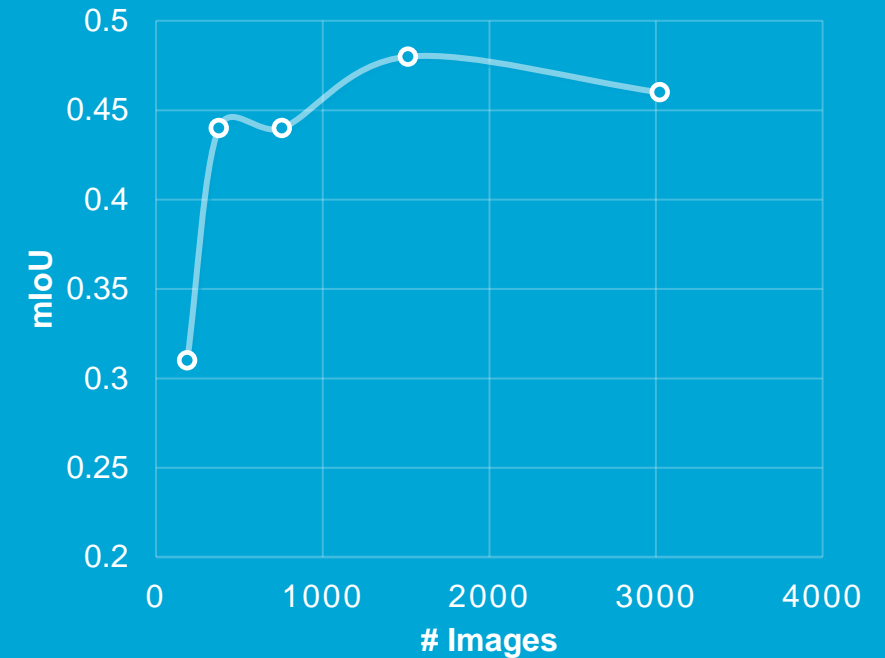
Table 8. Domain Adaptation



# Quantity of synthetic images

Model	IoU building	IoU roads	IoU other	mIoU
188	0.47	0.23	0.21	0.31
378	0.52	0.31	0.51	0.44
756	<b>0.56</b>	0.26	0.53	0.44
1512	0.52	<b>0.33</b>	<b>0.57</b>	<b>0.48</b>
3024	0.50	0.32	0.56	0.46

Table 4. Quantity Performance



Graph 1. Synthetic Learning Curve

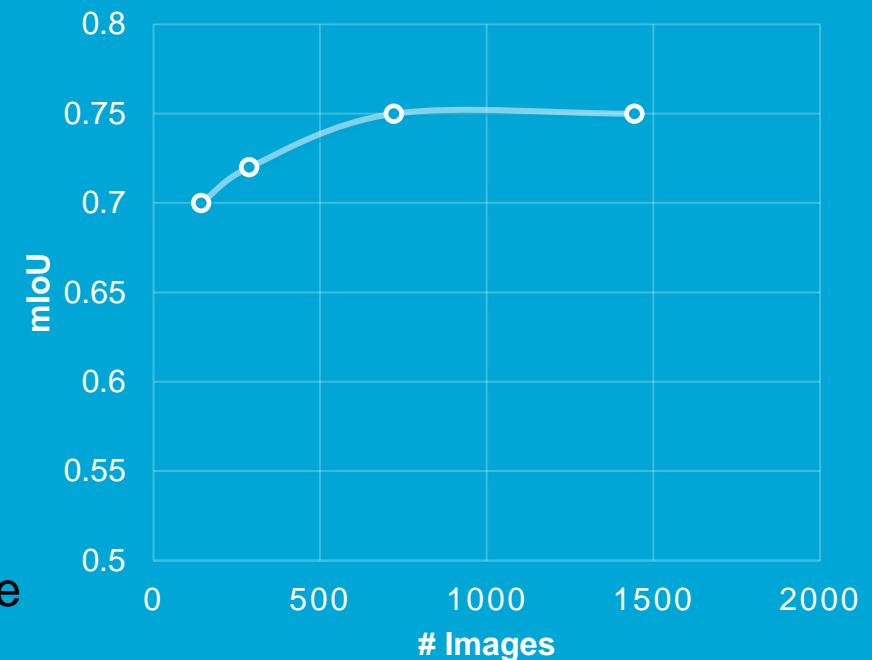
# A mix of Real and Synthetic Data

Model	IoU building	IoU roads	IoU other	mIoU
Real 100% (1444 img)	<b>0.82</b>	0.66	<b>0.79</b>	0.75
Real 80% (1156 img) Synt 20% (288 img)	0.81	<b>0.67</b>	<b>0.79</b>	<b>0.76</b>
Real 50% (722 img) Synt 50% (722 img)	0.81	0.65	<b>0.79</b>	0.75
Real 20% (288 img) Synt 80% (1156 img)	0.79	0.60	0.76	0.71
Synt 100% (1444 img)	0.49	0.39	0.31	0.35

Table 5. Mix real and synthetic data

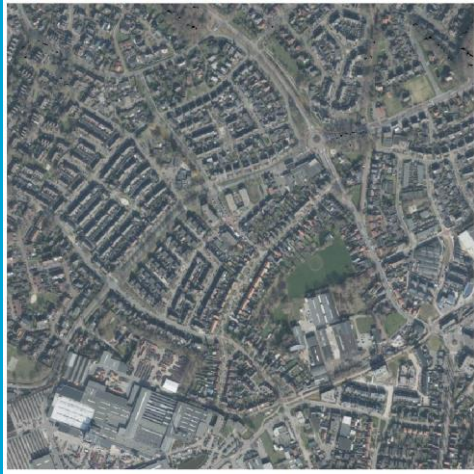
Model	IoU building	IoU roads	IoU other	mIoU
1444	<b>0.82</b>	<b>0.66</b>	<b>0.79</b>	<b>0.75</b>
722	0.81	0.65	<b>0.79</b>	<b>0.75</b>
288	0.79	0.61	0.77	0.72
144	0.79	0.58	0.76	0.70

Table 6. Training with 100% real imagery

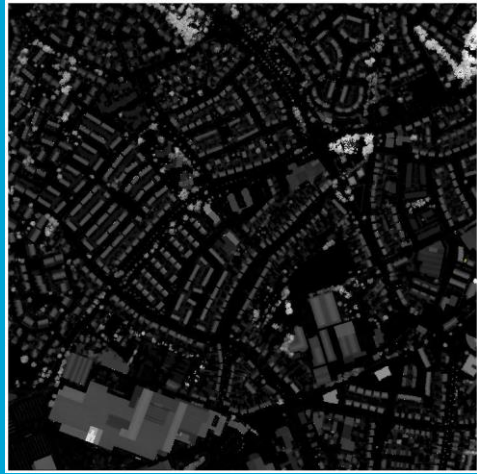


Graph 2. Real Learning Curve

# Cross-domain Visual Assessment



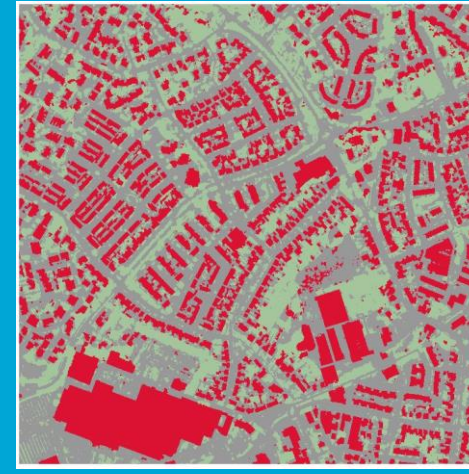
Haaksbergen



DSM



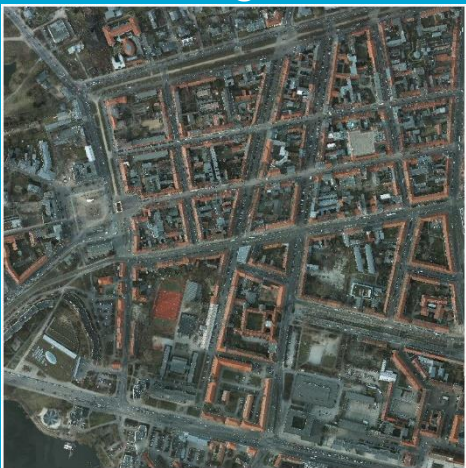
Ground Truth



Potsdam



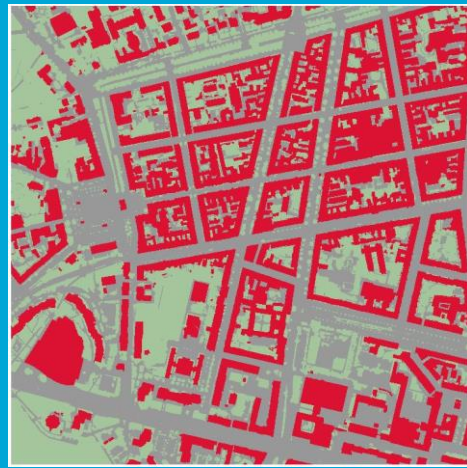
Potsdam - Synthetic



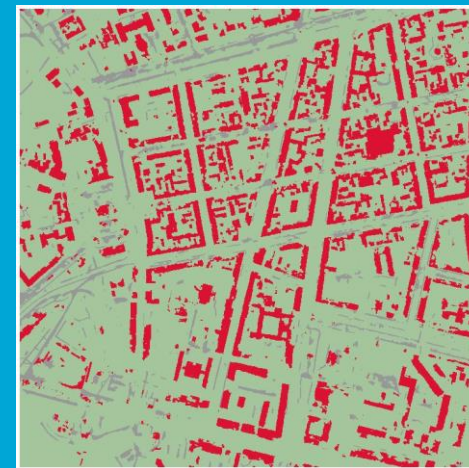
Potsdam



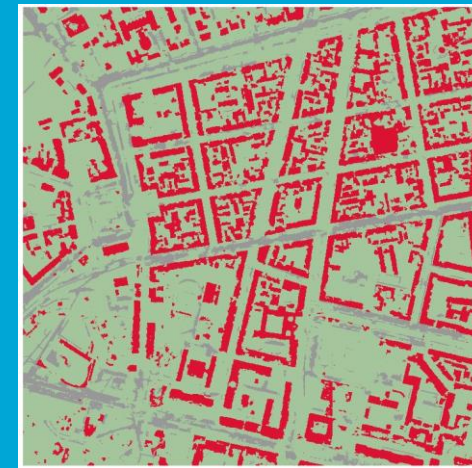
DSM



Ground Truth



Haaksbergen



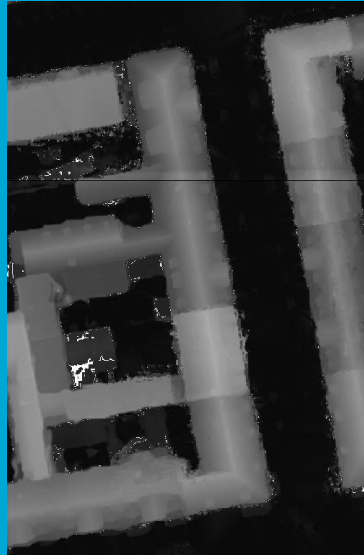
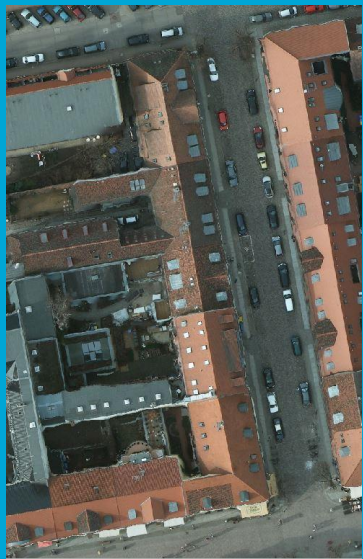
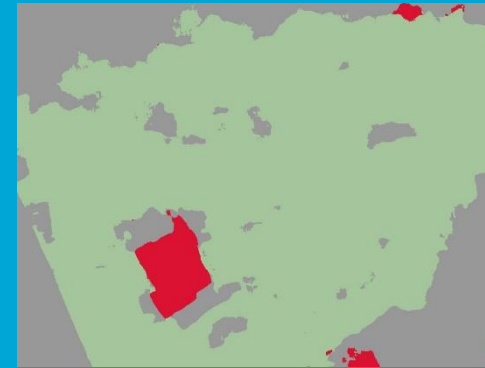
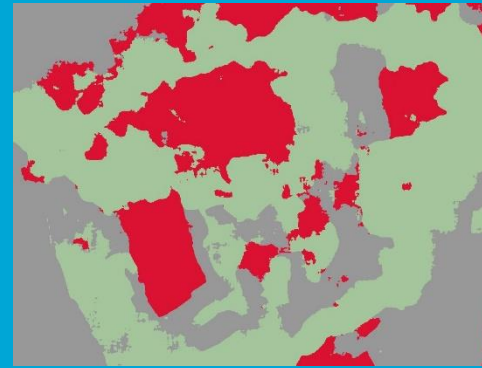
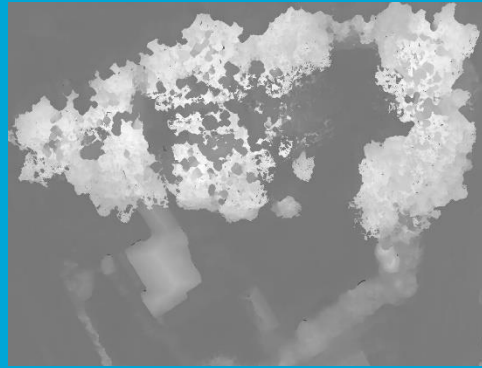
Haaksbergen -  
Synthetic

# Cross – Domain Scenarios

Training	Testing	IoU building	IoU roads	IoU other	mIoU
Potsdam	Haaksbergen	0.62	<b>0.35</b>	0.39	0.45
50% Potsdam – 50% Synthetic	Haaksbergen	<b>0.75</b>	0.31	<b>0.40</b>	<b>0.49</b>
Haaksbergen	Potsdam	0.54	0.13	0.35	0.34
50% Haaksbergen – 50% Synthetic	Potsdam	<b>0.66</b>	<b>0.20</b>	<b>0.38</b>	<b>0.42</b>

Table 7. Cross-Domain Scenarios

# Cross-domain Visual Assessment



True Ortho

DSM

Ground Truth

100% Real

50% real –  
50% Synthetic

# Conclusions

Training



Testing



To what extent can **synthetic data improve the current Deep Learning-based models** for automated semantic segmentation for aerial images?



Synthetic data improves performance when gap between domains is big

Real data with small gap has a robust performance

# Contributions



Cross-Domain Projects: Synthetic imagery helps to improve performance when lack of label data



Understanding the learning of Deep Learning models: Freedom of design helps to understand the learning process of the model



Starting Point to produce synthetic data: The potential of synthetic data is high → Detects approx. 95% of building pixels

# Limitations

Massive graphic computation for the creation of a virtual world

Limited realism of synthetic city

Insufficient size of texture's Library

Regular quality of training and testing data



# Future Work

Use of gaming engines to achieve more realism

Employ 3D models as City models for labelling process

A review of Deep Learning models trained with synthetic data

Thank you for your attention

Camilo Caceres



**READAR**  
real estate radar

# FuseNet Hyper-Parameters

Hyper-Parameters	Value
Loss Function	Weighted Cross Entropy
Optimizer	Adam
Optimizer Learning Rate	0.0001
Batch Size	4
Number of epochs of no improvement	20

The models are trained using a single GPU  
(rtx2080ti 12 GB)