Automated Building Damage Classification through the Use of Remotely Sensed Data

Case study: Hurricane Damage on St. Maarten

Daniël Kersbergen
3 July 2018

Source: Netherlands Red Cross (12 Sept. 2017), Cole Bay - Sint Maarten [georeferenced image], used under CC-BY4.0 as part of Open Imagery Network, retrieved from www.openaerialmap.org

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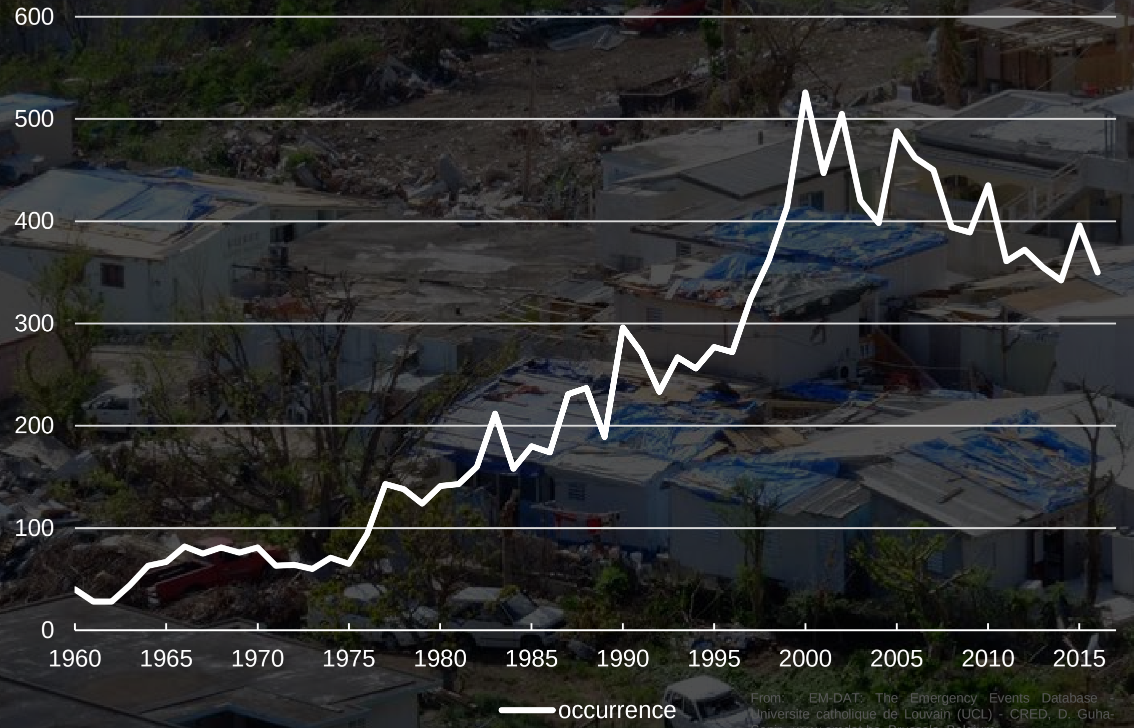
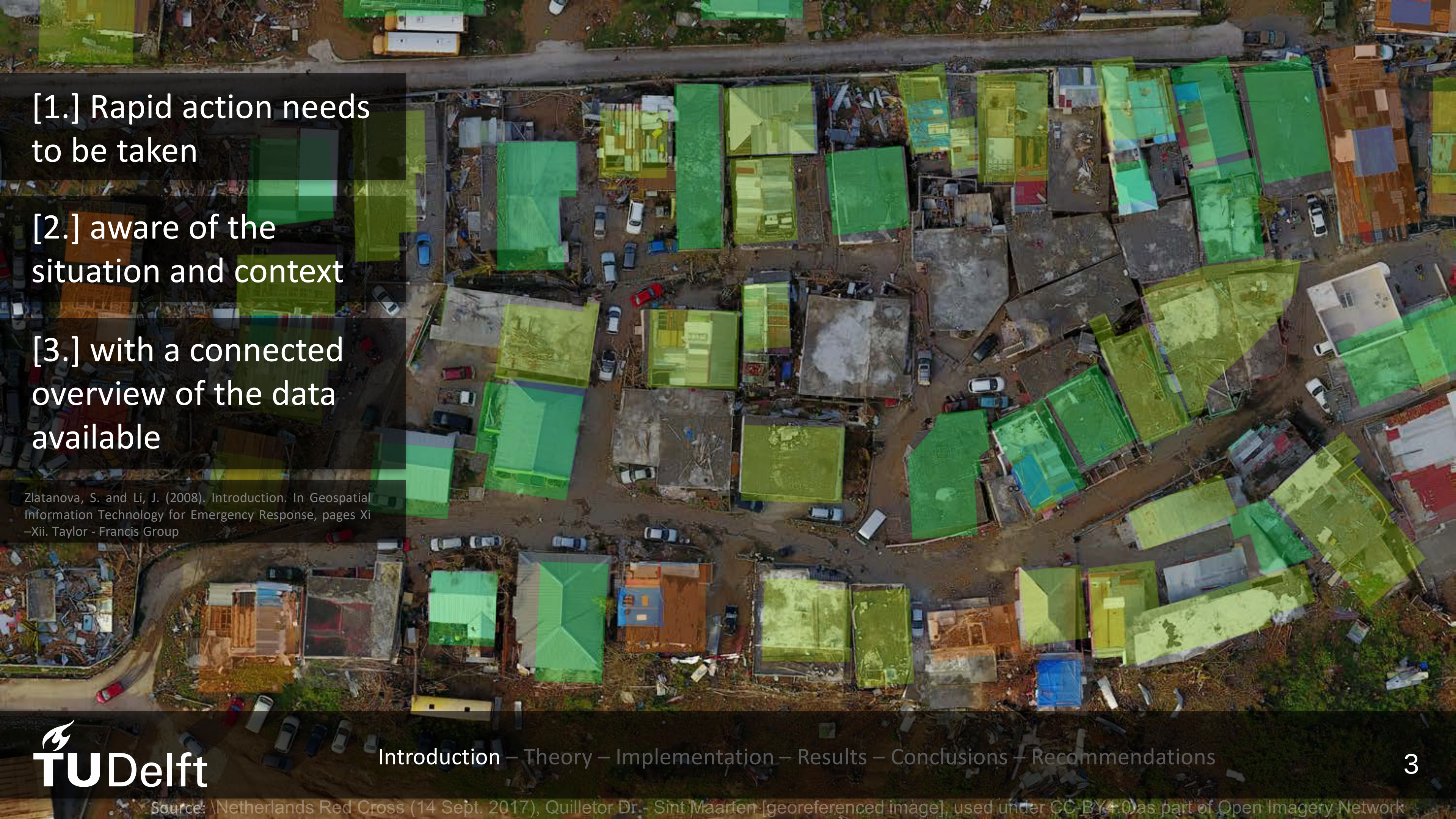


From: EM-DAT: The Emergency Events Database - Universite catholique de Louvain (UCL) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium

Source: Netherlands Red Cross (not publicly available)



[1.] Rapid action needs to be taken

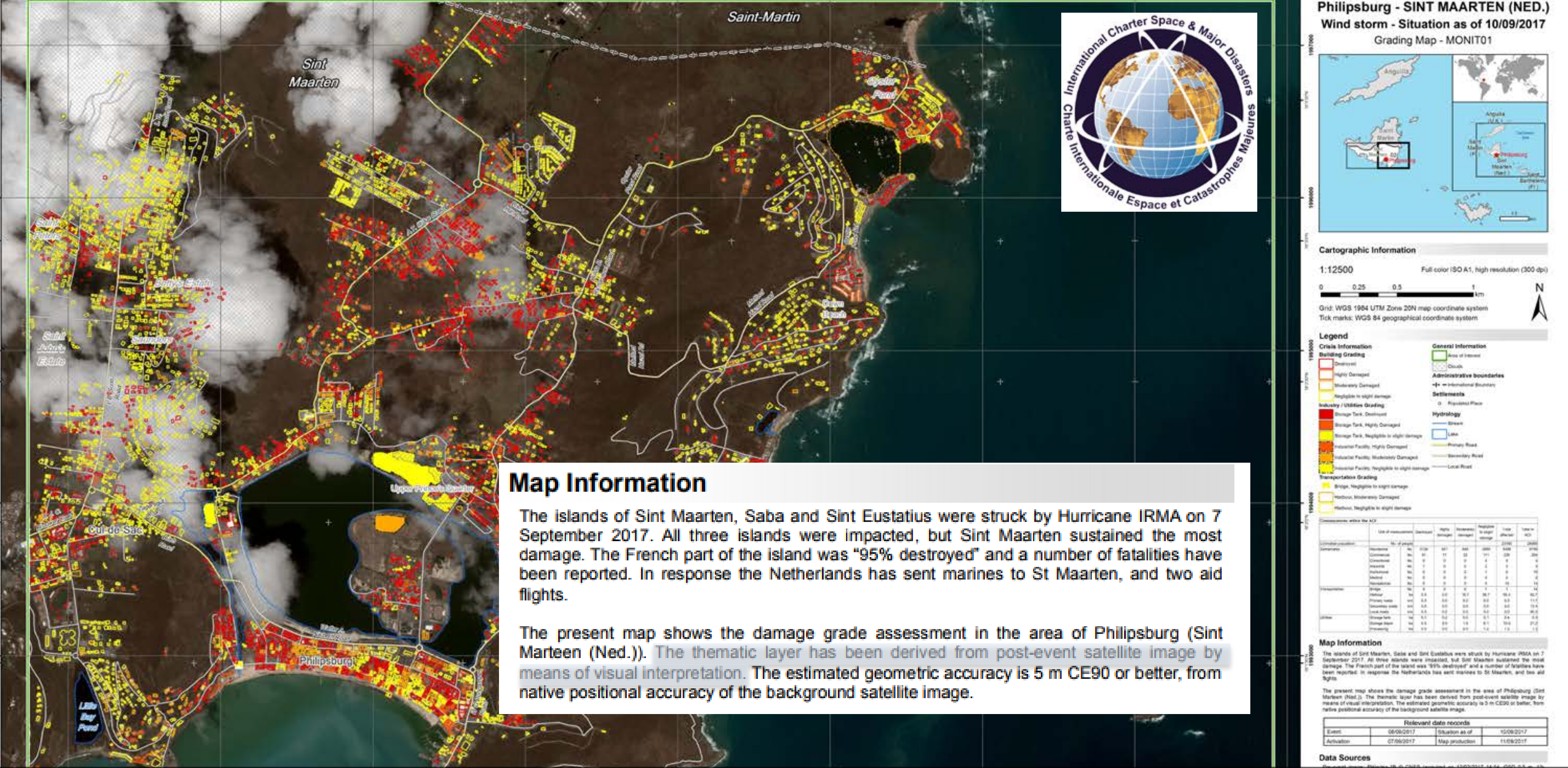
[2.] aware of the situation and context

[3.] with a connected overview of the data available

Zlatanova, S. and Li, J. (2008). Introduction. In Geospatial Information Technology for Emergency Response, pages Xi –Xii. Taylor - Francis Group

Source: Netherlands Red Cross (14 Sept. 2017), Quilletor Dr., Sint Maarten [georeferenced image], used under CC-BY 4.0 as part of Open Imagery Network

Source: Globalmedics RescUAV (2017)



Map Information

The islands of Sint Maarten, Saba and Sint Eustatius were struck by Hurricane IRMA on 7 September 2017. All three islands were impacted, but Sint Maarten sustained the most damage. The French part of the island was "95% destroyed" and a number of fatalities have been reported. In response the Netherlands has sent marines to St Maarten, and two aid flights.

The present map shows the damage grade assessment in the area of Philipsburg (Sint Marteen (Ned.)). The thematic layer has been derived from post-event satellite image by means of visual interpretation. The estimated geometric accuracy is 5 m CE90 or better, from native positional accuracy of the background satellite image.

Source: Copernicus EMS (2017) European Union

Question

Is the use of **remotely sensed data** a viable option for the **automatic classification** of hurricane inflicted **damage**?

Goal

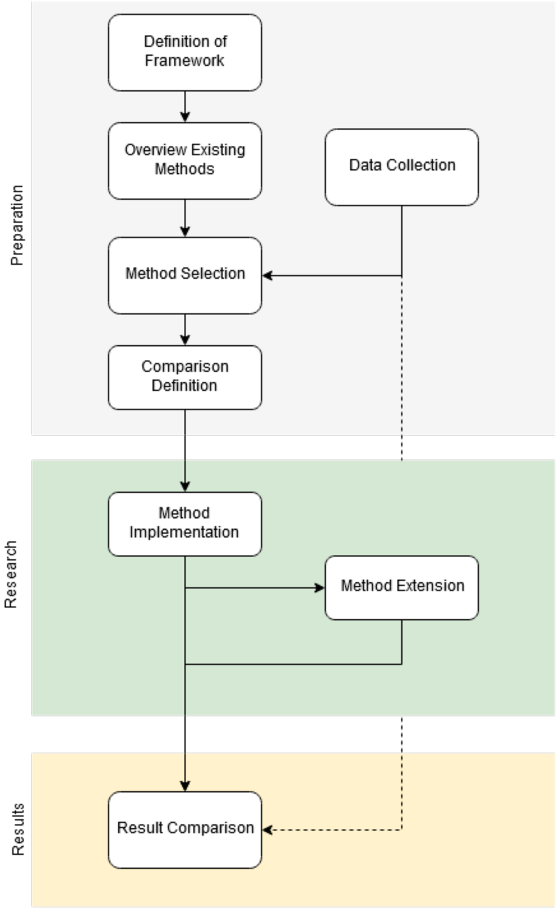
to find a method for the automatic classification of damage inflicted by hurricanes on the island of St. Maarten using remotely sensed data.

Sub-goals

- How is damage **determined**?
- What **criteria** are set for damage classification methods?
- Which methods already **exist**?
- How do these methods **perform**?
- How does the **state of the art** compare to these methods?

Methodology

- Preparation
- Research
- Results

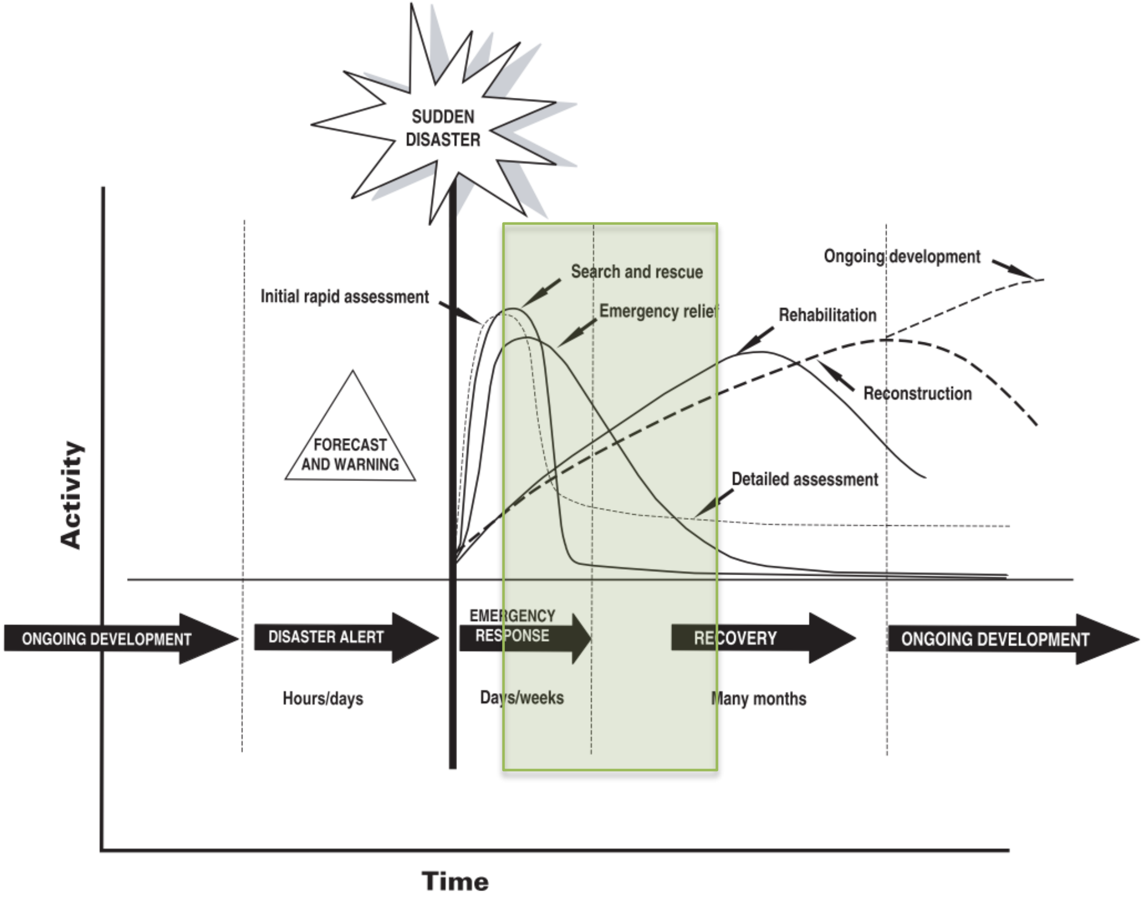


*"A disaster is a **<u>sudden, calamitous</u>** event that seriously **<u>disrupts</u>** the functioning of a community or **<u>society</u>** and causes human, material, and economic or environmental **losses** that exceed the community's or society's **ability** to cope using its own resources."*

International Federation of Red Cross and Red Crescent Societies (2017)

Window of opportunity

Christopher, D. and Doeglas, A. (2015). Time-Sensitive Remote Sensing.


SUDDEN
DISASTER
Initial rapid assessment
Search and rescue
Emergency relief
Ongoing development
Rehabilitation
Reconstruction
FORECAST
AND WARNING
Detailed assessment
Activity
ONGOING DEVELOPMENT
DISASTER ALERT
EMERGENCY
RESPONSE
RECOVERY
ONGOING DEVELOPMENT
Hours/days
Days/weeks
Many months
Time

Damage descriptors

- Damage Detection
- Damage Classification
- Damage Assessment

Damage Detection

Damage Classification

Damage Assessment

Method Assessment Framework

Requirement	Description
Accuracy	*Percentage of building damage classified correctly.*
Acquisition time	*Period from disaster to acquisition of data, travel time of delegates not included.*
Acquisition method	*The technique used for the procurement of the data, mostly limited by financial and time restrictions.*
Resolution	*The resolution of the data and information retrieved from method.*

Method Review

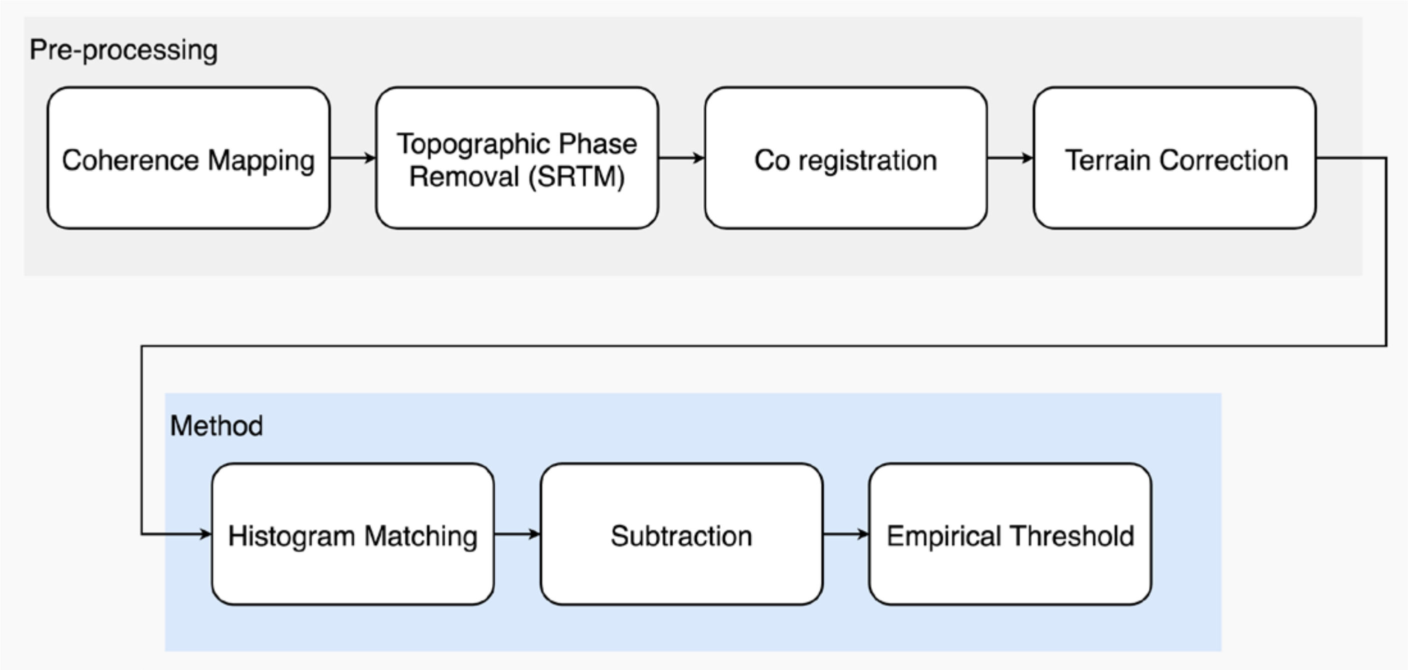
Method	Technique	Resolution	Acq. Time	Accuracy	Info Scale
(Antonietta et al., 2015)	Satellite Optical	0.8x0.8m	6 days	70-80%	B
(Brunner et al., 2010)	Satellite Optical and Satellite SAR	0.6x0.6m 1.1 x 1.0m	6 days	90%	B
(Li et al., 2017)	Satellite Optical	0.6x0.6m	6 days	70%	B
(Martha et al., 2015)	Satellite Optical	0.6x0.6m	6 days	n/a	N
(Menderes et al., 2015)	Aerial Optical	0.3x0.3m	Days	90%	BL
(Ozisik, 2004)	UAV Optical	n/a	Hours	70-80%	B
(Samadzadegan and Rastiveisi, 2005)	Satellite Optical	2.44x2.44m	3 Days	74%	B
(Vetrivel et al., 2016b)	UAV Optical	n/a	Hours	80-90%	B
(Yun et al., 2015)	Satellite SAR	2.7x22m	6 days	n/a	BL

Equalisation and Subtraction – Yun et al. (2015)

- Interferometric Synthetic Aperture Radar
- Based on Coherence
- Classification by threshold

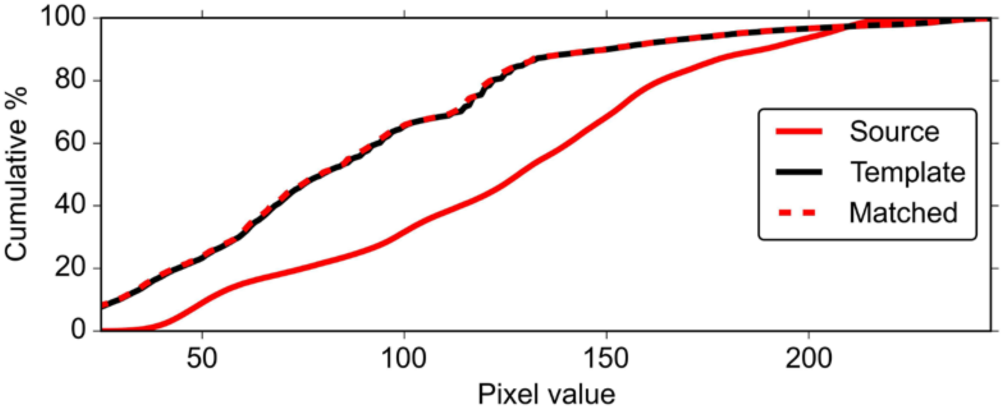
Equalisation and Subtraction – Yun et al. (2015)

Equalisation and Subtraction – Yun et al. (2015)



Equalisation and Subtraction – Yun et al. (2015)

- Histogram matching



Equalisation and Subtraction – Yun et al. (2015)

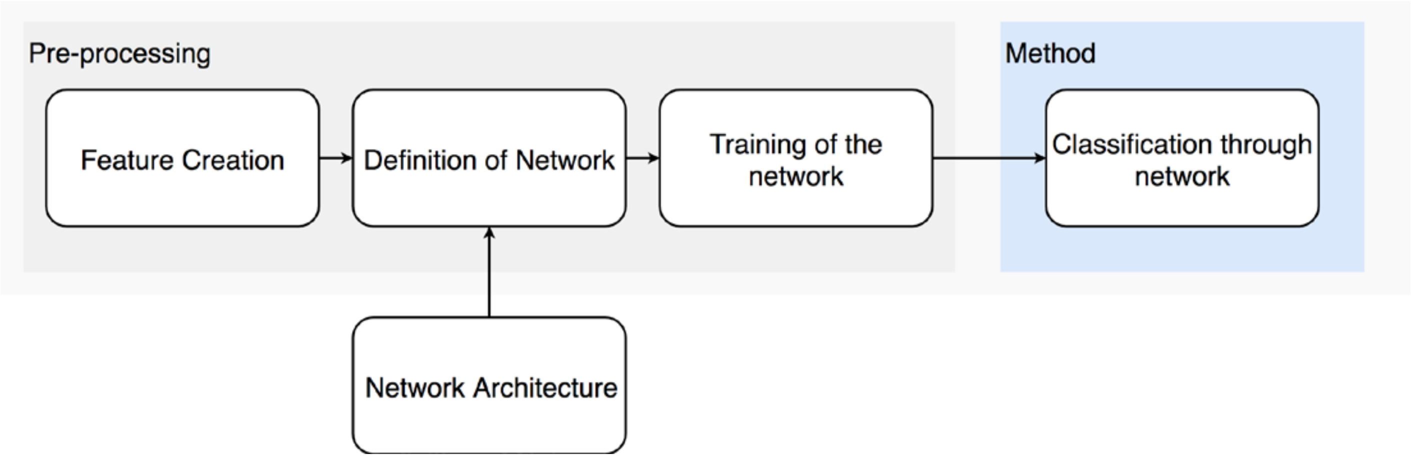
- Univariate image differencing

$$Dx_{ij}^{k} = x_{ij}^{k}(t_2) - x_{ij}^{k}(t_1) + C$$

Convolutional Neural Network– Vetrivel et al. (2016)

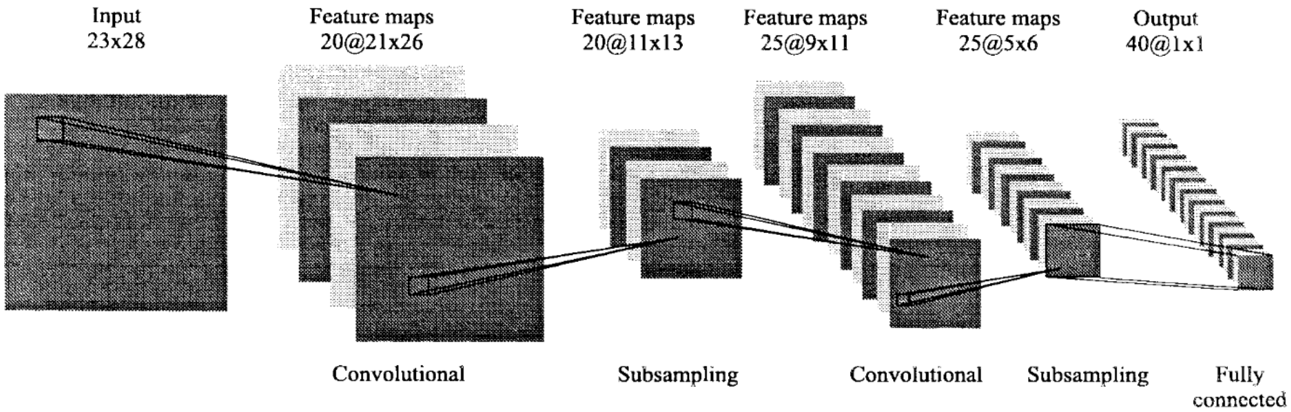
- Optical Data
- Machine learning – Network approach
- Variations

Convolutional Neural Network– Vetrivel et al. (2016)



Convolutional Neural Network– Vetrivel et al. (2016)

- (Convolutional) Neural Network



Convolutional Neural Network– Vetrivel et al. (2016)

- Architecture

CNN architecture for training from scratch

Layer number	Layer name	Properties
1	Input layer	Input image patch size: $100 \times 100 \times 3$
2	Convolutional	Number of filters: 9; filter size: 11×11
3	RELU	–
4	Maxpooling	Pool size 2×2
5	Convolutional	Number of filters: 21; filter size: 7×7
6	RELU	–
7	Maxpooling	Pool size 2×2
8	Convolutional	Number of filters: 41; filter size: 3×3
9	RELU	–
10	Maxpooling	Pool size 2×2
11	Fully connected	Size: 1×256
12	RELU	–
13	Dropout	Dropout ratio: 0.5
14	Fully connected	Size: 1×100
15	Fully connected	Size: 1×2
16	Softmax	–

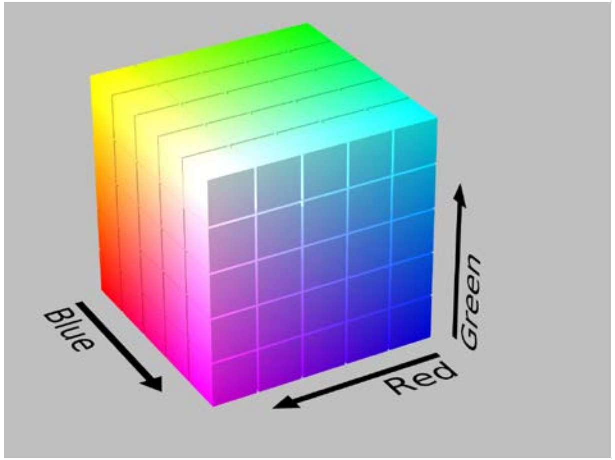
Background information

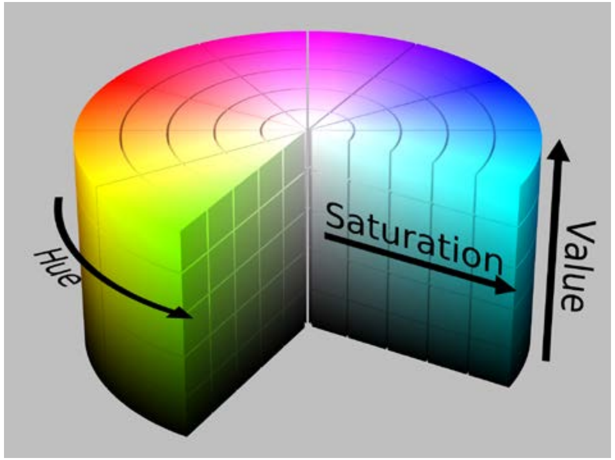
Colour information - Sensation

- **Brightness** of a colour, regarding the variance in light
- **Hue** of a colour, the similarity between colour, usually expressed in Red, Green, and Blue (RGB)
- **Colourfulness** of a specific area, the amount of hue in a feature
- **Lightness**, this is a description of brightness referenced to a white area
- **Chroma**, is the colourfulness referenced to lightness
- **Saturation**, is the colourfulness relative to the brightness.

Background information

Colour information - Sensation





Background information

Inter-rater statistics

- Accuracy

$$\text{accuracy} = \frac{\text{correctly classfied samples}}{\text{total classified samples}}$$

- Cohen Kappa Coefficient

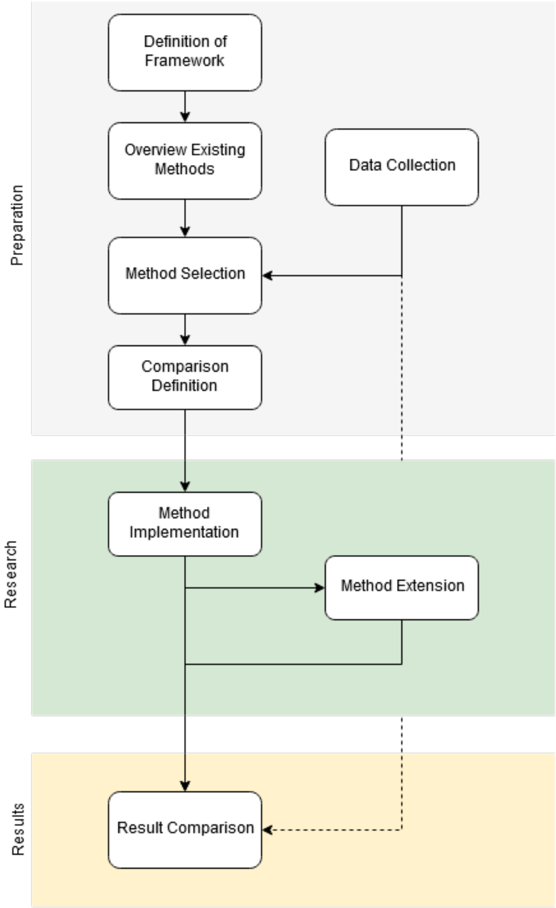
$$\kappa = \frac{P - E}{1 - E}$$

- F1-Score

$$F = \frac{2PR}{P + R}$$

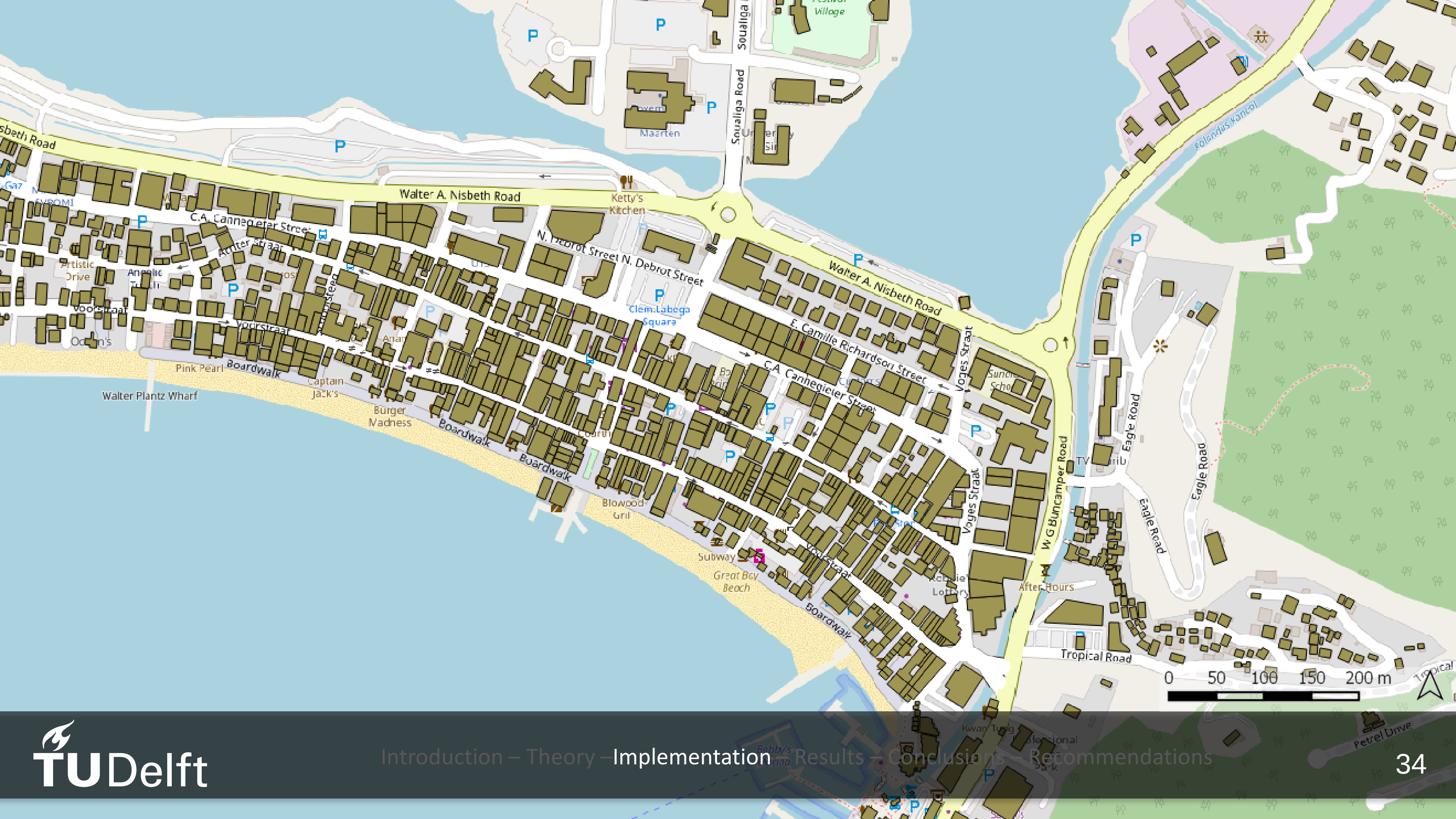
Implementation

	Optical UAV Data	Satellite SAR Data
Equalisation and subtraction	ESO	ESS
Convolutional Neural Network	CNO	CNS



Tools

- SNAP
- QGIS
- Python
- Tensorflow

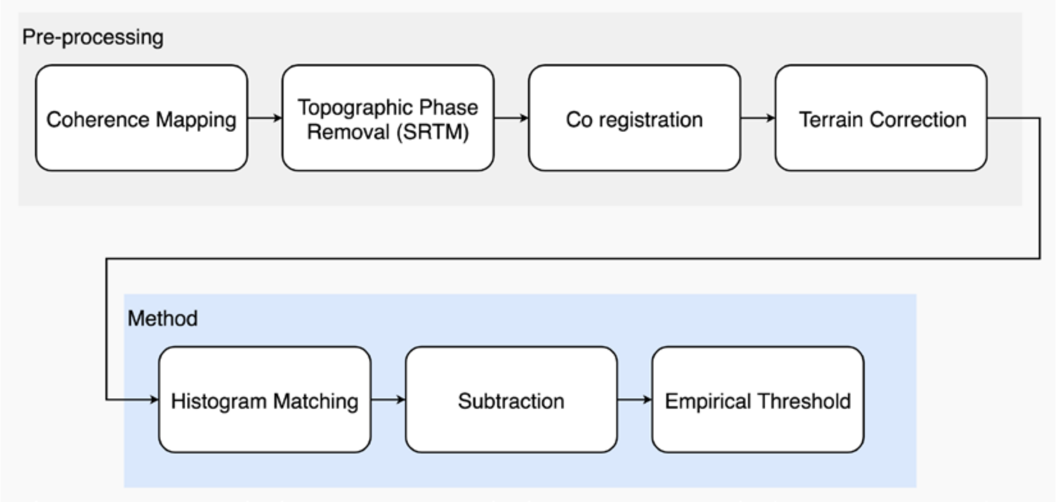

Walter A. Nisbeth Road
Walter A. Nisbeth Road
C.A. Cannegieter Street
C.A. Cannegieter Street
N. Debrot Street
E. Camille Richardson Street
Clem Labega Square
Ketty's Kitchen
Soualiga Road
Voges Straat
W G Buncamper Road
Eagle Road
Tropical Road
Boardwalk
Pink Pearl
Walter Plantz Wharf
Captain Jack's
Burger Madness
Blowood Grill
Subway
Great Bay Beach
After Hours
Petrel Drive
0 50 100 150 200 m

Implementation

- Equalisation and Subtraction

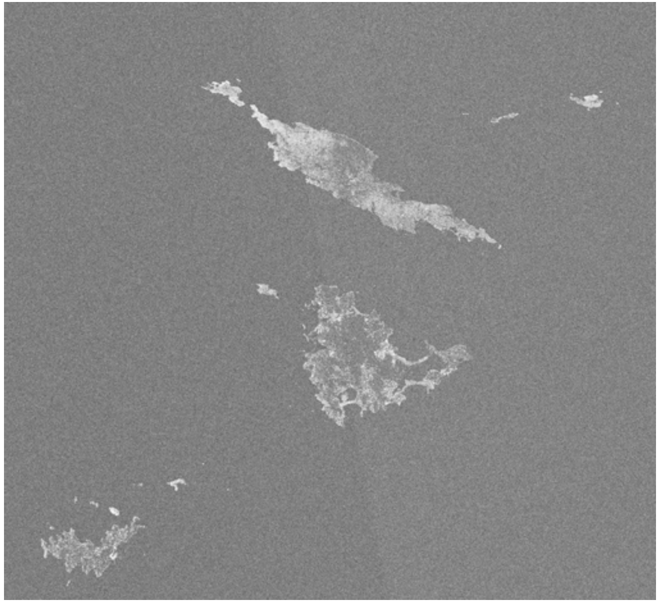
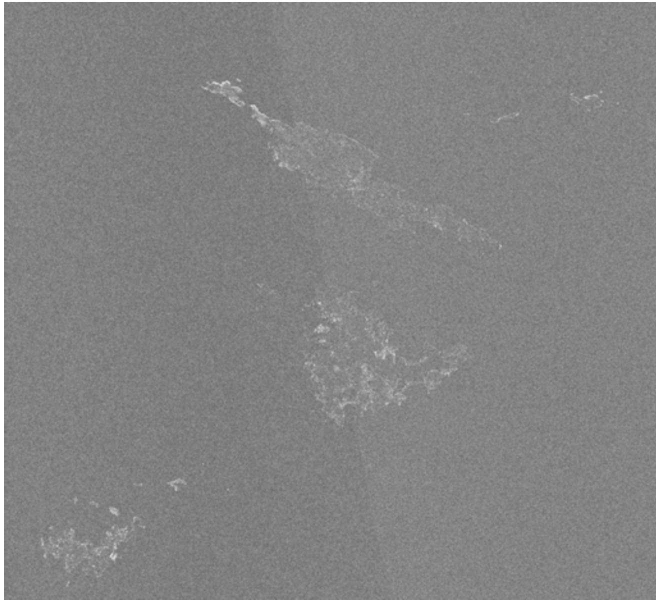
- *InSAR - ESS*

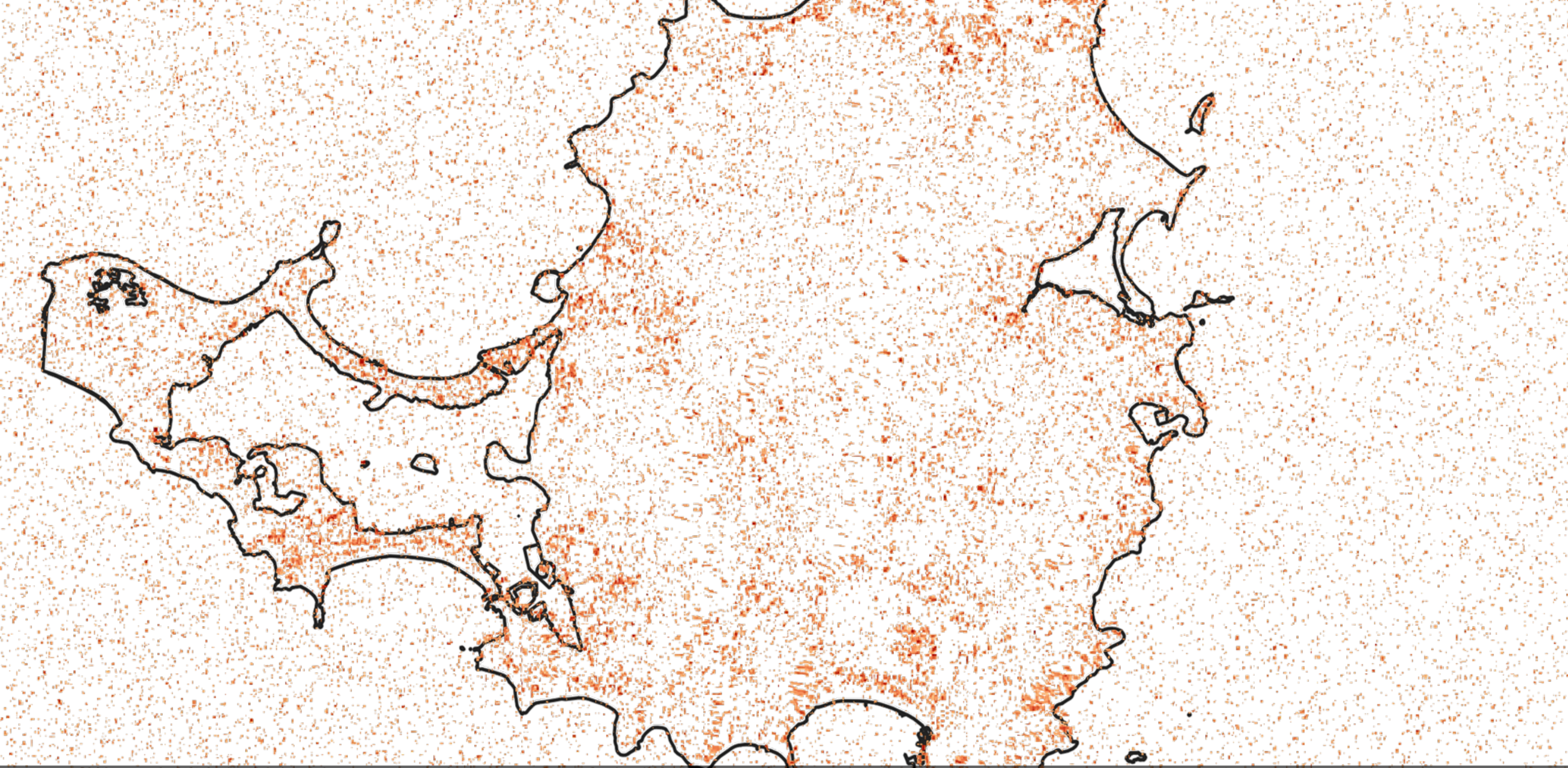
- *Optical - ESO*



Results

- Equalisation and Subtraction - ESS



Implementation

- Equalisation and Subtraction – ESO

- Pre-processing:
  - Abstraction to HSV values

- Method as for SAR


Hue
Saturation
Value

Implementation

- Convolutional Neural Network – (CNO)

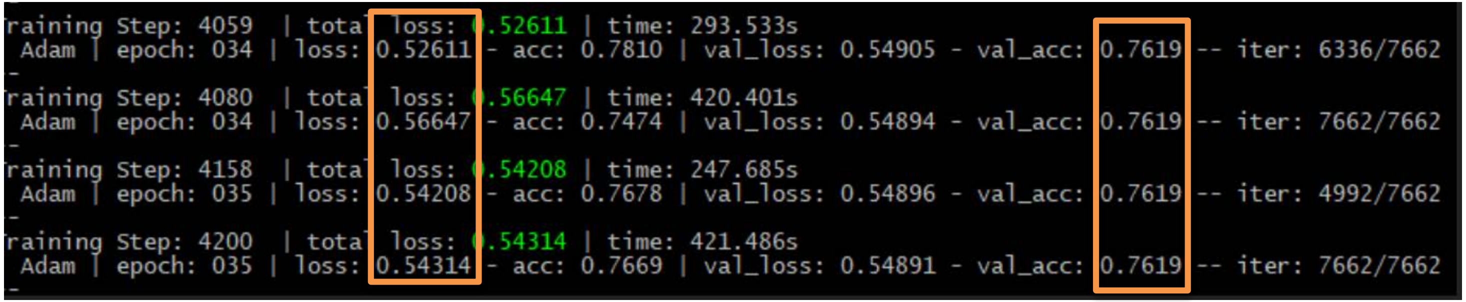
- Feature Creation
- Training
- Detection

Implementation

- Convolutional Neural Network – CNS

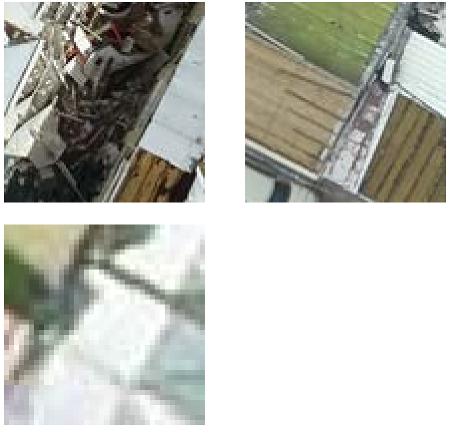
Results

- Convolutional Neural Network – CNO



Results

- Convolutional Neural Network - CNO



Results

	Optical UAV Data	Satellite SAR Data
Equalisation and subtraction	ESO	ESS
Convolutional Neural Network	CNO	CNS

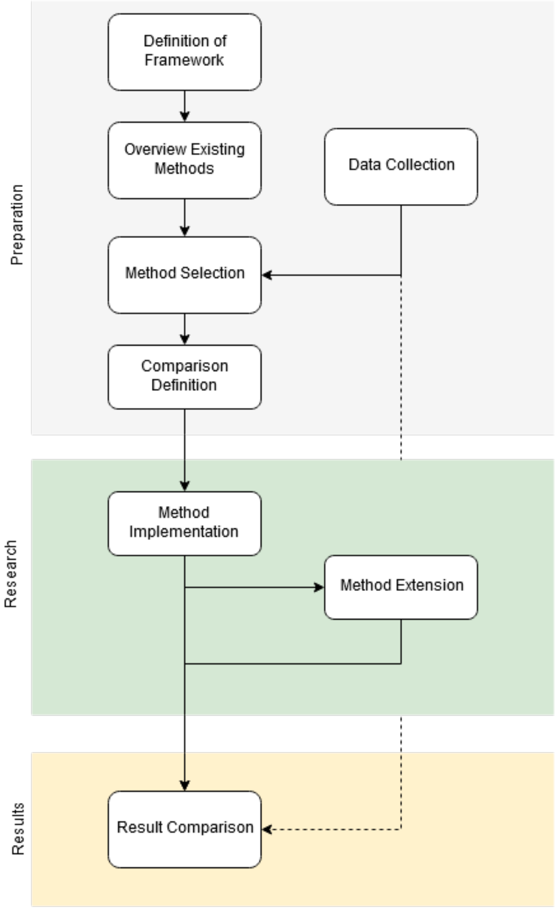
Results

- Comparison

- Equalisation and Subtraction
  Based on empircal **threshold** for damage detection
  Tested values, all values between 0.01 and 1.00
  Highest Kappa Scores Represented

- Convolutional Neural Network
  Based on detection by algorithm

- State of the art
  Classification by Copernicus



Results

- **Comparison**

- State of the art
  Classification by Copernicus

Copernicus	Damage Detection
Not affected	No Damage
Negligible to slight Damage	
Moderately Damaged	Damage
Highly Damaged	
Completely Destroyed	

Results

- Comparison

Technique	Threshold	Kappa Score	Avg. F1 Score
Equalisation and Subtraction			
Interferometry – ESS	0.30	0.059	0.54
Hue – ESO	0.11	0.070	0.47
Saturation – ESO	0.07	0.429	0.71
Value – ESO	0.21	0.389	0.69
Convolutional Neural Network			
Classification – CNO	n/a	0.000	0.21
Copernicus			
Classification	n/a	0.093	0.45

Results

- Extention

- Equalisation and Subtraction
  Based on empircal **threshold** for damage detection
  Tested values, all values between 0.02 and 1.00
  e.g. No< 0.02 <Minimal> 0.10 <Significant> 0.30 > Destroyed
  Highest Kappa Scores Represented

- Convolutional Neural Network
  Based on detection by algorithm

- State of the art
  Classification by Copernicus

Results

- Extention

- Convolutional Neural Network
  Based on detection by algorithm

```
--
Training Step: 4059  | total loss: 1.13057 | time: 297.569s
| Adam | epoch: 034 | loss: 1.13057 - acc: 0.5585 | val_loss: 1.14385 - val_acc: 0.5569 -- iter: 6336/7662
--
Training Step: 4080  | total loss: 1.12229 | time: 427.004s
| Adam | epoch: 034 | loss: 1.12229 - acc: 0.5760 | val_loss: 1.14372 - val_acc: 0.5569 -- iter: 7662/7662
--
Training Step: 4158  | total loss: 1.13377 | time: 252.872s
| Adam | epoch: 035 | loss: 1.13377 - acc: 0.5608 | val_loss: 1.14377 - val_acc: 0.5569 -- iter: 4992/7662
--
Training Step: 4200  | total loss: 1.15621 | time: 428.278s
| Adam | epoch: 035 | loss: 1.15621 - acc: 0.5435 | val_loss: 1.14375 - val_acc: 0.5569 -- iter: 7662/7662
--
```

Results

- Extention

- State of the art
  Classification by Copernicus

Copernicus	Damage Detection
Not affected	No Damage
Negligible to slight Damage	
Moderately Damaged	Partial Damage
Highly Damaged	Significant Damage
Completely Destroyed	Destroyed

Results

- Comparison

Technique	Thresholds	Kappa Score	Avg. F1 Score
Equalisation and Subtraction			
Interferometry – ESS	0.23 - 0.31 – 0.34	0.051	0.30
Hue – ESO	0.08 – 0.11 – 0.88	0.054	0.23
Saturation – ESO	0.08 – 0.08 – 0.31	0.250	0.37
Value - ESO	0.13 – 0.18 – 0.26	0.188	0.40
Convolutional Neural Network			
Classification – CNO	n/a	0.000	0.21
Copernicus			
Classification	n/a	0.078	0.24

Results

- Comparison

Requirement	Description
Accuracy	*Percentage of building damage classified correctly.*
Acquisition time	*Period from disaster to acquisition of data, travel time of delegates not included.*
Acquisition method	*The technique used for the procurement of the data, mostly limited by financial and time restrictions.*
Resolution	*The resolution of the data and information retrieved from method.*

Conclusions

- How is damage **determined**?
- What **criteria** are set for damage classification methods?
- Which methods already **exist**?
- How do these methods **perform**?
- How does the **state of the art** compare to these methods?

Is the use of **remotely sensed data** a viable option for the **automatic classification** of hurricane inflicted **damage**?

Conclusions

- How is damage **determined?**

Conclusions

- What **criteria** are set for damage classification methods?

Requirement	Description
Accuracy	*Percentage of building damage classified correctly.*
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Acquisition method	*The technique used for the procurement of the data, mostly limited by financial and time restrictions.*
Resolution	*The resolution of the data and information retrieved from method.*

Conclusions

- Which methods already **exist**?

Method	Technique	Resolution	Acq. Time	Accuracy	Info Scale
(Antonietta et al., 2015)	Satellite Optical	0.8x0.8m	6 days	70-80%	B
(Brunner et al., 2010)	Satellite Optical and Satellite SAR	0.6x0.6m 1.1 x 1.0m	6 days	90%	B
(Li et al., 2017)	Satellite Optical	0.6x0.6m	6 days	70%	B
(Martha et al., 2015)	Satellite Optical	0.6x0.6m	6 days	n/a	N
(Menderes et al., 2015)	Aerial Optical	0.3x0.3m	Days	90%	BL
(Ozisik, 2004)	UAV Optical	n/a	Hours	70-80%	B
(Samadzadegan and Rastiveisi, 2005)	Satellite Optical	2.44x2.44m	3 Days	74%	B
(Vetrivel et al., 2016b)	UAV Optical	n/a	Hours	80-90%	B
(Yun et al., 2015)	Satellite SAR	2.7x22m	6 days	n/a	BL

Conclusions

- How do these methods **perform**?
- How does the **state of the art** compare to these methods?

- Varying results
- Derivative of Yun et. al (2015) for optical workable results
- State of the art, usable in first phase

Conclusions

Is the use of **remotely sensed data** a viable option for the **automatic classification** of hurricane inflicted **damage**?

Yes, however:

- Detection has higher accuracy
- Technical knowledge required

Recommendations

- Optical Data
    - Cohesion
    - Layer combination
    - Geo-referencing
- SAR data
    - Aggregation
    - Higher Resolution
- Combination of Data
- Disaster Specific Damage Patterns
- Assessment Framework
- Inter-rater statistics

Thank you

Mentors: *Dr. Jorge Lopes Gil*
Dr. Stef Lhermitte
Company: *510 – Netherlands Red Cross*
Dr. Stefania Giodini
Co-reader: *Agung Indrajit MSc.*

Exam com.: *Luc Willekens*

TU Delft

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