Department of Geography, College of Science
National Taiwan University
Master Thesis

SAR影像的都市水體判釋：考量都市表面形態造成的雷達二次反射效果

Detecting urban water bodies from SAR images: Measuring surface morphology contributing to radar double bounce effect

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中華民國108年1月30日

Detecting water from space…

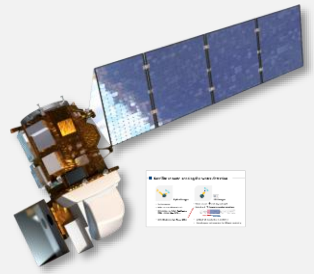
- Water bodies related topics:
  - Natural resources, ecological roles (Sakamoto et al., 2007; Schaffer-Smith et al.,2017)
  - Environmental impacts, human assets (Huang, Chen et al. 2018)

In the past…

Field survey

Nowadays,

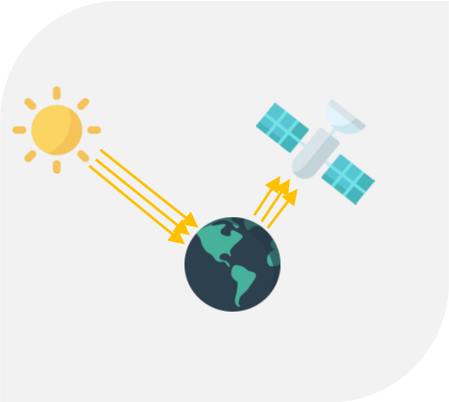
Satellite remote sensing



The launch of Landsat-1 in the US. in 1972.

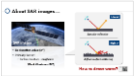
- ✓ Less labor investment
- ✓ At a global scale
- ✓ Regular and in-time surveying

Satellite remote sensing for water detection



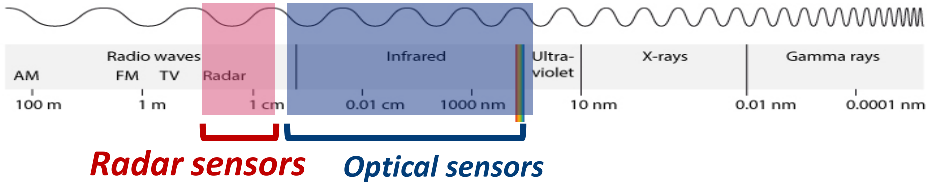
Optical images

- Passive sensors
- Reflectance at different bands
- Water index e.g. NDWI *(McFleeters 1996)*, mNDWI *(Xu 2006)*, …
- **Cons: Cloud coverage** *(Asner 2001)*



SAR images

- Active sensors → work day-and-night
- Radar band → **Overcome weather conditions**

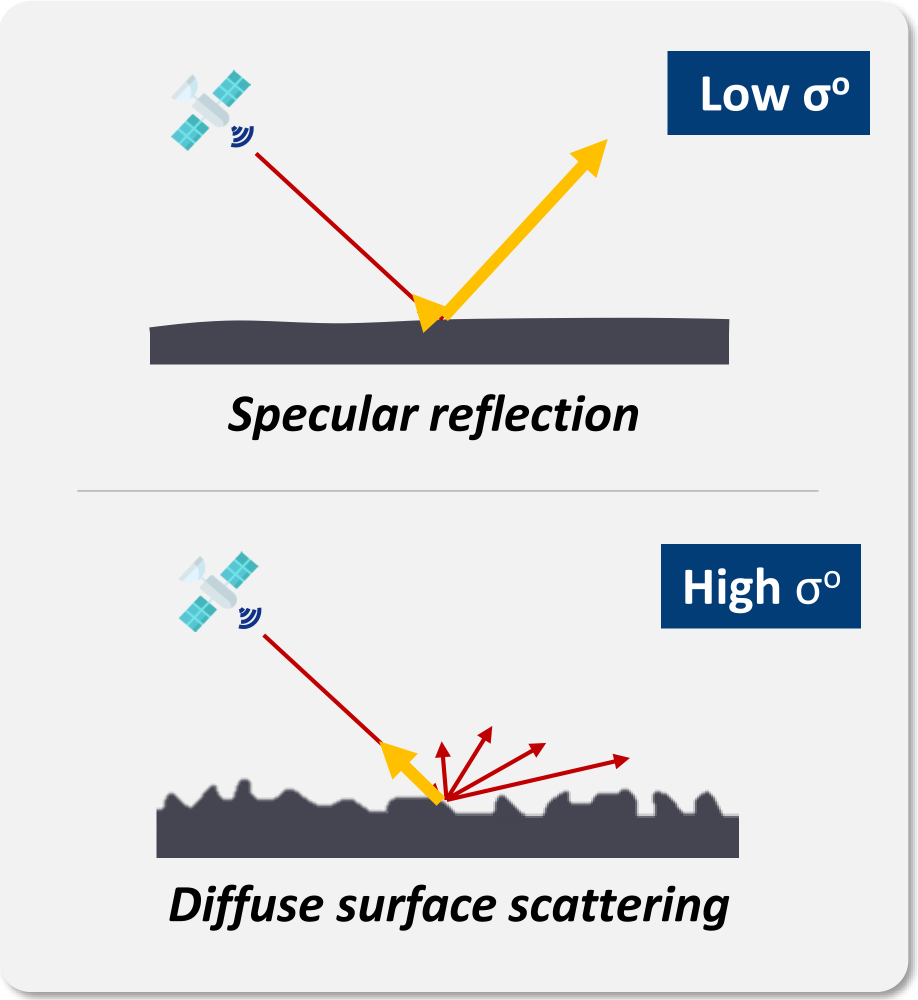


- **Sentinel-1A**, launched on 3 April 2014
- Globally open, various modes for different monitoring

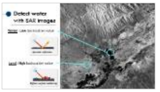
About SAR images…

- **Backscatter value (σᵒ)**
- Primary factor:
  - Surface structure – **roughness**

(Xia & Henderson 1997)

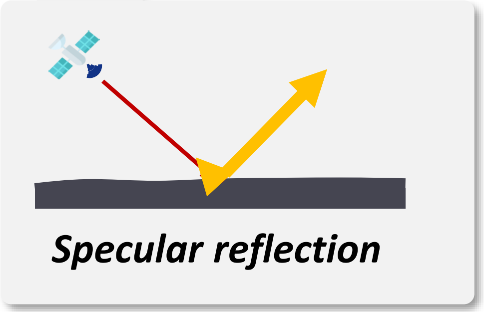


How to detect water?

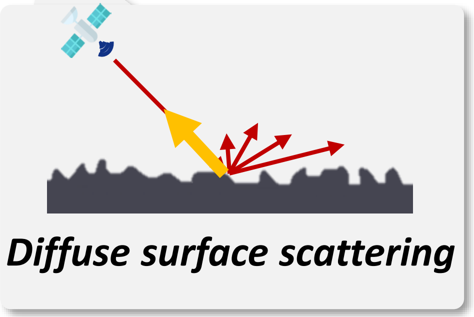


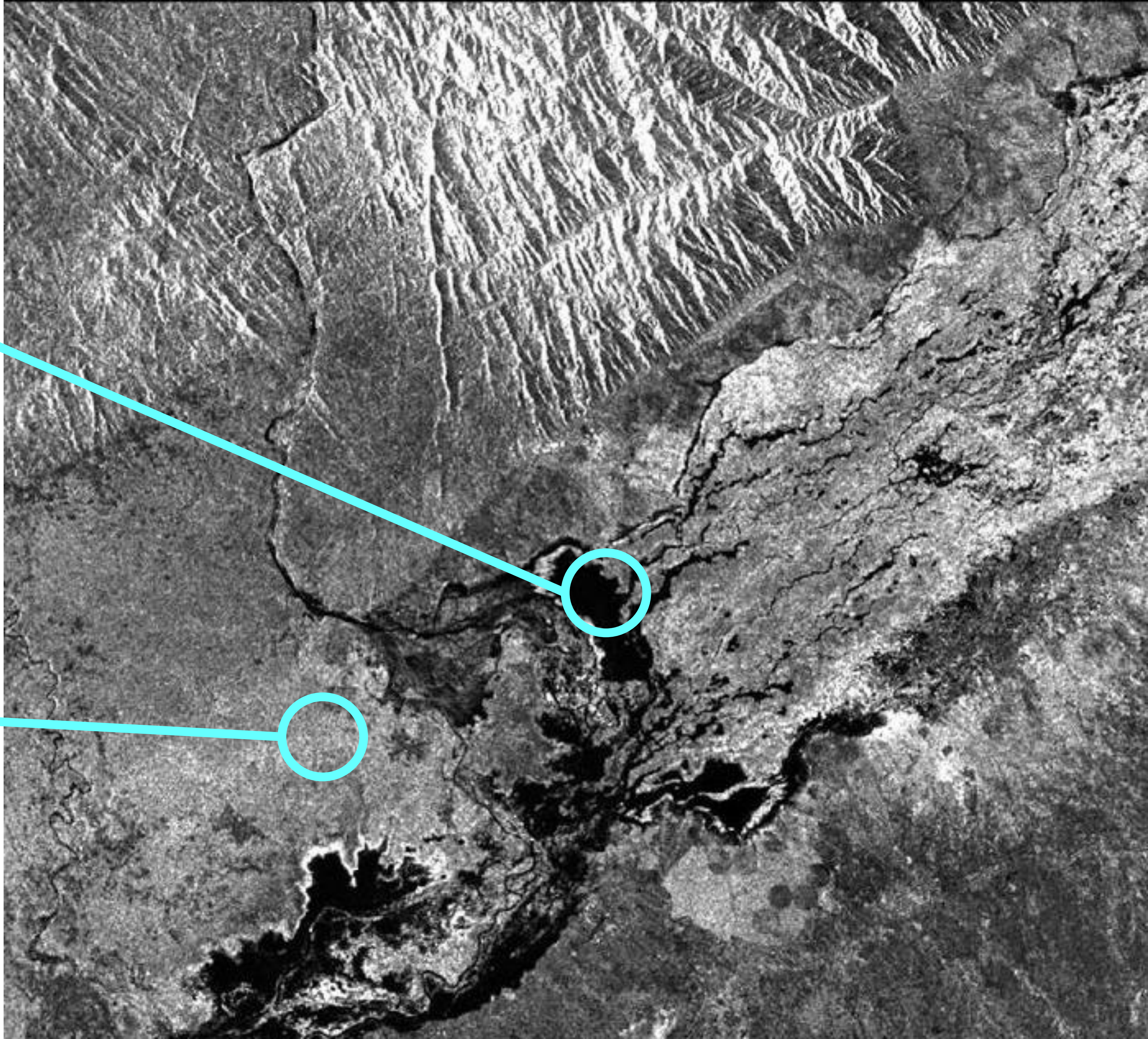
Detect water with SAR images

Water: Low backscatter value



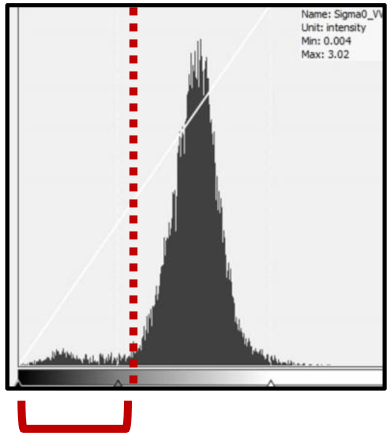
Land: High backscatter value



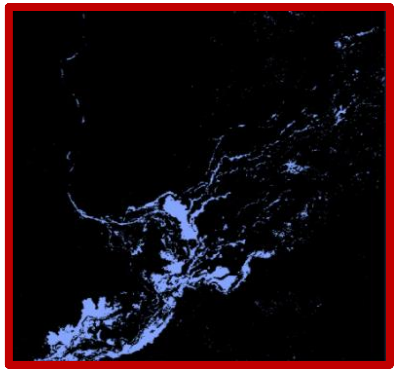


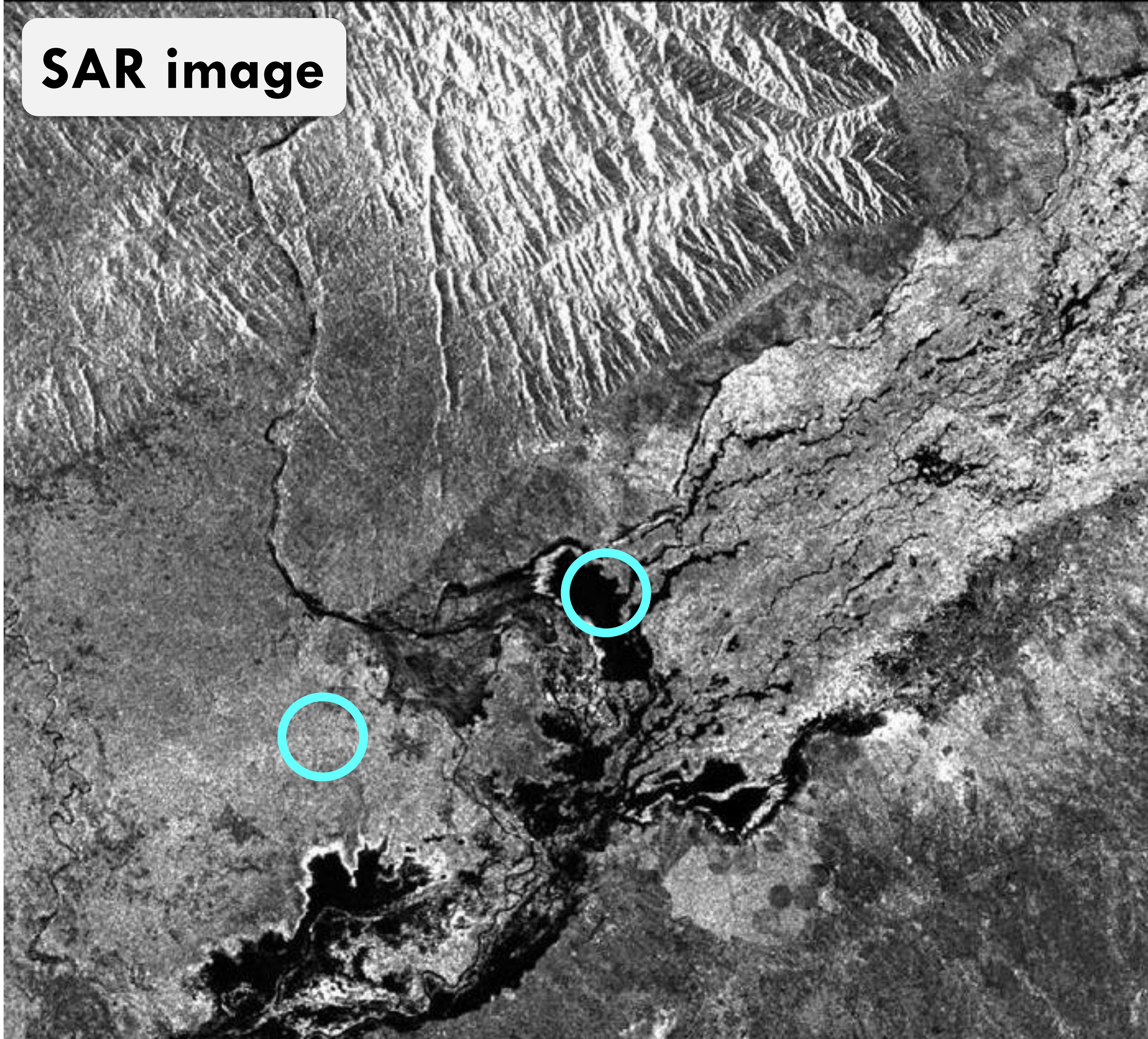
Detect water
with SAR images

Backscatter distribution



Water bodies

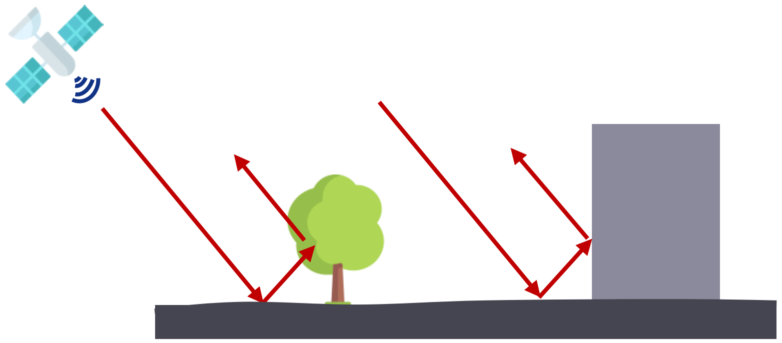




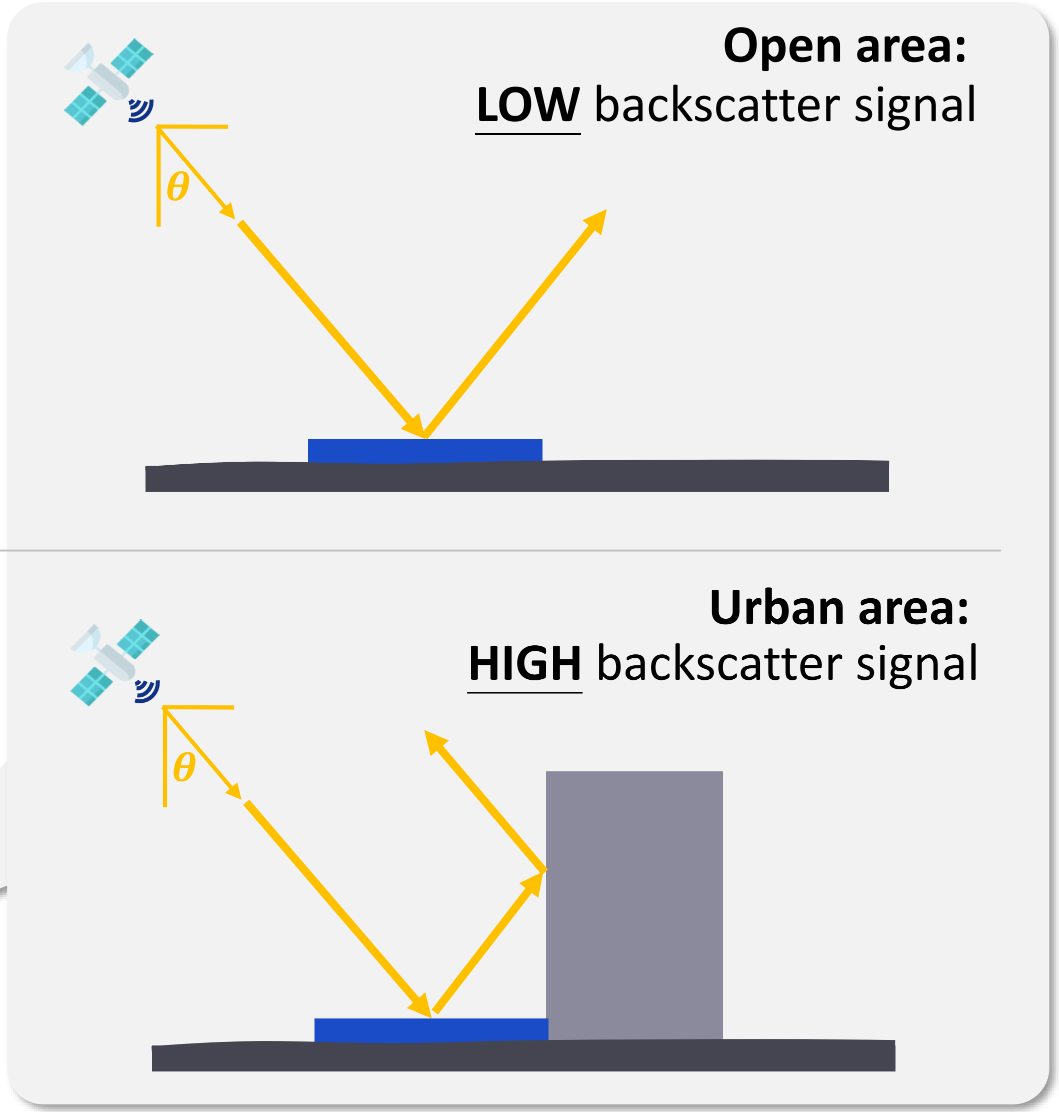
Double bounce effects

(Brunner et al. 2008)

- Vertical structures on the surface
  - e.g. Walls of building
- A strong scattering mechanism caused by a corner reflector



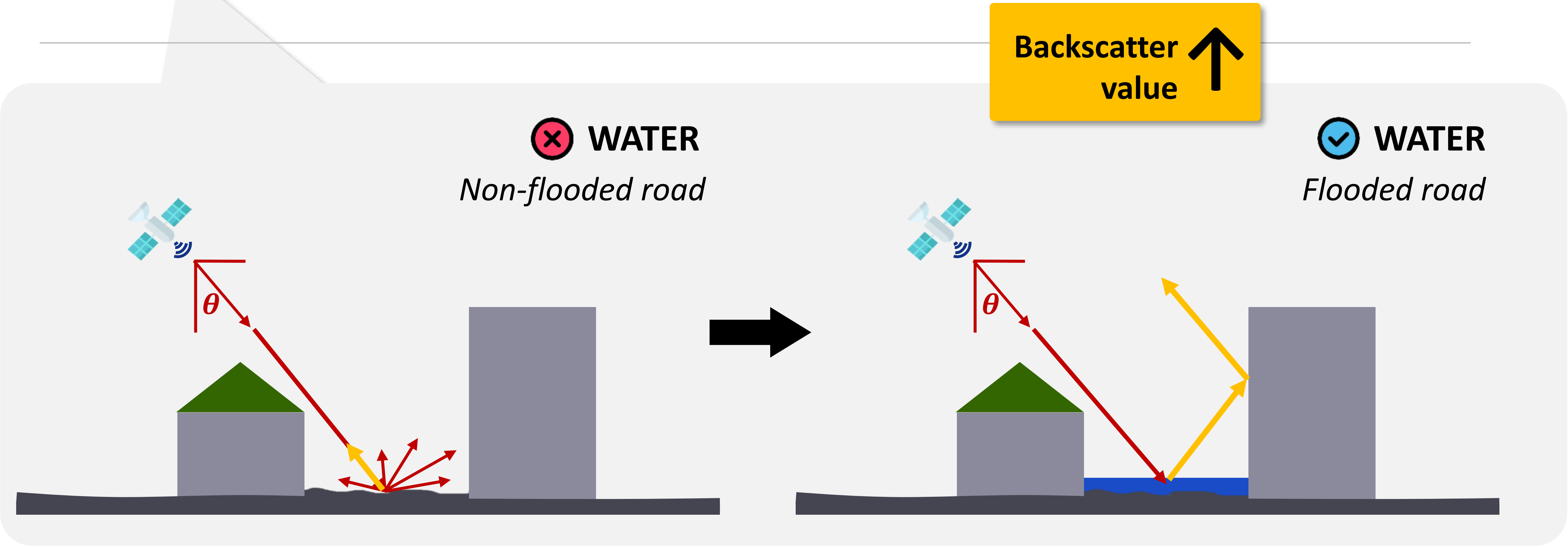
Double bounce effect



What happened to water's backscatter?

How does double bounce effect influence urban water detection?

- *The accuracy of urban water detection significantly decreased.* (Mason et al. 2010)
- *Flooding roads adjacent to buildings had higher backscatter values.* (Watanabe et al. 2010)



Detecting urban water in previous studies

1) Masking out interfered areas *(Mason et al. 2010; Giustarini et al. 2013)*
2) Detect urban areas with increasing backscatter response
   (Mason et al. 2014; Pulvirenti et al. 2016)

① Require **two** or more SAR images (need an image as reference)

② Finding **“additional”** water based on the referenced time

③ Double bounce effect **happens** in the entire urban area

④ Double bounce effect is treated with **the same rule** in the entire urban area

Relationship between
<u>double bounce effect</u> and <u>adjacent structure</u>

- Theoretical equations *(Franceschetti, Antonio & Daniele 2002)*
  - **Factors** of double bounce effect: Building height, texture of ground and buildings, building orientation, incident angle, …
- Empirical studies *(Brunner et al. 2008; Ferro et al. 2011)*
  - Intensity of double bounce effect **varies** with different building characteristics and SAR system parameters

How do these related to urban water detection?

- With different nearby buildings or structures, **intensity** of water's double bounce effect is **different** ➔ <u>Different backscatter value (σ^o)</u>

Low σ^o → WATER

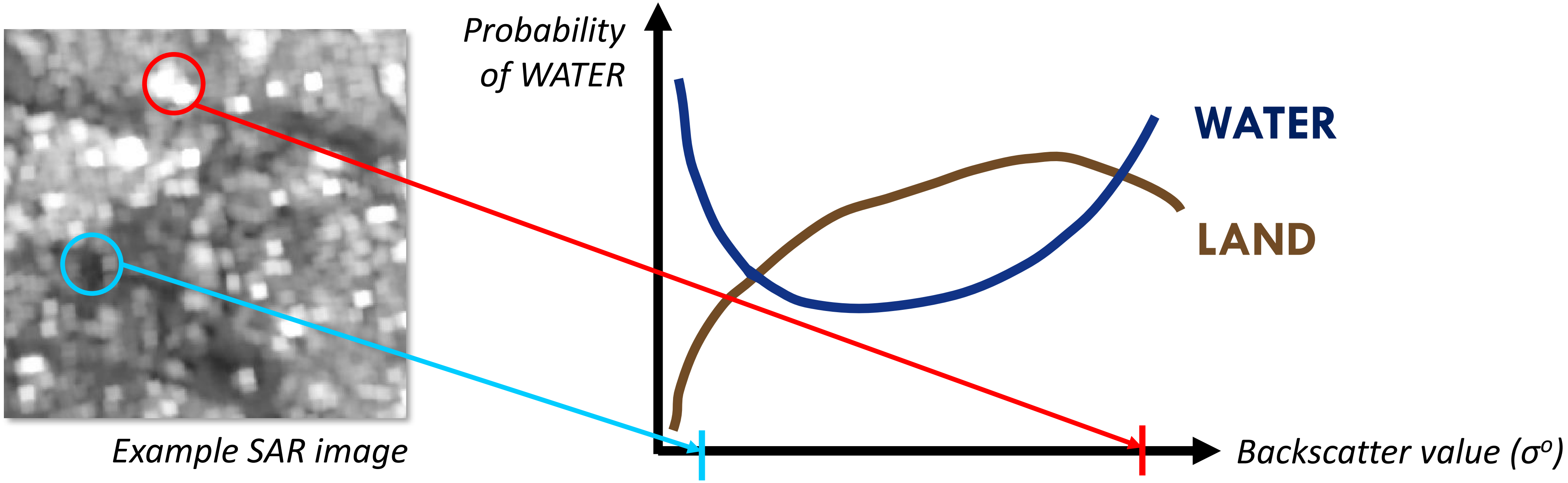
High σ^o → WATER

How do these related to urban water detection?

- With different nearby buildings or structures, **intensity** of water's double bounce effect is **different** ➔ **Different backscatter value (σº)**

Low σº → WATER

High σº→ WATER



Example SAR image

RESEARCH GAP

Methods for detecting urban water bodies:

- The effect is treated uniformly in space
- Characteristics of nearby structures aren’t considered
- Require multi-SAR images

How to control double bounce effect:

- Require assumptive, empirical parameters
- Require detailed data
- Difficult in large-scale applications
- Water is not the subject

RESEARCH OBJECTIVES

Highlights:

- **Single** SAR image
- **Without detailed** environmental data
- **Spatial difference** of double bounce effect

Propose an urban water detection framework integrating urban surface morphological factors:

1. **Mechanism & relationship**
   - How surface morphology contributes to double bounce effect
2. **Data to quantify urban surface morphology**
   - Digitized building data (vector) or DSMs and DEMs (raster)
3. **Generic model / modeling framework**
   - Feasible in other cities with varied urban landscape

METHODOLOGY

1. Study area & study unit
2. Data
3. Variables
4. Samples
5. Models

1 Study area & study unit

- A part of Taipei city (10 towns)
  - 大同區、中山區、松山區、內湖區、萬華區、中正區、大安區、信義區、南港區、文山區
- Study unit: 10m × 10m cell
  - The spatial resolution of SAR image
- Study interest:
  - **WATER** → Static water body
  - **LAND** → Impervious road

2 Data

WATER / LAND ← Backscatter signal (σ^o) & Urban morphology

Ground truth

Aerial orthophotos

Spatial resolution: 0.1m × 0.1m

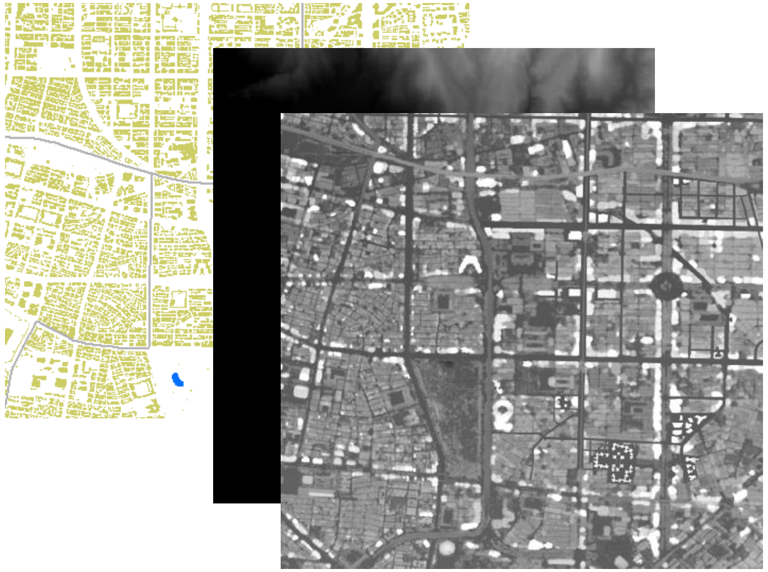
Backscatter value

Sentinel-1 SAR images

Spatial resolution: 10m × 10m

Surface morphological variables

Digitized building layer; DSM and DEM



Spatial resolution: DTM 20m, DSM 30m

2 Data

WATER / LAND ← Backscatter signal (σ°) & Urban morphology

Ground truth

Aerial orthophotos

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Spatial resolution: 0.1m × 0.1m

Backscatter value

Sentinel-1 SAR images

Spatial resolution: 10m × 10m

- **15 images**
- **Mean backscatter value**
- **Dry dates**
  - Compare with precipitation data
- **Same SAR system-related parameters**
  - C-band
  - Incidence angle: 32.9^o ~ 43.1^o
  - IW mode
  - VV polarization
  - Ascending images

2 Data

WATER / LAND ← Backscatter signal (σ°) & **Urban morphology**

Ground truth

Aerial orthophotos

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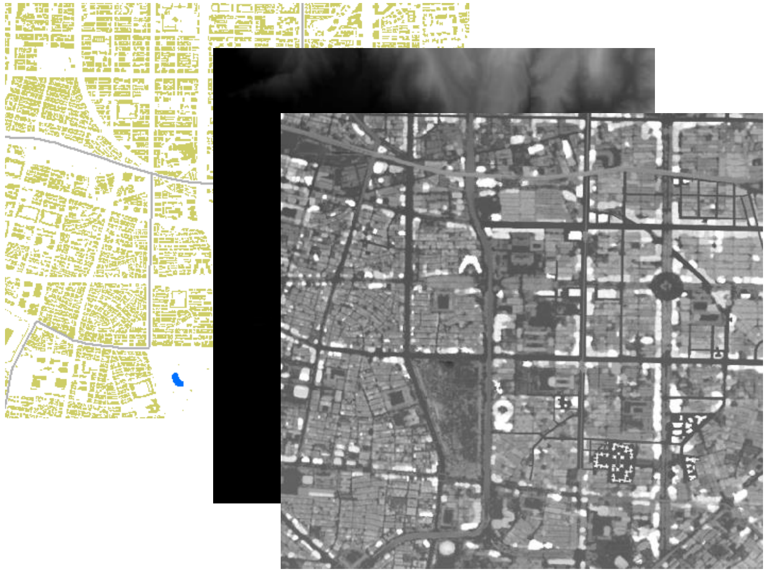

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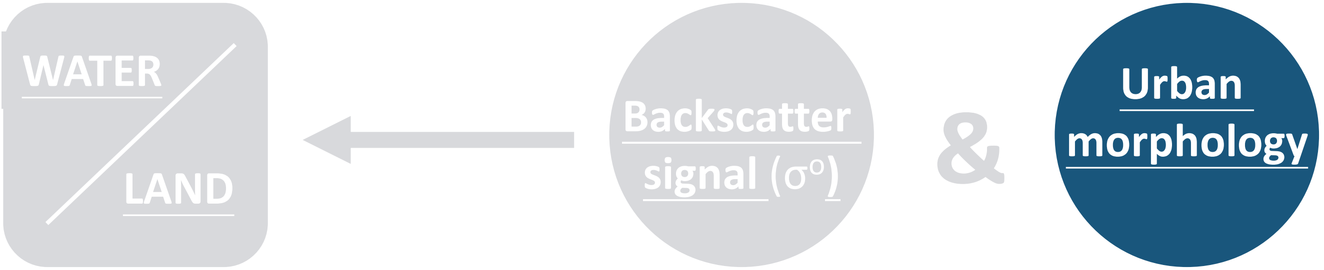


➢ Quantify urban surface morphology:

1. Digitized building layer

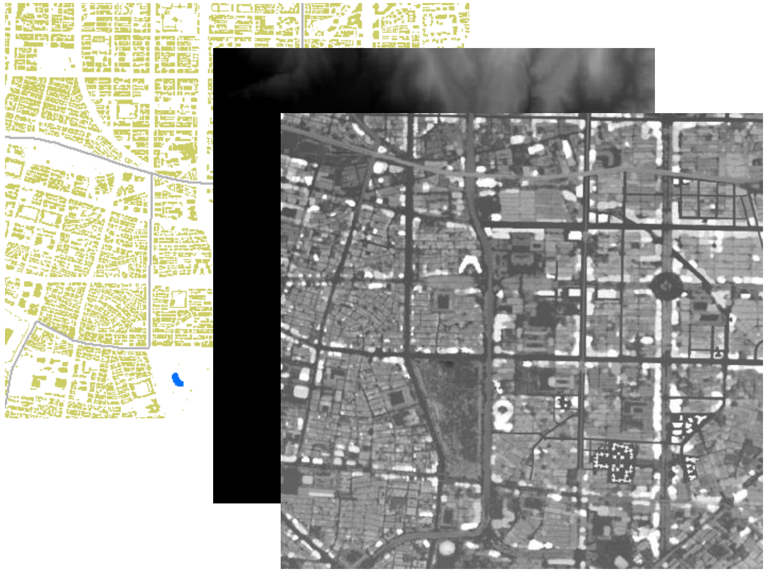
- Vector data
- Detailed investigation from the city government

2. DSM and DEM

- Raster data
- Has been more easily acquired nowadays
  e.g. LiDAR, flying UAVs
- **Free, open data**

Surface morphological variables

Digitized building layer; DSM and DEM



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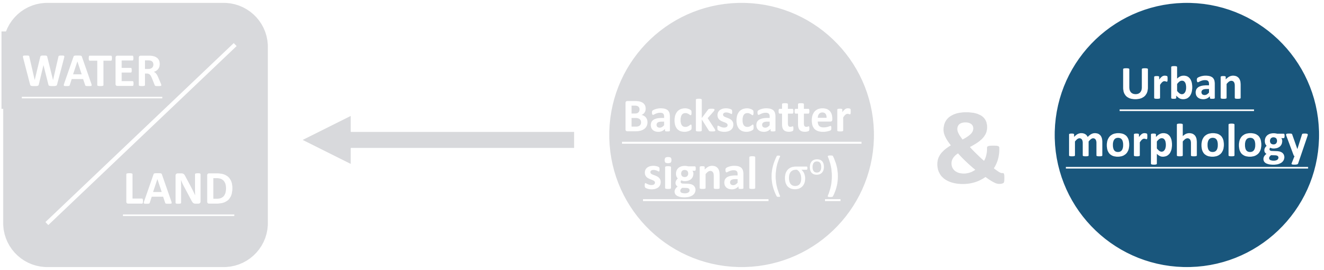

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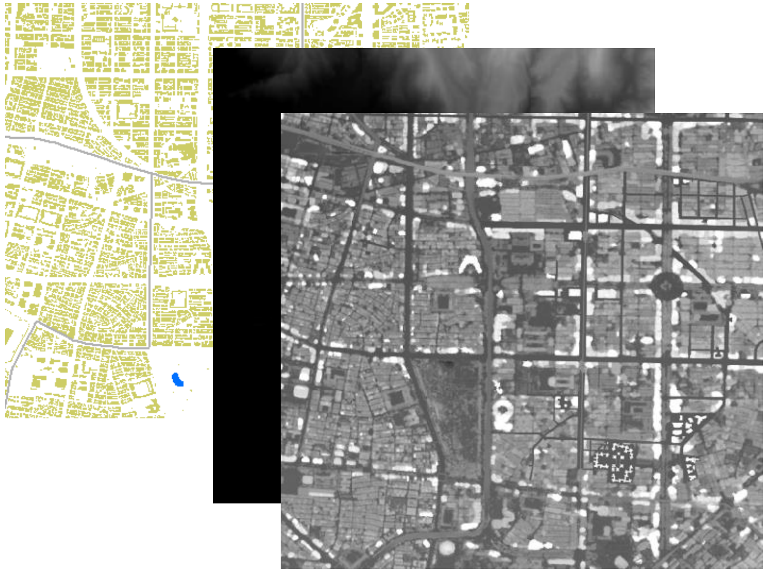
Surface morphological variables

Digitized building layer;
DSM and DEM



Spatial resolution: DTM 20m, DSM 30m

Data

WATER / LAND ← Backscatter signal (σ°) & **Urban morphology**

➢ **Quantify urban surface morphology:**

1. Digitized building layer

- Vector data
- Detailed investigation from the city government

- Each building's boundary → area and structural patterns
- Each building's attribute → building height

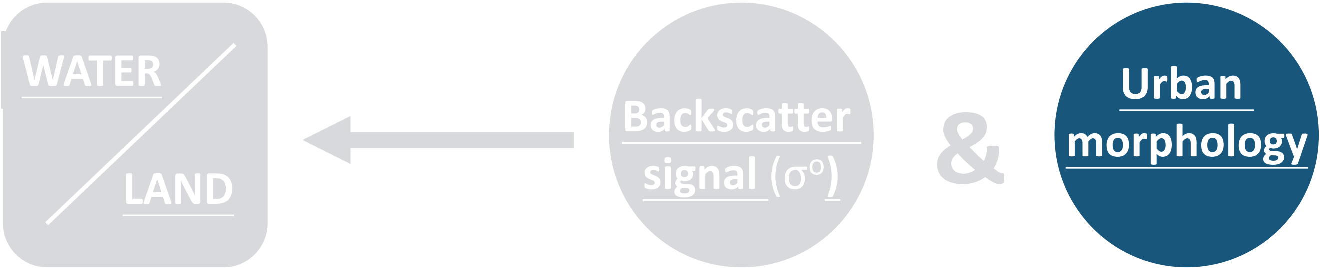
→ The characteristics and patterns of buildings

Surface morphological variables

Digitized building layer; DSM and DEM

Spatial resolution: DTM 20m, DSM 30m

2 Data



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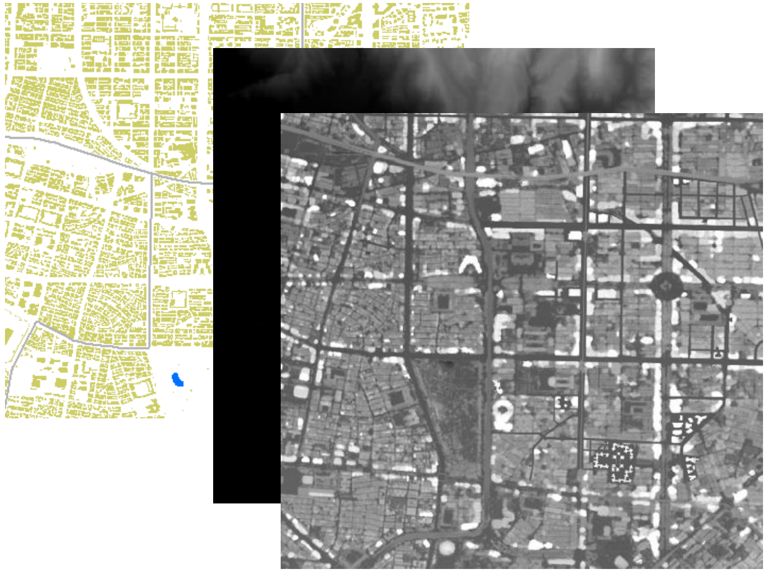
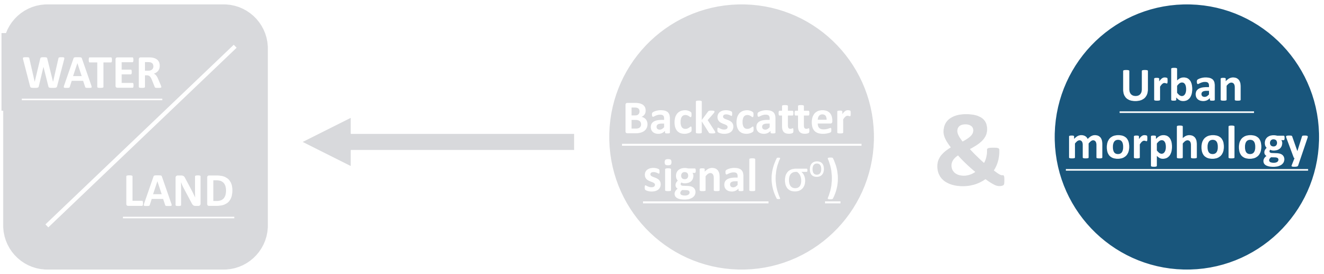
Surface morphological variables

Digitized building layer; DSM and DEM



Spatial resolution: DTM 20m, DSM 30m

Data



➢ **Quantify urban surface morphology:**

- DSM – DEM

  Næsset (1997); Popescu, Wynne, and Nelson (2002); Ural et al. (2011)

➔ **Surface of urban height**

Reference

Replot from: https://3dmetrica.it/dtm-dsm-dem/

2. DSM and DEM

- Raster data
- Has been more easily acquired nowadays e.g. LiDAR, flying UAVs
- **Free, open data**

3 Variables

Dependent variable

WATER
LAND

Independent variable

Backscatter signal (σ°)

&

Urban morphology

Binary class

WATER:

¾ 100% of water in the cell

¼ 1-99% of water in the cell

LAND:

0% of water in the cell

Backscatter value

$\boldsymbol{\sigma}^{\mathbf{0}} = 10 \times \log 10(amplitude)$

Unit: decibel

Urban morphological variables

1) Neighboring
2) **Horizontal** & **Vertical** aspects

Variables

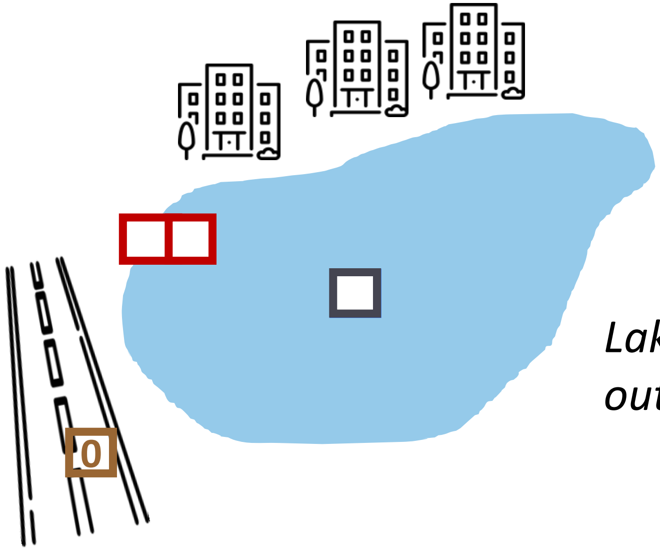
WATER / LAND ← Backscatter value (σ°) & Urban morphology

Ground truth

Aerial orthophotos

Spatial resolution: 0.1m × 0.1m

Digitize and random sampling



Lakes, ponds, outdoor pools, …

Binary	Digitized cell
Water (1)	Water body
Land (0)	Impervious road

Water type	
Water_edge	High double bounce potential
Water_inner	Low double bounce potential

3 Variables

Dependent variable

Independent variable

WATER
LAND

Backscatter signal (σ^o)

&

Urban morphology

Binary class

WATER:
¾ 100% of water in the cell
¼ 1-99% of water in the cell

LAND:
0% of water in the cell

Backscatter value

$$\boldsymbol{\sigma}^{\mathbf{0}} = 10 \times \log 10(amplitude)$$

Unit: decibel

Urban morphological variables

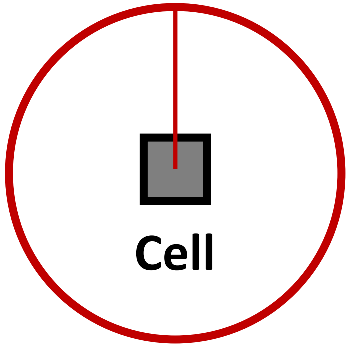
1) Neighboring
2) **Horizontal** & **Vertical** aspects

Variables

WATER / LAND ← Backscatter value (σ^o) & **Urban morphology**

1) Neighboring

- The spatial extent of double bounce effects: 120m
  - Road width and building height
    (Mason et al. 2007; Soergel, Thoennessen & Stilla 2003)



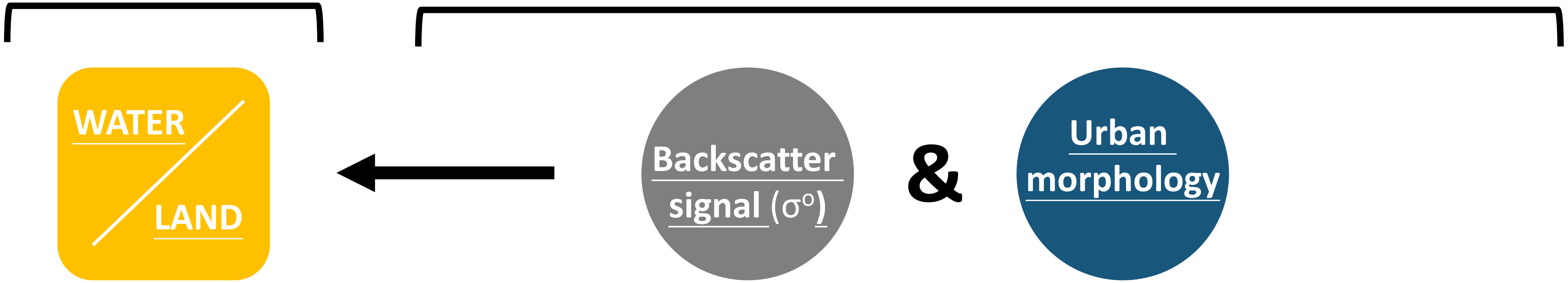
2) Calculating variables:

- Neighboring **horizontal** density → ***Horizontal aspect***
- Neighboring Max. **vertical** height
- Neighboring Mean **vertical** height
- Neighboring **vertical** height variation

→ ***Vertical aspect***

3 Variables

Dependent variable ***Independent variable***

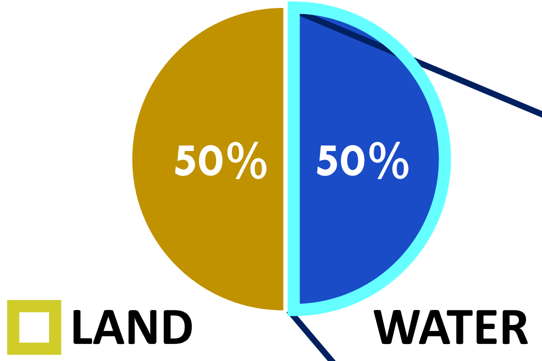


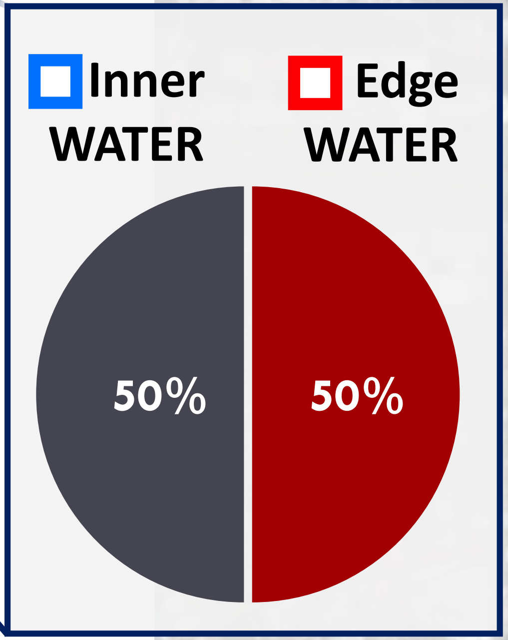
Binary class	*Backscatter value*	*Urban morphological variables*
WATER / LAND	σ^0	**Neighboring horizontal density** **Neighboring Max. vertical height** **Neighboring Mean vertical height** **Neighboring vertical height variation**

Study area, unit
Data
Variables
Samples
Models

4 Samples

- Training data
- Testing data





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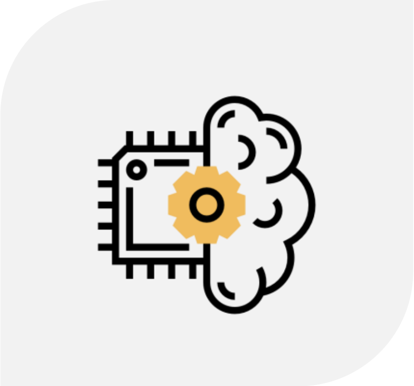
5 Models

Statistics-based model

- Logistic regression

→ Relationship



Machine learning-based model

- Support vector machine (SVM)
- Random forest (RF)

→ Model performances

RESULTS & DISCUSSION

URBAN WATER DETECTION:

Part1: Spatial difference of double bounce effect

Part2: Model performances

Part1. Spatial difference of double bounce effect

1) **Explore** double bounce effect among different water types

2) **The relationship** between urban morphology and double bounce effect

3) **Spatial distribution** of double bounce effect

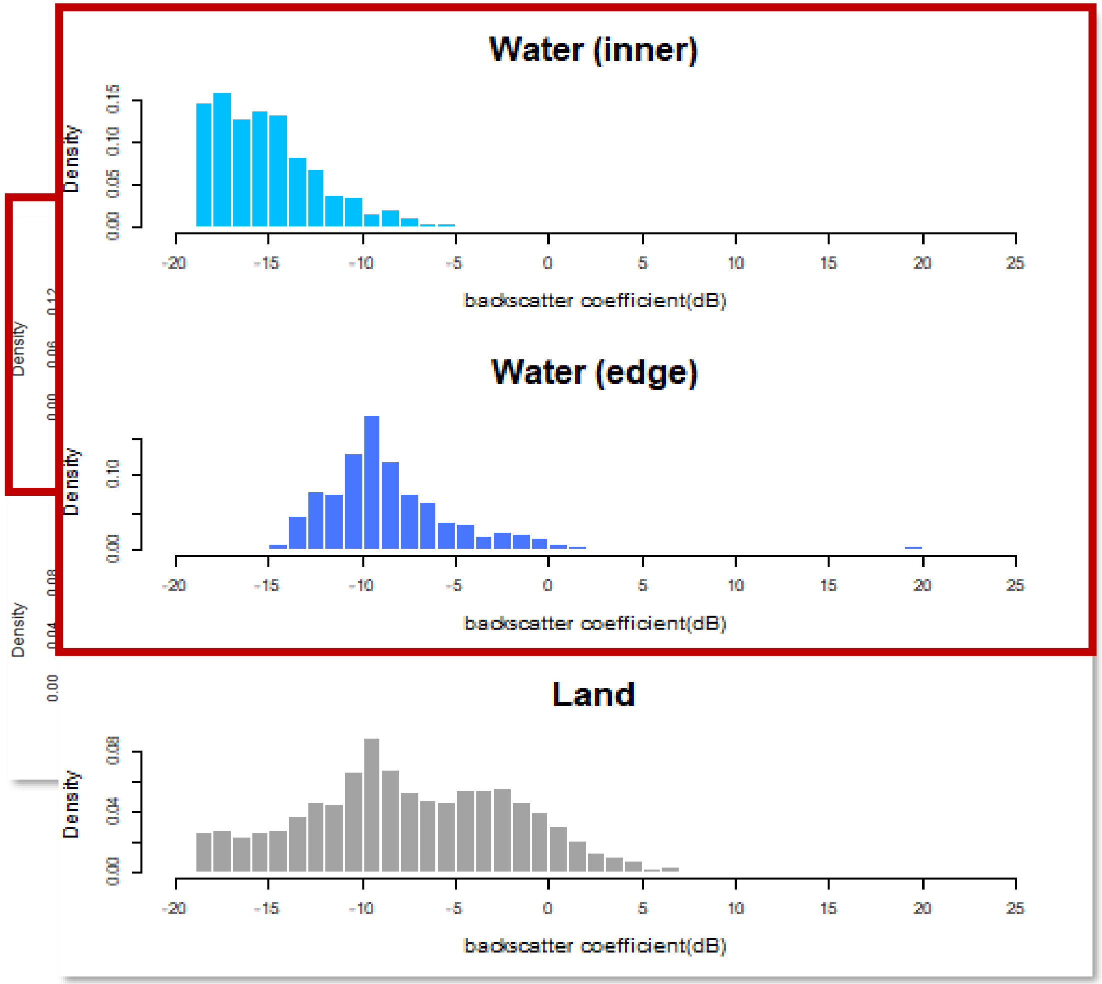
Part1. Spatial difference of double bounce effect

1) **Explore** double bounce effect among different water types

2) **The relationship** between urban morphology and double bounce effect

3) **Spatial distribution** of double bounce effect

1) **Explore** double bounce effect among different water types



➢ Edge WATER's $\overline{\sigma^0}$ vs. Inner WATER's $\overline{\sigma^0}$

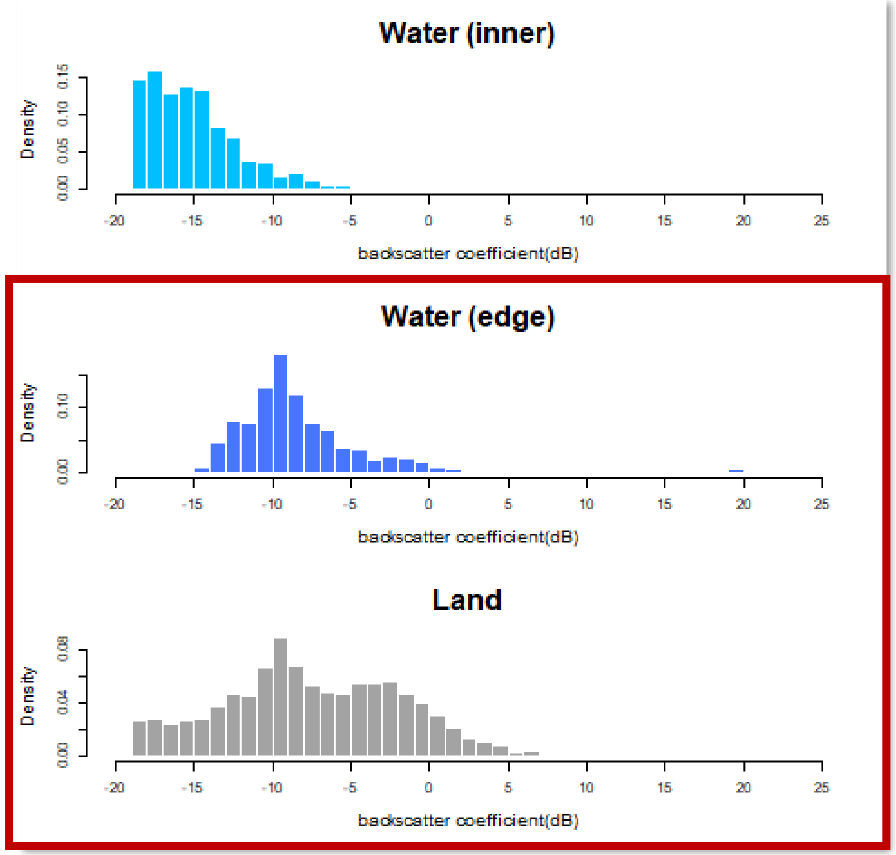
Two independent samples T-test

Water cell types	N	Mean	StDev.	SE.
Inner WATER cells	80	-14.41	2.59	0.289
Edge WATER cells	80	-8.14	4.45	0.498

95% Confidence interval for $\mu_{inner} - \mu_{edge}$: $-7.409 \sim -5.131$
Alternative hypothesis: True difference in means is not equal to 0
$t = -10.892$; degree of freedom $= 126.96$; p-value $< 2.2 \times 10^{-16}$

① $\overline{\sigma^0}_{inner}$ is different from $\overline{\sigma^0}_{edge}$
② $\overline{\sigma^0}_{edge} > \overline{\sigma^0}_{inner}$

1) **Explore** double bounce effect among different water types



➢ Edge WATER's $\overline{\sigma^0}$ vs. LAND's $\overline{\sigma^0}$

Two independent samples T-test

Types	N	Mean	StDev.	SE.
Edge WATER cells	80	-7.21	6.83	0.764
Impervious LAND cells	80	-8.09	6.18	0.691

95% Confidence interval for $\mu_{inner} - \mu_{edge}$: $-1.149 \sim 2.920$
Alternative hypothesis: True difference in means is not equal to 0
t = 0.8599; degree of freedom = 156.45; p-value = 0.3912

① It is hard to tell difference from $\overline{\sigma^0}_{\text{WATER\_edge}}$ and $\overline{\sigma^0}_{\text{LAND}}$ (p-value = 0.3912)

→ **Could be the reason of mis-classification in urban areas**

1) **Explore** double bounce effect among different water types

➢ Differentiating specific WATER type & LAND

- **Water type:**
  - Inner water
  - Edge water
- **Models:**
  - Null model
    → NO morphological variables
  - Main model
    → ADD morphological variables

Model	Overall Accuracy	Model	Overall Accuracy
Inner water		Edge water	
Null models		*Null models*	
Thresholding	0.929	Thresholding	0.786
Logistic regression	0.930	Logistic regression	0.791
Support Vector Machine	0.931	Support Vector Machine	0.799
Random Forest	0.898	Random Forest	0.723
Main models		*Main models*	
(Characteristics and patterns of buildings)		*(Characteristics and patterns of buildings)*	
		ogistic regression	0.820
		upport Vector Machine	0.895
		andom Forest	0.885
		face of urban height)	
Logistic regression	0.928	Logistic regression	0.797
Support Vector Machine	0.952	Support Vector Machine	0.859
Random Forest	0.956	Random Forest	0.878

**** Recommended Practice for flood mapping. 2015. United Nations – Office of Outer Space Affairs (UN-SPIDER).***

Our proposed models

1) **Explore** double bounce effect among different water types

➢ Differentiating specific WATER type & LAND

Inner WATER vs. LAND

- Null models have overall accuracies **over 0.92**

Model	Overall Accuracy	Recall
Inner water		
Null models		
Thresholding	0.929	0.939
Logistic regression	0.930	0.945
Support Vector Machine	0.931	0.949
Random Forest	0.898	0.883
Main models		
(Characteristics and patterns of buildings)		
Logistic regression	0.932	0.939
Support Vector Machine	0.966	0.988
Random Forest	0.959	0.958
(Surface of urban height)		
Logistic regression	0.928	0.949
Support Vector Machine	0.952	0.976
Random Forest	0.956	0.941

1) **Explore** double bounce effect among different water types

➢ Differentiating specific WATER type & LAND

Edge WATER vs. LAND

① Poor in null models

② Adding urban morphological variable,

- **Overall accuracy ↑ (0.79 → 0.90)**
- **94%** of **edge water** is detected (Null **81%** ➔ **94%**)

Model	Overall Accuracy	Recall
Edge water		
Null models		
Thresholding	0.786	0.805
Logistic regression	0.791	0.841
Support Vector Machine	0.799	0.820
Random Forest	0.723	0.714
Main models		
(Characteristics and patterns of buildings)		
Logistic regression	0.820	0.817
Support Vector Machine	0.895	0.941
Random Forest	0.885	0.844
(Surface of urban height)		
Logistic regression	0.797	0.786
Support Vector Machine	0.859	0.890
Random Forest	0.878	0.848

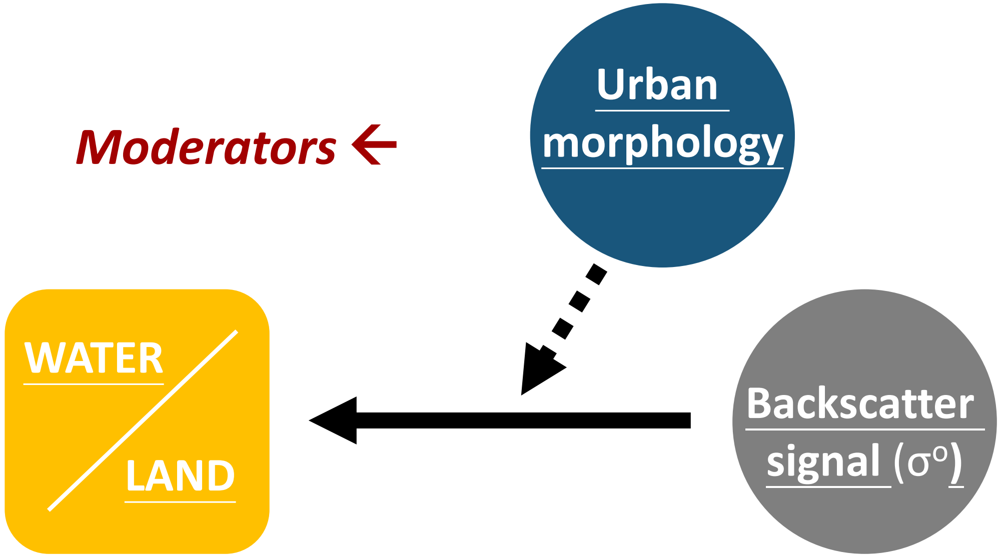
Part1. Spatial difference of double bounce effect

1) **Explore** double bounce effect among different water types

2) **The relationship** between urban morphology and double bounce effect

3) **Spatial distribution** of double bounce effect

2) **The relationship** between urban morphology and double bounce effect



Logistic regression:

- $\sigma^o \times$ *neighboring surface morphological variables*

$$\underbrace{\ln\left(\frac{P}{1-P}\right)}_{\text{WATER / LAND}} = \beta_0 + \underbrace{\beta_1\sigma^0}_{\text{Backscatter value } (\sigma^o)} + \underbrace{\beta_2\sigma^0 \times horizontal\_density + \beta_3\sigma^0 \times vertical\_mean\_height + \beta_4\,\sigma^0 \times vertical\_height\_variation}_{\text{Interaction terms}}$$

WATER / LAND ***Backscatter value (σº)*** ***Interaction terms***

$\sigma^o \times$ urban surface morphology variables

2) **The relationship** between urban morphology and double bounce effect

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \underbrace{\beta_1\sigma^0}_{\text{Backscatter value }(\sigma^0)} + \underbrace{\beta_2\sigma^0 \times \text{Neighnoring horizontal density} + \beta_3\sigma^0\text{Neighboring mean vertical height}}_{Backscatter\ value(\sigma^0) \times surface\ morphology\ variables}$$

Variable	Coefficient	Standard error	z score	P(>|z|)		VIF
Intercept	-1.908	0.086	-22.074	$< 2 \times 10^{-16}$	***	
Backscatter	-0.357	0.012	-28.652	$< 2 \times 10^{-16}$	***	1.41
Backscatter × Neighboring horizontal density	0.847	0.061	13.819	$< 2 \times 10^{-16}$	***	1.11
Backscatter × Neighboring mean vertical height HIGH	0.106	0.020	5.406	6.4×10^{-8}	***	1.34

Significance codes:
***: Significant at α = 0.001
**: Significant at α = 0.01
*: Significant at α = 0.05
. : Significant at α = 0.1

① **Main effect of σ^0**
② **Interaction terms**
③ **Total effect of backscatter value (σ^0)**

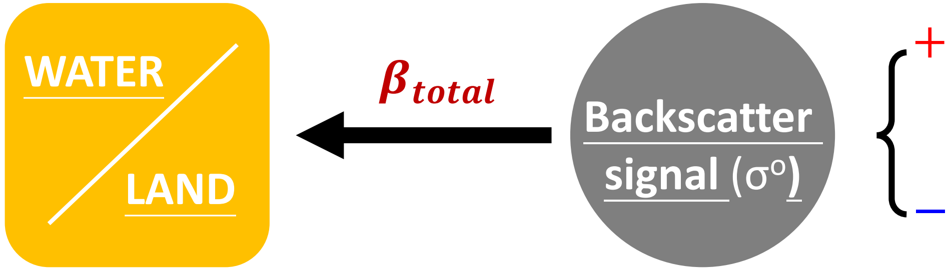
3) **Spatial distribution** of double bounce effect

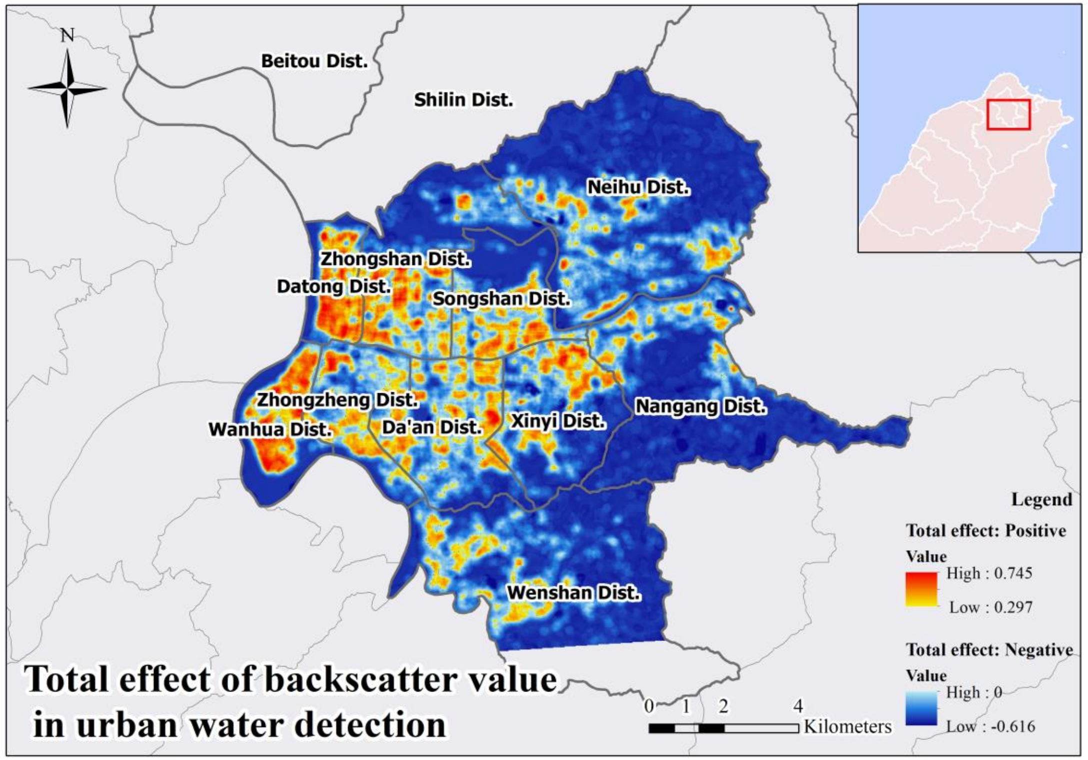
➢ Spatial distribution of σ^0's total effect

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1\sigma^0 + \beta_2\sigma^0 \times horizontal\_density + \beta_3\sigma^0 \times vertical\_mean\_height + \beta_4\,\sigma^0 \times vertical\_height\_variation$$

$$= \beta_0 + \underbrace{(\beta_1 + \beta_2 \times horizontal\_density + \beta_3 \times vertical\_mean\_height + \beta_4 \times vertical\_height\_variation)}\times\sigma^0$$

$$= \beta_0 + \boldsymbol{\beta_{total}} \times \sigma^0$$





Total effect of backscatter value in urban water detection

Different neighboring urban morphology,

Different β_{total} in space

→ Spatial heterogeneity of σº

Brief summary of Part1. Spatial difference of double bounce effect

Similar part:

① Low σ^0 implies water
(Brivio et al., 2002; Henry et al., 2006)

② Double bounce effect
(Franceschetti, Antonio & Daniele 2002; Ferro et al. 2011; Brunner et al. 2008)

- Building width
- Road width

→ ***Neighboring horizontal density***

- Building height

→ ***Neighboring vertical height***

➔ **Match with small-scale studies using theoretical equations & empirical studies)**

What we've further explored:

Double bounce effect is treated uniformly in urban areas… (Mason et al. 2014; Pulvirenti et al. 2016)

① Difference of water's backscatter and double bounce effect in space

② The dominance of neighboring horizontal density

Part2: Model performances

Inner validation:

- Model: Taipei City
- Data: Taipei City

> ➢ ***Highest overall accuracy model***
> ➢ ***Characteristics of building*** *or* ***urban height***

Cross-city validation:

- Model: Taipei City
- Data: **Taichung City**

> ➢ ***Generic models?***

Part2: Model performances

Inner validation:

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➢ ***Highest overall accuracy model***
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Cross-city validation:

- Model: Taipei City
- Data: **Taichung City**

➢ ***Generic models?***

Inner validation:

- Model: Taipei City
- Data: Taipei City

Pooled WATER

(25% inner WATER; 25% edge WATER; 50% LAND)

	Characteristics and patterns of buildings	Surface of urban height
Main models	*(Overall accuracy; Recall)*	*(Overall accuracy; Recall)*
Logistic regression model	0.852; 0.914	0.853; 0.909
SVM model	0.881; 0.923	0.890; 0.944
RF model	0.900; 0.965	0.905; 0.966

① Models: **RF model** has highest accuracy

② **Characteristics of buildings** or **Surface of urban height**?

- Similar performances

Inner validation:

- Model: Taipei City
- Data: Taipei City

Testing data: Edge WATER
(50% edge WATER; 50% LAND)

From Null model to Main model:

- Overall accuracy: **0.78 → 0.88**
- Detected **edge water: 71% → 88%**

	Characteristics and patterns of buildings	Surface of urban height
Null models	*(Overall accuracy; Recall)*	*(Overall accuracy; Recall)*
Thresholding	0.777; 0.707	0.777; 0.707
Main models		
Logistic regression model	0.775; 0692	0.792; 0.718
SVM model	0.840; 0.851	0.878; 0.881
RF model	0.867; 0.881	0.878; 0.882

Part2: Model performances

Inner validation:

- Model: Taipei City
- Data: Taipei City

> *Highest overall accuracy model*
> *Characteristics of building or urban height*

Cross-city validation:

- Model: Taipei City
- Data: **Taichung City**

> ***Generic models?***

Cross-city validation:

- Model: Taipei City
- Data: **Taichung City**

Model	Overall Accuracy	Recall
Training data: Samples of Taipei city		
Null model		
Thresholding	0.868	0.919
Main models		*False alarm: 0.18*
(Characteristics and patterns of buildings)		
Logistic regression model	0.897	0.970
SVM model	0.853	0.980
RF model	0.878	0.842
(Surface of urban height)		
Logistic regression model	0.902	0.973
SVM model	0.735	0.694
RF model	0.814	0.813

Testing data: Pooled WATER

(25% inner WATER; 25% edge WATER; 50% LAND)

Pooled WATER vs. LAND

(25% inner WATER; 25% edge WATER; 50% LAND)

From Null model to Main model:

- Overall accuracy: **0.868 → 0.902**
- **98%** of **water** can be detected

False alarm: 0.17; 0.28

Cross-city validation:

- Model: Taipei City
- Data: **Taichung City**

➢ Performance of specific WATER:

Testing data: Edge WATER
(50% edge WATER; 50% LAND)

Edge WATER vs. LAND
(50% edge WATER; 50% edge LAND)

From Null model to Main model:

- Overall accuracy: **0.82 ➔ 0.88**
- Detected **edge water**: **85% ➔ 95%**

False alarm: 0.19; 0.29

Model	Overall Accuracy	Recall
Training data: Samples of Taipei city		
Null model		
Thresholding	0.815	0.846
Main models		*False alarm: 0.30*
(Characteristics and patterns of buildings)		
Logistic regression model	0.874	0.937
SVM model	0.832	0.951
RF model	0.804	0.800
(Surface of urban height)		
Logistic regression model	0.878	0.944
SVM model	0.706	0.650
RF model	0.745	0.773

Brief summary of Part2. *Model performances*

Data
to quantify urban morphology

① **Recommend "DSM-DEM" for urban height**
- Calculation loading
- Detailed building layer not available

Models
for water detection

② **Machine learning model has highest accuracy**
- **Edge water's** overall accuracy = **0.88** *(Null: 0.78)*
- **93%** of **water** is detected *(Null: 84%)*
- **88%** of **edge water** is detected *(Null: 71%)*

③ **Generic models for cross-city applications**
- **Edge water's** overall accuracy = **0.88** *(Null: 0.82)*
- **98%** of **water** is detected *(Null: 92%)*
- **95%** of **edge water** is detected *(Null: 85%)*

To sum up, when detecting urban water…

- From **Part 1. Spatial difference of double bounce effect**

Property of double bounce effects:

1. Intensity **difference** of water's double bounce effect in space

Mechanism of double bounce effects:

2. Importance of **neighboring horizontal density**

- From **Part 2. Model performances**

Data:

3. Advantage of **"DSM-DEM"** to summarize contribution from neighboring structures

Generic model / modeling framework:

4. Increased **overall accuracy** and **percentage of detected water**
5. **Single-city data** to capture radar's physical process of double bouncing

LIMITATIONS

1. The **direction** of SAR system and **orientation** of buildings
2. The **spatial extent** of double bounce effect
3. The **proportion** between WATER & LAND;

   inner WATER & edge WATER

CONCLUSIONS

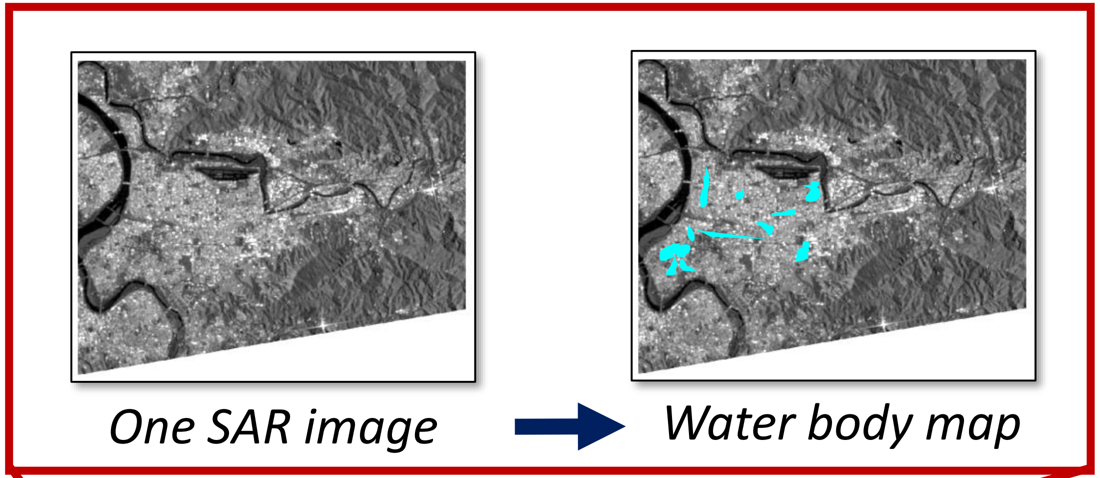
- Significance

***Remote sensing** data and images + **GIS** techniques,*

- ➢ Detecting framework related to urban water/flood mapping
- ➢ A general approach to consider radar contributions from nearby structures
  - Without detailed data
- ➢ Required data is all free and open
- ➢ Generic model for cross-city water detection
  - From one-city data

CONCLUSIONS (cont.)

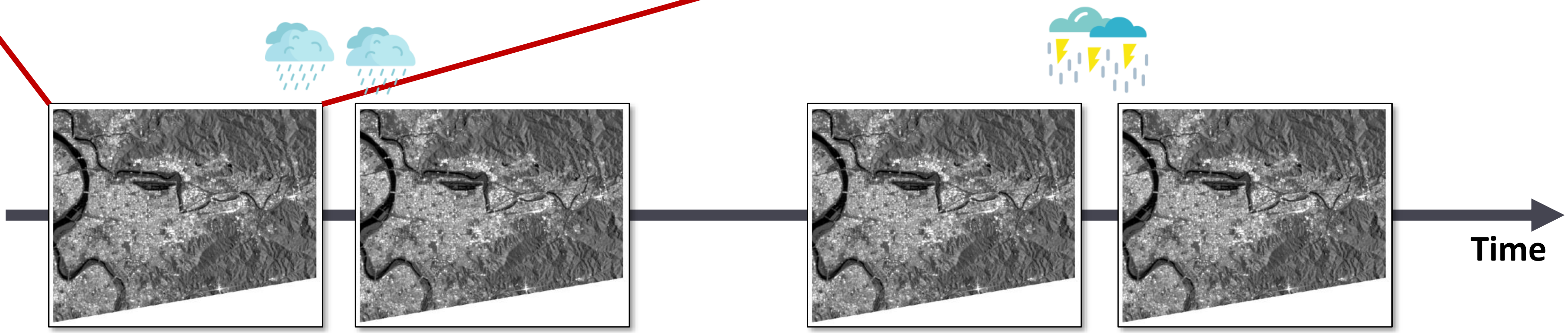
From this study:



Future applications:

Temporal scale of urban water detection

- *Weather effects*
- *Additional water bodies*
- *Event-induced water bodies*



Thank you!

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