EGU General Assembly 2023
HS3.1 - Hydroinformatics: data analytics, machine learning, hybrid modelling, optimisation
Room 3.29/30 on Monday, 24 April 2023, 09:05-09:15

Fluvial land cover classification by using *CSC deep learning method* with UAV airborne images

<Acknowledgments>
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科研費
KAKENHI

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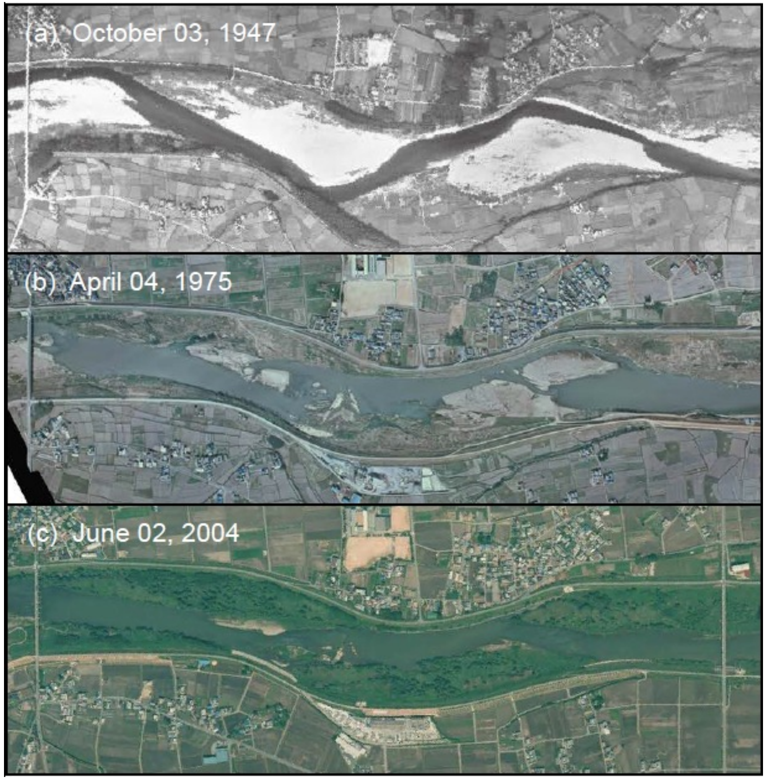
Introduction

Research background: *riparian vegetation management*

- ✓ **Vegetation overgrowth** in fluvial floodplains and sand bars has become a serious problem for river management worldwide.

  - ➢ Decreasing ***Flood Flow Capacity***
  - ➢ Changing ***Groundwater Levels***,
  - ➢ ***Hyporheic Processes***,
  - ➢ ***Sediment and Nutrient Cycles***,
  - ➢ ***Riparian Ecosystems*** and
  - ➢ ***Original Riverine Landscapes***

- ✓ ***Long-term monitoring*** of fluvial geomorphological changes, including sediment and vegetation dynamics



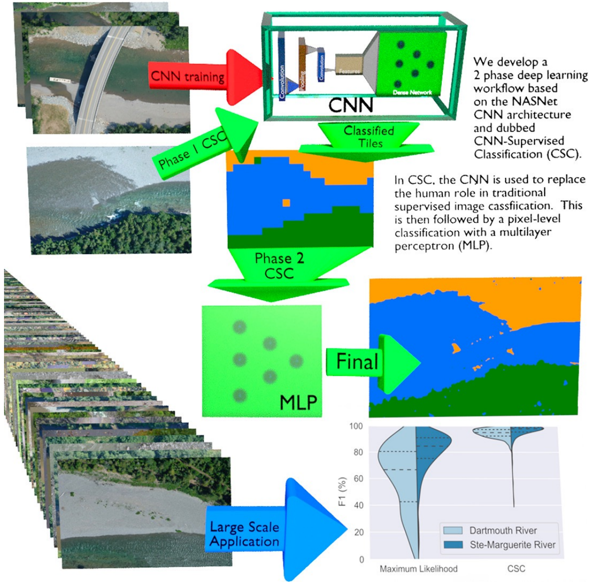
Miyamoto & Kimura, *WRR*, 2016, DOI: (10.1002/2015WR018528)

Research purposes: *developing a deep learning method*

✓ To investigate ***a deep learning method*** for fluvial land cover classification using aerial imagery of ***UAV*** (Unmanned Aerial Vehicles)

- Modifying/applying the deep learning method, ***CSC**** (***CNN-Supervised Classification***)

- Examining ***its applicability*** for the fluvial land cover classification in the Kinu River, Japan



Carbonneau et al., Remote Sensing of Environment, 2020, https://doi.org/10.1016/j.rse.2020.112107

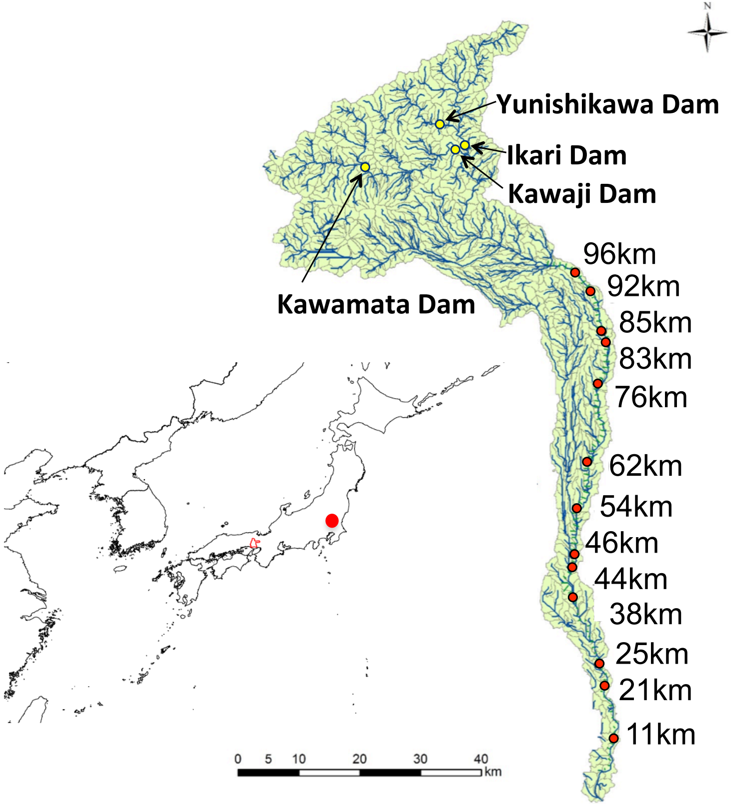
UAV Measurements

Target river basin: *the Kinu River*

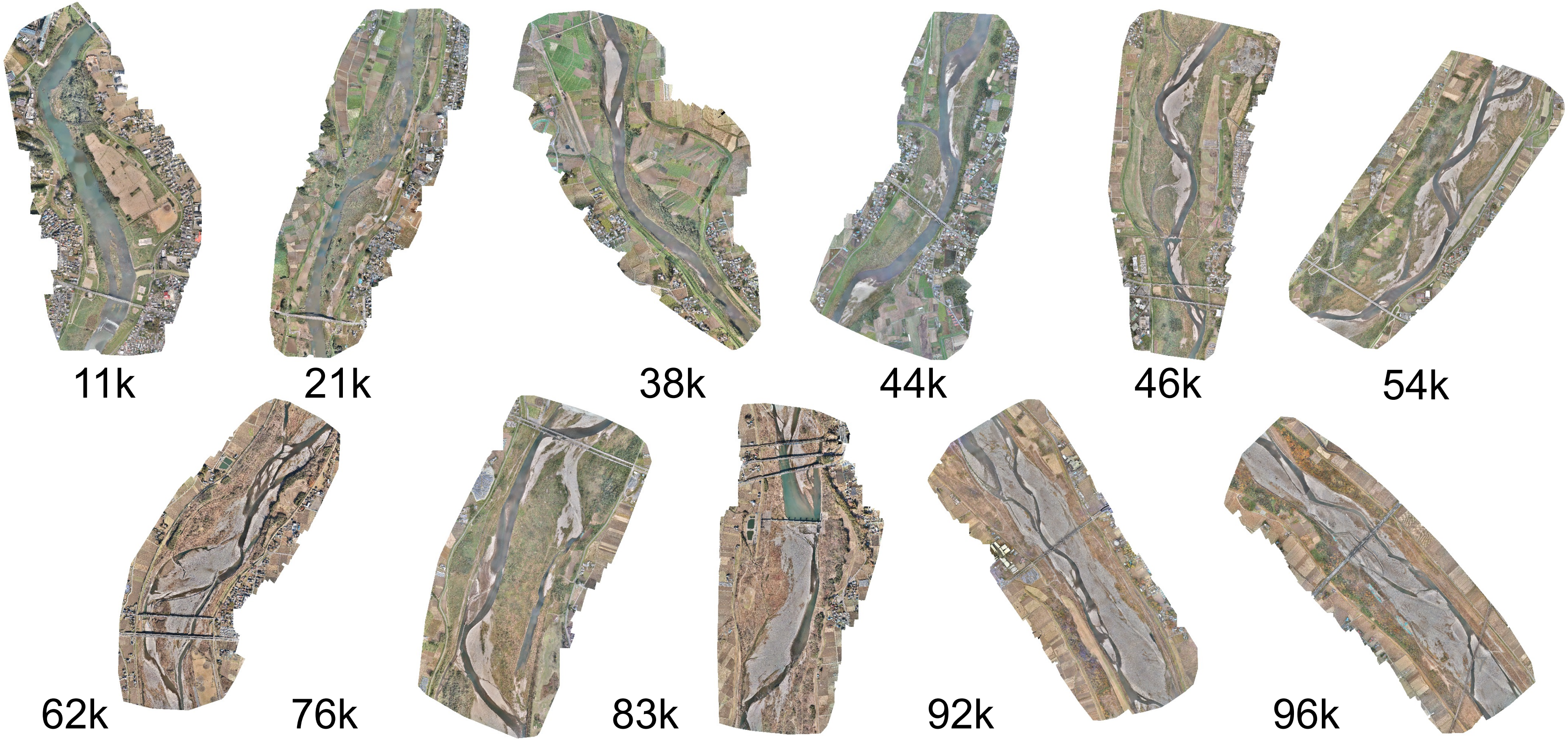
- ✓ River basin area: **1,760km²**
- ✓ Main river channel length: **177km**
- ✓ **UAV** measurements **in 2015-2019**
- ✓ **51 river sections** of RGB orthorectified images were taken aerially
- ✓ The spatial resolution of images: **4 cm per pixel**

PHANTOM3 ADVANCED (DJI)

eBee (senseFly)

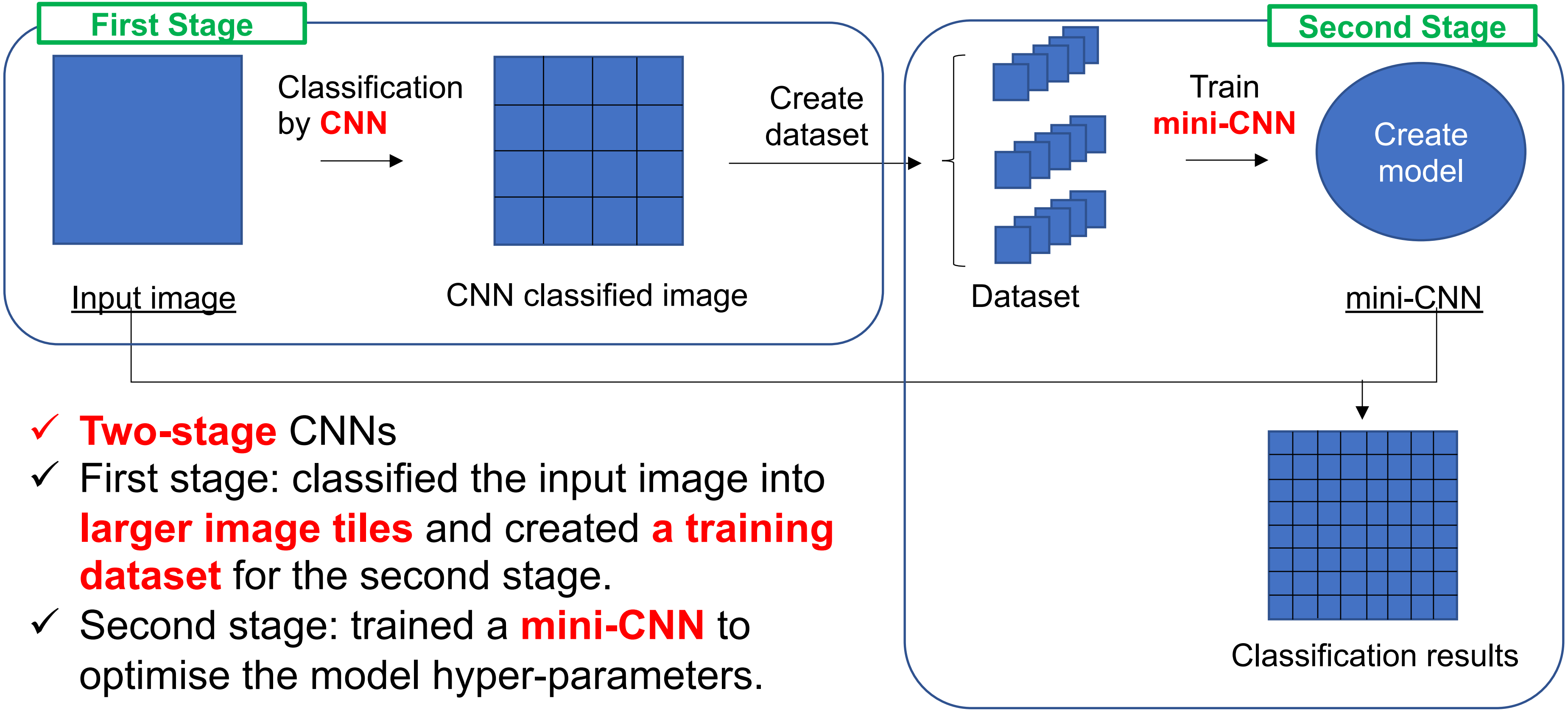


UAV orthorectified RGB images: *the Kinu River, 2016*



Methods

Deep learning: *CSC (CNN Supervised Classification)*



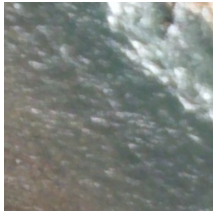
- ✓ **Two-stage** CNNs
- ✓ First stage: classified the input image into **larger image tiles** and created **a training dataset** for the second stage.
- ✓ Second stage: trained a **mini-CNN** to optimise the model hyper-parameters.

Land cover classes in CSC

- ✓ **7** land cover classes
- ✓ Image tiles extracted from the UAV images **in 200 * 200 pixels (7m)**

	Water surface	Gravel	Sand	Farm-land	Grass	Tree	Artificial land	Total
#	3,095	2,608	1,369	3,067	2,981	3,055	1,935	21,450

- ✓ The image tiles in a total of **85,800** through data augmentation for fine-tuning in the CSC first stage


Water surface


Gravel


Sand


Grass


Tree


Farmland


Artificial land

CNN fine-tuning in the CSC first stage

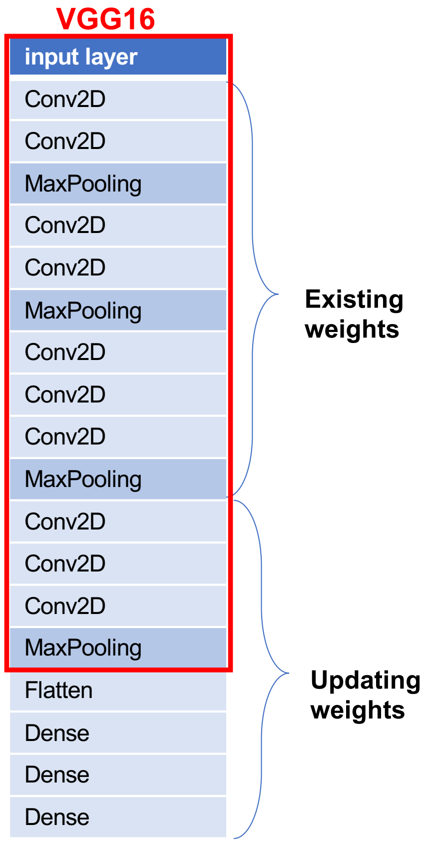
- Used the **VGG16** in the CNN architecture
- Retraining methods: **fine-tuning**
- Evaluation index : ***F1_Score***
- Hyper-parameter search: **Grid Search**

$$F1\_Score = 2\times\frac{Precision \times Recall}{Precision + Recall}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

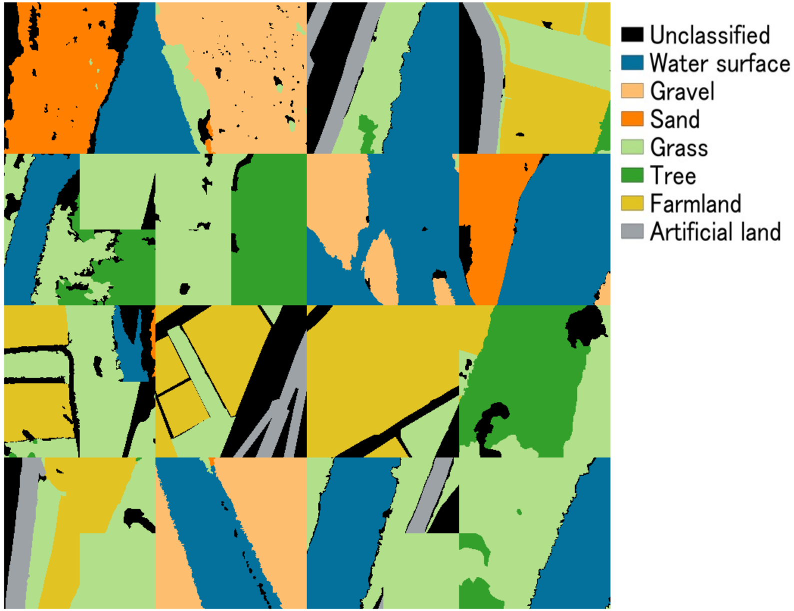
	Predicted Positive	Predicted negative
Ground truth Positive	TP	FN
Ground truth negative	FP	TN



Mini-CNN development in the CSC second stage

✓ Investigated the **structure of mini-CNN** and its **hyper-parameters** that can classify image class with high accuracy

Image mosaic



True labels

Results and Discussion

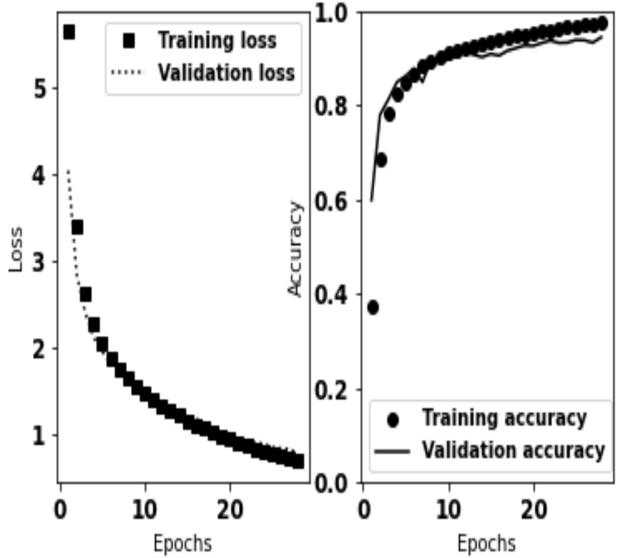
CNN fine-tuning in the CSC first stage

✓ Best hyper-parameters:

Patch size: 200x200pixel, Freeze layer: 7 Learning late: 10^{-6}

✓ Classification report

	Precision	Recall	F1-score	Support
Water surface	0.994	0.988	0.991	2497
Gravel	0.982	0.958	0.969	2106
Sand	0.924	0.927	0.926	2178
Grass	0.910	0.917	0.914	2380
Tree	0.946	0.926	0.936	2443
Farmland	0.938	0.976	0.957	2486
Artificial land	0.962	0.960	0.961	3070
Accuracy			0.951	17160
Macro avg.	0.951	0.950	0.950	17160
Weight. Avg.	0.951	0.951	0.951	17160

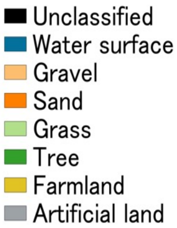


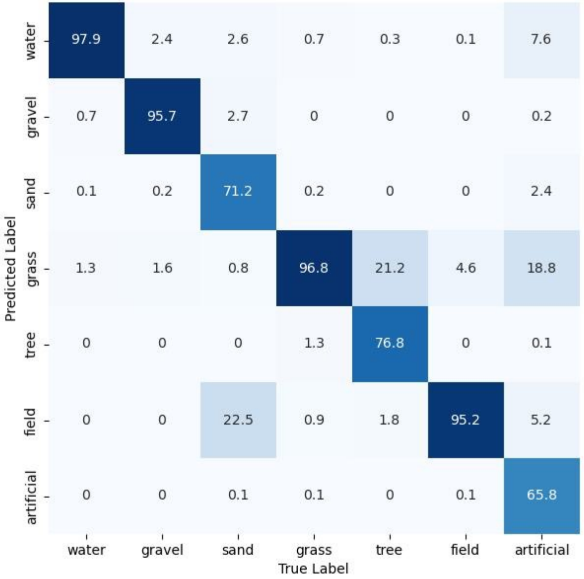
Learning curves

Mini-CNN development in the CSC second stage

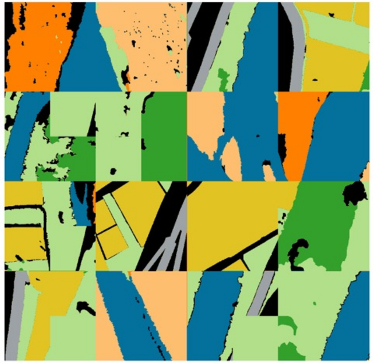
✓ Best hyper-parameters:

- ➢ Patch size: 21pixel
- ➢ Learning late :10^{-3}
- ➢ CNN samples :4.0×10^{5}
- ➢ Filter size: 100pixel

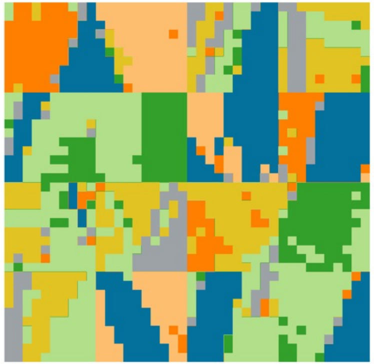




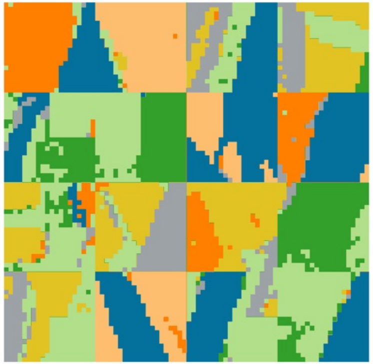
RGB image



True labels

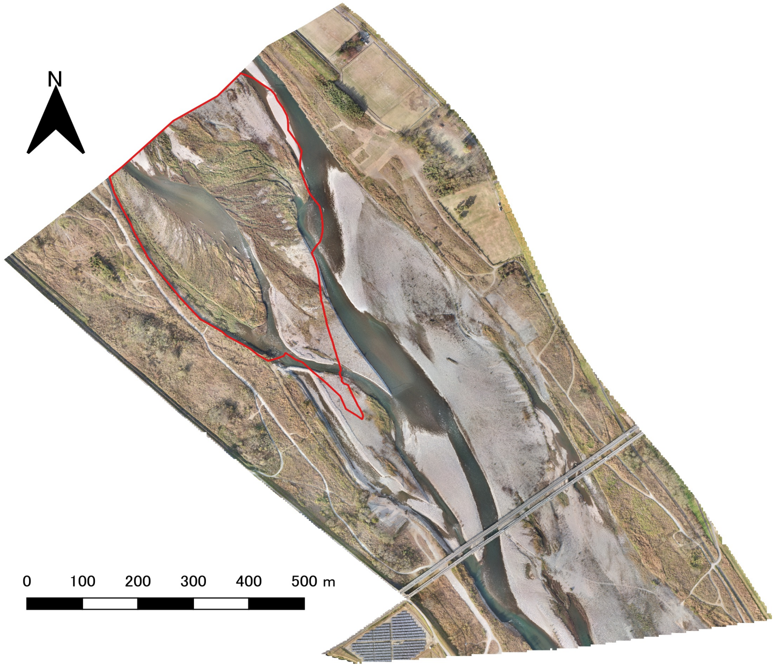


CNN result F1 = 87.0

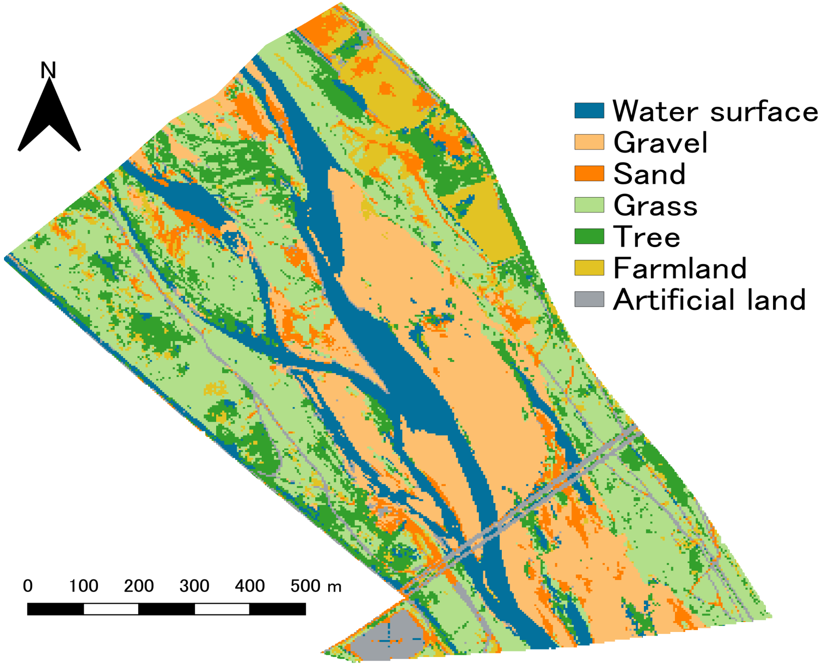


CSC result F1 = 90.4%

Land cover classification in the Kinu River (1)



Orthorectified image

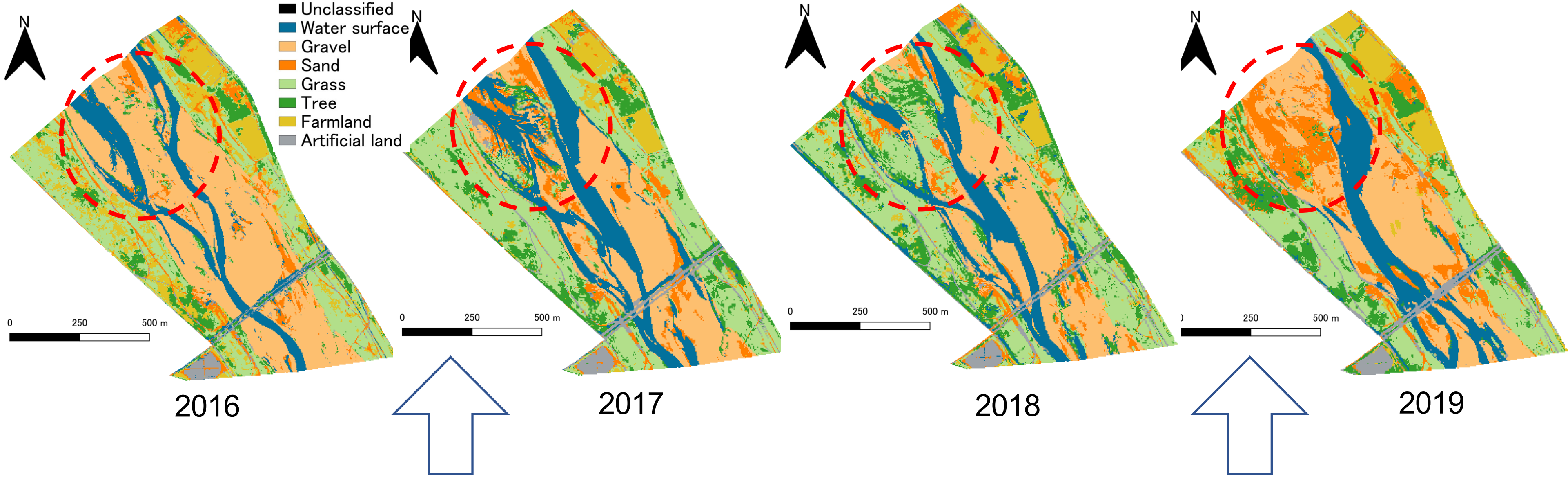


Classification result

The Kinu River at 92k in 2018

Land cover classification in the Kinu River (2)

- 2016 → 2019



Small flooding

Large flooding

The Kinu River section at 92k

Concluding remarks

- ✓ Investigating ***a deep learning method, CSC***, for fluvial land cover classification using aerial imagery of ***UAV***

  - ➢ The weighted average F-measure for the optimised CSC model was ***90.4%***. This confirmed that the optimised CSC could reproduce the land cover classes with enough accuracy.

  - ➢ The CSC application to the RGB orthorectified images of the Kinu River in Japan showed that ***the CSC deep learning method could accurately classify temporal changes in fluvial geomorphologies***, including the significant differences before and after the severe floods.

  - ➢ Future work would be needed to ***improve some land cover*** classifications with lower accuracy and to verify further ***the applicability*** of the method ***to other rivers with different fluvial characteristics***.

Thank you for your kind attention!