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# Flood flow modelling coupled with ML-based land cover detection from UAV and satellite river imagery

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# INTRODUCTION

## Background

**Vegetation overgrowth and forest expansion** have become a serious problem

- decreasing **Water Flow Capacity at Flooding**
- changing Riparian Ecosystems and Original Riverine Landscapes

It would be necessary to **continuously monitor the vegetation dynamics and their effects on flood disasters** for a long period of time.

Kurobe River @3k, 28th,Nov,2017

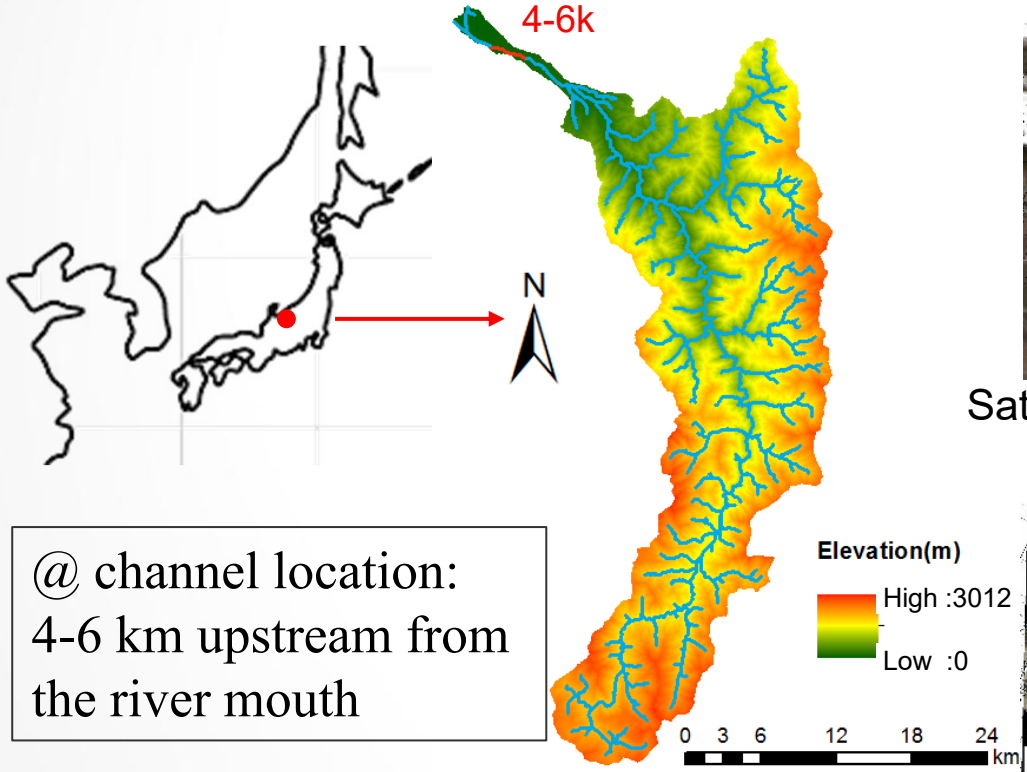
## Purpose

This presentation examined a new method

✓ **Coupling flood flow modelling with the machine learning (ML)-based land cover detection from the Unmanned Aerial Vehicle (UAV) and satellite river imagery.**

# FIELD SITE : Kurobe River

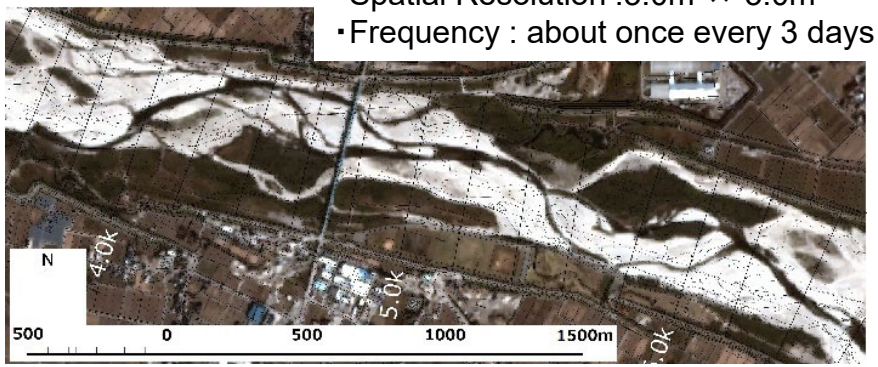
## FIELD SITE




@ channel location:
4-6 km upstream from the river mouth

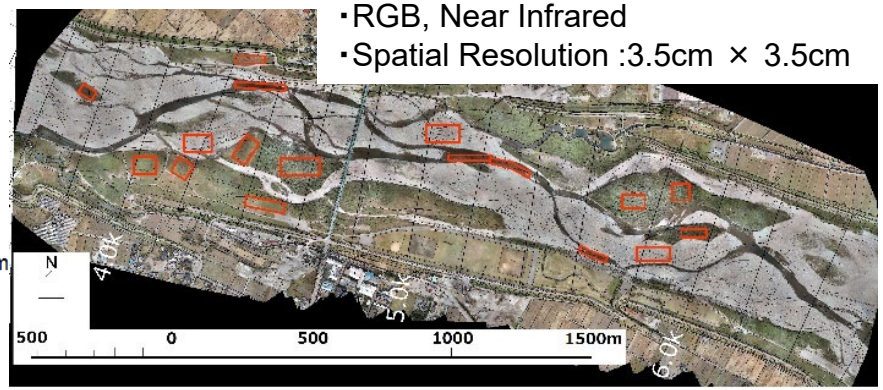
## IMAGES

- RGB, Near Infrared
- Spatial Resolution :3.0m × 3.0m
- Frequency : about once every 3 days




Satellite Image, 8th Nov. 2018(from Planet Company)
**(High-frequency Image)**

- RGB, Near Infrared
- Spatial Resolution :3.5cm × 3.5cm




training data

UAV Image, 5th Nov. 2018
**(High-resolution Image)**

The UAV and Satellite images were taken in the **Kurobe River** channel on November 2018, which was ***a braided channel with a well-vegetated gravel bed***.

# METHODS (Outline)

## 1. Creating Training and Validation Image Data for ML

- The UAV and Satellite river imagery were combined for an ML.
- RGB and NIR(Near InfraRed) bands were used.

## 2. Land Cover Detection by ML with the Image Data

- The method used was **Random Forest (RF)** in the scikit-learn.
- **F-measure** was used to evaluate the accuracy of the land cover detection.

## 3. Coupling the ML-based Land Covers with a Flood Flow model

- The detected riverine land covers were converted into **the roughness coefficients** for a two-dimensional **flood flow analysis.**
- We examined the reproducibility of flood flow simulation results.

# METHODS（Random Forest , F-measure）

## Land Cover Detection by a Machine Learning

Images(Training data)
- Satellite images
- UAV images

✓ Training

Machine Learning Algorithm
RF(Radom Forest)

✓ Ground cover detected by applying to the satellite images

✓ Test

Images(Validation data)

## Evaluate the accuracy of the land cover detection results

$$F-measure = \frac{2Recall \cdot Precision}{Recall + Precision}$$

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

| | | True condition | |
|---|---|---|---|
| | | positive | negative |
| Predicted condition | positive | TP (True positive) | FP (False positive) |
| | negative | FN (False negative) | TN (True negative) |

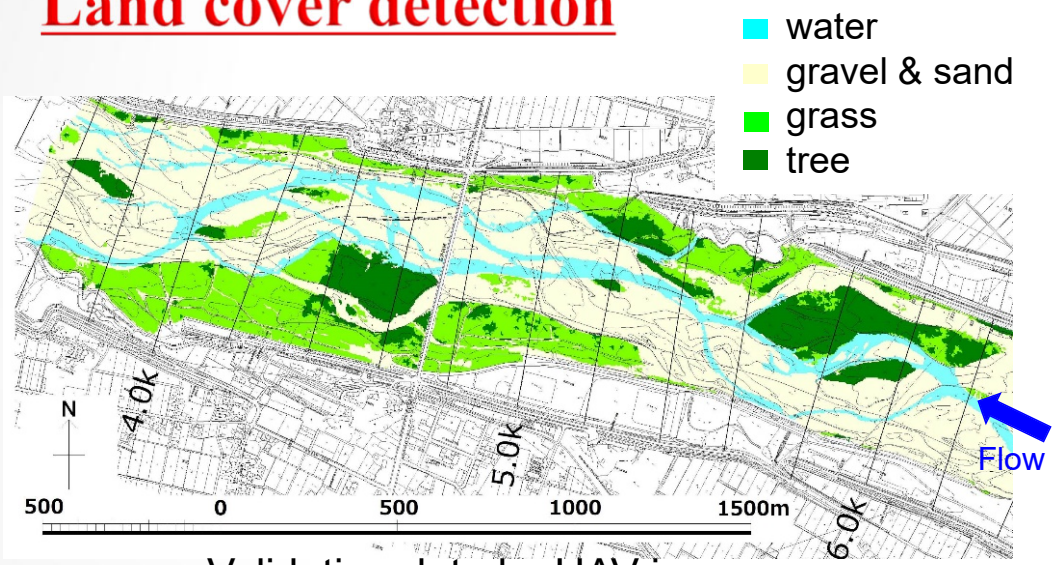
# METHODS（Flood flow analysis）

## Model Conditions

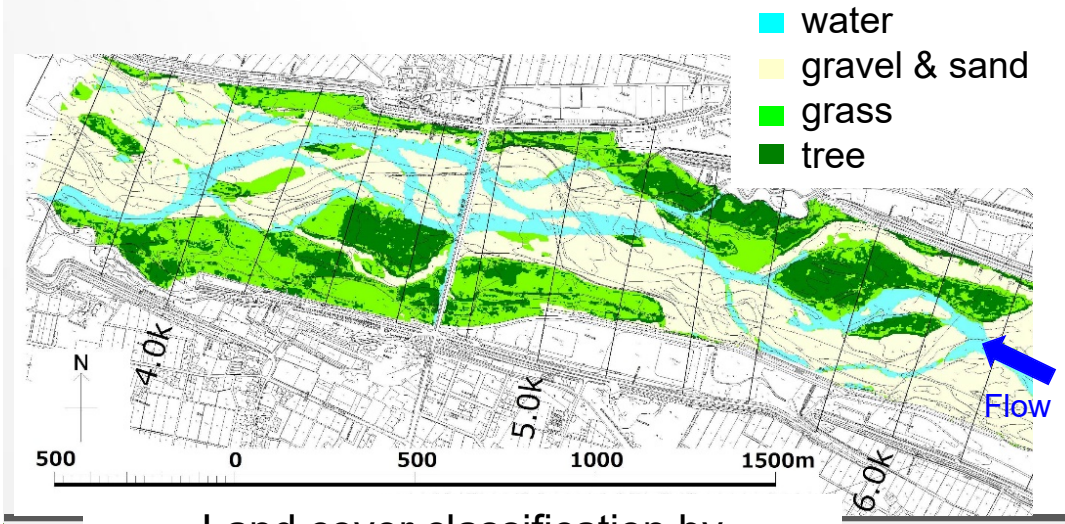
| | |
|---|---|
| Analysis Model | Two-Dimensional Flood Flow Model |
| Analysis Section | 4-6 km upstream from the river mouth in Kurobe River |
| Mesh Size | 10m × 10m |
| Flood Discharge | 5,200$m^3$/s (Planned Discharge in Flood Protection) |
| Riverine Land Cover | ・Validation Data from UAV imagery<br>・Land Cover Detection Data by RF with Satellite Images |
| Roughness Coefficients | The following values were arithmetically averaged for calculation.<br>・water:0.04<br>・gravel/sand:0.04<br>・grasse:0.06<br>・tree:0.10 |

# RESULT(Land cover detection)

## Land cover detection




Validation data by UAV images




Land cover classification by
RF with satellite images (RGB+NDVI)

## F-measure

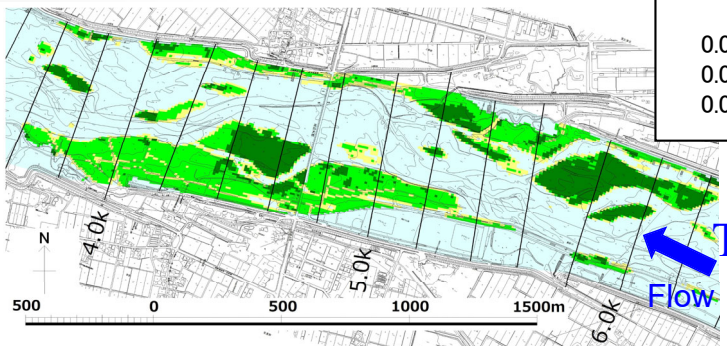
| Land Cover | Dataset for ML |
|---|---|
| | RGB＋NDVI |
| Water | 0.78 |
| Gravel & sand | 0.89 |
| Grass | 0.65 |
| Tree | 0.59 |
| ALL | 0.79 |

- ✓ Land covers were classified into water, gravel & sand, grass, and tree.
  ***(Difficult to classify trees and grass from only satellite image information due mainly to low spatial resolution.)***
- ✓ Overall F-measure was 0.79.

# RESULT(The flood flow simulation)

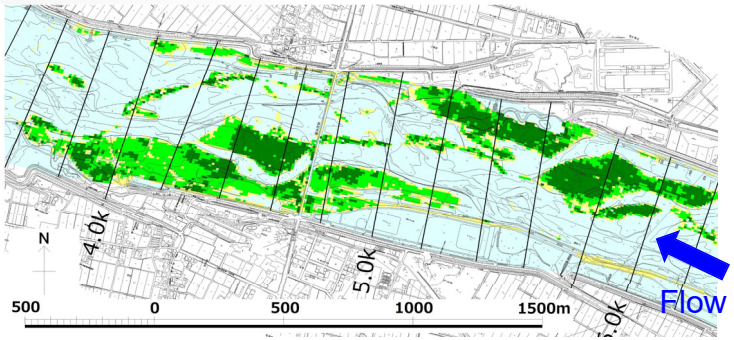
## The results of Land cover detection

Converted into the roughness coefficients of the two-dimensional flood flow analysis by arithmetic mean



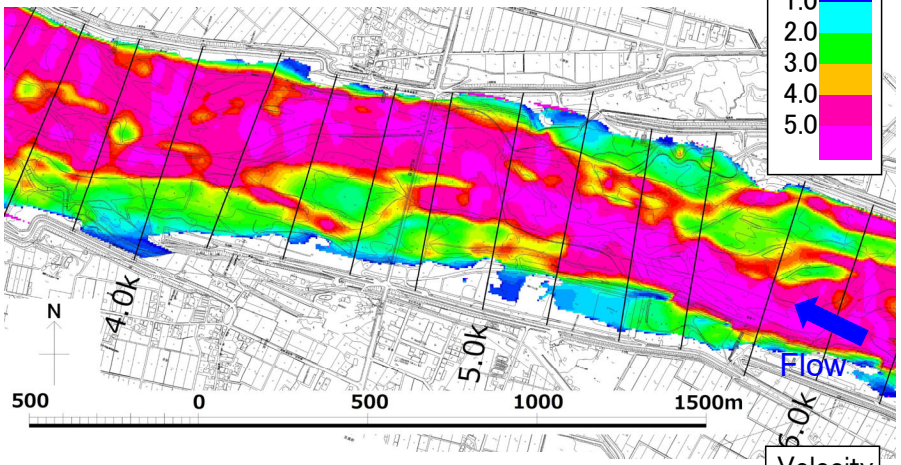

Roughness coefficient(Validation data)

The flood flow simulation

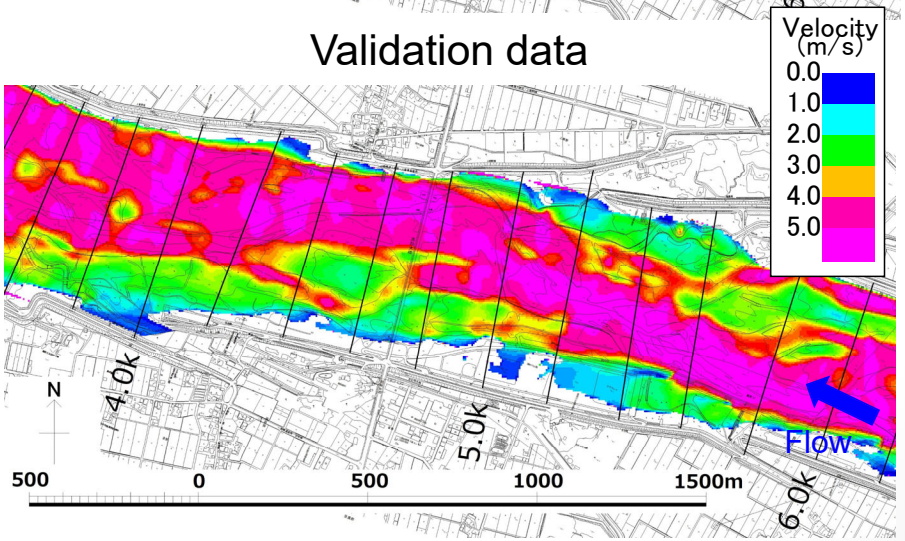



Roughness coefficient(ML-based land covers)

## The velocity field



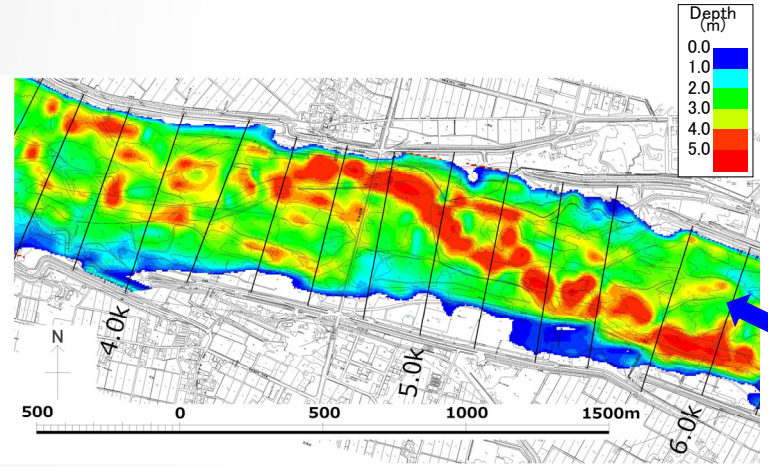

Validation data



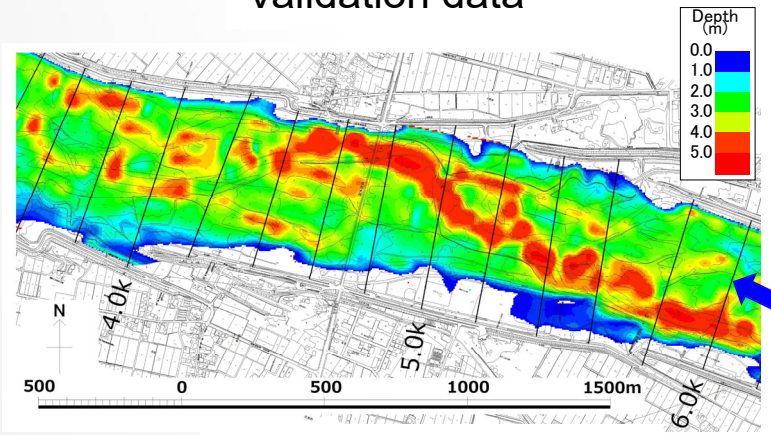

ML-based land covers

# RESULT(The flood flow simulation)

## The water depth field

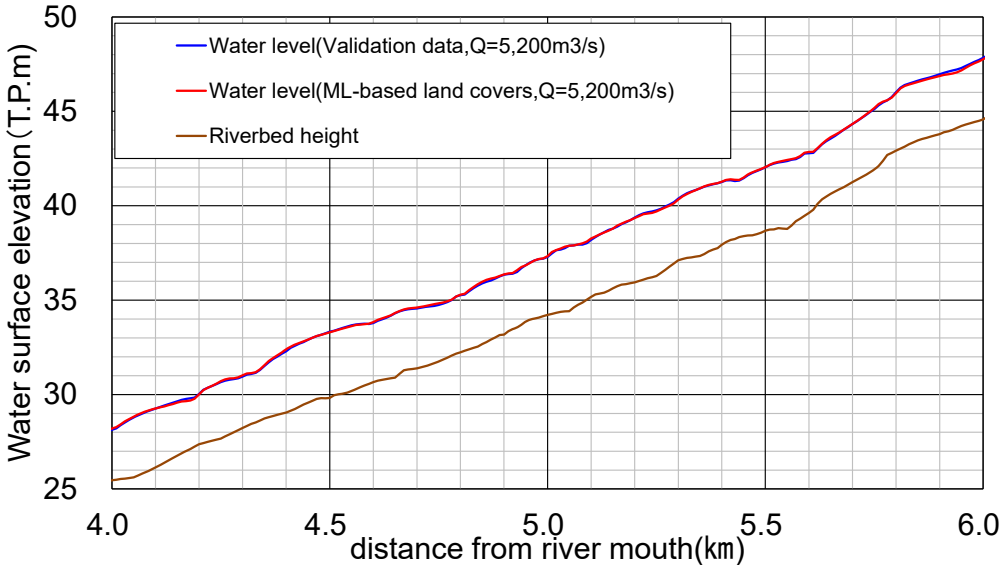


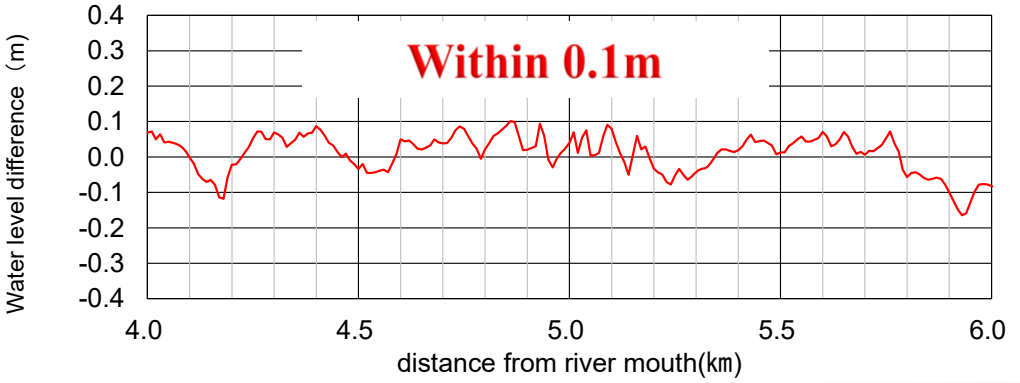

Validation data




ML-based land covers

## The water surface profile




✓ The flood flow simulation could reproduce the water surface profile of flood flows with high accuracy

# CONCLUDING REMARK

- Combining the high- and low-resolution images in the RF could **effectively detect riverine land covers** from the satellite images with a certain degree of accuracy.
- The flood flow simulation could **reproduce the velocity field and water surface profile of flood flows with high accuracy**.

- These results strongly suggest the effectiveness of coupling the current flood flow modelling with the ML-based land cover detection for **grasping the most vulnerable portions in river flood management**.
- In the future, it is necessary to clarify **the influence of machine learning detection accuracy** of riverine land covers on their application of flood flow simulation.

**Thank you for attention!**