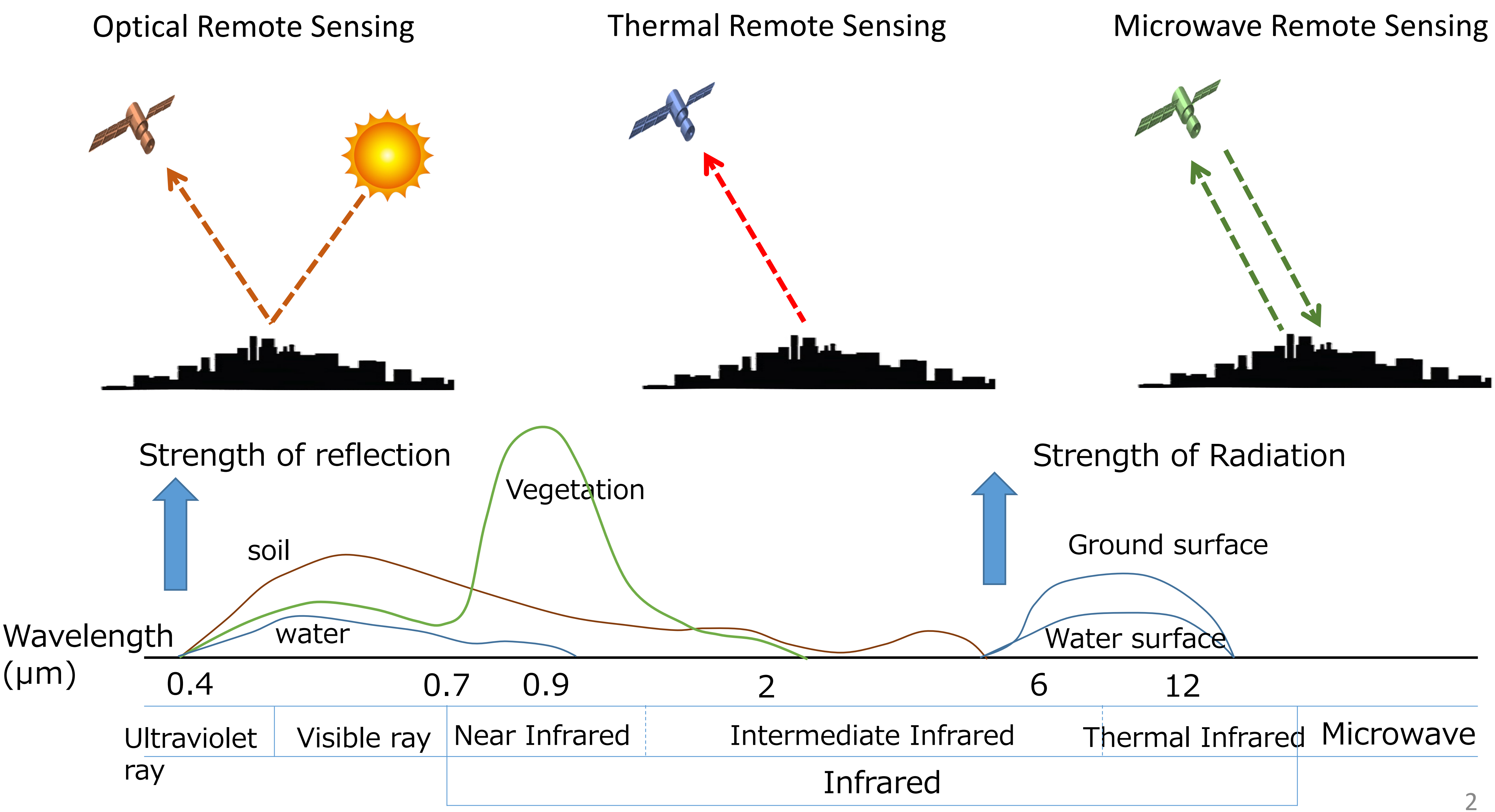
Analysis Method Using Optical Satellite Data

Masahiko Nagai

Director,   Center for Research and Application for Satellite Remote Sensing

Professor,   Graduate School of Sciences and Technology for Innovation

Yamaguchi University

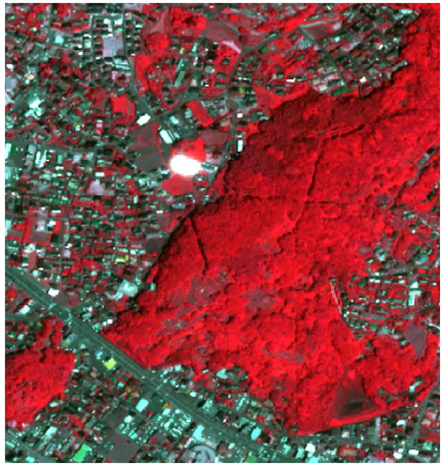

Optical Remote Sensing
Thermal Remote Sensing
Microwave Remote Sensing
Strength of reflection
Vegetation
soil
water
Wavelength
(μm)
Strength of Radiation
Ground surface
Water surface
0.4
0.7
0.9
2
6
12
Ultraviolet ray
Visible ray
Near Infrared
Intermediate Infrared
Thermal Infrared
Microwave
Infrared

Optical Remote Sensing　　Thermal Remote Sensing　　Microwave Remote Sensing

ALOS
(True Color Image)

＜Applications＞
Landslide･Volcano
Flood･Tsunami
Building Damage

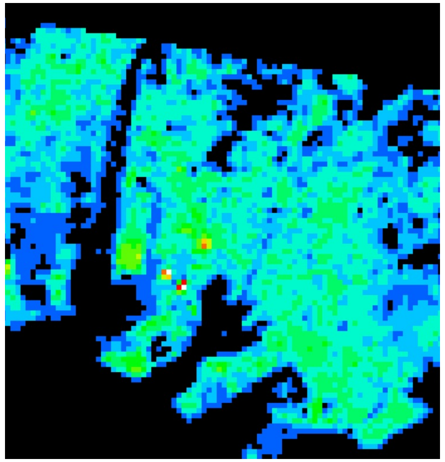
GRUS-1, PlanetScope
WorldView, Pleiades,
SPOT, Sentinel-2
ALOS-3



Pleiades
(False Color Image)

＜ Applications ＞
Landslide
Volcano･Lava flow
Flood･Tsunami

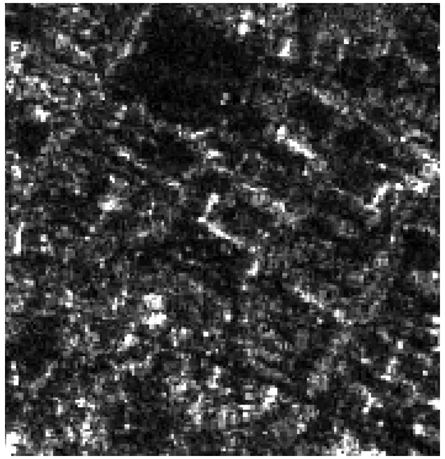
GRUS-1, PlanetScope
WorldView, Pleiades,
SPOT, Sentinel-2
ALOS-3



ASTER
(Thermal Image)

＜ Applications ＞
Volcano
Forest Fire
City Fire

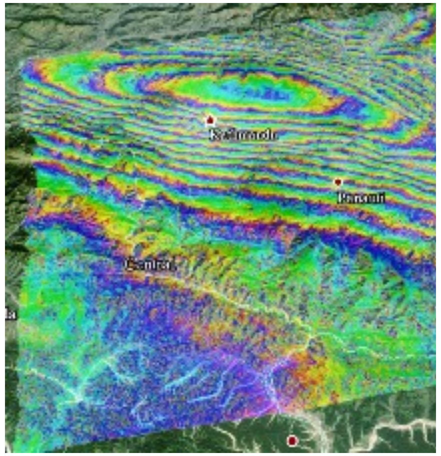
ASTER, MODIS,



ALOS-2
(SAR Image(Amplitude))

＜ Applications ＞
Flood･Tsunami
Landslide

ALOS-2, Sentinel-1
TerraSAR-X,
Rardarsat



ALOS-2
(SAR Image(Phase))

＜ Applications ＞
Land Deformation
Building Collapse
Liquefaction

ALOS-2, Sentinel-1
TerraSAR-X,
Rardarsat

Introduction

- Building a larger time-series training dataset for different satellites brings following **constraints-**
  - The interpretation of EO images **needs expert knowledge**, so annotation is a time- consuming and resource-intensive procedure.
  - **buying** enough scenes just for training data preparation for each satellite will be **very expensive** and **not very practical.**
  - Many **new micro-satellites** are getting launched and these **do not have enough images in their archived data** to prepare a large training dataset. Or we have to wait till the time they get enough images captured to use our models.

Satellite data harmonization

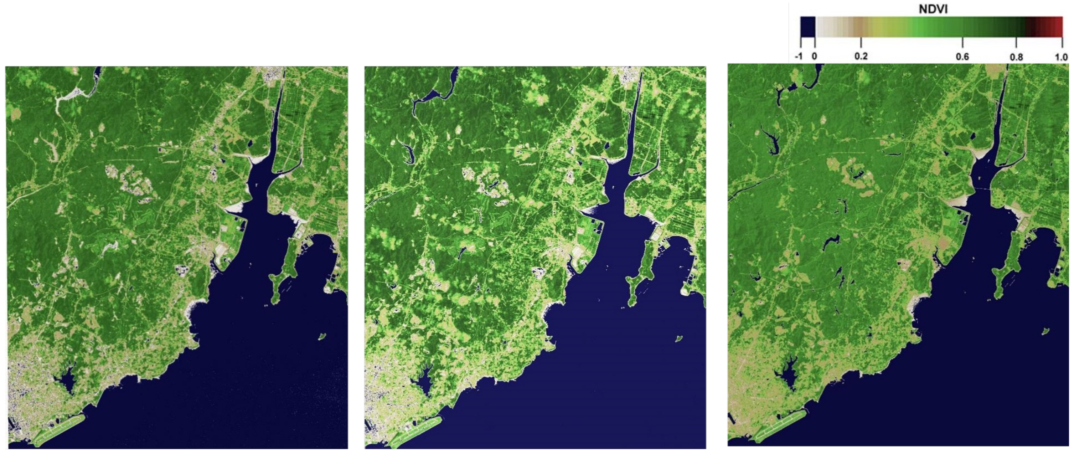
- Different satellite have different wavelength definitions for bands, along with the atmospheric influence, calibration errors, and even orbital overpass time influences the final results.
- Harmonization tries to minimize the differences among inter- and intra- satellites data.

PlanetScope PS2
Date: 2022-08-05
Local Time: 10:34 am.

PlanetScope PSB.SD
Date: 2022-08-05
Local Time: 10:11 am.

GRUS-1A
Date: 2022-08-05
Local Time: 10:47 am.

NDVI product Before Harmonization



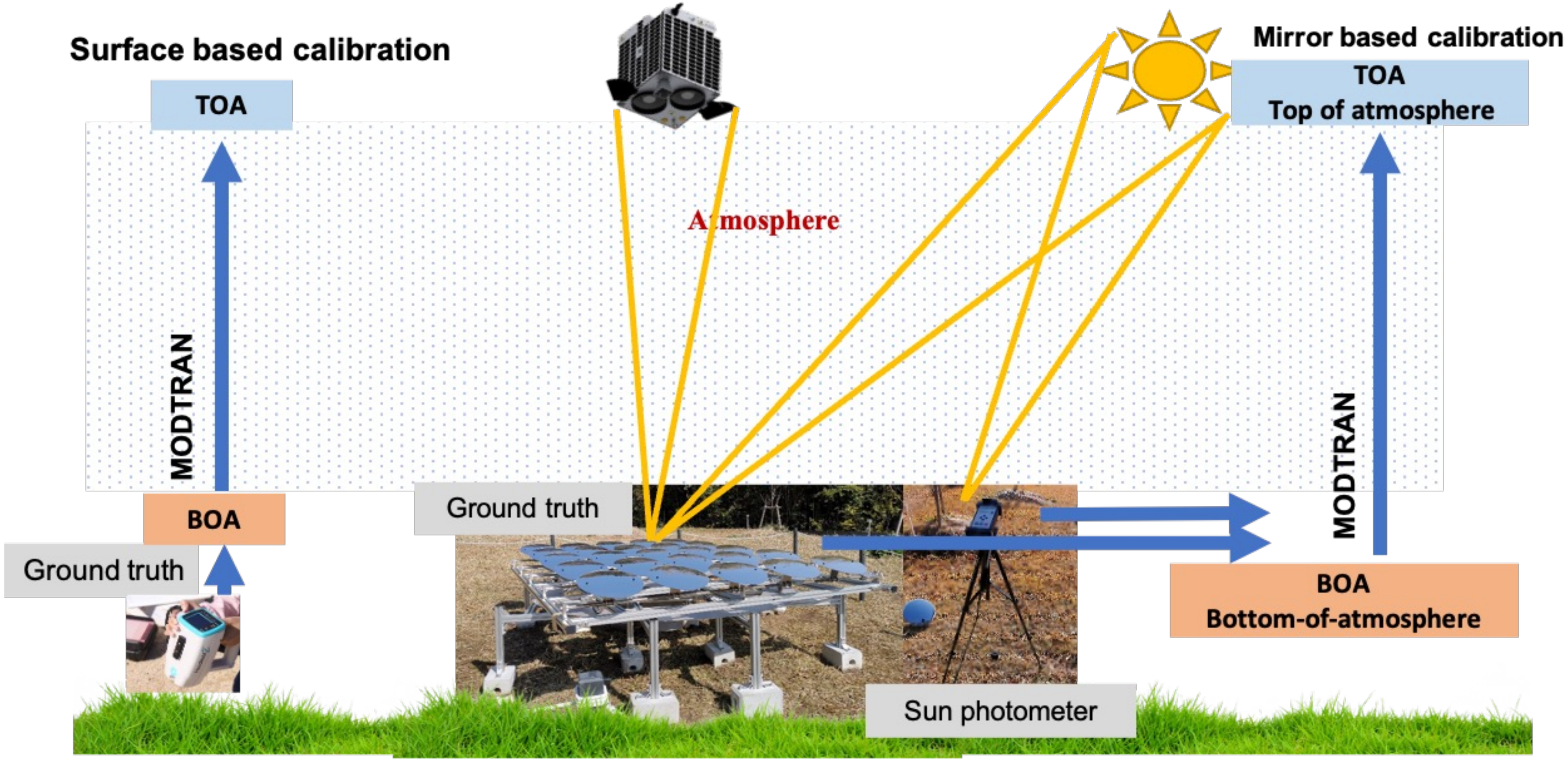
PlanetScope PS2
Date: 2021-08-05
Local Time: 10:34 am.

PlanetScope PSB.SD
Date: 2021-08-05
Local Time: 10:11 am.

GRUS-1A
Date: 2021-08-05
Local Time: 10:47 am.

NDVI product After Harmonization

How satellite harmonization performed



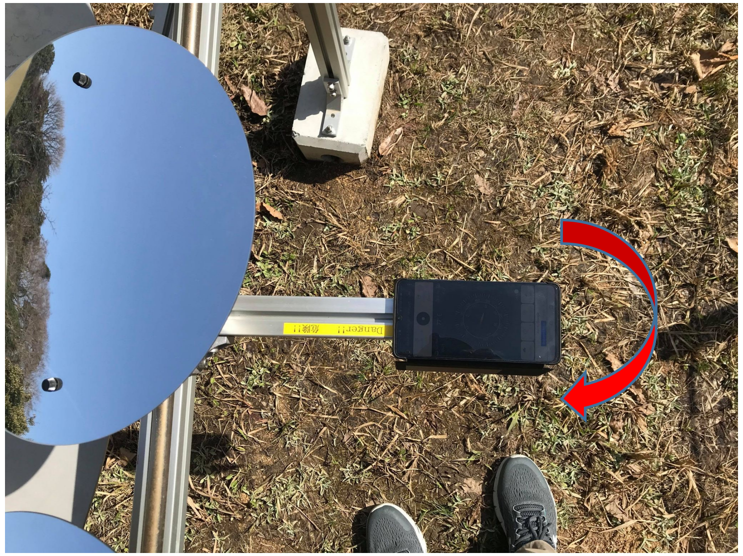
Overview of the calibration and harmonization* setup at Yamaguchi University

* Ichikawa, D.; Nagai, M.; Tamkuan, N.; Katiyar, V.; Eguchi, T.; Nagai, Y. Development and Utilization of a Mirror Array Target for the Calibration and Harmonization of Micro-Satellite Imagery. Remote Sens. 2022, 14, 5717. https://doi.org/10.3390/rs14225717

Characteristics of Mirror Array Target

In according to the tasking and scheduling for satellite observation, the mirror reflectors have been set up by adjusting a precise azimuth and tilt angles to get maximum reflectance from the mirrors.

A key for tilt angle adjustment

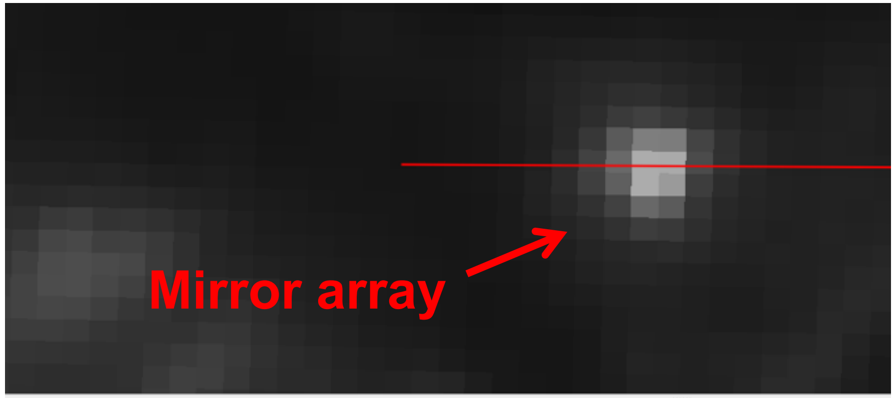


A key for azimuth angle adjustment

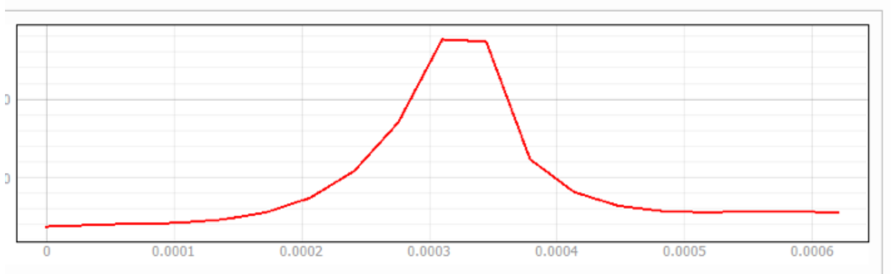
Mirror reflectors after adjustment

Observation of Mirror Array Target by GRUS-1A

2021-02-22



Band 1 image

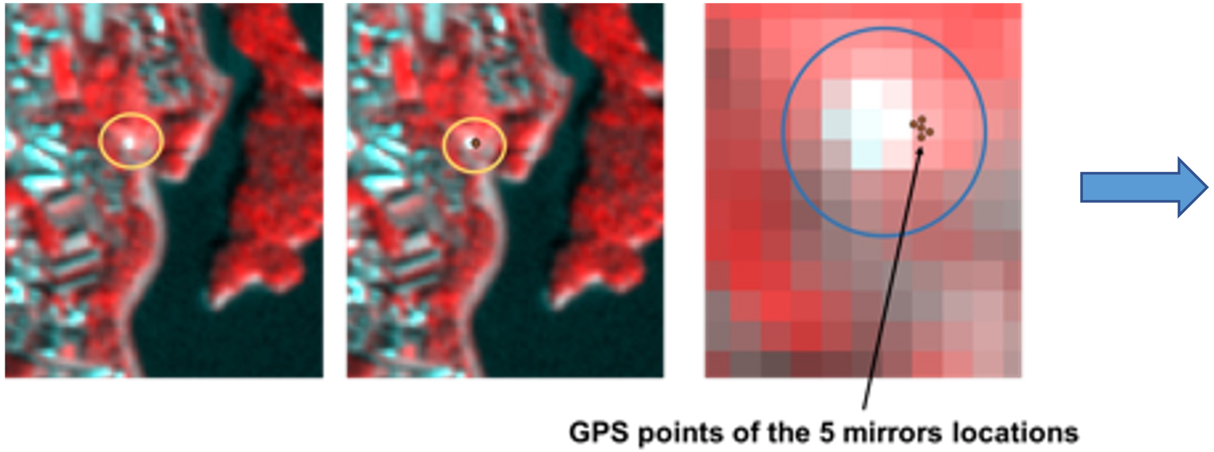


Pixel value

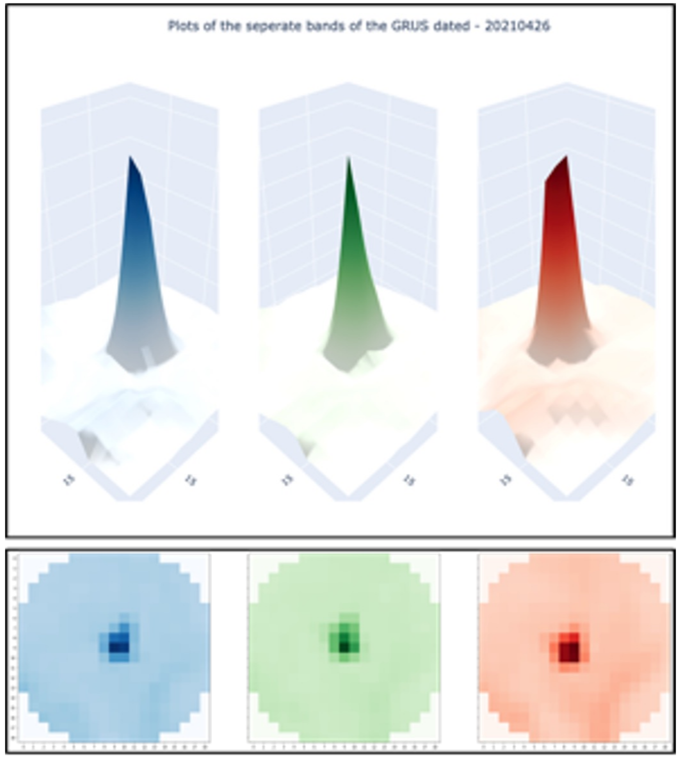
Observation of Mirror Array Target by Cartosat2E

The spread of light spectrum around the satellite image pixel of the ground mirror reflector

The mirror reflector can precisely estimate a sub-pixel band registration accuracy and improve image quality of color composite images.
The distribution and spread of light energy reflected from the mirrors show that YUCARS mirror array station has a potentiality to construct a point spread function of in-flight image

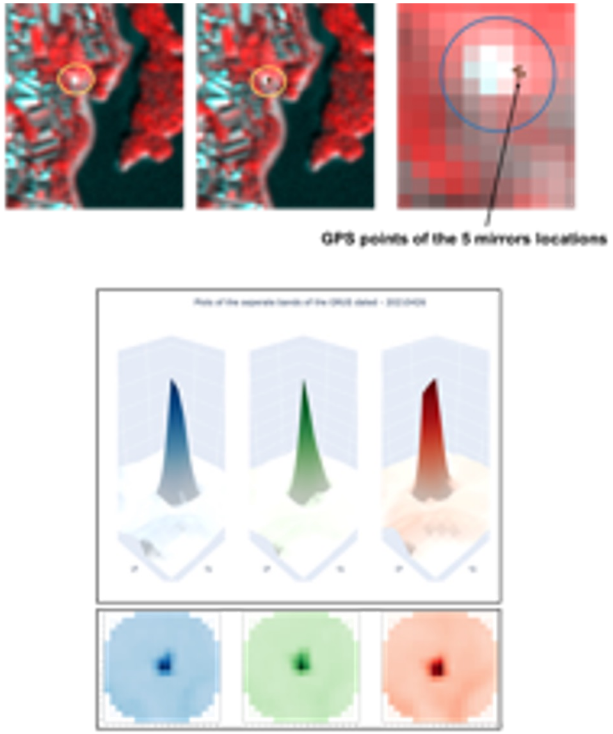


GRUS image of YUCARS mirrors



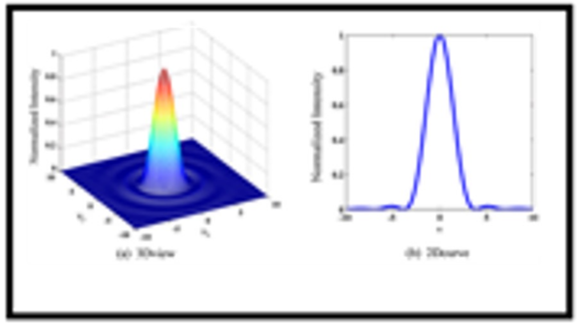
GRUS1-A 2021-04-26

Estimation of IPSF Parameter



GRUS1-A 2021-04-26

GRUS1 Satellite image of mirror reflector



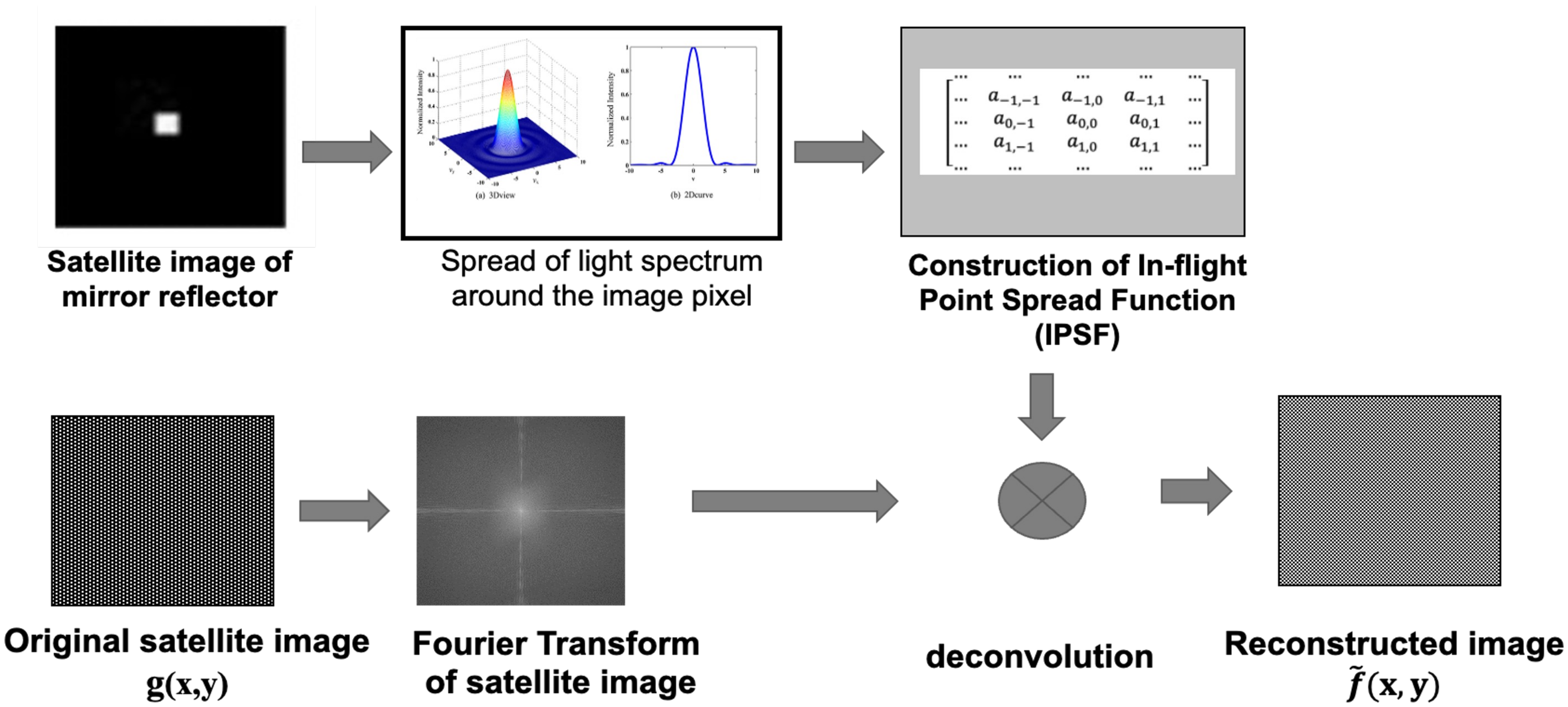
Spread of light spectrum around the image pixel

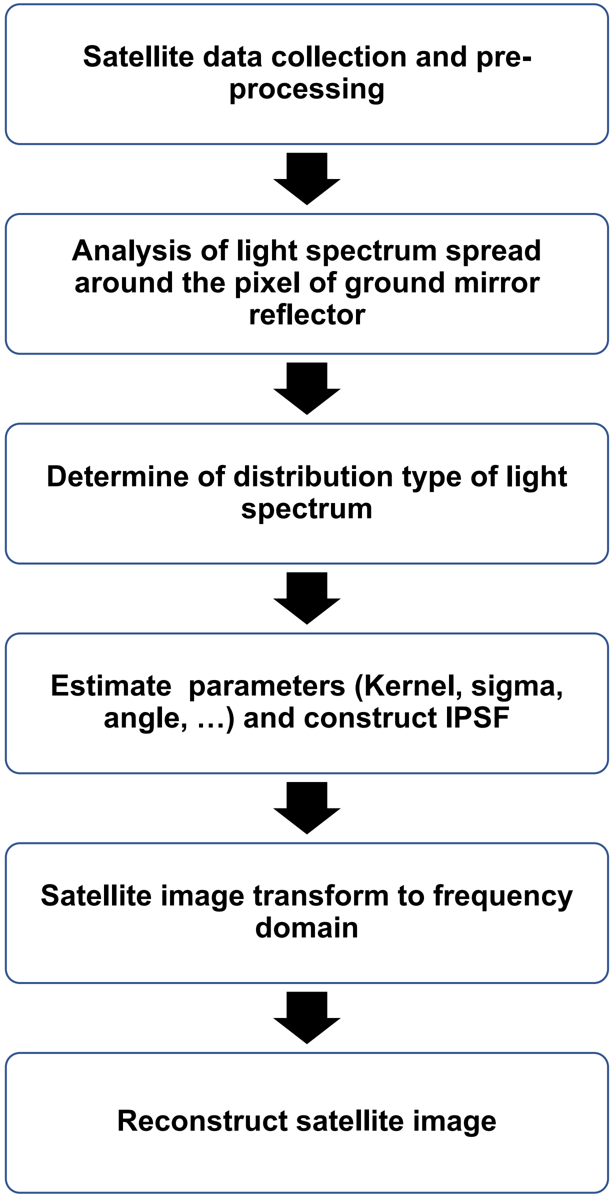
$$\begin{bmatrix} \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & a_{-1,-1} & a_{-1,0} & a_{-1,1} & \cdots \\ \cdots & a_{0,-1} & a_{0,0} & a_{0,1} & \cdots \\ \cdots & a_{1,-1} & a_{1,0} & a_{1,1} & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}$$

Construction of In-flight Point Spread Function (IPSF)

Development of Point Spread Function – IPSF

Calibration by IPSF

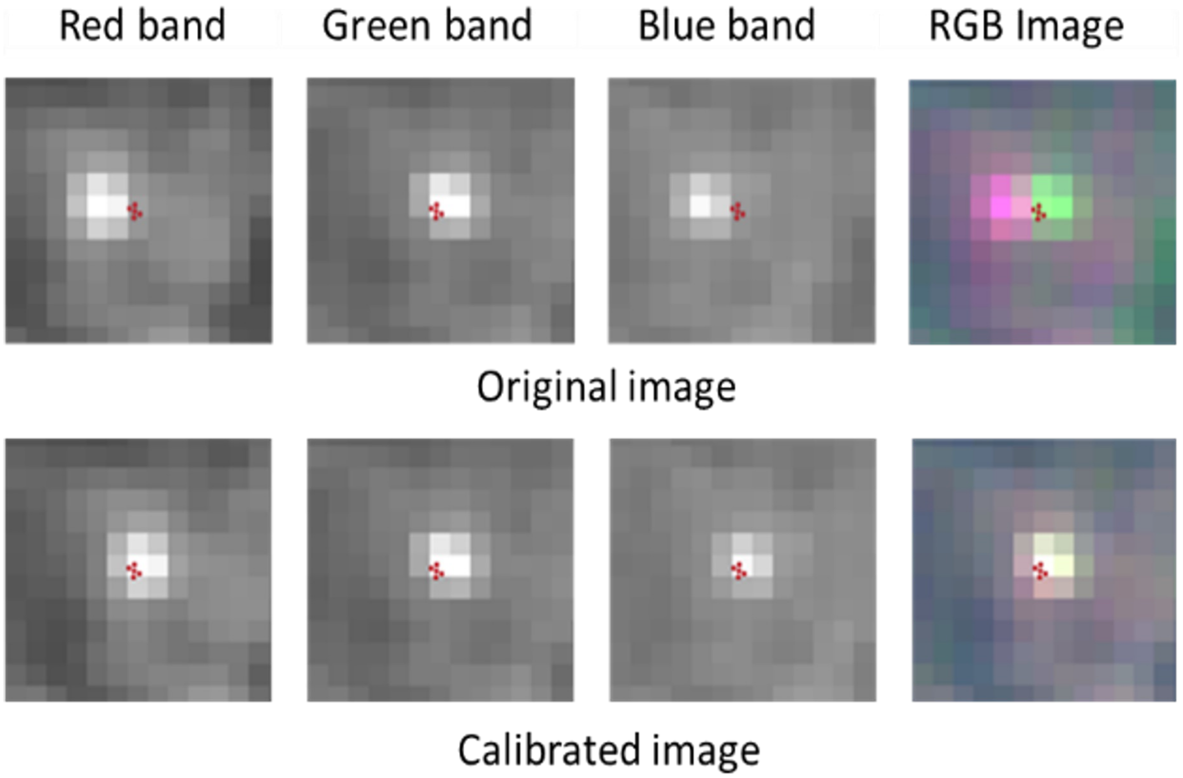




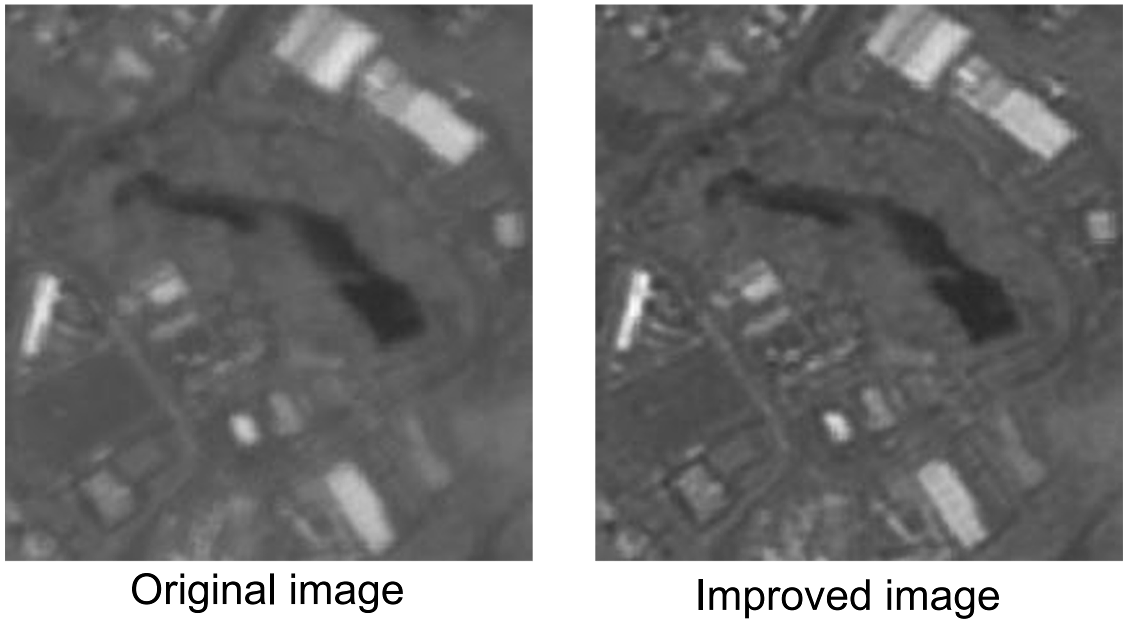
Mirror reflectors and Point Spread Function for optical satellite data calibration

Result of Calibration by Mirror Array Target

GRUS1-A 2021-02-22



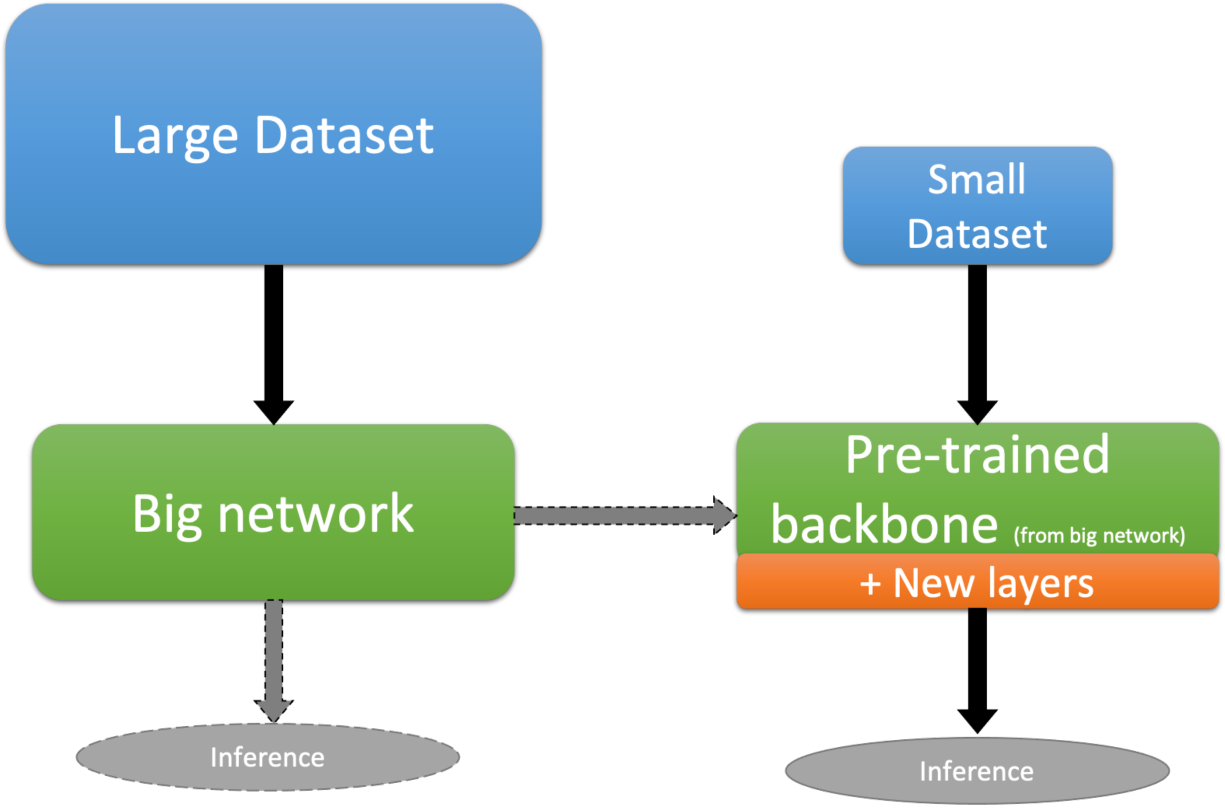
Improving band registration



Deblurring the image

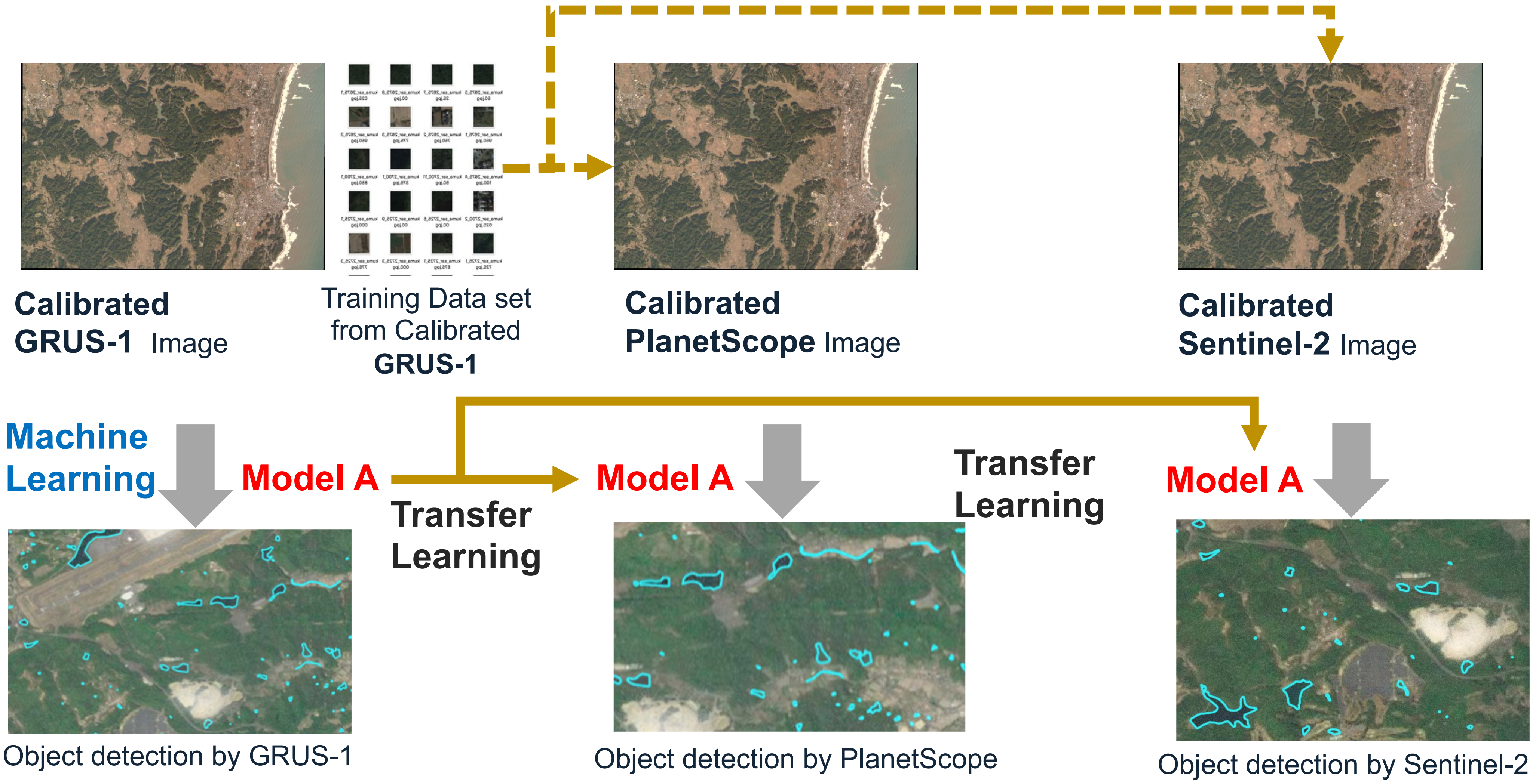
Transfer learning

Transferring knowledge from the networks trained on larger dataset (source dataset) to the target dataset containing similar but not same input data.



What if we don't have very large dataset for satellite images with enough diversity? And how to make one?

Transfer Learning with Data Harmonization



Data used

Satellite constellation

AXELSPACE

5 GRUS satellites

planet.

~200 PlanetScope satellites

GRUS1A

Spectral bands	Panchromatic	450-900 nm
	Blue	450-505 nm
	Green	515-585 nm
	Red	620-685 nm
	Red Edge	705-745 nm
	Near Infrared	770-900 nm
	Swath	57+ Km
Ground resolution	Panchromatic	2.5 m
	Multispectral	5.0 m

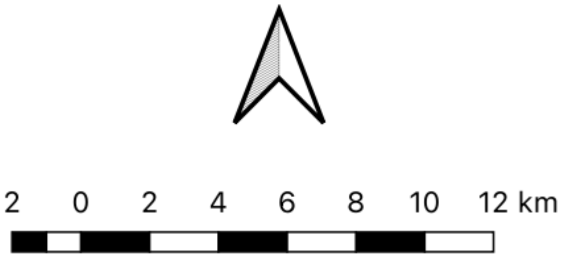
PlanetScope PS2

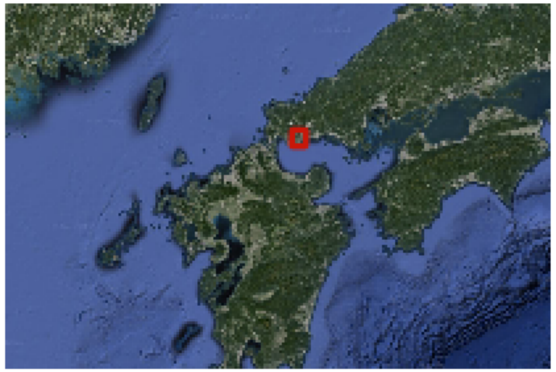
PlanetScope PSB.SD

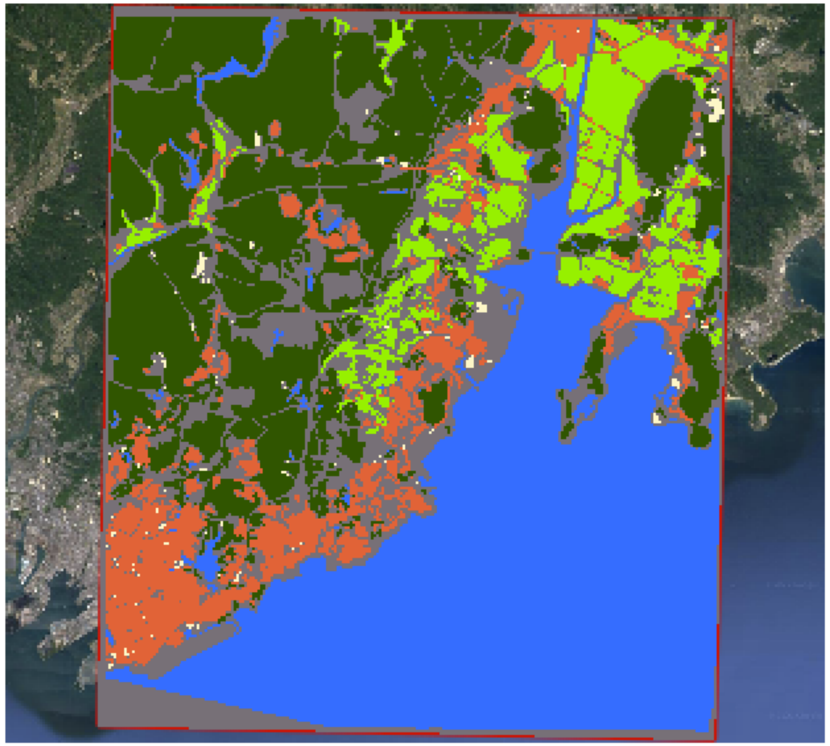
Instrument	PS2	PSB.SD
Spectral Bands	Blue: 455 - 515 nm Green: 500 - 590 nm Red: 590 - 670 nm NIR: 780 - 860 nm	Blue: 465 - 515 nm Green: 513 - 549 nm Red: 650 - 680 nm Red-Edge: 697 - 713 nm NIR: 845 - 885 nm
Resolution	3.125 m	

Study area and classes

- Area:
  - Ube area in Yamaguchi Prefecture, Japan.
- Classes:
  - Agriculture
  - Water
  - BareLand
  - BuildUp
  - Forest





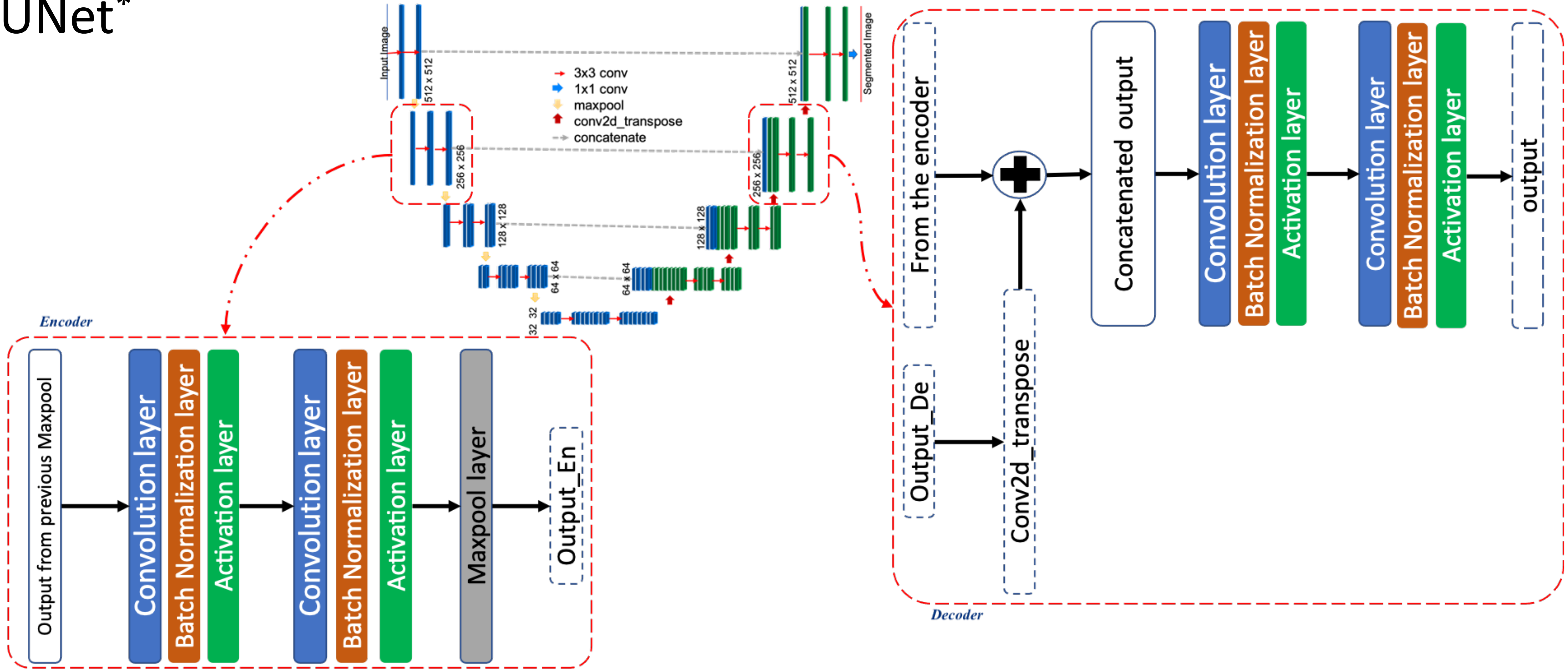


Study area

Image chips were created using sliding window non-overlappingsampling method.

Network Used

- UNet*



* Katiyar, V.; Tamkuan, N.; Nagai, M. Near-Real-Time Flood Mapping Using Off-the-Shelf Models with SAR Imagery and Deep Learning. *Remote Sens.* **2021**, *13*, 2334. https://doi.org/10.3390/rs13122334

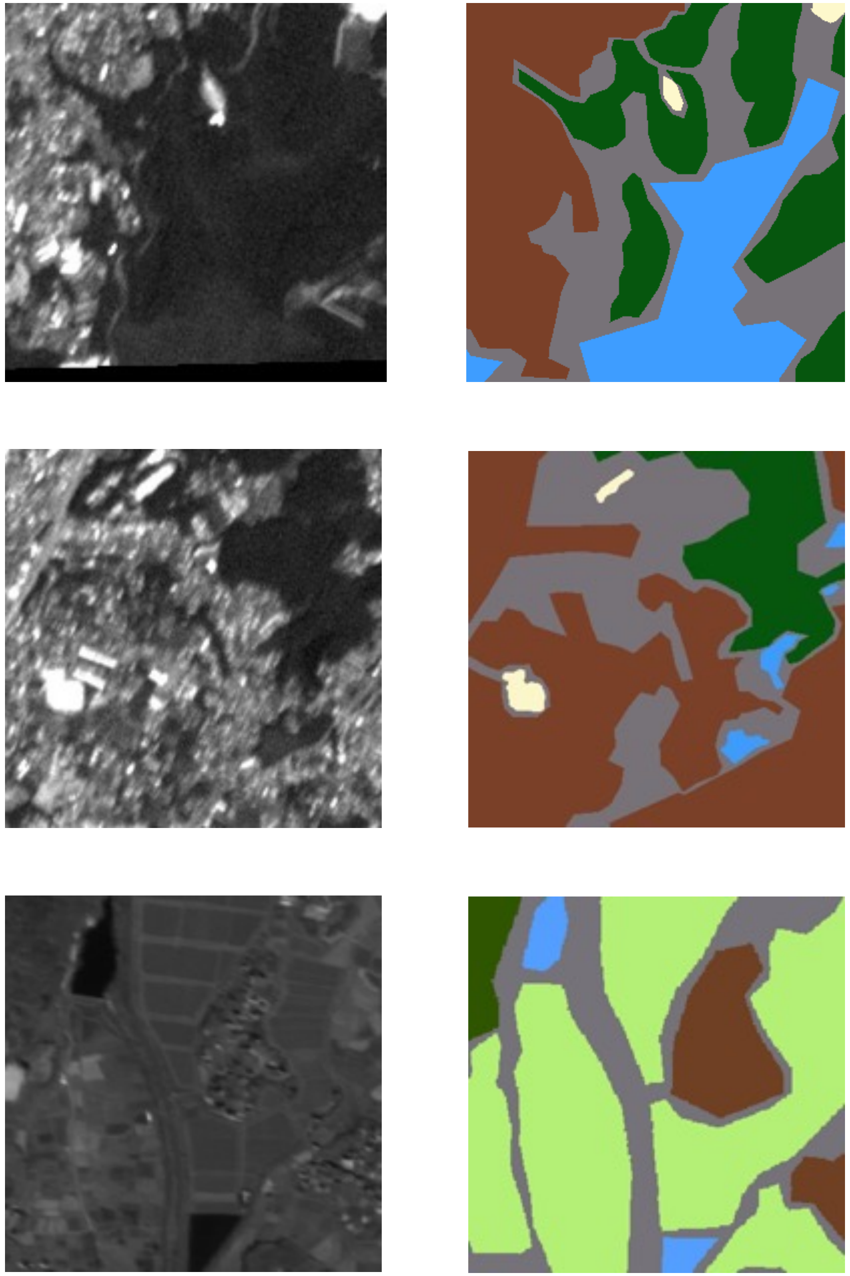
Experiments by different datasets

- Network trained on Original images-
  - Trained on GRUS and transfer to PS2.
  - Trained on GRUS and transfer to PSB.SD.

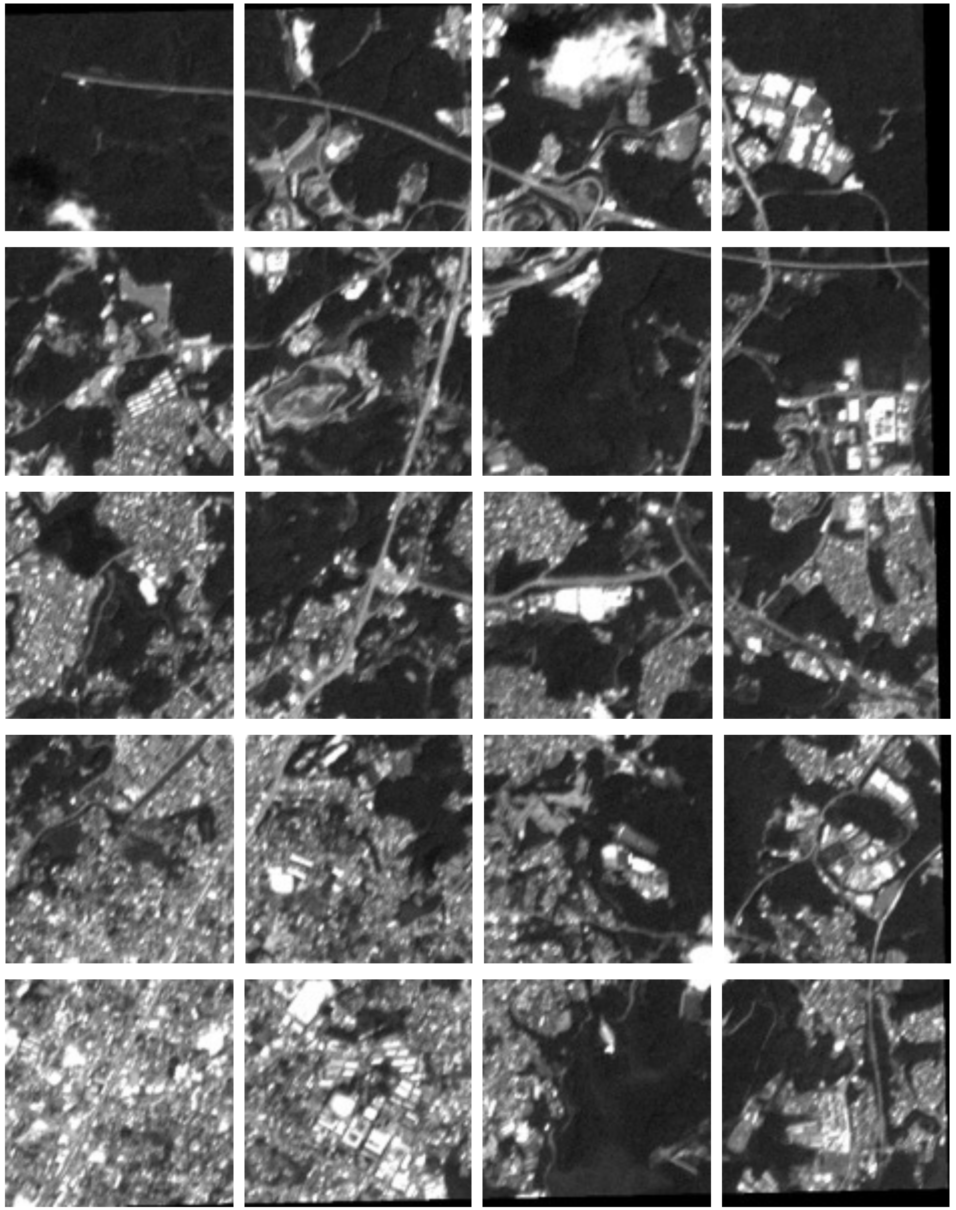
- Network trained on Calibrated images-
  - Trained on GRUS and transfer to PS2.
  - Trained on GRUS and transfer to PSB.SD.

Example tiles used for the training

- The ‘Other’ class is where the class type was not certain or cloud or cloud-shadow was present.
- In our study we have worked with only five defined LULC classes (Agriculture, Water, Bareland, Build-Up, and Forest).

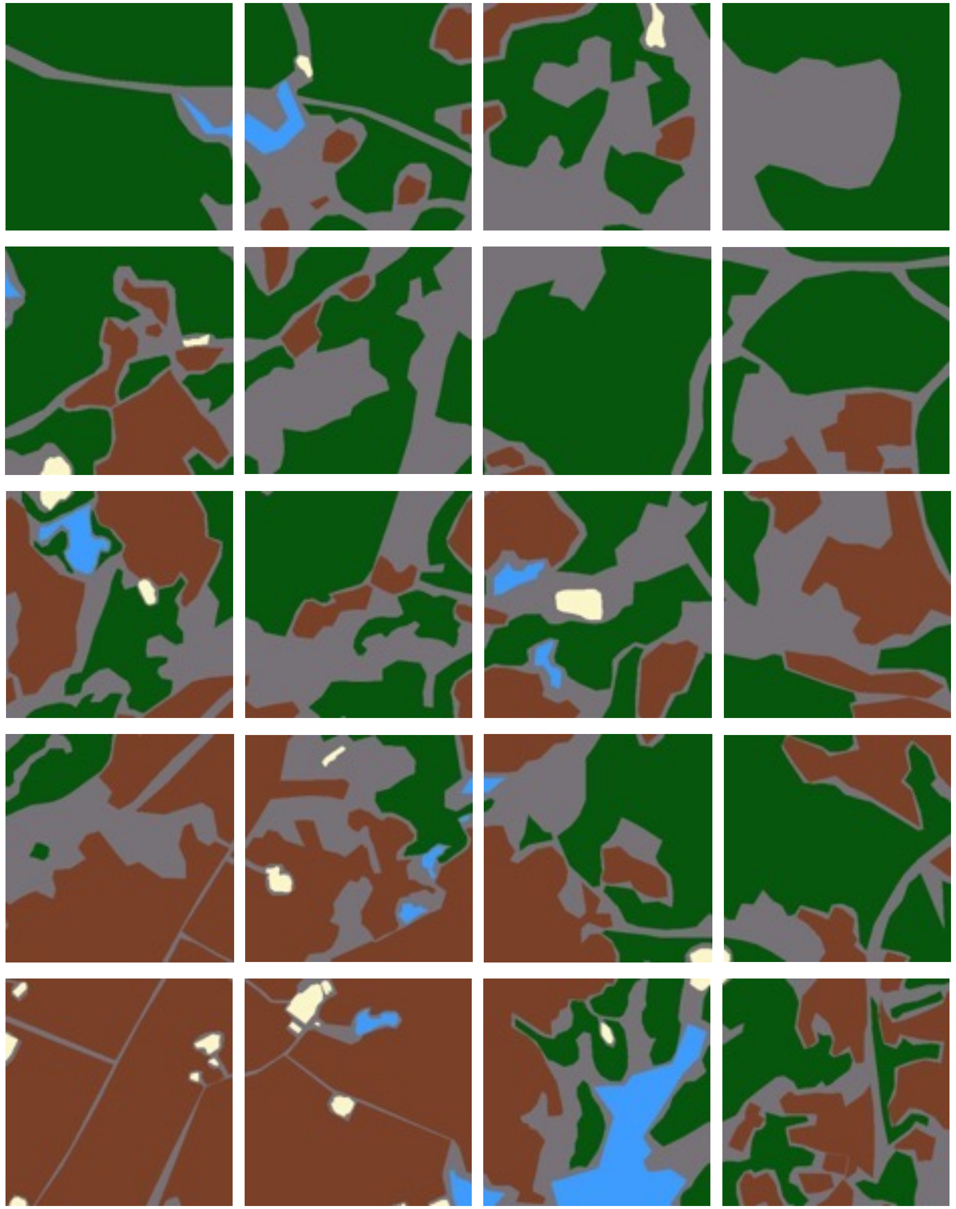


Part of GRUS-1 satellite image



Corresponding non-overlapping tiles

LULC classes for the previous image-part



Corresponding non-overlapping tiles

Results

		Accuracy				
		Agriculture	Water	Bare Land	Build Up	Forest
Original	GRUS-> PS2	0.71	0.79	0.63	0.72	0.82
	GRUS -> PSBSD	0.73	0.83	0.65	0.71	0.82
Calibrated	GRUS-> PS2	0.75	0.84	0.70	0.71	0.89
	GRUS -> PSBSD	0.79	0.88	0.69	0.73	0.88

Conclusion

- Even when the targeted dataset is very small transfer learning with harmonization give **notable improvement**.
- This is an important observation as **creation of large dataset for each satellite separately can be avoided**.
- Also, Image harmonization can help us to **create a larger dataset** by **combining various micro-satellite images after harmonisation**. This kind of training dataset may play an important role for future development in the remote sensing domain. Also, this will help us to build a high frequency time-series dataset.

Thank you for your kind attention

YAMAGUCHI UNIVERSITY