Detection of Boulders on Ryugu Using Deep Learning

Suomi Seki[1, 2], Toru Kouyama[2], Xuanchao Fu[1, 2] , Wenhao Shen[1, 2], Chikatoshi Honda[3], Ichiro Yoshikawa[1]

([1]The University of Tokyo, [2] National Institute of Advanced Industrial Science and Technology, [3]The University of Aizu)

Contents

Background

- Asteroid Ryugu: formed through reaccumulation following the catastrophic disruption of its parent body [Sugita 2019 etc.]
- Comparing regional characteristics of boulder number density, size, and shape on asteroids reveals geological processes experienced by the asteroid.

For example：

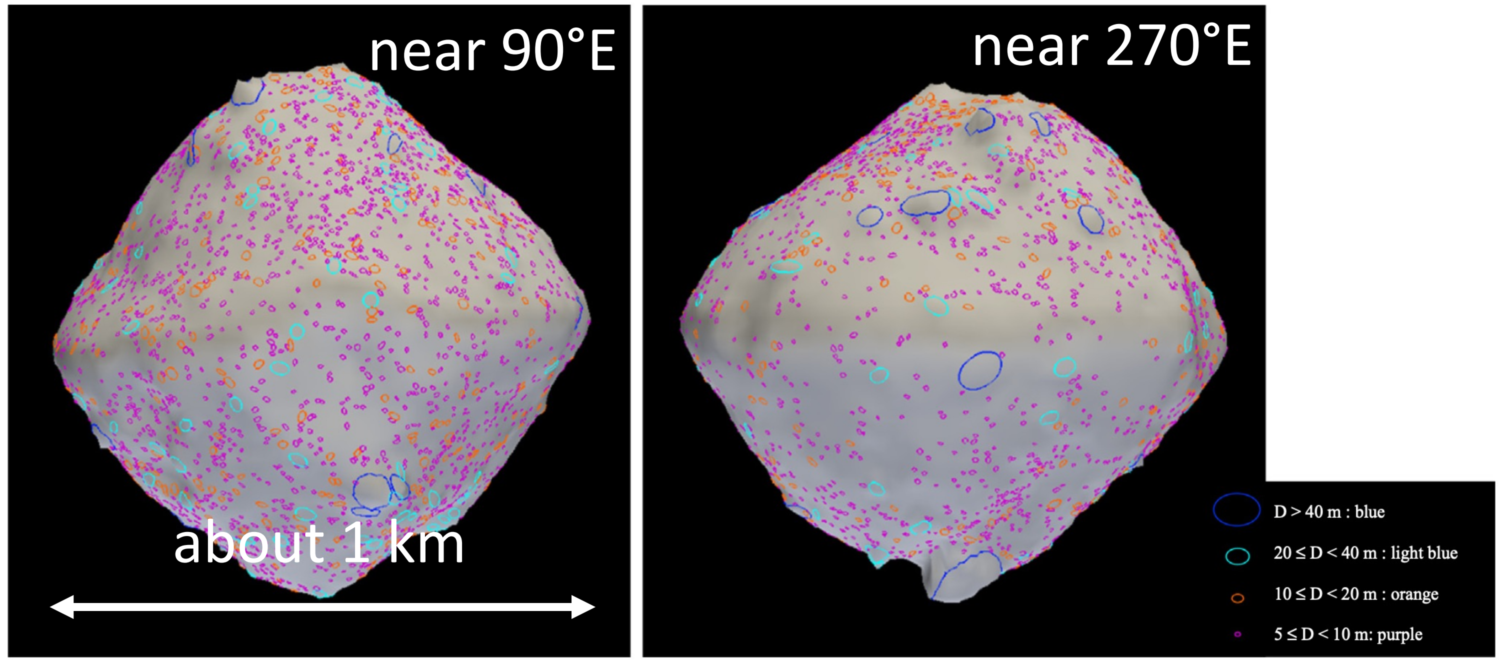
- Number Density reveals
  - The movement of boulders due to impacts from other celestial bodies or changes in gravity. [Michikami 2019]
- Size Frequency Distribution reveals
  - The behavior of boulders around artificial craters. [Michikami 2022, Ogawa 2022]

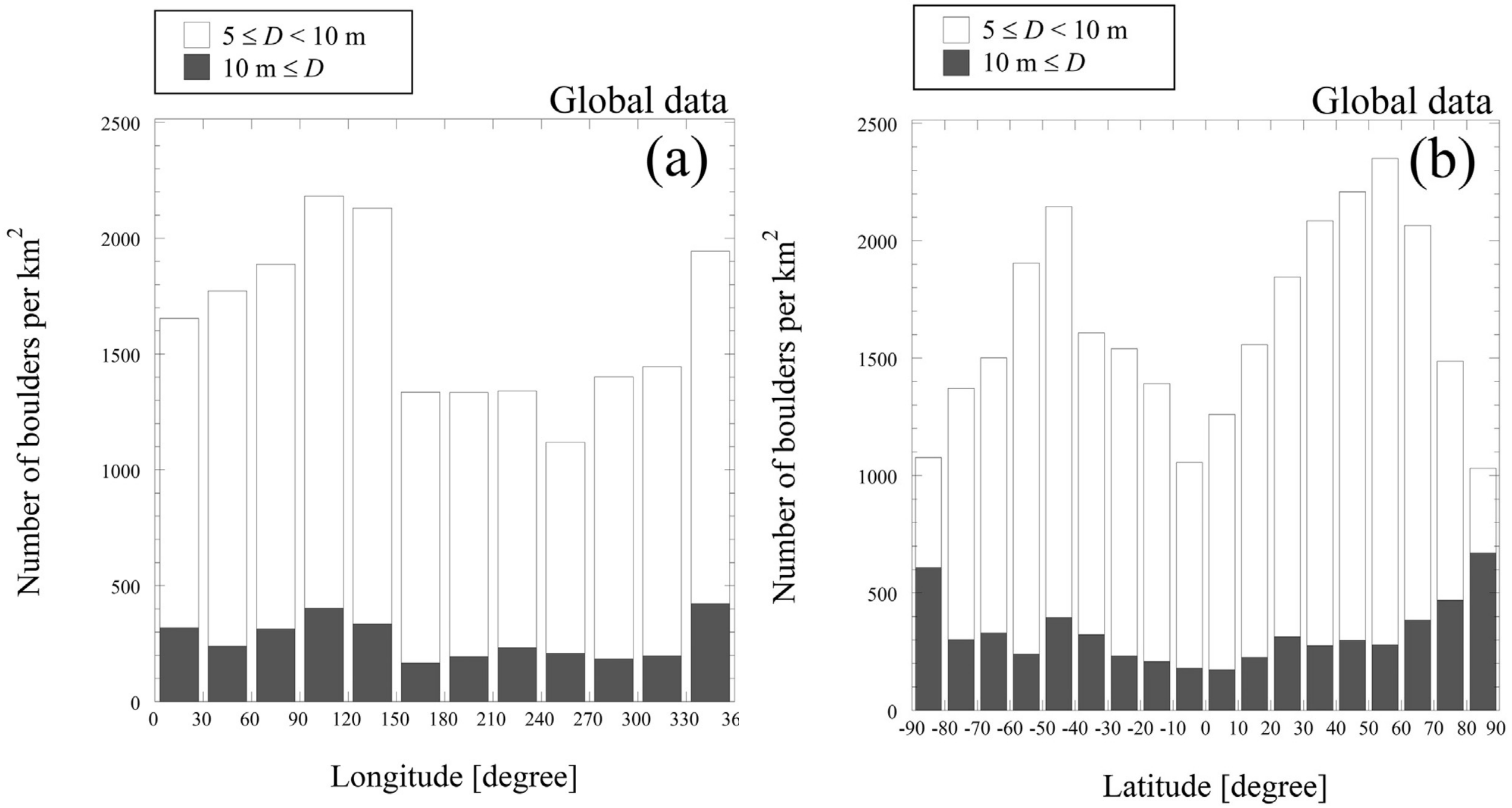
[Sugita 2019] Sugita, S, et al. "The geomorphology, color, and thermal properties of Ryugu: Implications for parent-body processes." *Science* 364.6437 (2019): eaaw0422.

[Ogawa 2022] Ogawa, K., et al. "Particle size distributions inside and around the artificial crater produced by the Hayabusa2 impact experiment on Ryugu." *Earth, Planets and Space* 74.1 (2022): 1-10.

Previous Studies – Boulder Number Density

- Ryugu boulder number density, boulders > 5 m
- Ryugu, Bennu: top-shaped, equatorial rigde
  - boulders migrated toward the equatorial direction
- Possible reason for the low number density in the equatorial region
  - Recent migration trends: Equator → higher latitudes (Sugita 2019)
  - Smaller boulders (particles) are easier to move
  - Larger boulders are buried beneath small boulders



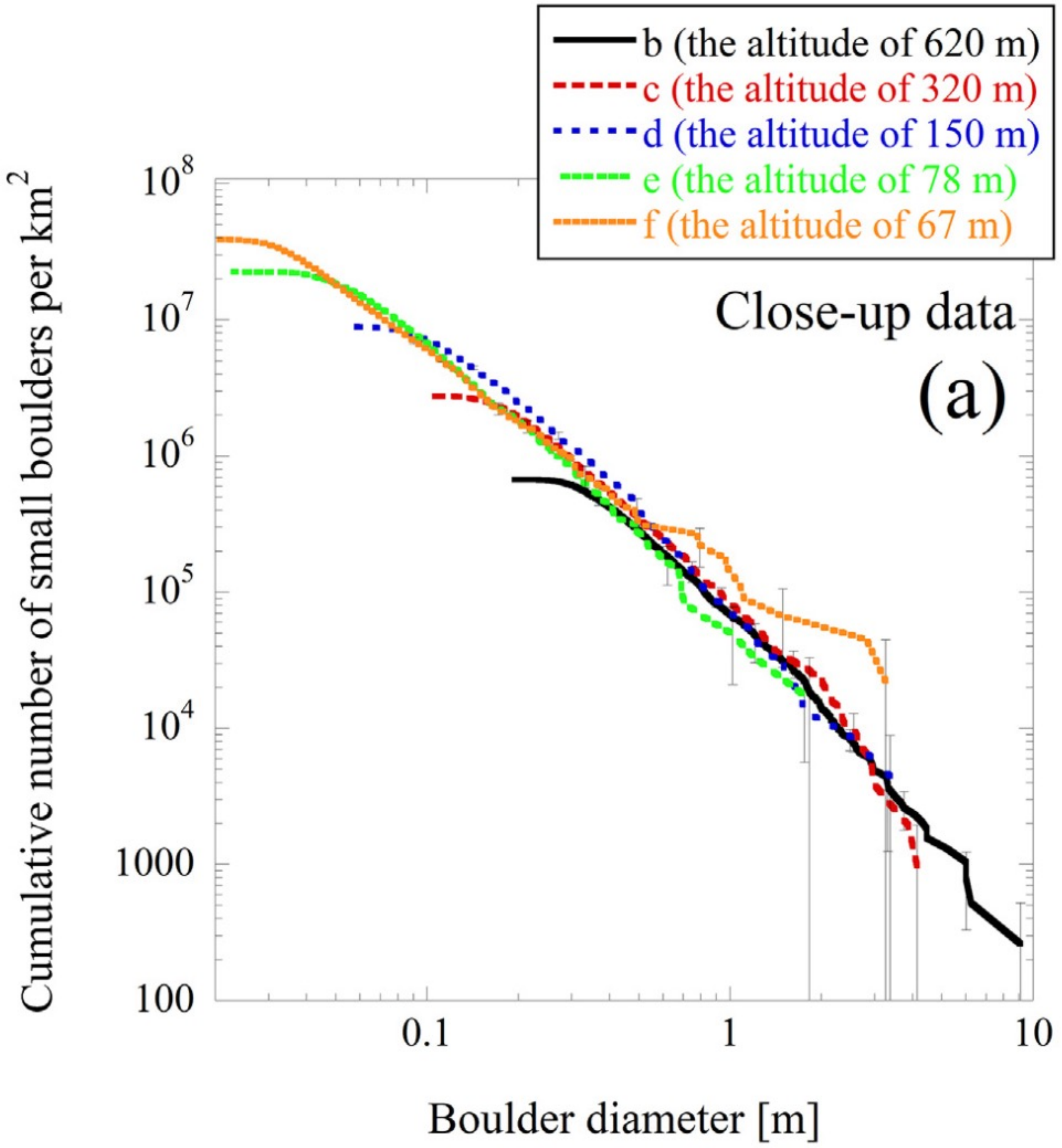


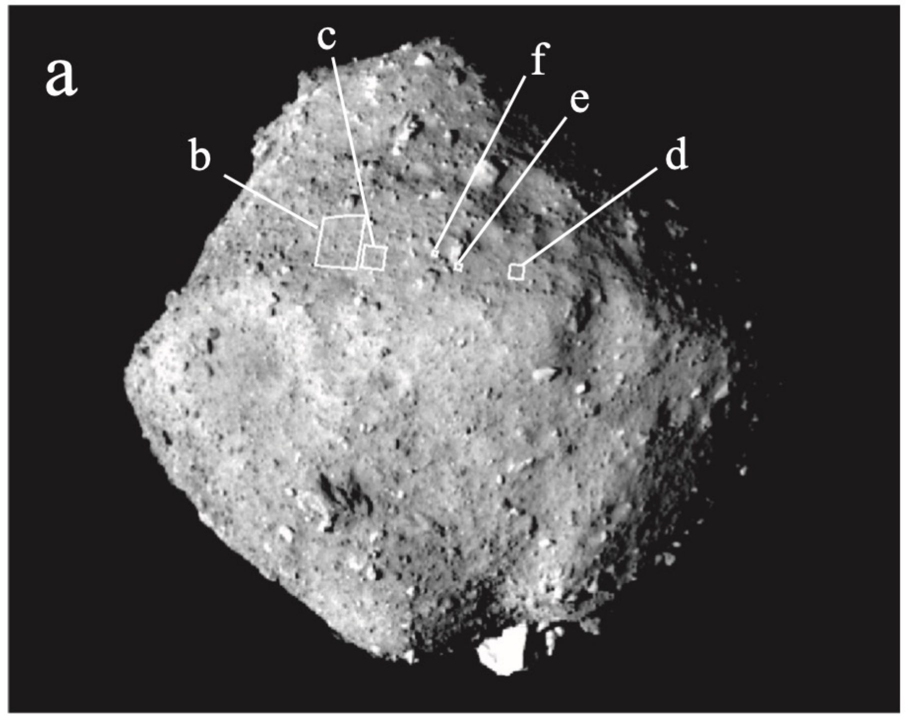
Boulder Number Density

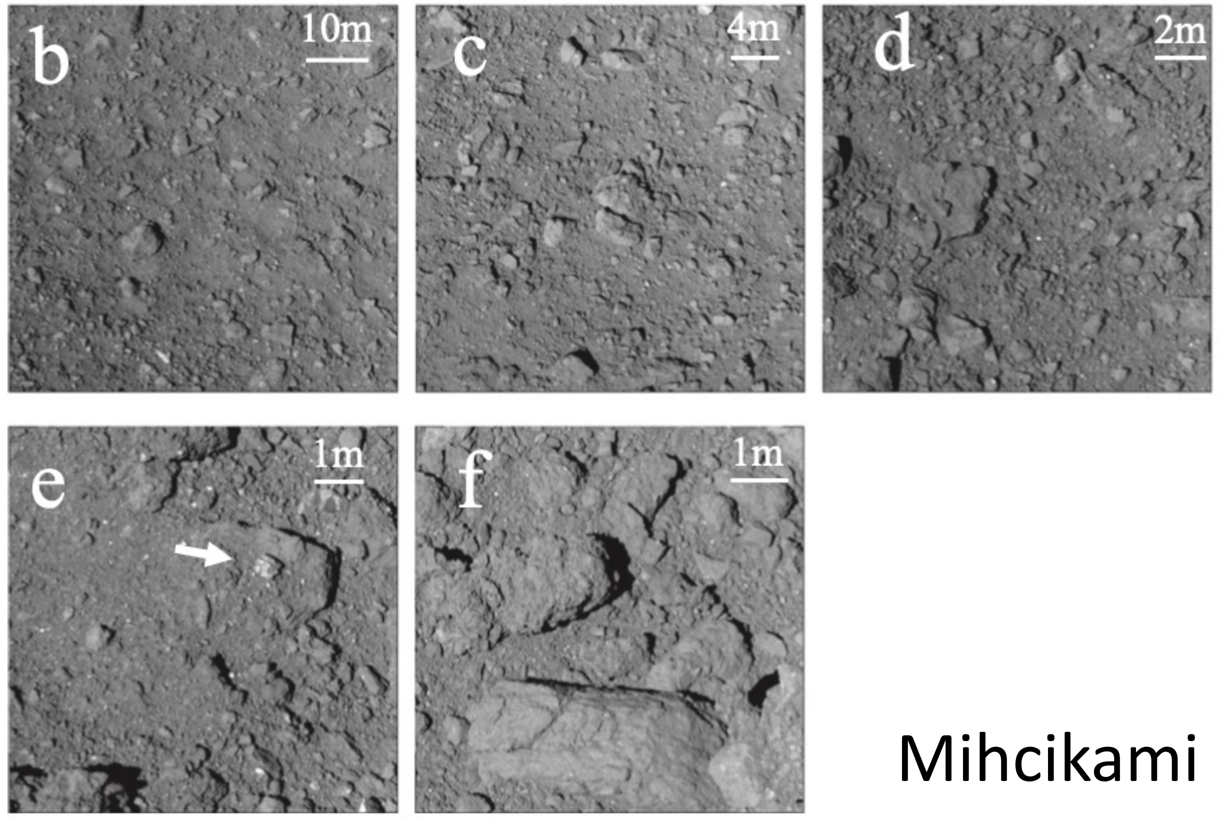
[Michikami 2019] Michikami, T, et al. "Boulder size and shape distributions on asteroid Ryugu." *Icarus* 331 (2019): 179-191.

Previous Studies – Boulder Size Frequency Distribution

- The size frequency distribution of boulders on the asteroid follows a **power-law**.
- This distribution is utilized for comparisons between **different regions** and **with other celestial bodies.**



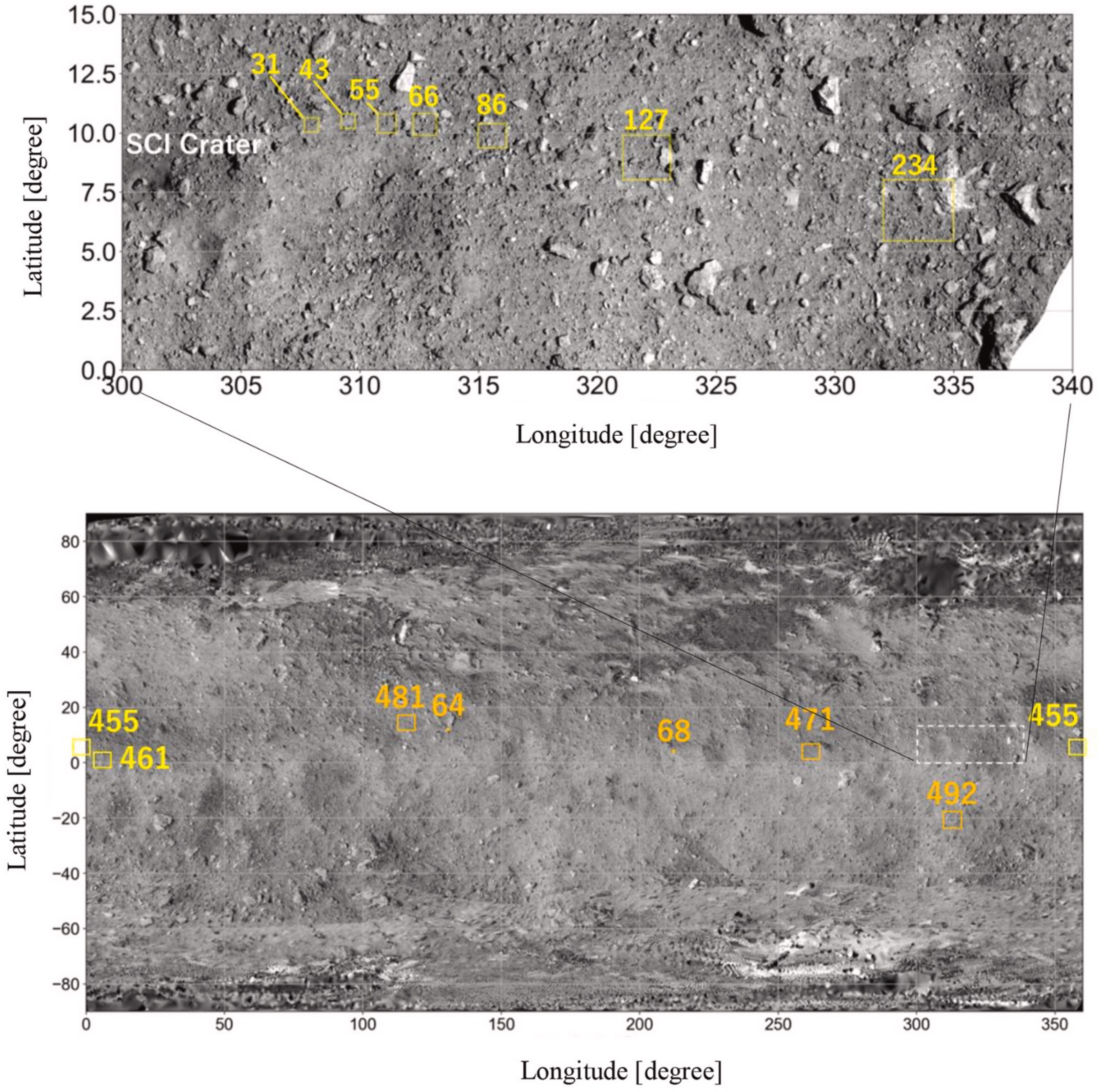


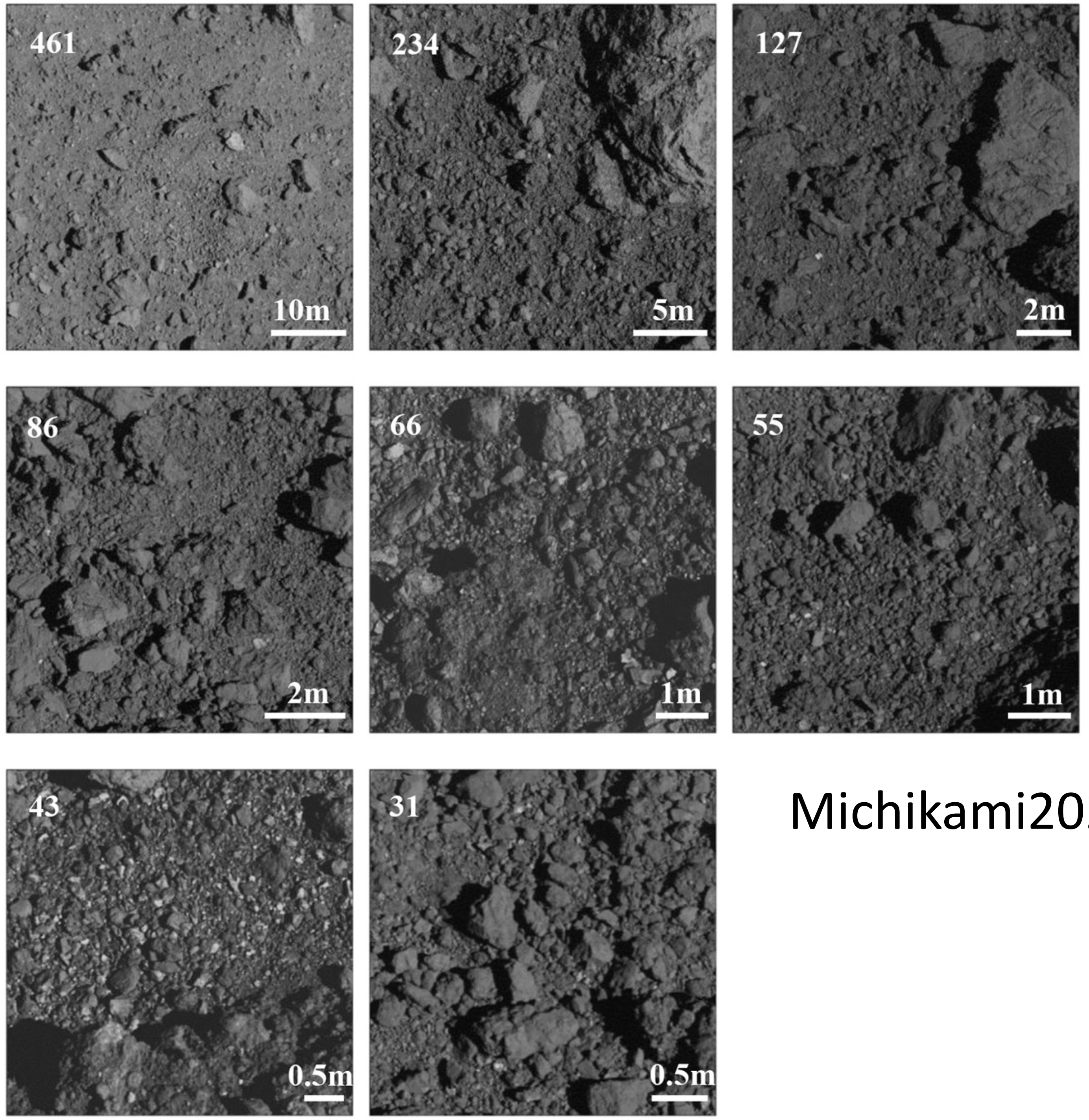


Mihcikami 2019

Previous Studies – Boulder Size Frequency Distribution

- Compare boulder size frequency distributions in different regions of Ryugu

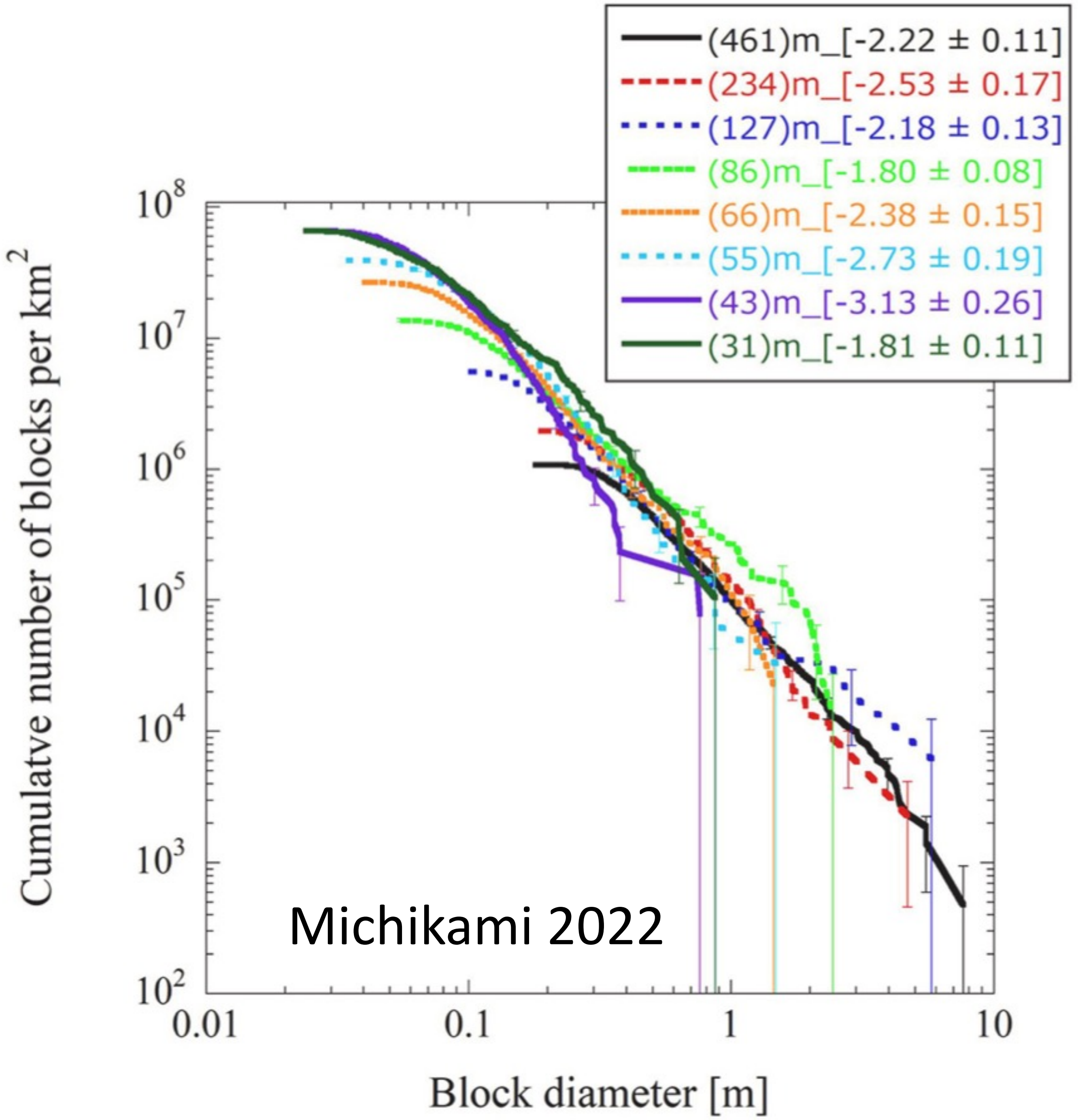


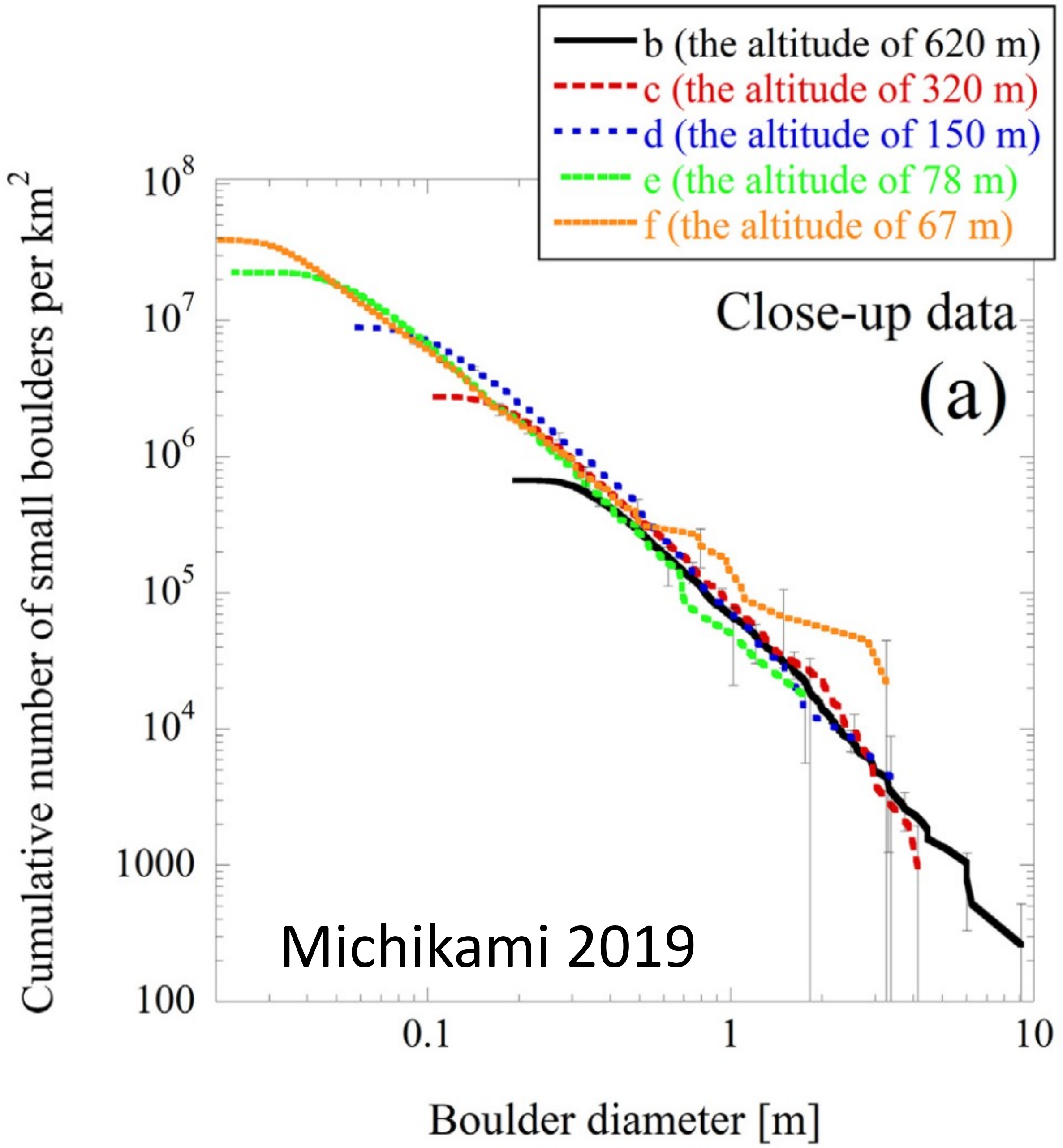


Michikami2022

Previous Studies – Boulder Size Frequency Distribution

- no tendency over the size range
  - cf. Michikami 2019
  - How power-indices are correlated with boulder size ranges ? → next slide



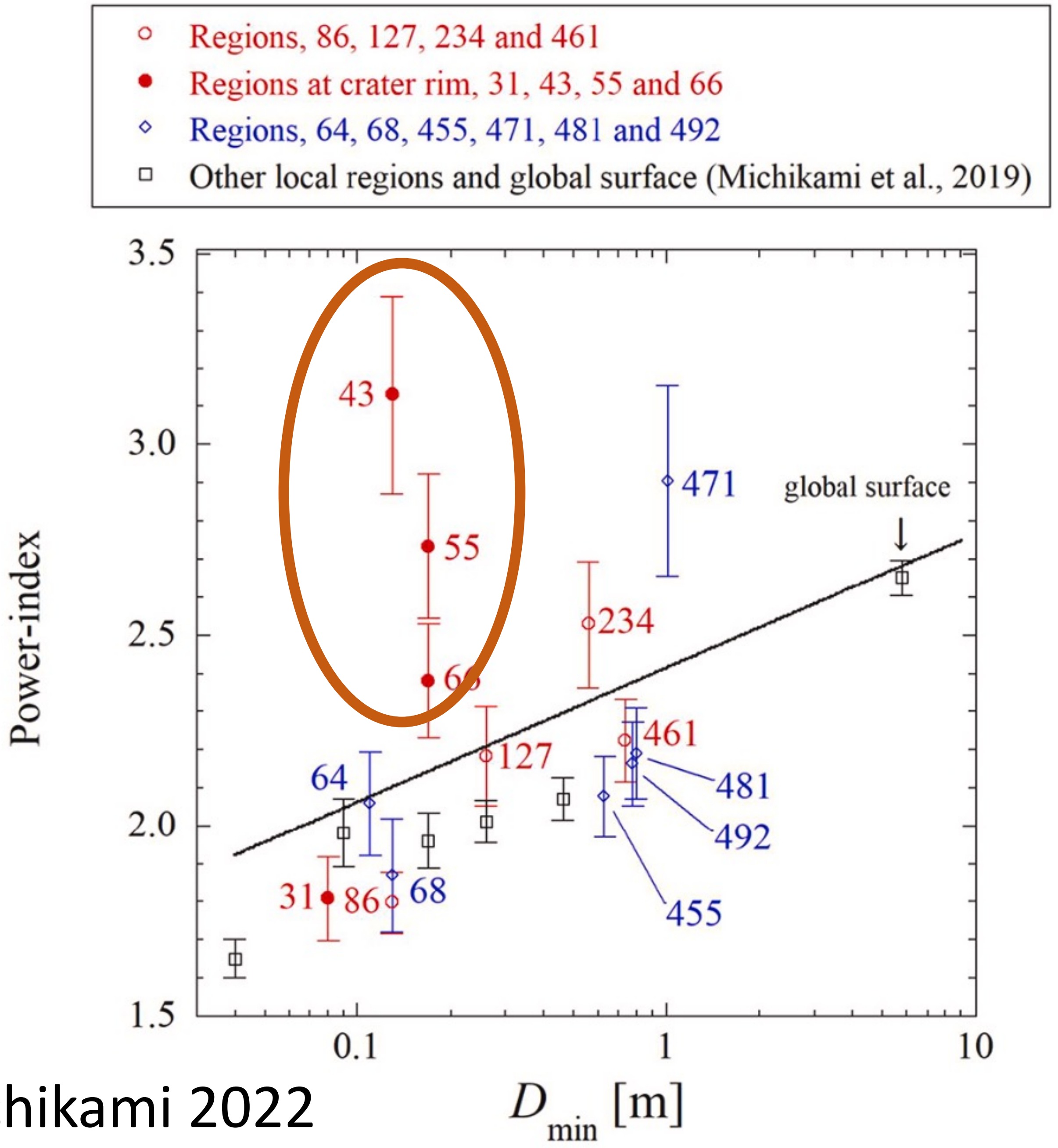


Previous Studies – Boulder Size Frequency Distribution

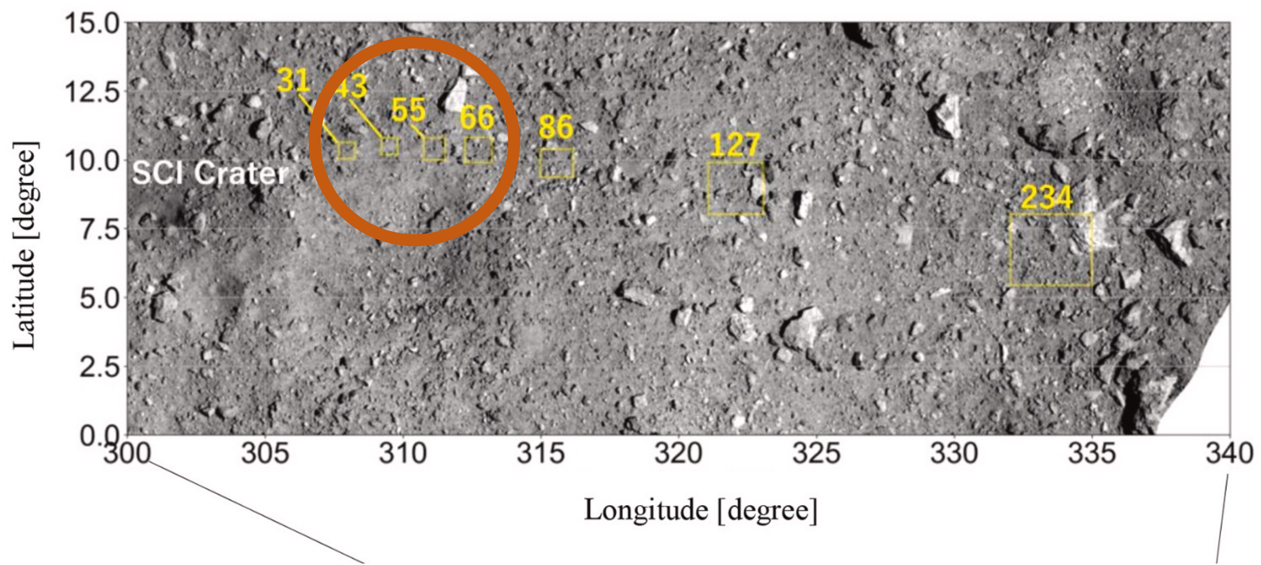
- Correlation between min diameter and power-index
- Weak correlation

Area43, 55, 66 → crater rim

- Small Carry-on Impactor experiment
- Fine boulders inside the crater were moved
- Boulders were fragmented during the experiment



Michikami 2022



Purpose of the Research

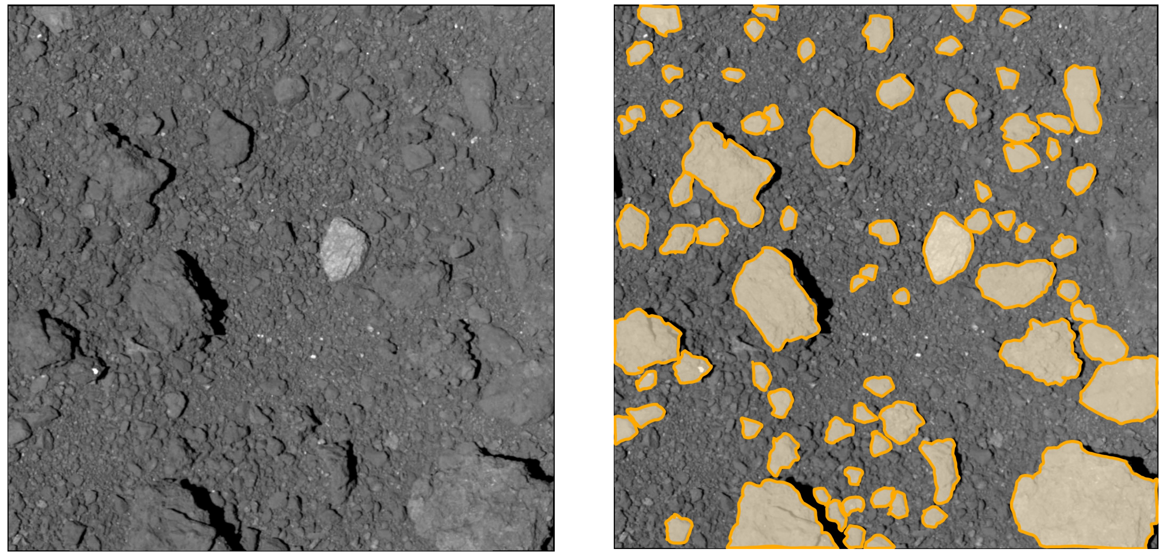
- **Obtaining a global-scale size frequency distribution manually is challenging**
  - Previous research: 1,000 boulders per image
    ⇔ ONC/v-band, close-up: 300 images
- Automate boulder detection using **deep learning**
- Obtaining boulder size, shape and other characteristics
  For Example：
  - boulders below 5 meters in size on a global scale
  - boulders inside and outside the artificial crater

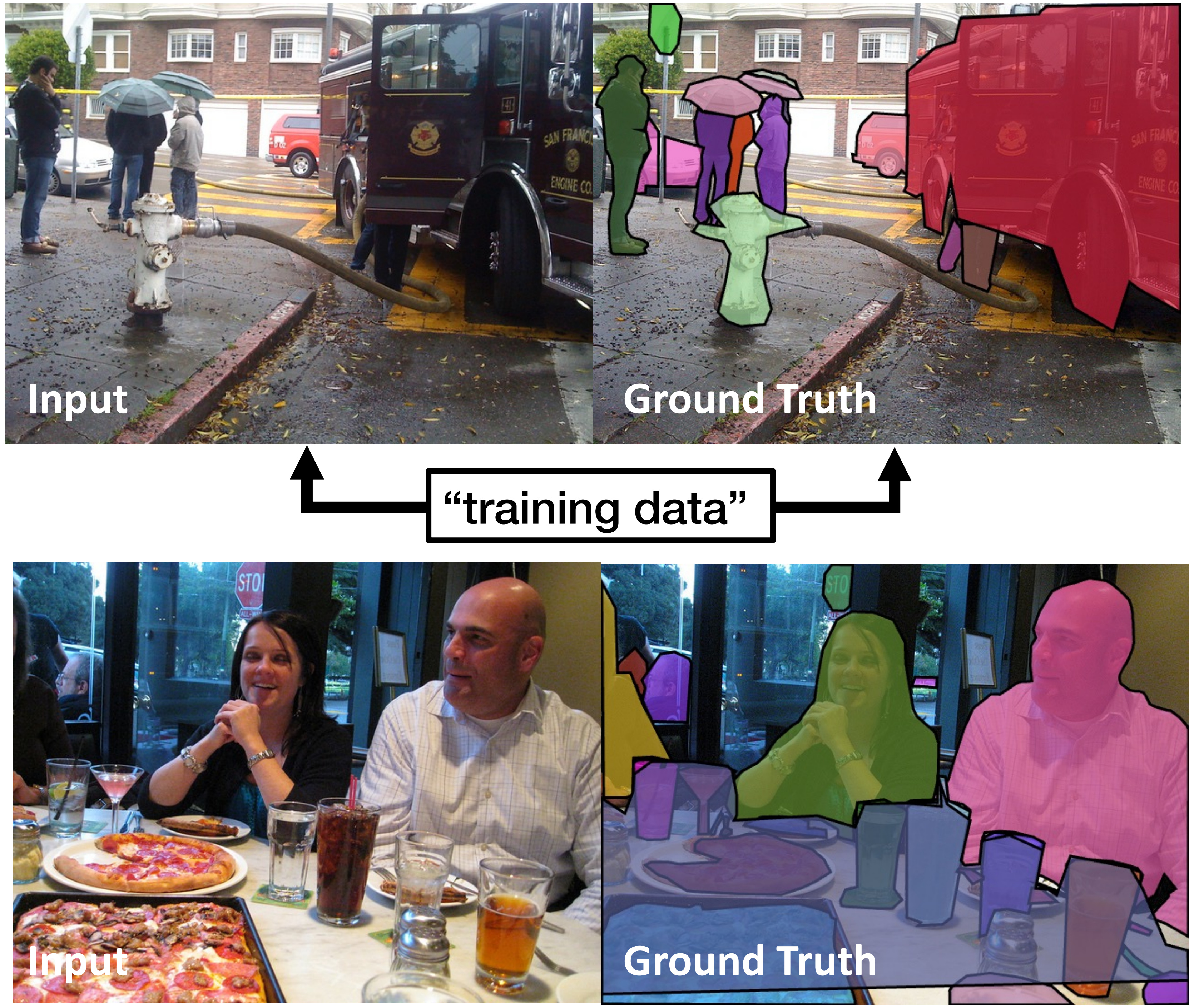
Contributions：

- Utilizing the ONC archive
- Publish deep learning models and datasets
- Publish global boulder database (future plan)

Instance Segmentation

- Instance Segmentation is a deep learning task that divides an image into polygons
- cf. Object Detection
  - Enclosing objects with bounding boxes
  - By Instance Segmentation, **contour** and **major axis angle** can be obtained
- Preparing Training Data
  - Annotated data for boulders
  - Crowdsourcing





Images from https://cocodataset.org/

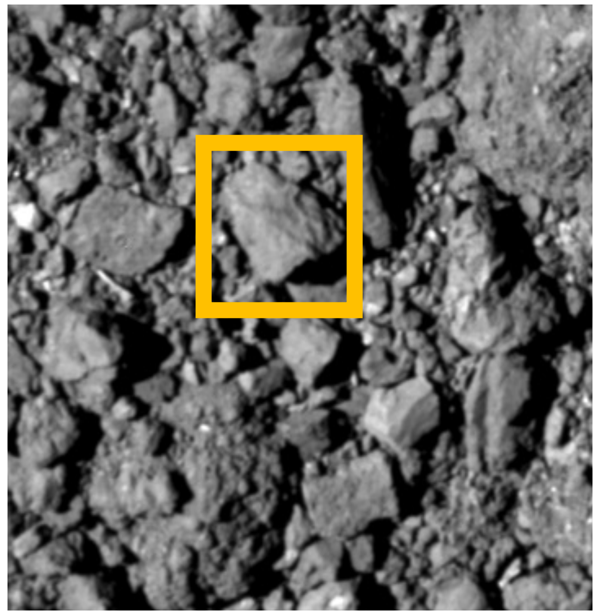
Mask R-CNN

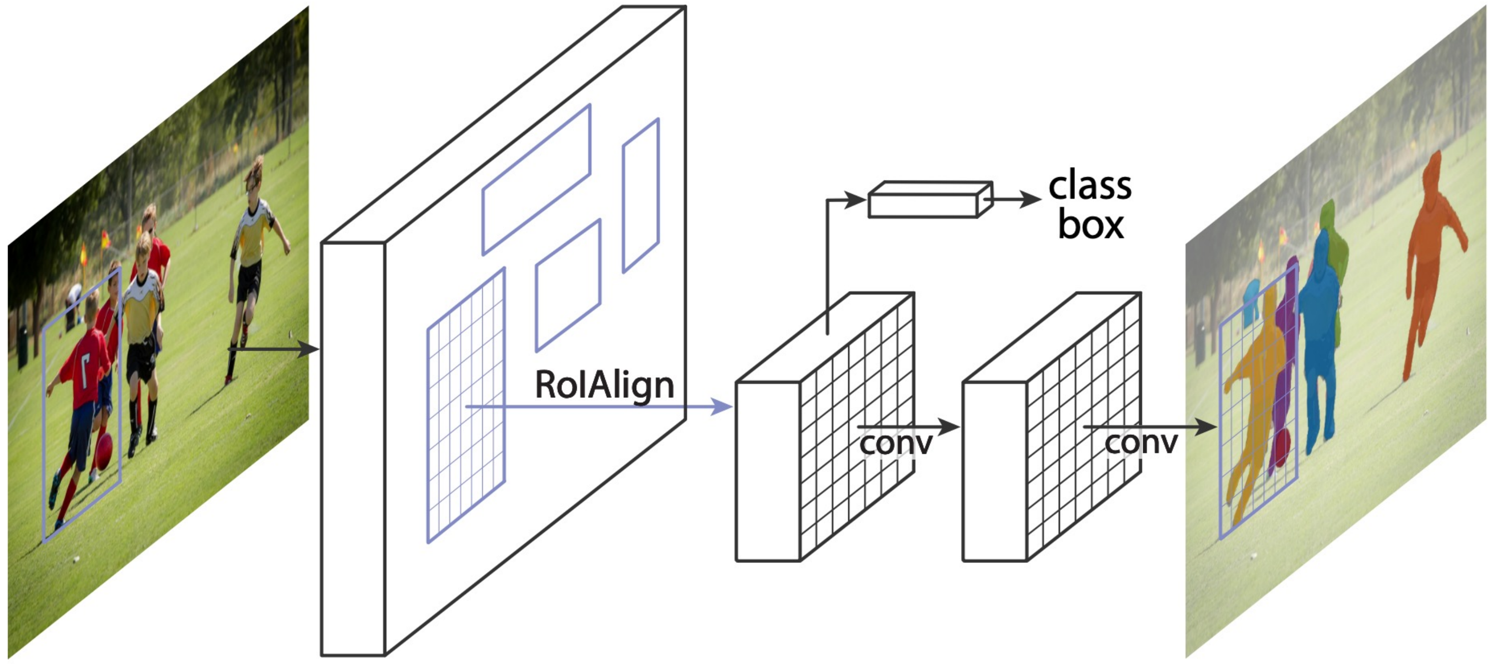
Components

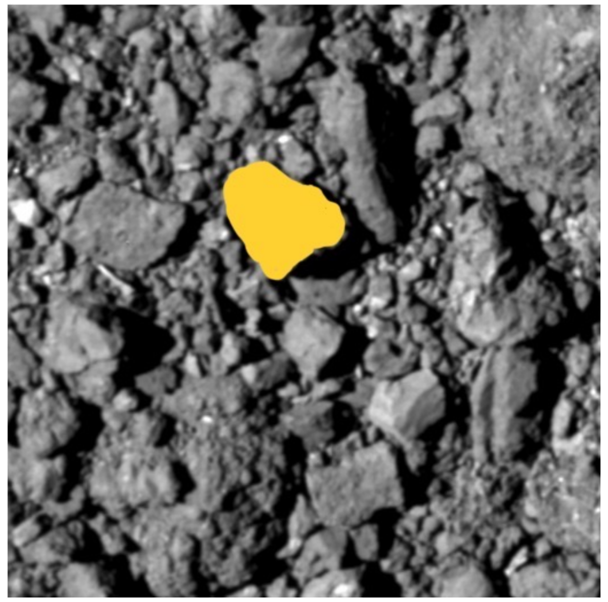
- Backbone Network: Extracts feature maps
- Region Proposal Network (RPN): Proposes candidate object regions
- ROI Align: Aligns feature maps to predict accurate masks

Workflow

- Bounding Box Prediction: Identifies object locations
- Mask Prediction: Refines object segmentation at the pixel level





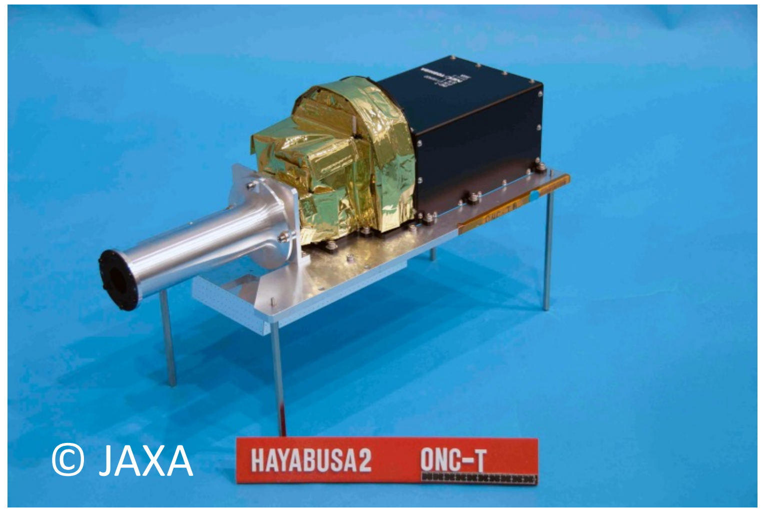


He, Kaiming, et al. "Mask r-cnn." *Proceedings of the IEEE international conference on computer vision*. 2017.

Data Source

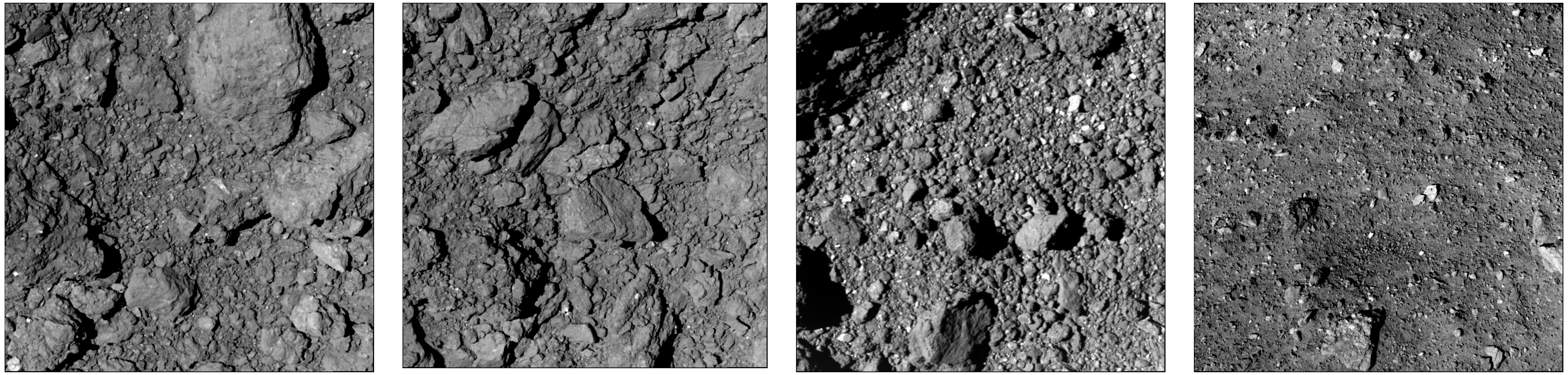
- **Ryugu: Hayabusa2, Optical Navigation Camera** (ONC, Telescopic)
  - 7-band spectral camera

Band	ul	b	v	Na	w	x	P
Center wavelength(nm)	397.5	479.8	548.9	589.9	700.1	857.3	945.1



  - Resolution: ~0.006°/pix = 10 cm/pix at 1 km altitude

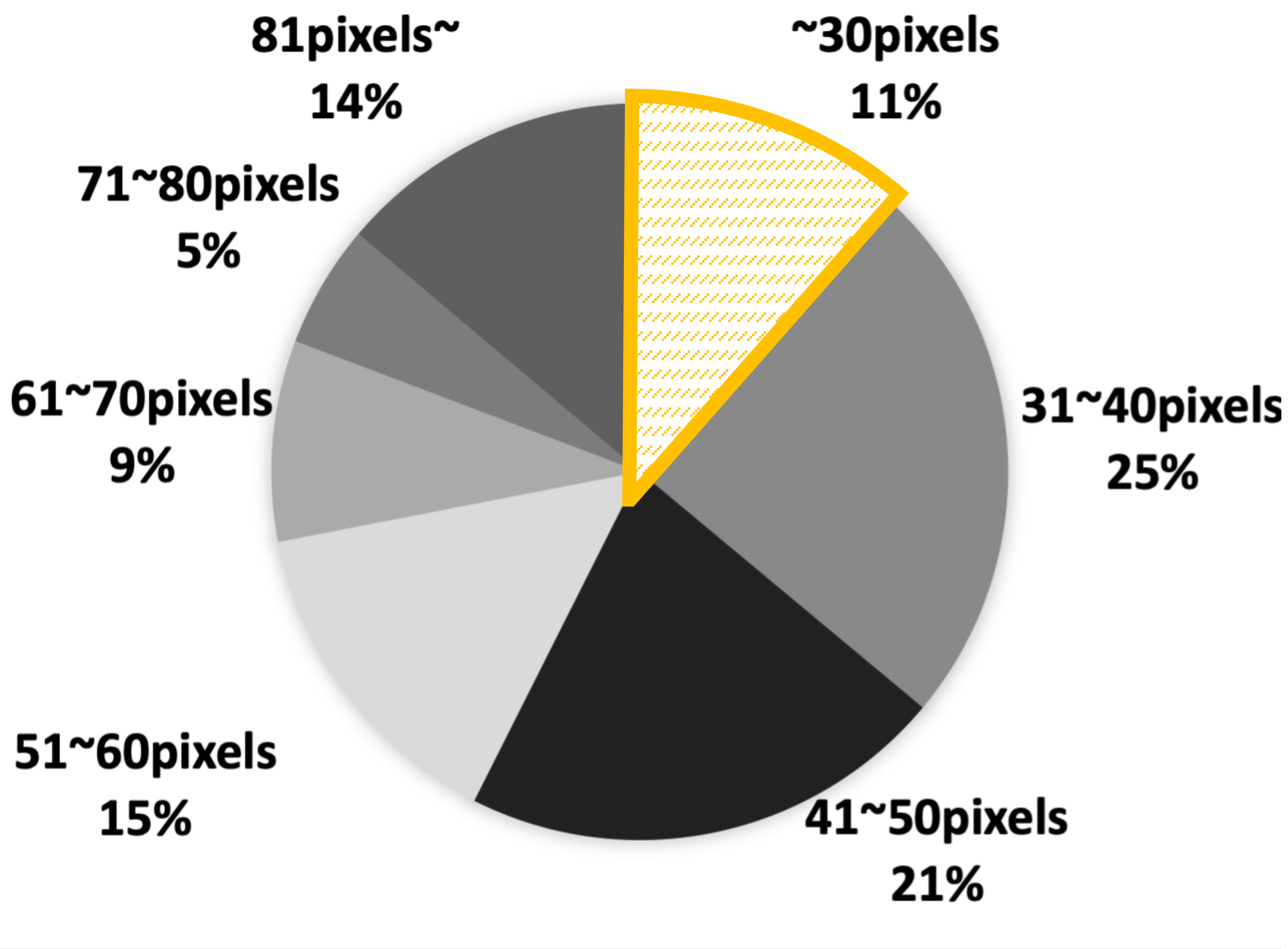
- **Data Source**
  - Data release from ISAS/JAXA DARTS (Ryugu proximately phase)
    http://darts.isas.jaxa.jp/pub/hayabusa2/onc_bundle



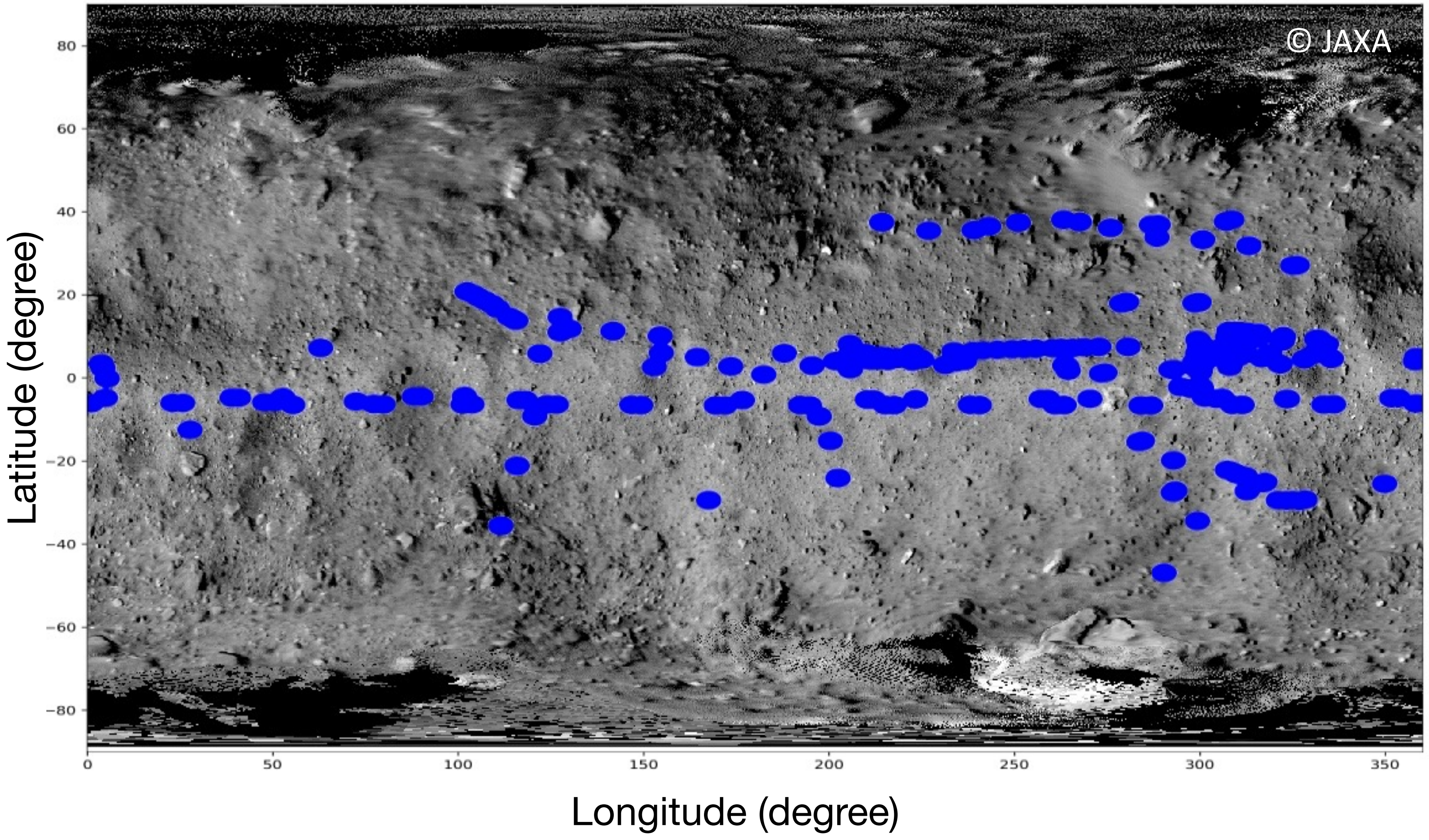
Dataset - Overview

Dataset detail

- Altitude < 5 km, 2 cm/pix
- 275 images (training: 220, validation: 27, test: 28)
- 20420 labels, COCO json style



Boulder sizes in the training data

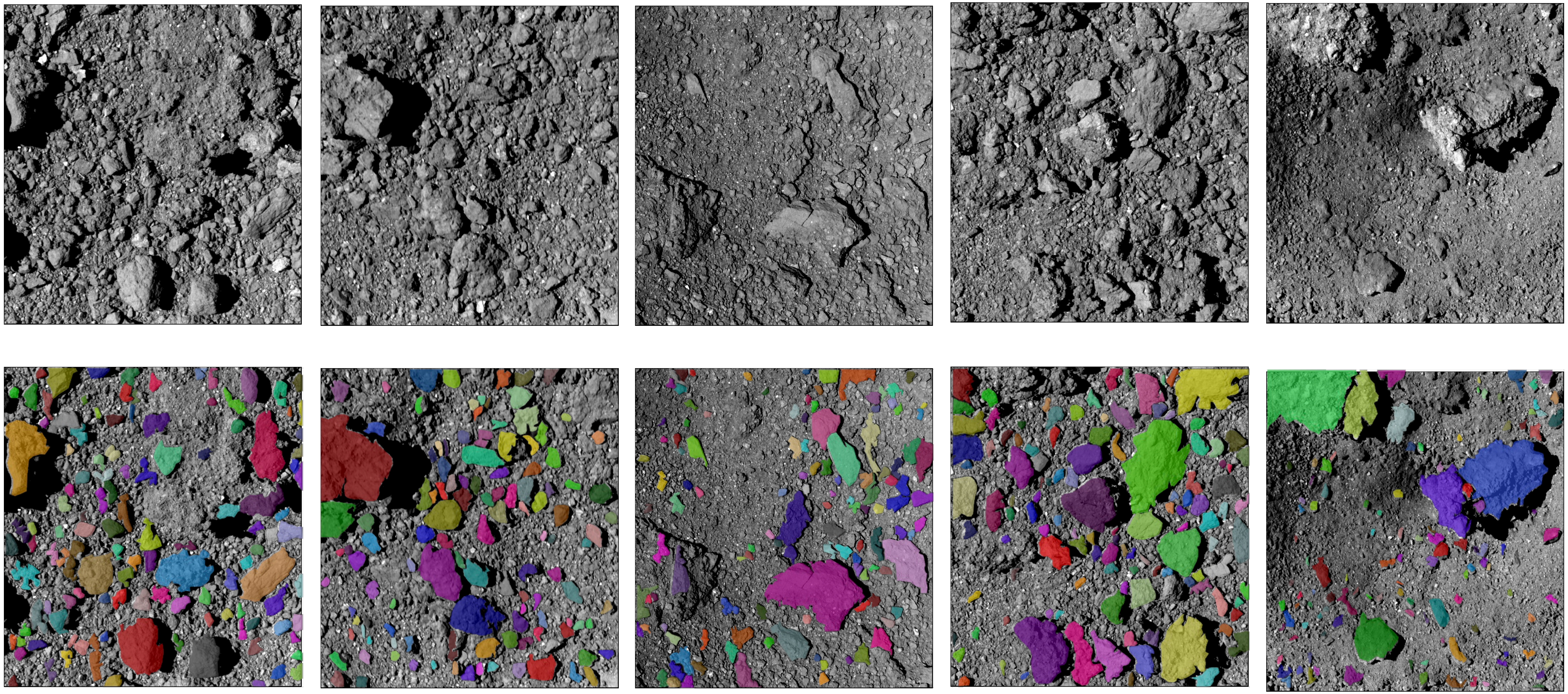


Location of images used for the training data

Dataset - Samples

Input

Ground Truth



https://github.com/suomiosu/Ryugu-boulder-dataset

Evaluation Metrics

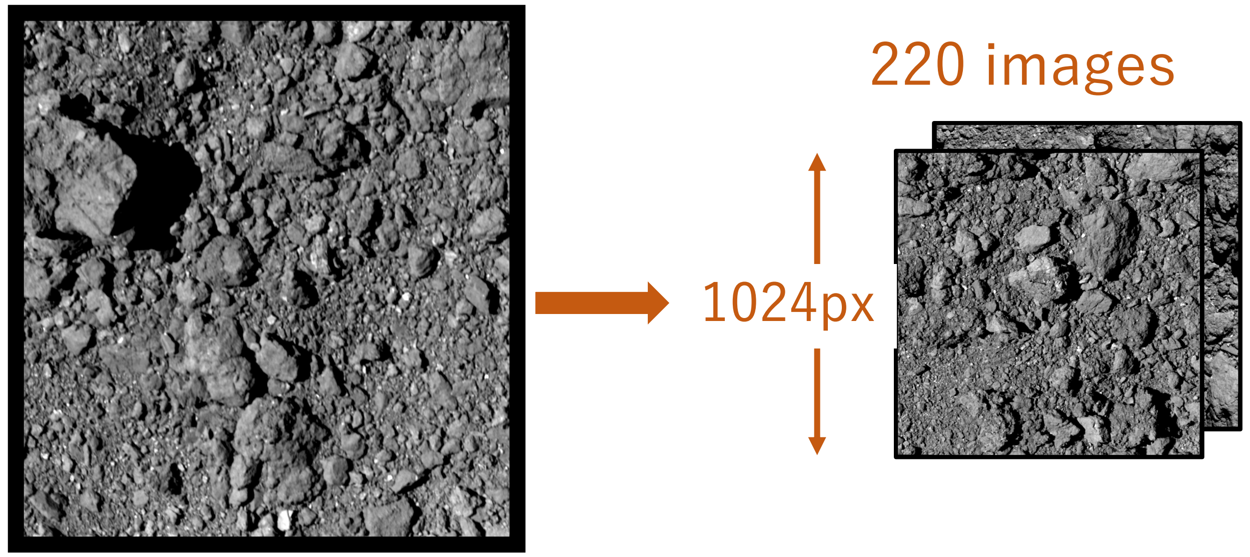
- Pixel-level evaluation metrics are unnecessary
- Some boulders are not included in the Ground Truth
  - minimize false negatives → maximize Recall
  - Boulders not present in the Ground Truth are compared against the size frequency distribution
- Calculating Recall based on IoU criteria
  - IoU measures the overlap between predicted and ground truth regions.

$$\mathrm{IoU} = \frac{\text{Area of Intersection}}{\text{Area of Union}}$$

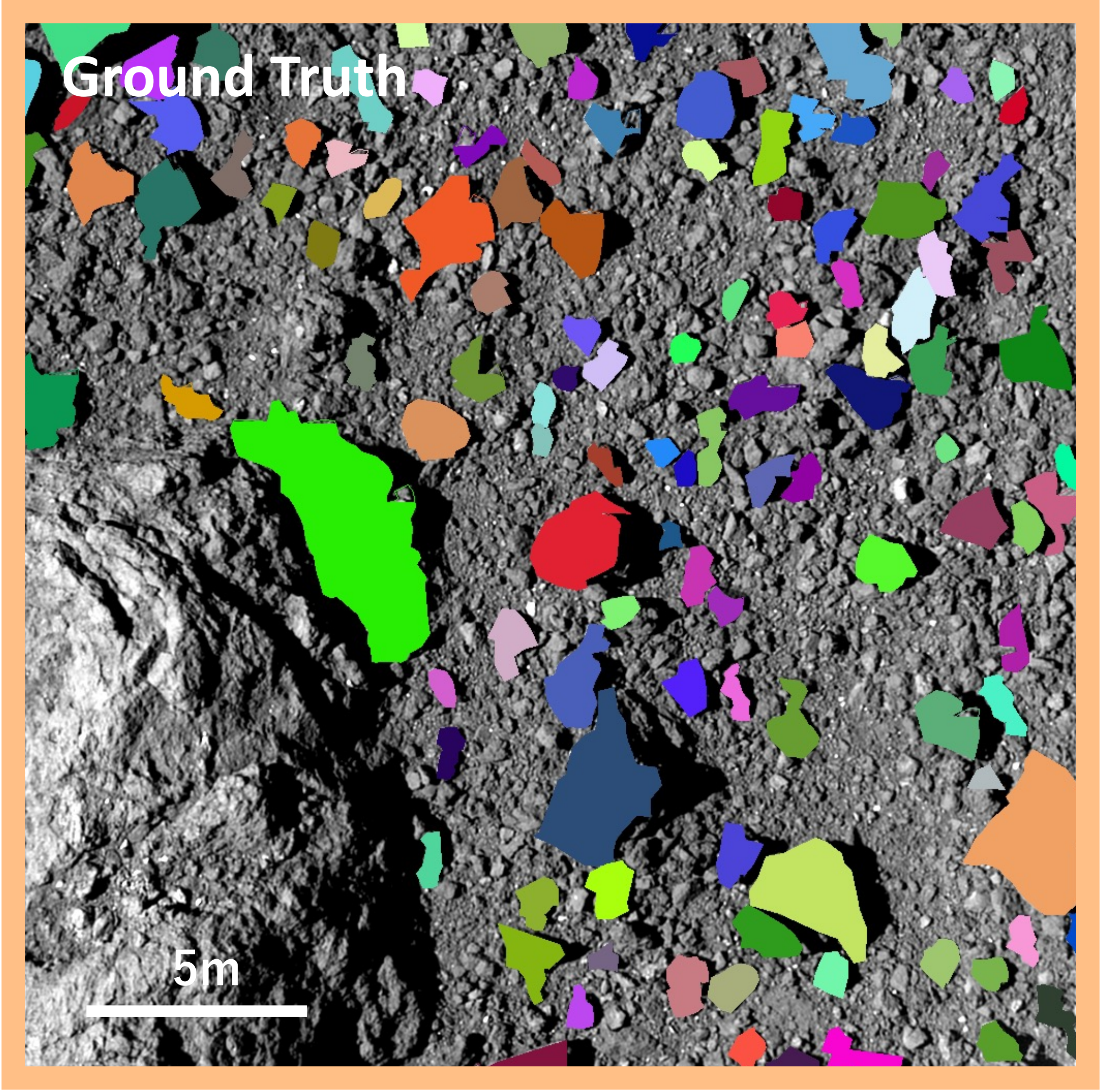
- Setting IoU > 50% as the threshold for correctness

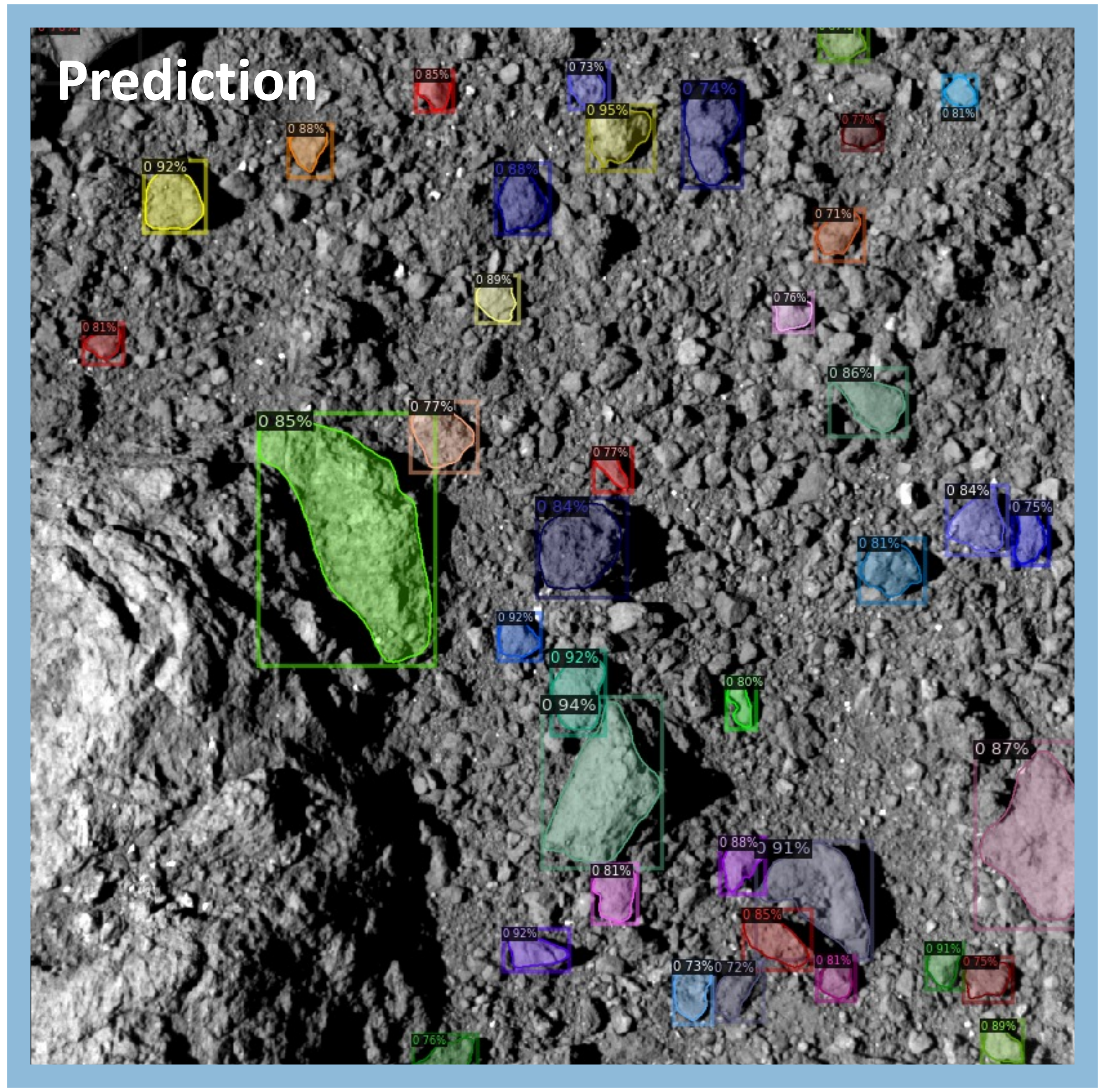
$$\text{Recall} = \frac{\text{number of correctly detected boulders}}{\text{number of boulders in Ground Truth}}$$

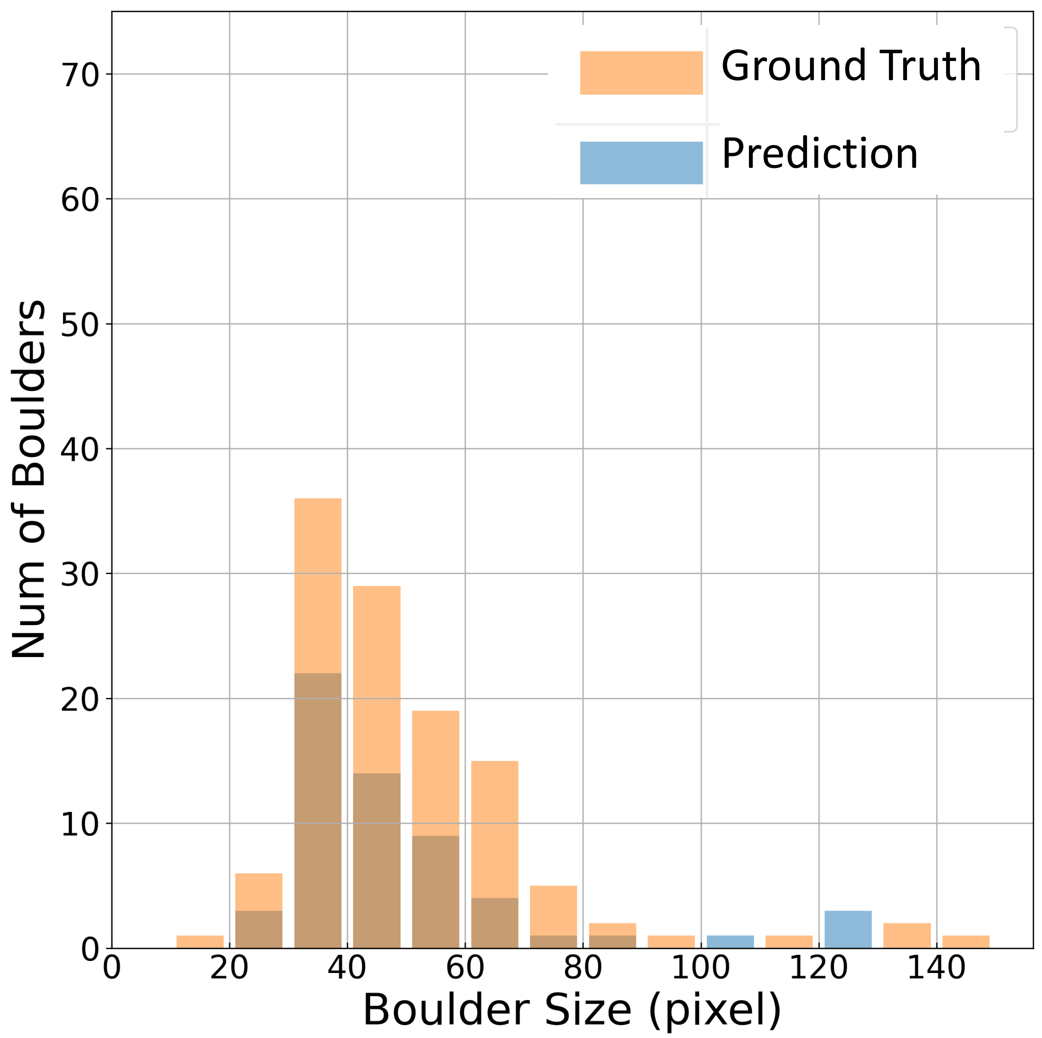
Results with Mask R-CNN, 1024*1024 images



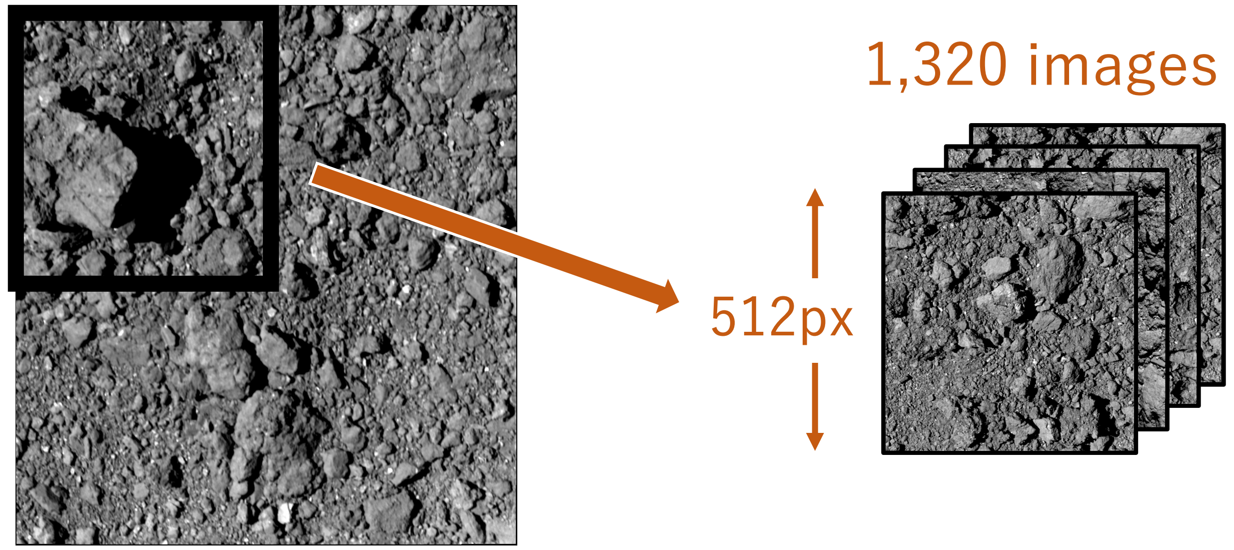
- image size: 1024 px, quantity: 220 images, iteration: 3,600





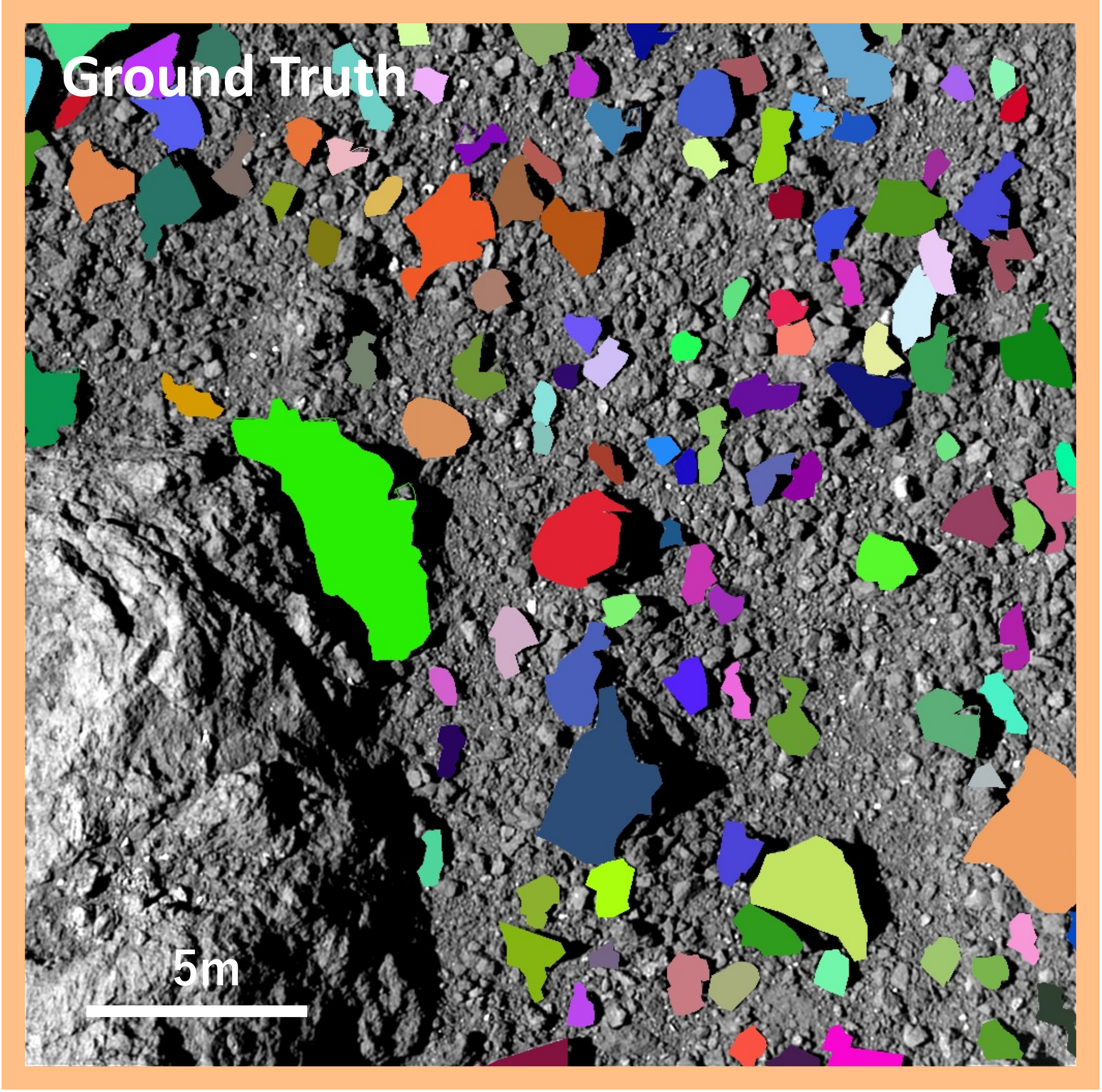


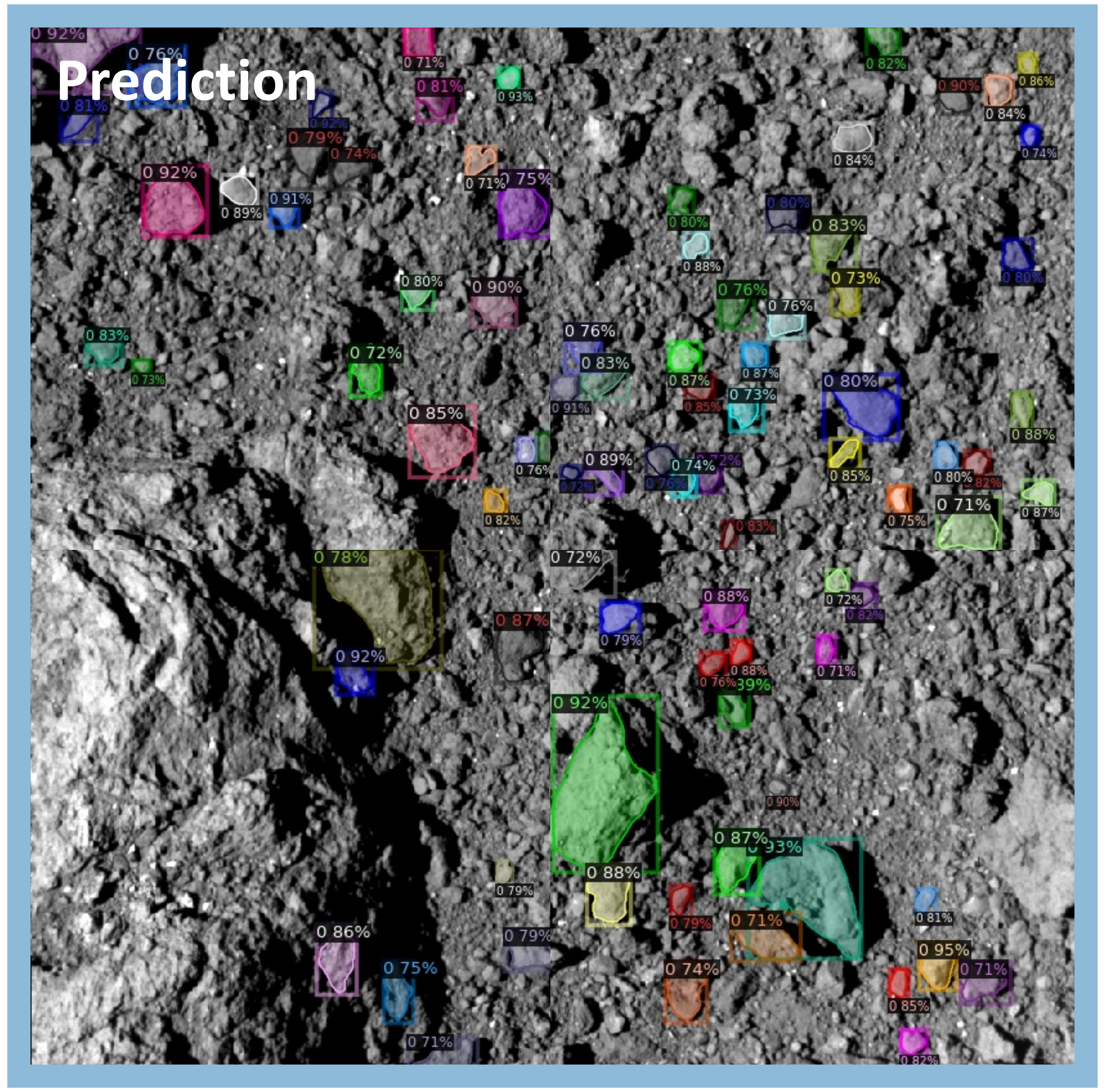
Results with 512*512 images

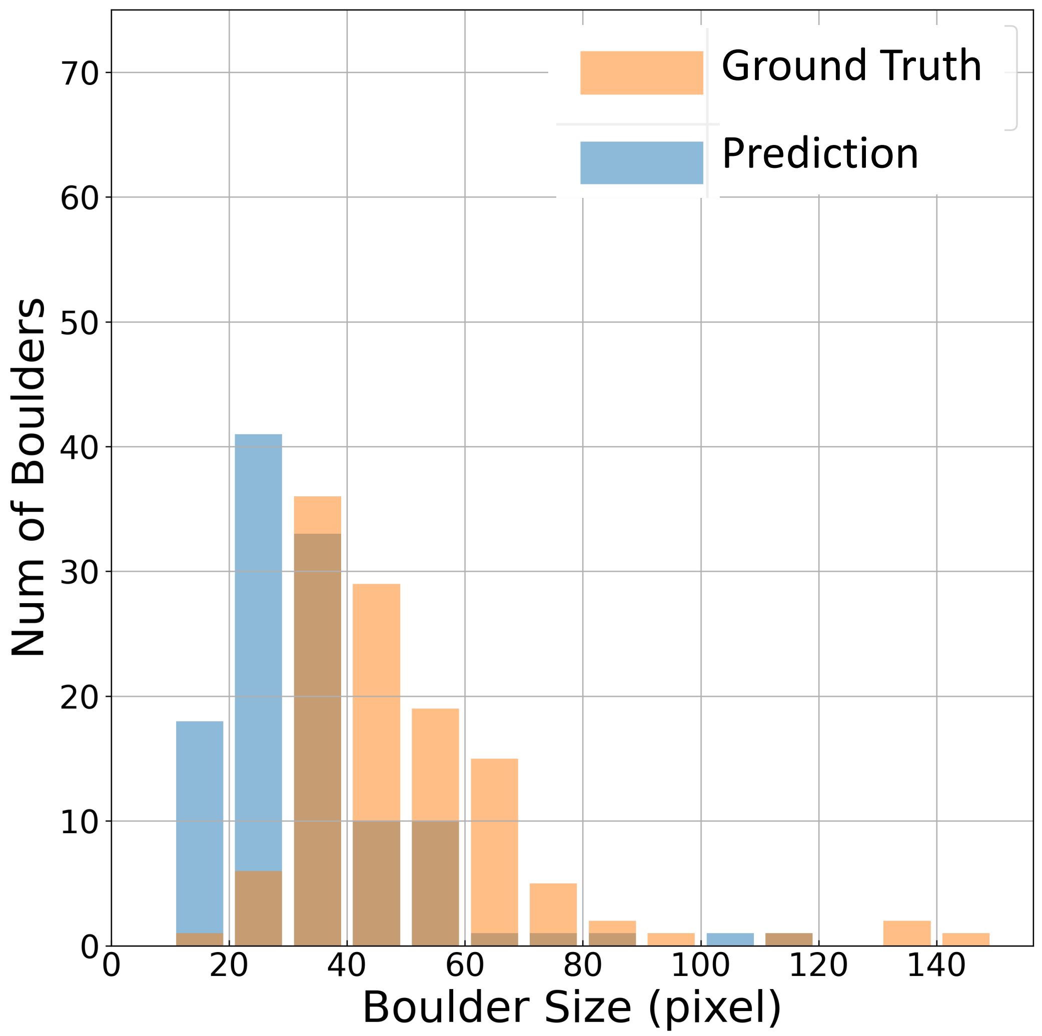


- image size: 512 px, quantity: 1,320 images, iteration: 2,400
- Detected boulders in the range of 10 ~ 40 pixels increased
  - Detection accuracy (recall) for 30~40 pixels: 97%

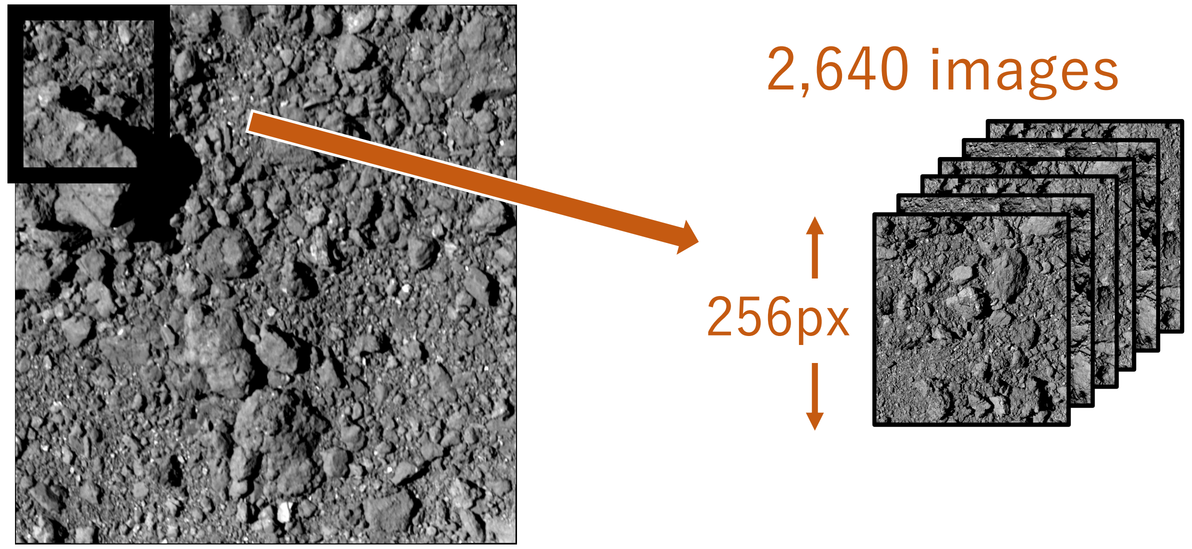
Recall = (Num of correctly detected boulders) / (Num of annotated boulders in the GT labels)



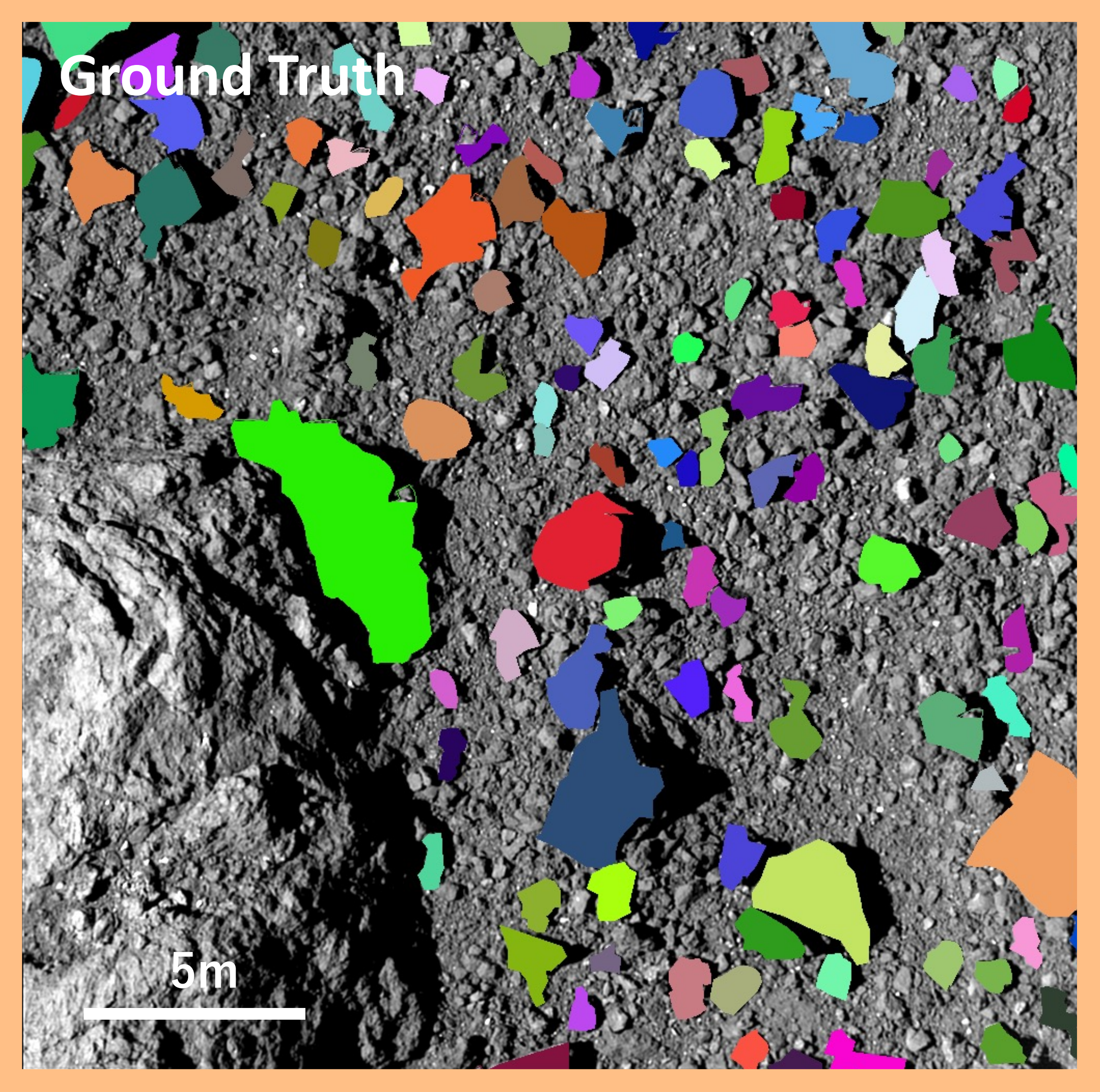


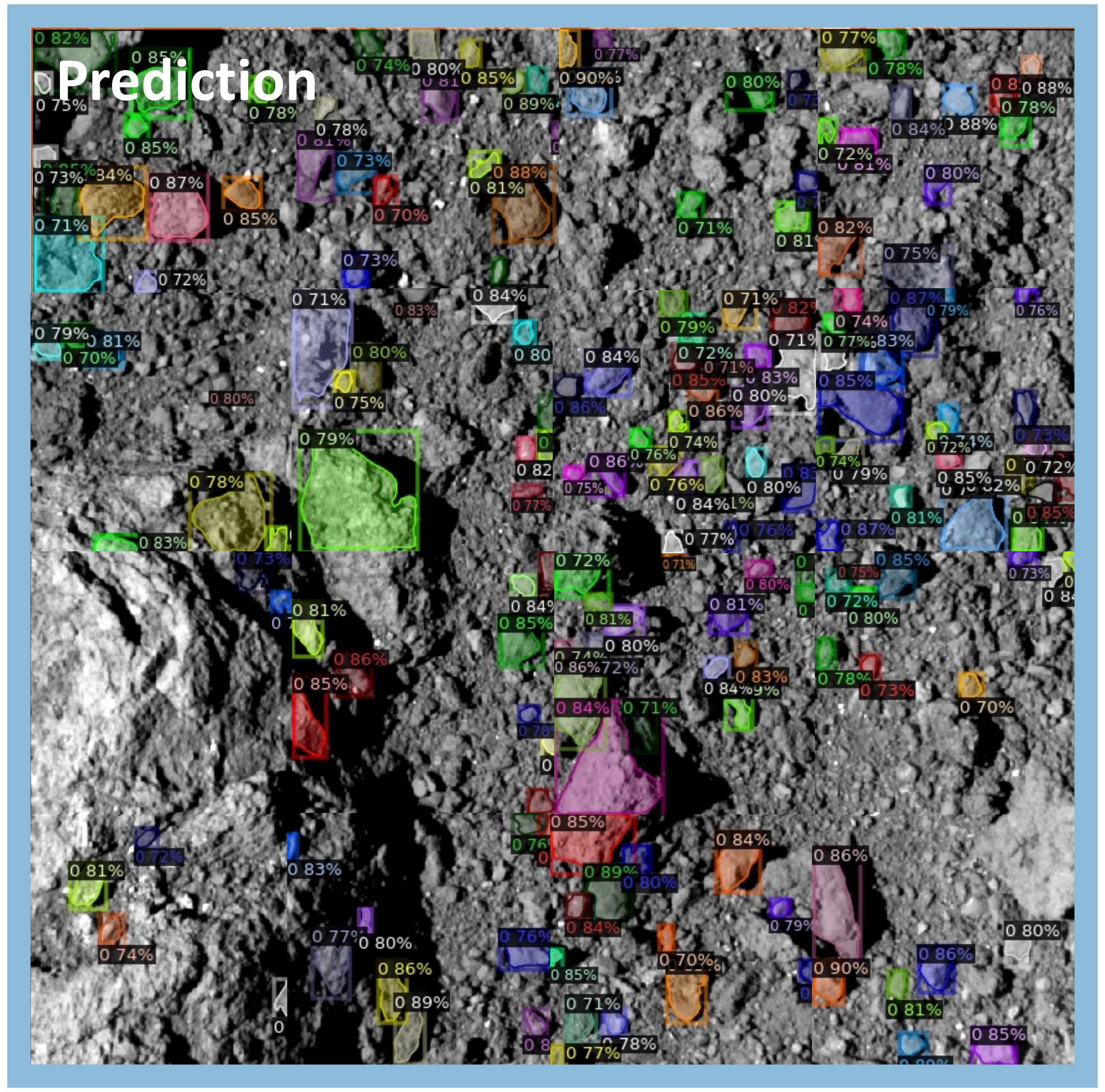


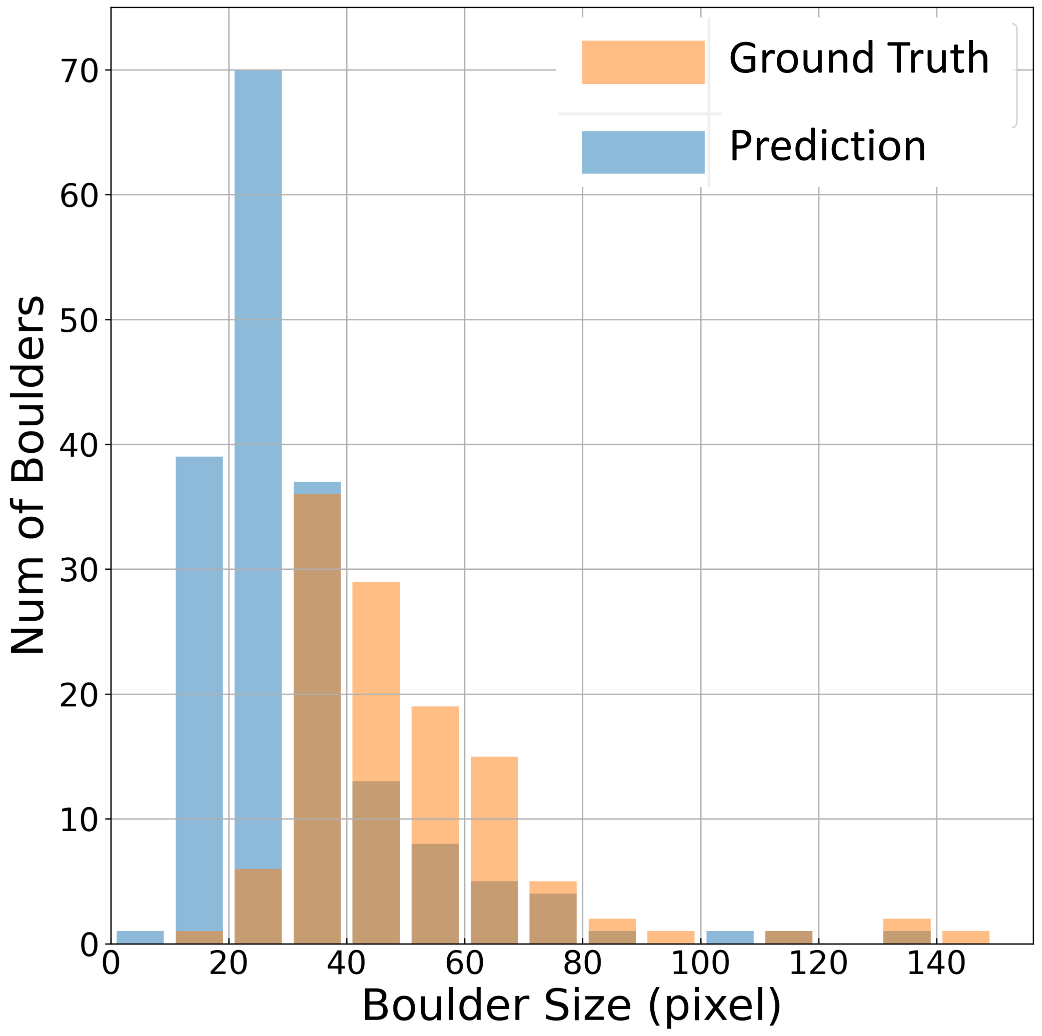
Results with 256*256 images



- image size: 256 px, quantity: 2,640 images, iteration: 2,500
- The detection of boulders not present in the training data became possible.
  - ・Boulder features could be extracted through image scaling.
  - ・The increase in the number of training data instances led to an increase in the number of parameter update cycles.

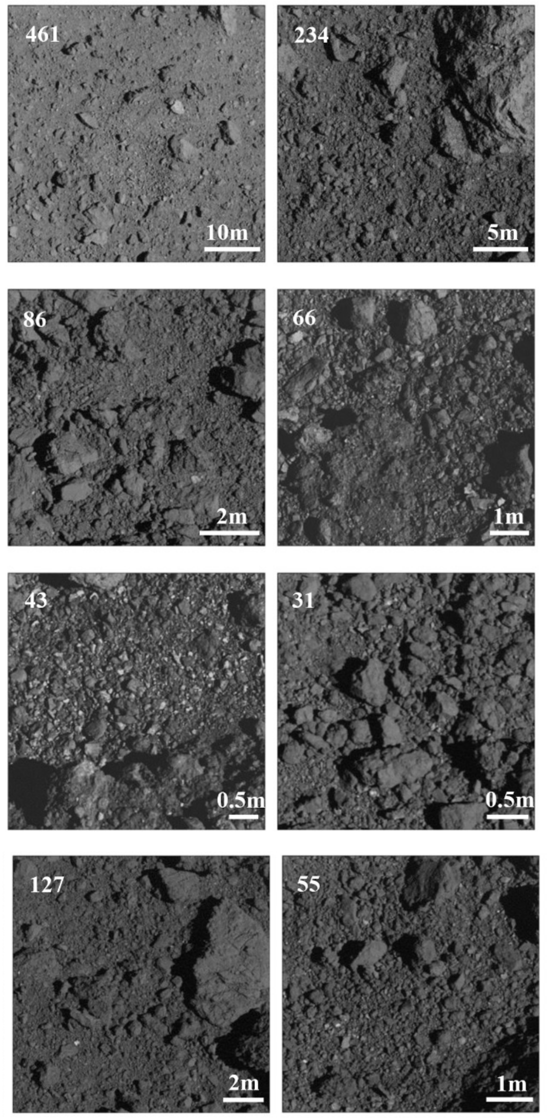


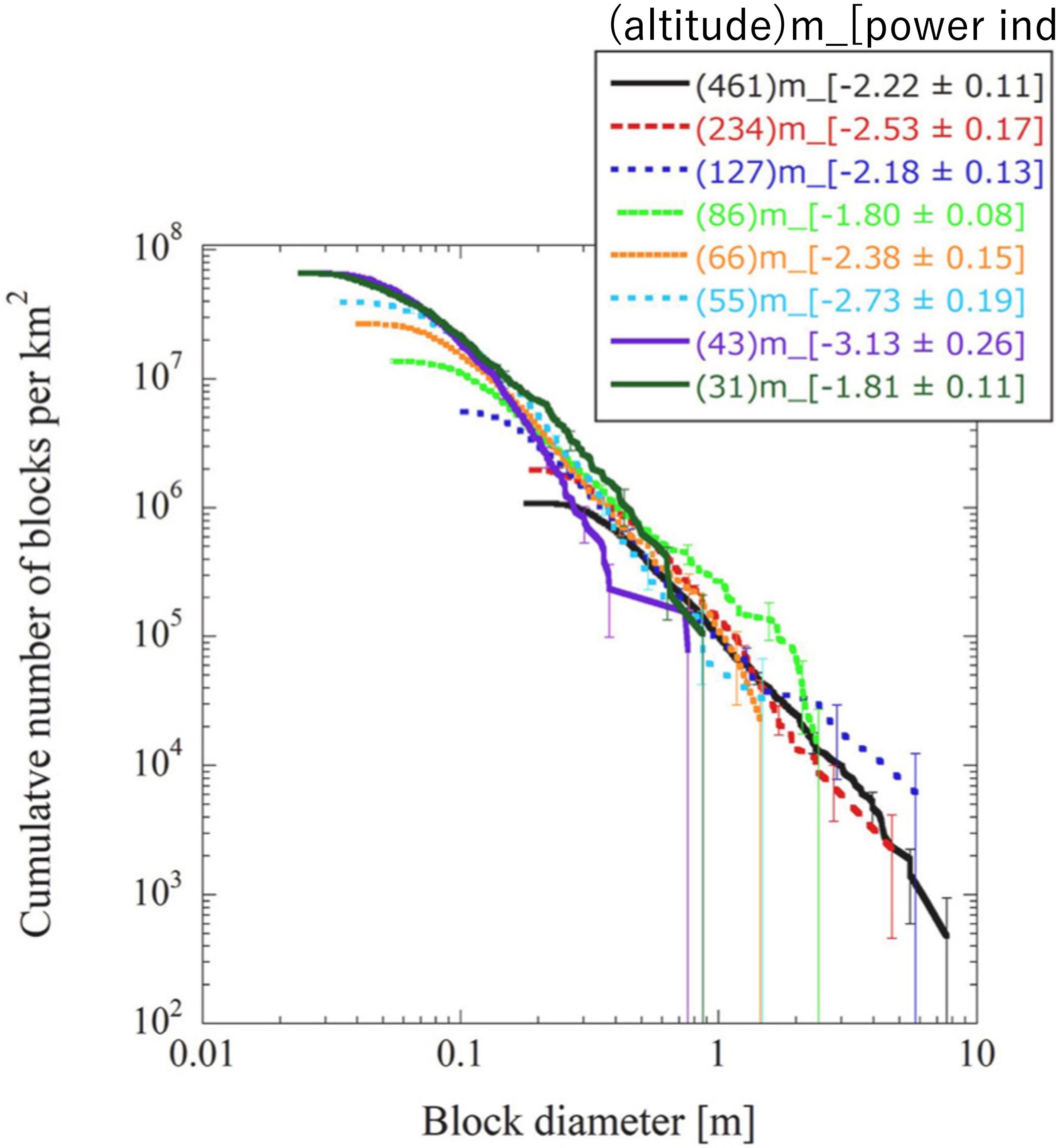




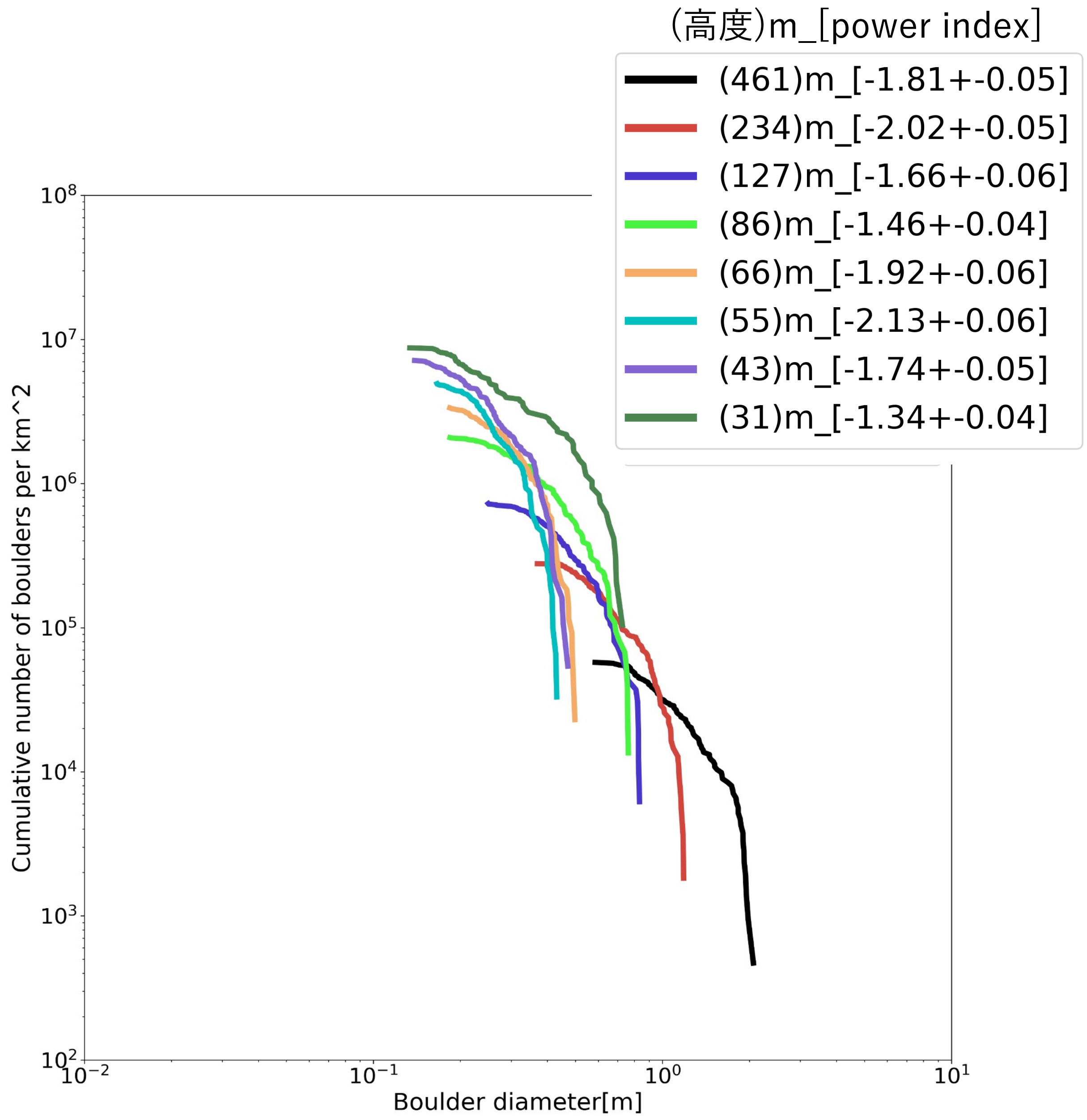
Boulder Size Frequency Distribution

- Compared the boulder size frequency distribution in Michikami 2022 with detected boulders by the deep learning model



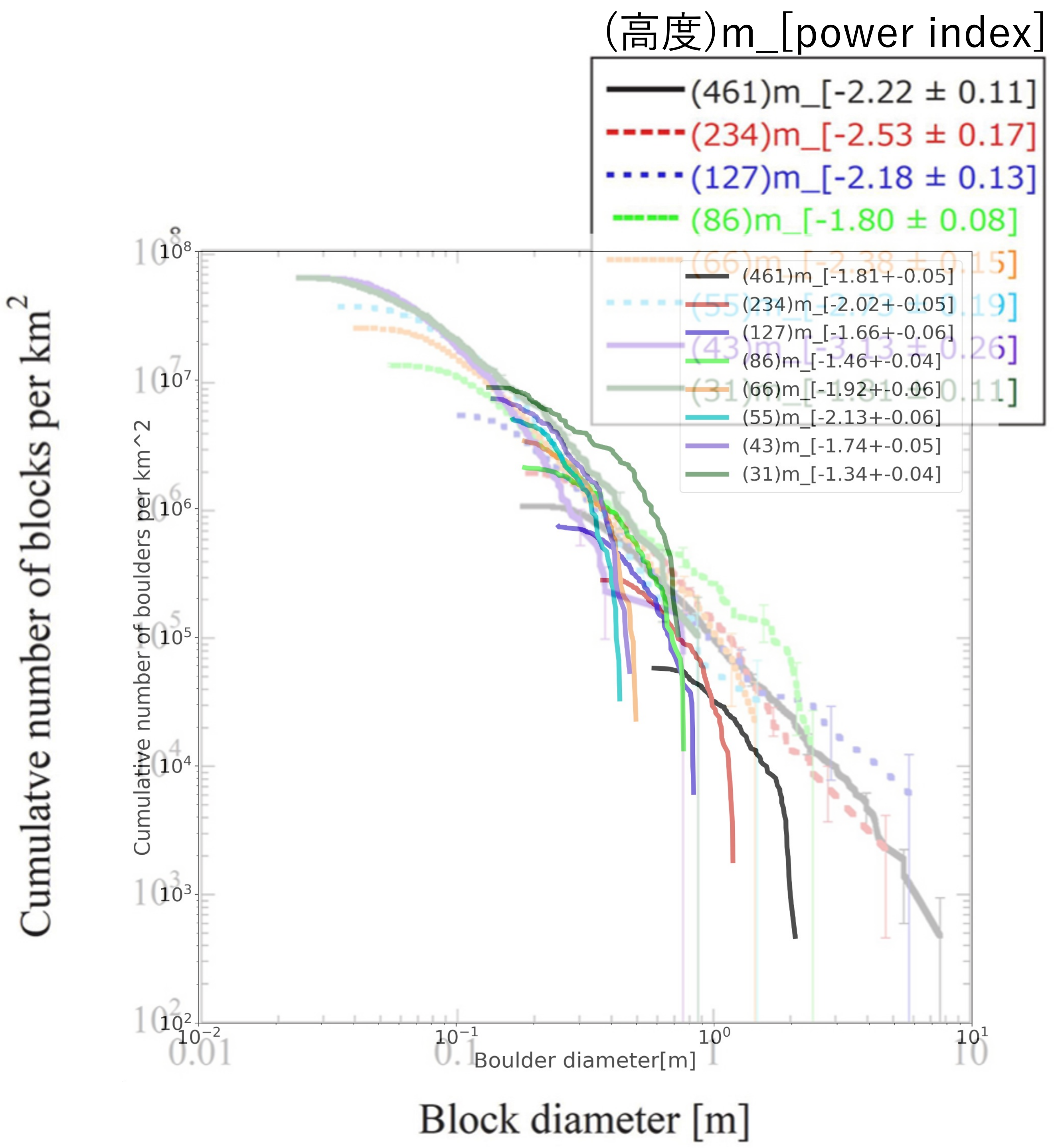


Boulder size frequency distribution in Michikami 2022



Boulder size frequency distribution detected by the deep learning model

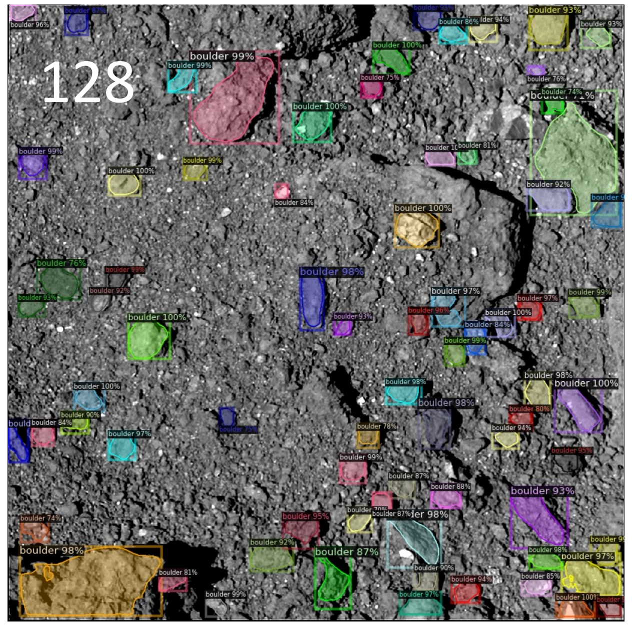
Boulder Size Frequency Distribution

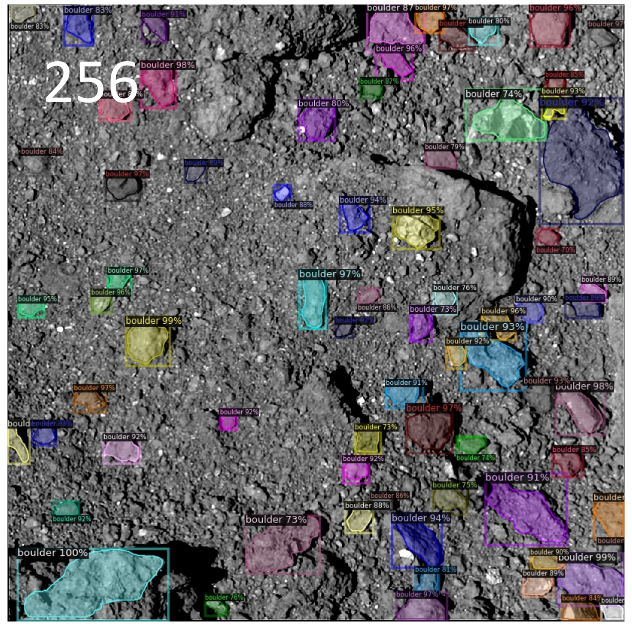


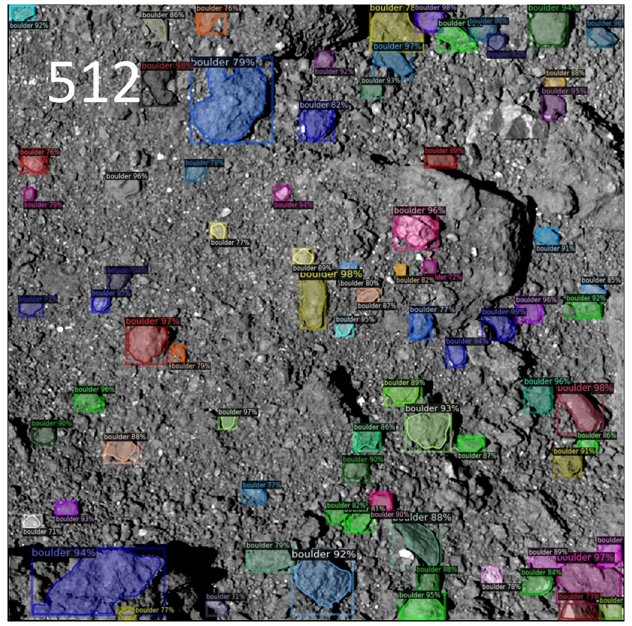
- Processing time per image: 0.04 seconds (size: 256x256 pixels)
  - Detection time for the left boulder: 5.12 seconds
- Visual inspection results align within the range of 0.1 to 1 meter
- Fewer detections for boulders with <50 pixels (0.15m to 2.25m)
  - Higher power index values
- The detection accuracy does not correspond to visual inspection

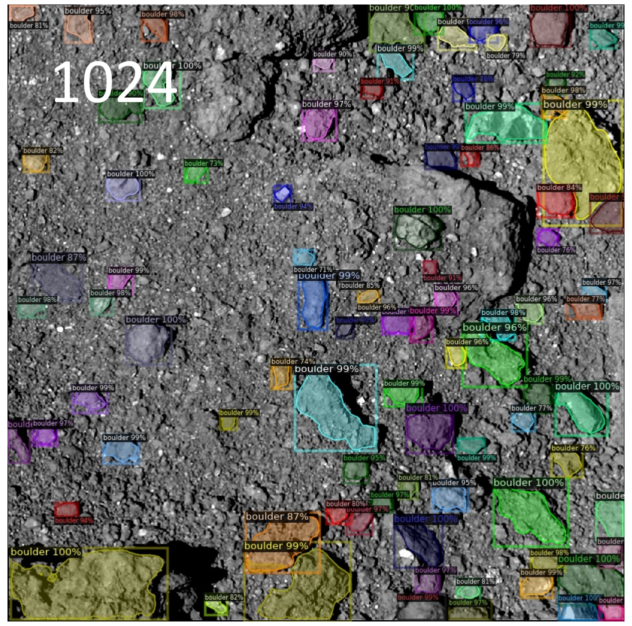
Current work

- Training with scaled images (enlarged or reduced)
  - no tendency over size





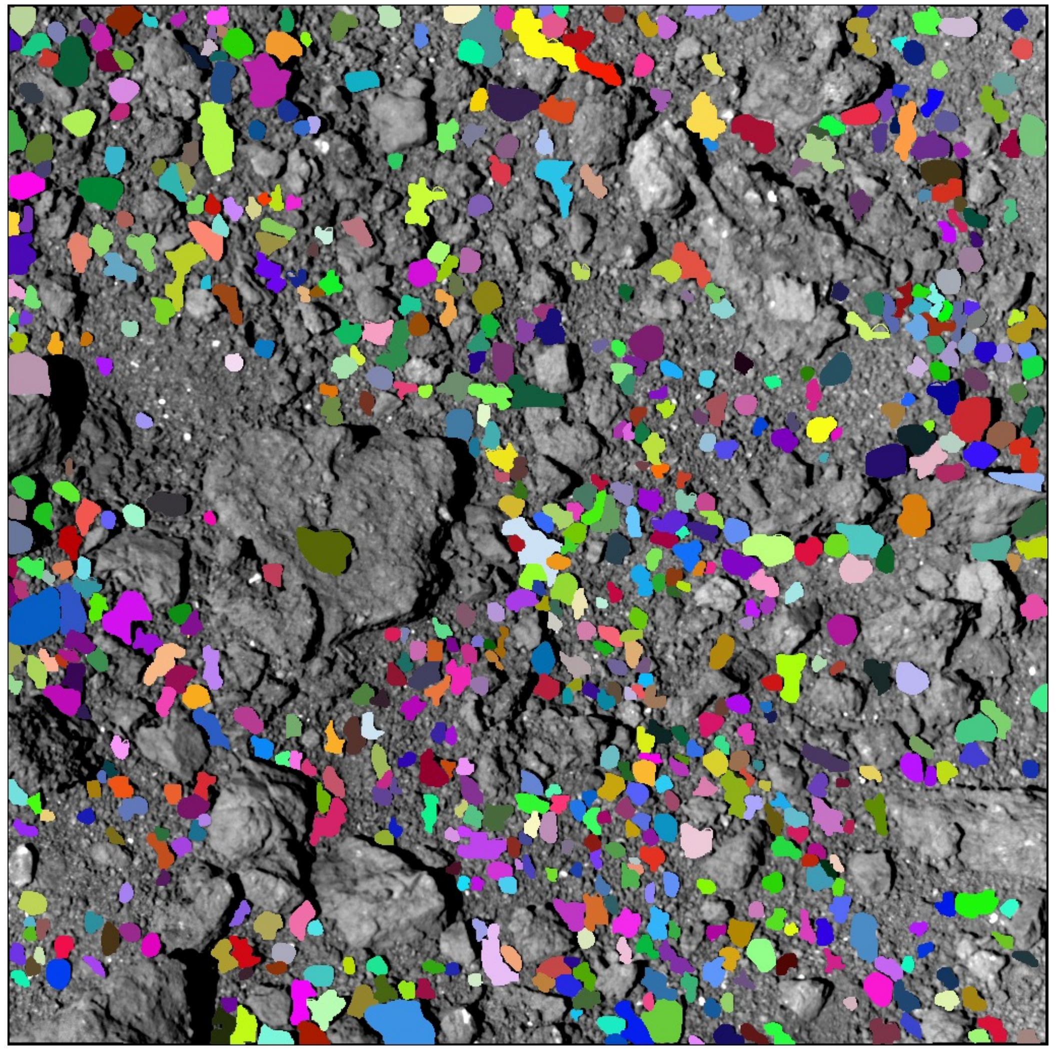


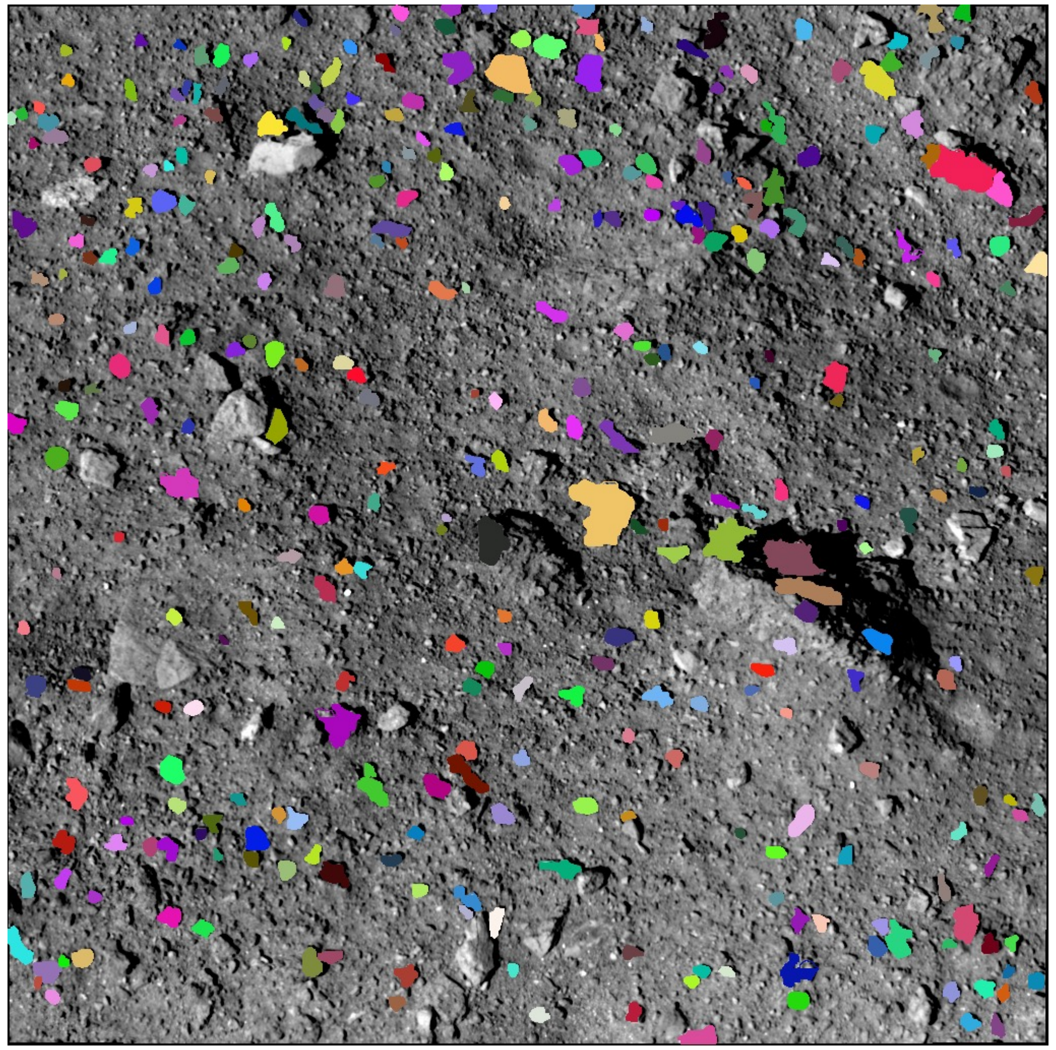


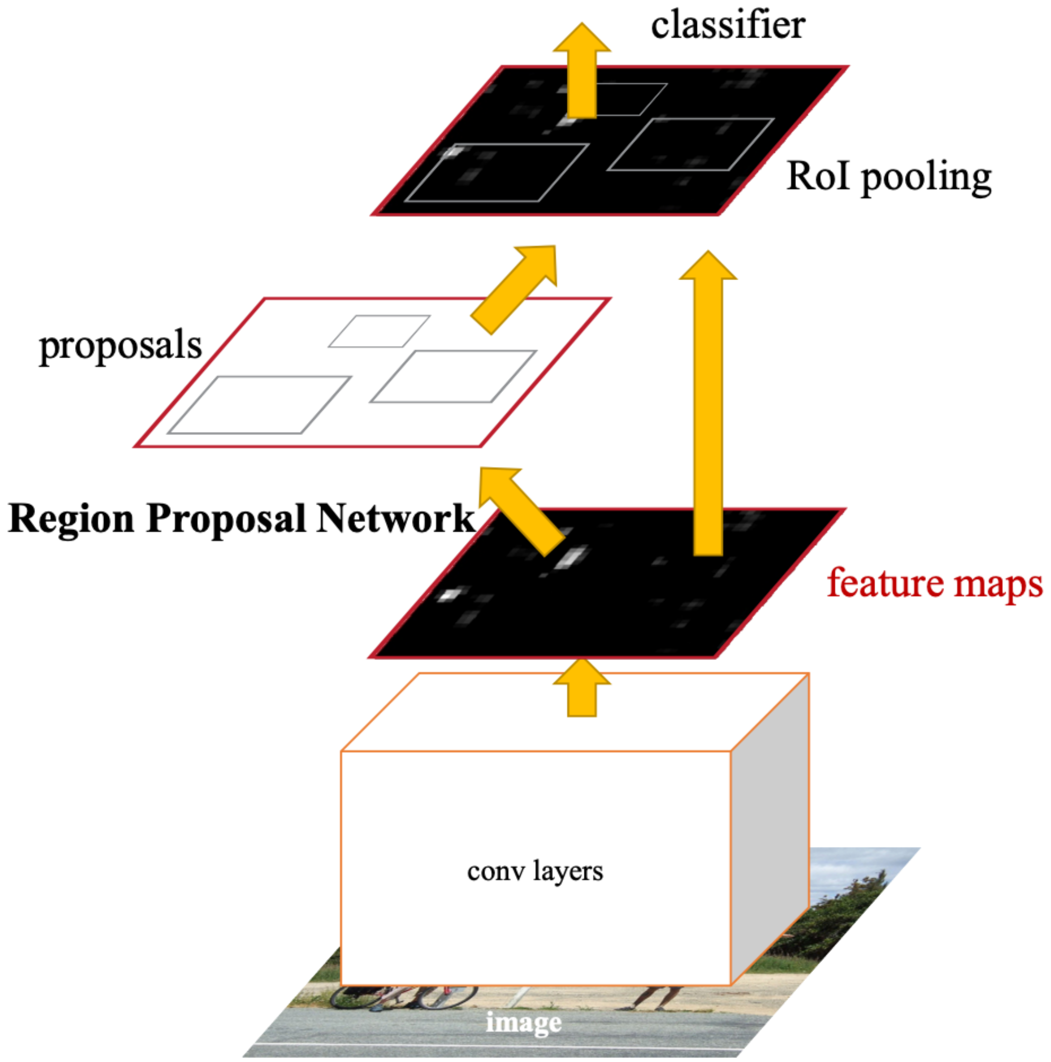
- Reducing the depth of the Background and RPN layers
- Modifying loss functions and validation metrics
- Increasing the number of samples in the dataset

Current work

- Training with scaled images (enlarged or reduced)
  - no tendency over size
- Reducing the depth of the Background and RPN layers
- Modifying loss functions and validation metrics
- Increasing the number of samples in the dataset







Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems*, *28*.

Conclusion and Future Work

- The goal of this study is to create **a boulder database for Ryugu using ONC archive data**
  - released annotation data for 275 images with boulders of 30 pixels or larger
  - using deep learning to achieve global-scale boulder detection
- By using Mask R-CNN model,
  - Boulders in the annotation, >30pix
    Recall: over 90%
  - The detection accuracy of small boulders can be improved
- Currently working on improving detection accuracy for boulders not in the annotation, <30pix
  - Training with scaled images (enlarged or reduced)
  - Reducing the depth of the Background and RPN layers
  - Modifying loss functions and validation metrics
  - Increasing the number of samples in the dataset
- Evaluation metrics
  - Detection accuracy of 95% for ground truth labels.
  - Reproduce boulder size frequency distributions in previous studies