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# A Study on Beach Vegetation Classification by using CNN on the Nijigahama Beach in Japan

Seiji Ito[1], Hiromu Yamashita[2], Kohei Oka[1], Tomohisa Konishi[1] and Yoshinari Oguro[1]
Kohei Cho[1] and Kyaw Sann Oo[2]
[1]Hiroshima Institute of Technology, 2-1-1 Miyake, Saeki-ku, Hiroshima 731-5193, Japan,
Email: seiji@cc.it-hiroshima.ac.jp
[2]Former Hiroshima Institute of Technology, 2-1-1 Miyake, Saeki-ku, Hiroshima 731-5193, Japan,

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**ABSTRACT: Coastal plants grow in halomorphic soil, and when the sandy beach disappears, the growing area for costal plants becomes smaller. The growth of coastal plants, in addition, has the effect of suppressing wind-blown sand, and it is useful for suppressing the reduction of sandy beaches. Therefore, conservation of coastal plants also contributes to coastal conservation. A vegetation map that showing growing area of coastal plants is one of the important information for monitoring the growth of costal plants. Therefore, we aim to automatically generate vegetation maps from images taken by Unmanned aerial vehicle (UAV). The purpose of this study is to classify coastal plants automatically for generating vegetation maps from UAV observation images. The study area is a part of the Nijigahama coast in Yamaguchi Prefecture, Japan, and this coast grow relatively many coastal plants grow on this coast in the Seto Inland Sea. The UAV observation images are divided into square region and each region is classified. A convolutional neural network (CNN) is applied for the classification, and the number of classification categories are four: Vitex rotundifolia, Carex kobomugi, Dianthus japonicus and Soil. The observation date is July 15, 2021, and the four observation images taken are used for the classification simulation. Using three images as training data and one image as validation data from the observation images data set. We have been obtained good results with classification accuracies of more than 70% in all simulations.**

## 1. Introduction

In Japan, the area of the coast which is important for people's lives and the environment is decreasing year by year(MLIT Japan, 2020). The reason for this decrease is the reduction of sediment flowing from rivers due to the construction of dams and river embankments. Therefore, coastal plants also decline due to habitat loss, and some coastal plants species are listed on the Red Data List (Sawada 2014). Costal plants have characters to restrain direct sunlight and sea breezes, as well as being resistant to salt contained in the soil, moreover the covering of the leaves suppresses flying sand. Therefore, the conservation of coastal vegetation leads not only to the conservation of species, but also to the conservation of the coast itself (Oka 2010). In order to conserve coastal plants, it is necessary to periodically conduct field surveys and draw vegetation maps. A vegetation map can track changes over time in a target area and is an important basic resource for clarifying the factors of the growing environment that differ depending on the vegetation species (Oka 2017). The quadrat method is the mainstream method for vegetation maps, in which the target area is divided into small quadrates and all vegetation species growing in each quadrate are identified and recorded. Based on the records, the coverage or community density is calculated according to the purpose, and mapping is performed (Fujiwara 1997). However, the field survey using the quadrature method requires steady work, and it takes a lot of time and effort. Recently, it is possible to observe the wide area with inexpensive UAV (Unmanned Aerial Vehicle) relatively easily, and applications for the generation of wide vegetation maps also have been reported. However, drawing a vegetation map from the observed UAV observation images also requires a lot of time and effort. Therefore, the purpose of this study is to classify vegetation species in order to automatically draw a vegetation map from UAV image data.

As similar studies, there is a method to discriminate the vegetation species of trees in mountainous areas from UAV observation images(Suzuki 2016). This study covers a very wide area, and the target species is trees, which are different from shrubs and herbs that are treated in this study. Other proposals include tree extraction in river areas (Saito 2018) and research on crop extraction in farmland (P. Lottes 2017). The purpose of these methods is to extract a specific species, not to discriminate between multiple species.

In this study, we classify images observed by UAV using a convolutional neural network (CNN). First, we create a data set that divides multiple UAV observation images necessary for CNN training into square regions and assigns correct labels to those regions. There are four classification items, which are the dominant species of coastal vegetation in the test site: Vitex rotundifolia, Carex kobomugi, Dianthus japonicus and Soil. Since the Dianthus japonicus were flowering at the time of observation, they occupied a large area relatively.

## 2. OBSERVATION

The target area is Nijigahama Beach, Hikari City, Yamaguchi Prefecture, Japan (Fig.1). This coast is one of the large-scale natural coasts in the Seto Inland Sea, with the Shimada River flowing in the western part of the coast and coastal plants growing extensively. DJI Mavic 2 Zoom was used as the observation equipment (Fig.2).

In similar studies, The UAV is equipped with a dedicated camera such as a near-infrared camera, and observation data is obtained from that camera, but we obtain the observation data with a standard camera. Since only the visible bands can be observed, classification is not easy, but it has the advantage of being able to classify even images observed by the standard camera without installing a special sensor. The flight altitude was set at 15m. Although this is generally a low altitude, the target species were small compared to other studies, and the altitude was such that they could be visually recognized from the observation images. The spatial resolution is about 2.4mm/pixel when the target area is observed under this shooting condition. One of the observation images from this UAV is shown in Fig.3, The observation date and time was around 11:00 am on July 15, 2021, and the weather at that time was fine. In this image, there is vitex rotundifolia community in the lower, and carex kobomugi community spreads from the center to the upper, purple color area of left is flower of dianthus japonicus.

Three of the observed images are used as learning data, and one is used as evaluation data. In addition, these images are divided into 50×50 sizes, and each region is classified. Fig. 4 shows an example of each classification item for a 50x50 region. In order to add teacher labels to these regions, all regions were visually labeled. However, when multiple items existed in a region, the item with the largest area in the region was assigned as the teacher label. Moreover, some regions were also garbage, plant species other than classification items. These were treated as non-classified regions.

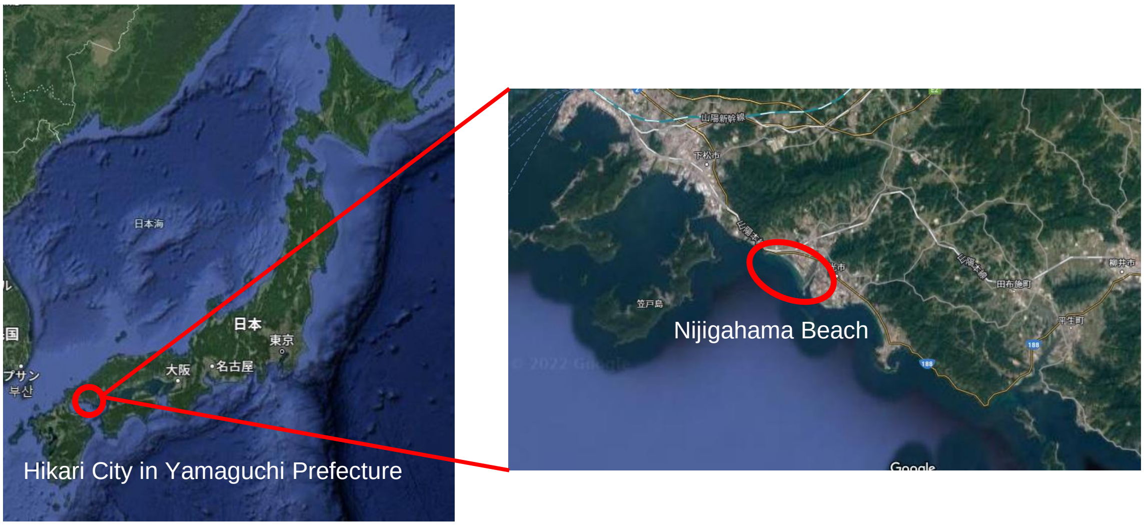


Fig.1 Target area: Nijigahama Beach (@google)

Fig.2 The observation equipment

Fig. 3 A sample of observation image

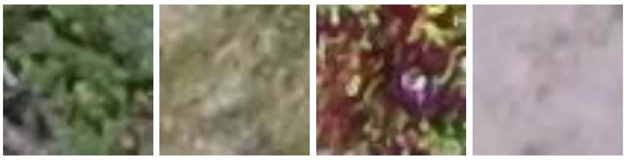

Fig.4 Samples of each classification item
Vitex rotundifolia, Carex kobomugi, Dianthus japonicus and Soil from the left.

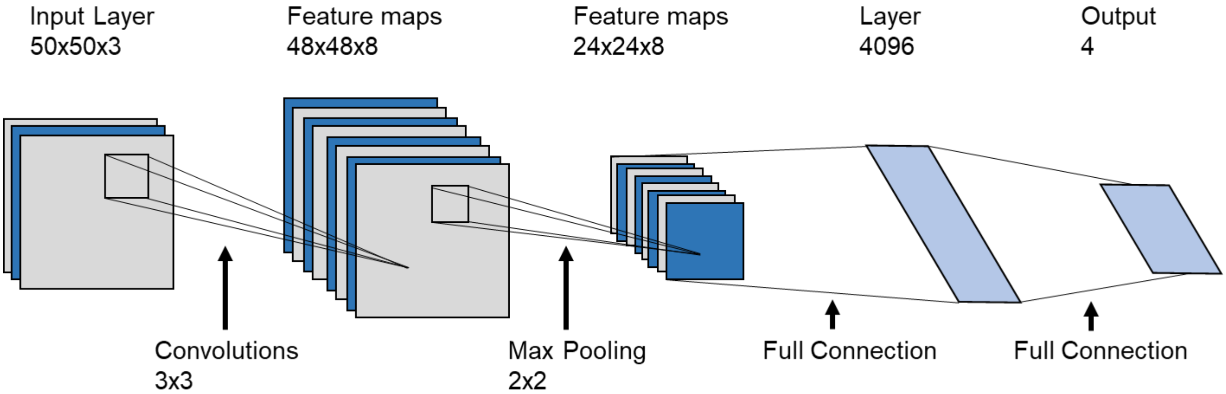


Fig.5 A CNN Structure of this study

Table 1 The number of regions as the created datasets

| Region size | Training data | Evaluation data |
|---|---|---|
| 25x25 | 5,763 | 4,780 |
| 50x50 | 14,230 | 1,188 |
| 100x100 | 3,593 | 299 |

## 3. Classification method and simulations condition

In this study, we used a convolutional neural network to classify each region. Figure 5 shows the structure of the CNN used in this study. As shown in this figure, it is a very simple structure with one convolution layer and one pooling layer. Semantic segmentation methods such as SegNet and U-Net are included and are considered suitable for the purpose of this study. However, it is very difficult and impractical to manually classify plant species pixel by pixel for creating label data. Since it is relatively easy to assign labels for each region, we used CNN which can classify for each region. The structure of the CNN in this study consists of five layers: an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer (See Fig.5). The pooling layer applies max pooling, and the output layer applies the softmax function.

In this study, we experimentally verify the relationship between the difference in region size and the classification accuracy. The smaller the area size, the more detailed the vegetation map can be generated, but the amount of information for classification is reduced and the classification accuracy may be lowered. On the other hand, if the area size increases, the amount of information increases and classification accuracy may increase, but multiple classification items may exist in one area, and the reliability of label data may decrease. Therefore, in this study, we also created datasets with two types of region sizes, 25x25 and 100x100, and performed simulations. Each layer size in the CNN structure was changed appropriately according to the region size. The number of regions of each created dataset are shown in the Table.1. When CNN is learned by using each dataset, the data is augmented by rotating the regions.

## 4. Classification results

This chapter explains the classification results and the vegetation maps created from the results.

First, the classification results will be shown and discussed. Table 2 shows the classification accuracy for each dataset. Although it is a possibility of improving the accuracy if various parameters can be adjusted a little more, high accuracies of 70% or more have been obtained for the evaluation data regardless of the size of the dataset. Moreover, it is found that the larger the region size, the higher the classification accuracy. Although difference of the number of evaluation data, it is considered the difference in the amount of information contained in data as mentioned above. Table 3 shows the details of Table 2. The values of the diagonal components of these tables represent the accuracy of each classification item, and the others represent the rate of incorrect answers. Accuracies of Vitex rotundifolia and Carex kobomugi is high in the 50x50 and 100x100 results, but Dianthus japonicus is low accuracy in any result. Dianthus japonicus has a lower occupied area than Vitex rotundifolia and Carex kobomugi, and the number of training data is also less than those. Since 100x100 regions tend to include vegetations, the Soil classification accuracy is low as 30.0% and the number of results classifying into Soil is low. Therefore, it is suggested that these neural networks tend to be classified into dominant species items.

Next, the generated vegetation maps will be shown and discussed. Fig. 5 shows the vegetation maps of classification results and label data from Fig. 1 as original image. When creating the label data, we checked only at the target area without checking at the around area. Since, it was very difficult to judge the vegetation in the case of the 25x25 size region, the vegetation map based on label data is more unnatural than the classification result. The vegetation maps obtained by any classification result are similar to the label data. Detailed vegetation maps can be obtained by smaller size region but are less reliable. On the other hand, it is difficult to classify vegetation species growing a small area such as Dianthus japonicus with a larger size region as the result of 100x100. On the other hand, it is difficult to classify vegetation species growing a small area such as Dianthus japonicus in a larger size region as the result of 100x100. Therefore, it has been suggested that it is better to classify by the area of 50x50 size in this study.

Table 2 The classification accuracy

| Region size | Evaluation data |
|---|---|
| 25x25 | 70.8% |
| 50x50 | 75.1% |
| 100x100 | 78.0% |

Table 3 The details of the classification accuracy

| 25x25 size | | Label | | | |
|---|---|---|---|---|---|
| | | Vitex rotundifolia | Carex kobomugi | Dianthus japonicus | Soil |
| Classification result | Vitex rotundifolia | **72.7%** | 14.3% | 24.8% | 24.9% |
| | Carex kobomugi | 9.8% | **72.9%** | 33.3% | 12.7% |
| | Dianthus japonicus | 0.9% | 2.5% | **38.4%** | 1.2% |
| | Soil | 16.6% | 3.3% | 3.4% | **61.2%** |

| 50x50 size | | Label | | | |
|---|---|---|---|---|---|
| | | Vitex rotundifolia | Carex kobomugi | Dianthus japonicus | Soil |
| Classification result | Vitex rotundifolia | **87.1%** | 14.4% | 37.1% | 23.3% |
| | Carex kobomugi | 5.5% | **82.4%** | 28.7% | 9.4% |
| | Dianthus japonicus | 0.4% | 1.9% | **32.2%** | 0.0% |
| | Soil | 7.0% | 1.4% | 1.8% | **67.4%** |

| 100x100 size | | Label | | | |
|---|---|---|---|---|---|
| | | Vitex rotundifolia | Carex kobomugi | Dianthus japonicus | Soil |
| Classification result | Vitex rotundifolia | **80.1%** | 9.1% | 18.4% | 40.0% |
| | Carex kobomugi | 15.3% | **86.4%** | 39.8% | 30.0% |
| | Dianthus japonicus | 0.5% | 3.0% | **35.9%** | 0.0% |
| | Soil | 4.1% | 1.4% | 5.8% | **30.0%** |

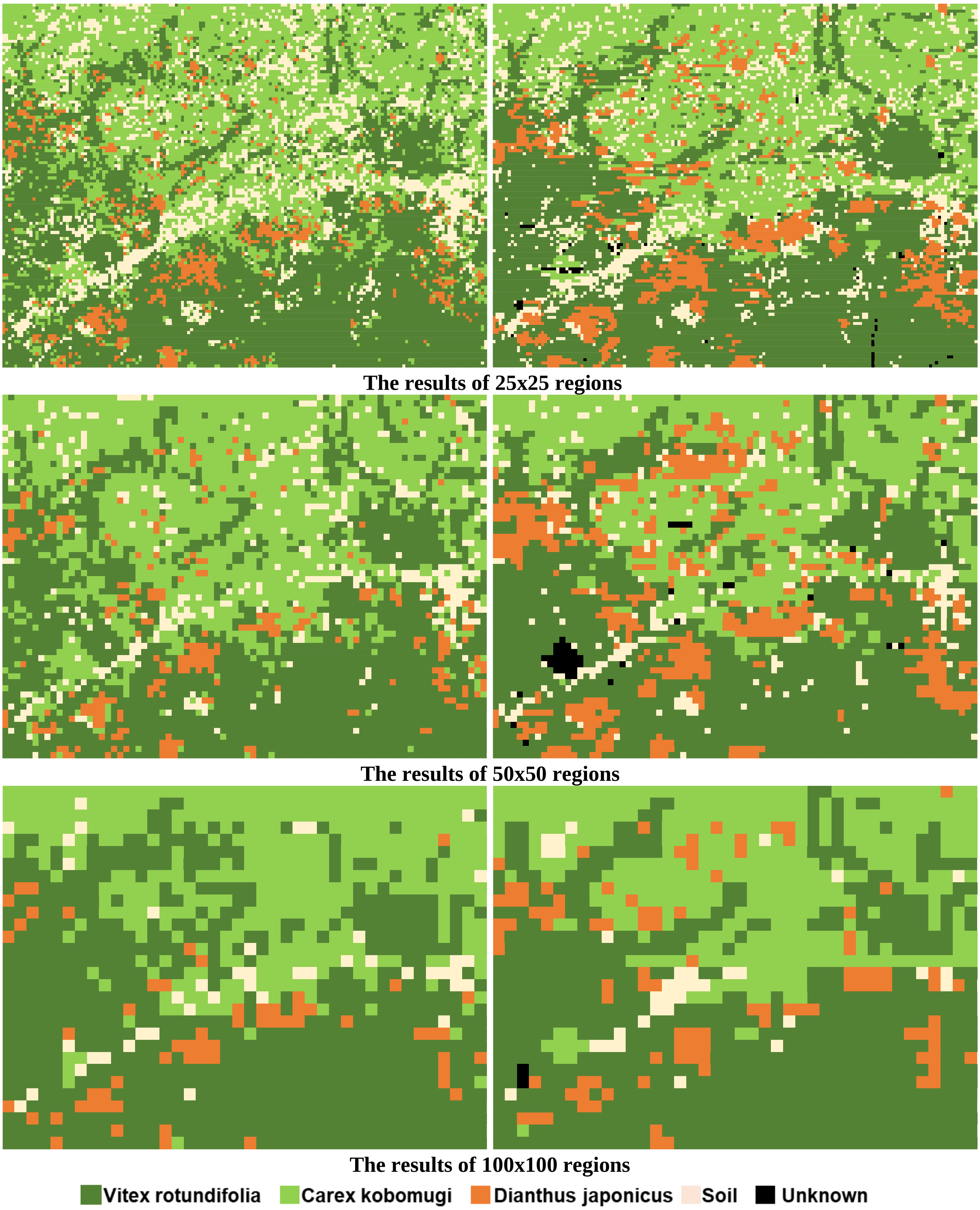


**Fig. 5  The vegetation maps by each region (Left: CNN classification results, Right: Label data)**

## 5. Conclusion

In this study, we classified coastal plants using CNN for the purpose of automatically creating vegetation maps of Nijigahama beach from UAV observation images. Three kinds of classification simulations were performed with different region sizes. We obtained good results with classification accuracies of more than 70% in all simulations, but the classification accuracies of species with small growing areas was low. The vegetation map was drawn from the classification results, and the 50x50 size was the most suitable. In the future works, we will simulate increased the number of classification items and various data with different time periods.

**References:**


MLIT(Ministry of Land, Infrastructure, Transport and Tourism) Japan, 2020, The Seacoast Law and Basic Policy for Coastal Conservation, Retrieved Sep 8, 2022, https://www.mlit.go.jp/river/kaigan/main/coastplan/bp.pdf (in Japanese)

Sawada, Y., 2014, The listing status to red lists and the problems to conservation of coastal sand dune plants in Japan, Japan Association for Landscape Ecology, 19 (1), pp.25-34 (in Japanese)

Oka, K., 2010, Coastal Environment and Biodiversity -Samples of Coastal Plants Conservation Restoration-, Journal of The Japanese Society of Revegetation Technology, 35(4), pp.503-507 (in Japanese)

Oka, K., 2017, Conservation and zonation of coastal sand dune plant communities in Nijigahama, Yamaguchi Prefecture, Japan. Journal of Nature Restoration and Conservation, 9(1), pp.27-34 (in Japanese)

SAITO, M., 2018, DEVELOPMENT OF RIVER CHANNEL MAINTENANCE VIA AUTOMATIC DISCRIMINATION OF VEGETATION USING UAV AND DEEP LEARNING, 74(4), pp.I_829-I834 (in Japanese)

Fujiwara, K., 1997, Methodology of Vegetation Analysis and Mapping based on Phytosociology and Vegetation Science, Bulletin of YOKOHAMA National University, 23(1), 13-46, 1997 (in Japanese)

Suzuki, T., 2016, Vegetation Classification Using a Small UAV Based on Superpixel Segmentation and Machine Learning, Journal of The Remote Sensing Society of Japan, 36(2), pp. 59-71 (in Japanese)

P. Lottes, 2017, UAV-Based Crop and Weed Classification for Smart Farming, IEEE International Conference on Robotics and Automation (ICRA), pp. 3024-3031, Singapore