

Multitemporal monitoring of forest indicator species using UAV and machine learning image recognition

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Research Article

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Abstract

In natural restoration, it is important to improve the efficiency of monitoring. Remote sensing using unmanned aerial vehicle (UAV) platforms plays a major role in improving monitoring efficiency. UAV platforms are particularly suited for monitoring long-term, multitemporal changes. The objectives of this study were to develop a standard protocol for monitoring multitemporal changes in forest indicator species using a UAV platform, to evaluate multitemporal changes, and to examine the factors contributing to these changes. The study site was a forest located within Takaragaike Park (Sakyo-ku, Kyoto, Japan), and *Rhododendron reticulatum* was selected as the study species. The distribution of *R. reticulatum* flowers was identified from 2019 to 2023 using image recognition with artificial intelligence. A mesh was used as a spatial unit, and standardized values (Z values) were tabulated to evaluate the abundance and changes in the number of *R. reticulatum* flowers over time. The method used in this study showed very high accuracy in image recognition at multitemporal periods, indicating that it is useful for long-term monitoring. It was also able to detect the effects of forest management and the impact of vegetation succession. The new method is expected to become one of the standard protocols for understanding multitemporal changes in forest indicator species.

Introduction

In natural restoration, it is important to make monitoring more efficient and to use the time spent on monitoring for management (Langhammer 2019; Dale et al. 2019; Harvey et al. 2019). Remote sensing plays a significant role in improving monitoring efficiency. In recent years, UAV platforms have joined platforms such as satellites and manned aircraft in remote sensing. Although UAV platforms are less efficient than these platforms in terms of area coverage, UAV platforms are unrivaled by other remote sensing platforms in terms of spatial resolution, cost efficiency, flexibility, and time required to capture an image (Pádua et al. 2017). In monitoring, accurately capturing changes in the distribution of indicator species across the study area and identifying the drivers of these changes is an important research topic (Dronova et al. 2021). The application of a UAV platform enables the efficient acquisition of the distribution of indicator species across the study area and allows for cost-effective ecosystem health assessment (Dronova et al. 2021). Therefore, UAV platforms are also suitable for monitoring long-term, multitemporal changes, a research topic that has not been fully explored (Marques et al. 2019; Dronova et al. 2021). In particular, there is a clear lack of research on the application of UAV platforms for the long-term, multitemporal monitoring of forests (Ecke et al. 2022).

The growing use of UAV platforms in ecosystem research has created a diversity of approaches for collecting, processing, and analyzing information, increasing the need to develop standardized protocols for mapping using UAV platforms (Gomez and Purdie 2016; Tmušić et al. 2020). Therefore, the objectives of this study were to develop a standardized protocol for understanding multitemporal changes in forest indicator species using a UAV platform, to evaluate multitemporal changes, and to examine the factors that contribute to these changes.

Methods

Study site

Takaragaike Park (Sakyo-ku, Kyoto, Japan) is an urban planned park managed by the City of Kyoto with a publicly recognized area of 128.9 ha. The study area was 109.4 ha of forest in the park area (hereafter referred to as “Takaragaike Forest”) (Fig. 1). In the study area, *Pinus densiflora* forests are distributed around the ridges, and *Quercus serrata* forests are distributed around the valleys. Deciduous broad-leaved forests account for 88% of the forests (Niwa et al. 2020). Once used as satoyama, these forests are now largely unmanaged, and problems such as progressive vegetation succession and increased feeding damage by deer have emerged, making forest management problematic. In March 2022, the Takaragaike Forest Conservation and Restoration Council formulated a “Forest Management Vision” for Takaragaike Forest, and forest management efforts have begun, with the restoration of biodiversity as one of the goals.

Target species

In this study, *Rhododendron reticulatum* was selected as the target species. *R. reticulatum* is a species of wild azalea that grows naturally in many secondary forests in the Kansai region of Japan (Morimoto and Yoshida 1998). *R. reticulatum* is a familiar plant in the Kansai region, and its conservation is significant because it is a symbolic species of secondary forests (Nakajima et al. 2016). *R. reticulatum* grows in light forests dominated by deciduous broadleaf trees and blooms in spring before the deciduous broadleaf trees in the taller tree layer have expanded their leaves. Therefore, the flowers can be photographed from above if the blooming period is targeted.

In Japan, the impact of feeding damage on vegetation is becoming more noticeable due to the increase in deer population density. *R. reticulatum* is subject to feeding damage by deer (Hashimoto and Fujiki 2014), and in the study area it is declining due to feeding damage by deer. In addition, the density of evergreen broad-leaved trees is increasing in the study area due to vegetation succession caused by decreased human management; this has led to a decrease in the number of *R. reticulatum*, which prefer light forests. Therefore, *R. reticulatum* is a suitable indicator for capturing changes in vegetation and the effects of forest management in the study area.

Identifying the distribution of flowers of *R. reticulatum*

A method was established by Niwa (2022) to identify the distribution of *R. reticulatum* flowers using a UAV platform. Following that method, the distribution of *R. reticulatum* flowers was monitored between 2019 and 2023. The blooming of *R. reticulatum* in the study area was observed in early April, and UAV photographs were taken on days when the flowers were judged to be close to full bloom (Table 1). A DJI Phantom 4 Pro or DJI Mavic 2 Pro was used to take images at an altitude of 130 m, with a front wrap rate of 80% and a side wrap rate of 60%. Although the aircrafts used were different, all images were 5472 × 3078 pixels in size. The acquired images were processed using SfM-MVS Photogrammetry (hereafter

referred to as “photogrammetry”) to create an ortho-mosaic image. The xyz coordinates of the ground control points surveyed by real-time kinematics were imported into the photogrammetry software, and their positions were corrected. The photogrammetry software used in this study was Agisoft Photoscan Pro. Ver. 2.0.0. The ground resolution of the generated ortho-mosaic images is shown in Table 1.

Picterra (<https://picterra.ch/>), an online, artificial intelligence-based image recognition service, was used to extract the flowers of *R. reticulatum*. Picterra uses machine learning to create a detector of the image, which can then be used to extract the desired geographic feature from the ortho-mosaic image. A major feature of this technology is that geographic features can be detected with high accuracy from a small number of training data and can be exported as geographic information such as polygons and points. In the training area where *R. reticulatum* flowers were distributed, *R. reticulatum* flowers were traced by visual interpretation, and patch polygons were created. Training area additions were repeated several times while the detection results were monitored. The final detector was created from randomly selected six training areas of 100 m² (five with flowering individuals and one without flowering individuals) (Fig. 2), with 43 patch polygons of *R. reticulatum* flowers. The detector used was the same as that used by Niwa (2022) and was created with ortho-mosaic images from 2019. The same detector was used in other years to extract patch polygons of *R. reticulatum* flowers throughout the study area.

Separate from the training area, four 100 m × 100 m accuracy verification areas were set up (Fig. 2). Patch polygons of *R. reticulatum* flowers exported from Picterra and ortho-mosaic images from the same shooting date were overlaid in a geographic information system (GIS) at a scale of 1:100 to verify the accuracy of the extraction results. The patch polygons exported from Picterra were classified into *R. reticulatum* flower and others (i.e., false positives), and if there were undetected *R. reticulatum* flowers (i.e., false negatives), patch polygons were manually created. The area of the patch polygons was tabulated to verify the detection accuracy. This accuracy verification area was unique to this study and was the same for all five years. The GIS software used was Esri ArcGIS.

Data analysis

A 10 m × 10 m mesh polygon was created in the analysis area as a spatial unit for comparing the abundance of flowers of *R. reticulatum* in multitemporal periods. The patch polygon area of *R. reticulatum* flowers for each year was calculated for each mesh. Although the UAV was used to take photographs on days when the flowers were judged to be near full bloom, the total patch polygon area of *R. reticulatum* flowers was considered to vary from year to year due to flower richness and phenology. Therefore, the area calculated for each mesh was standardized by year. To evaluate the abundance of *R. reticulatum* flowers over time, the standardized values (Z values) for the five years were summed. To evaluate the change over time, the Z value in 2023 was subtracted from the Z value in 2019.

In the Takaragaike Forest, there is an area where a fence was installed in March 2017 to prevent deer from entering in order to protect *R. reticulatum* from deer feeding damage (Fig. 2). The area protected by the fence measures 3,453 m², of which 1,269 m² on the east side had all evergreen broadleaf trees cut down in June 2018. To verify whether the conservation effect of forest management on *R. reticulatum*

could be evaluated, we compared the mesh totals by dividing the fenced area by whether evergreen broadleaf trees had been cut or not.

In 2020, Niwa et al. applied a UAV platform to create a vegetation map of the Takaragaike Forest; this map had high accuracy and spatial resolution of community boundaries (Fig. 3). Vegetation types reflecting the increase in evergreen broadleaf trees due to vegetation succession were presented in the map. To evaluate the relationship between the increase in evergreen broadleaf trees due to vegetation succession and the abundance of *R. reticulatum* flowers, mesh totals were compared for each vegetation type.

Results

Identification of the distribution of azalea flowers

The results of extracting *R. reticulatum* flowers by image recognition were extremely accurate, with an overall accuracy of 96.9% or higher (Table 2). Precision was more than 99.8%, and the influence of false positives was thought to be negligible, since it is extremely unlikely that a flower that is not *R. reticulatum* will be recognized as an *R. reticulatum* flower. Recall was 99.0% or higher, except for in 2023, when it was very rare for a *R. reticulatum* flower not to be detected as a *R. reticulatum* flower, and the effect of undetected flowers was negligible. A lower recall occurred in 2023 because there were areas of undetected *R. reticulatum* in shaded areas.

The total area of the patch polygons of *R. reticulatum* flowers varied from year to year (Fig. 4). Therefore, it was difficult to evaluate the changes over time using absolute values of area. The area calculated for each mesh was standardized by year (Fig. 5) using the same class classification. In all years, meshes with high Z values tended to be found around the ridges, while meshes with low Z values tended to be found at the foot of the mountains. The Z values for the five years were summed (Fig. 6), and the Z values for 2023 minus the Z values for 2019 are shown in Fig. 7. Even in areas with large five-year Z value totals, there were some areas with a decreasing trend between 2019 and 2023, and others with an increasing trend.

For each vegetation type, the sum of the 5-year Z values and the 2023 Z values minus the 2019 Z values were tabulated to test for differences among vegetation types by multiple comparisons (Tukey–Kramer method) (Table 3). The total 5-year Z values were significantly larger for areas A3 and A4, smaller for areas B1 and B2, and significantly different between areas A1 and A4. The 2023 Z values minus 2019 Z values were smaller for areas A4, B1, and B2 and significantly different between areas A1 and A3.

For each of the two areas within the deer-proof fence, the sum of the 5-year Z values and the 2023 Z value minus the 2019 Z value were tabulated, and the differences between the two areas were evaluated using a t-test (Table 4). Both the sum of the 5-year Z values and the 2023 Z value minus the 2019 Z value were significantly greater in the areas where all evergreen hardwoods were cut down in 2018.

Discussion

Understanding changes in the flowering of *R. reticulatum* at multitemporal periods

By applying the method of Niwa (2022), I was able to determine the distribution of *R. reticulatum* flowers at multitemporal intervals. The accuracy of the image recognition was very high, and the results demonstrated that the method is useful for multitemporal monitoring. Machine learning and deep learning algorithms are becoming increasingly popular in vegetation identification, but the large amount of training data required and the high computational cost are problematic (de Castro et al. 2021). In this study, an online service was used to identify flowers of *R. reticulatum* in UAV images. Although this service requires a fee, image recognition can be performed with very little training data, and the data is processed in the cloud for high processing speed. As the amount of environmental information acquired by UAVs is expected to increase in the future, this research method, which does not require researcher effort or local equipment investment for image recognition, is considered to be one of the most promising options. In addition, training data from a particular location in other study sites and environments (de Castro et al. 2021) can be used in other research, which would be especially important in long-term monitoring. In this study, detectors created with the 2019 training data were applied to the other four years, showing an efficient method suitable for long-term monitoring.

The method used in this study was suitable for *R. reticulatum* because it blooms in spring before the deciduous broadleaf trees in the higher tree layer open their leaves, and its pink flowers are conspicuous. This method can be applied to other species if the following conditions are met: the flowers are not hidden by trees in the upper layers and the color of the flowers is distinctive. In addition, since *R. reticulatum* grows naturally in many secondary forests in the Kansai region of Japan (Morimoto and Yoshida 1998), this method could be widely applied in areas beyond the Takaragaike Forest.

The total area of patch polygons of *R. reticulatum* flowers varied from year to year. The reasons for this may include changes in the number of *R. reticulatum* individuals, changes in the number of flowers of individual *R. reticulatum*, and phenological discrepancies. Although it is difficult to identify the factors, the standardized Z values can be aggregated to allow comparison over time without the influence of interannual variation. The method of comparing standardized Z values using the mesh as the spatial unit may become one of the standard protocols for understanding multiperiod changes in forest indicator species.

Factors of change over time

R. reticulatum grows in light forests dominated by deciduous broadleaf trees and declines as evergreen broadleaf trees increase with vegetation succession (Morimoto and Yoshida 1998). The area where all evergreen broadleaf trees were cut down within a deer-proof fence was found to have an increased amount of *R. reticulatum* flowers in the field; both the sum of the 5-year Z values and the 2023 Z value minus the 2019 Z value were significantly greater in the area where all evergreen broadleaf trees had

been cut down. This indicated that the number of *R. reticulatum* flowers was greater and tended to increase in the areas where all evergreen broadleaf trees had been cut down. Thus, it is clear that the methods used in this study can be used to evaluate the effectiveness of forest management practices to conserve *R. reticulatum*, such as the installation of fences to prevent deer from entering the area and the felling of evergreen broad-leaved trees.

In aggregate for each vegetation type, the total 5-year Z values were significantly larger for A3 and A4, smaller for B1 and B2, and significantly different between A1 and A4. Furthermore, the 2023 Z value minus the 2019 Z value was significantly different between A1 and A3 and was smaller for A4, B1, and B2. These results indicate that A3 and A4 contain vegetation types with many *R. reticulatum* flowers, but with a declining trend, especially in A4, and that B1 and B2 have few *R. reticulatum* flowers and a declining trend. The *P. densiflora*–*R. reticulatum* community (A) has a high cover of *R. reticulatum* but also contains mixed evergreen broadleaf trees, especially A4, which has the highest evergreen broadleaf tree cover (Niwa et al. 2020). Thus, the method used in this study could detect a decreasing trend in the flowering of *R. reticulatum* caused by the increase in evergreen conifers due to vegetation succession.

Declarations

Competing interests

No, I declare that the authors have no competing interests as defined by Springer, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

Funding

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Ethical Approval

Not applicable

Author Contributions Statement

H. N. wrote the main manuscript text and prepared all figures. H. N. designed an investigation plan and conducted a field survey.

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Tables

Table 1 to 4 are available in the Supplementary Files section.

Figures

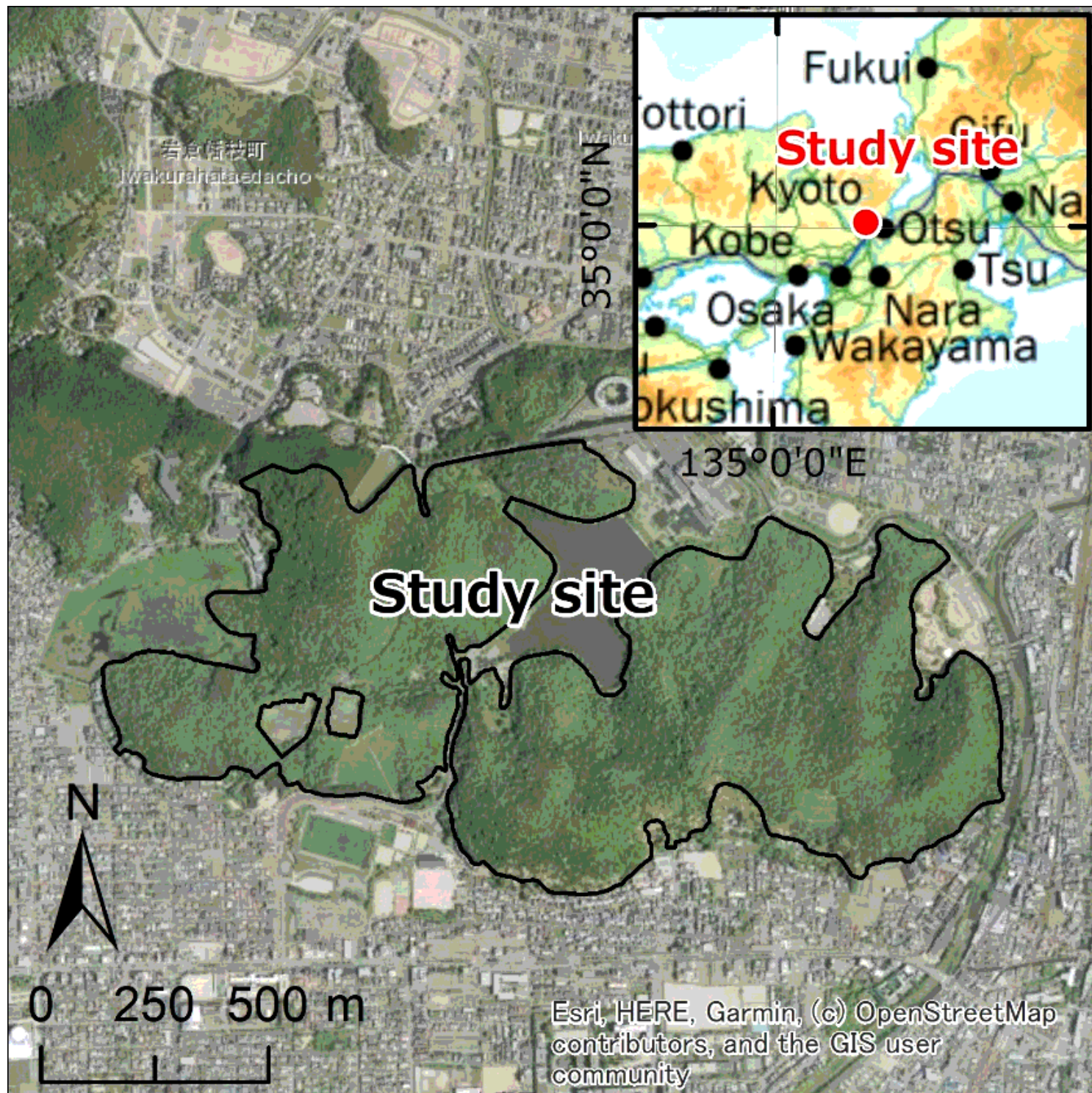


Figure 1

The study site.

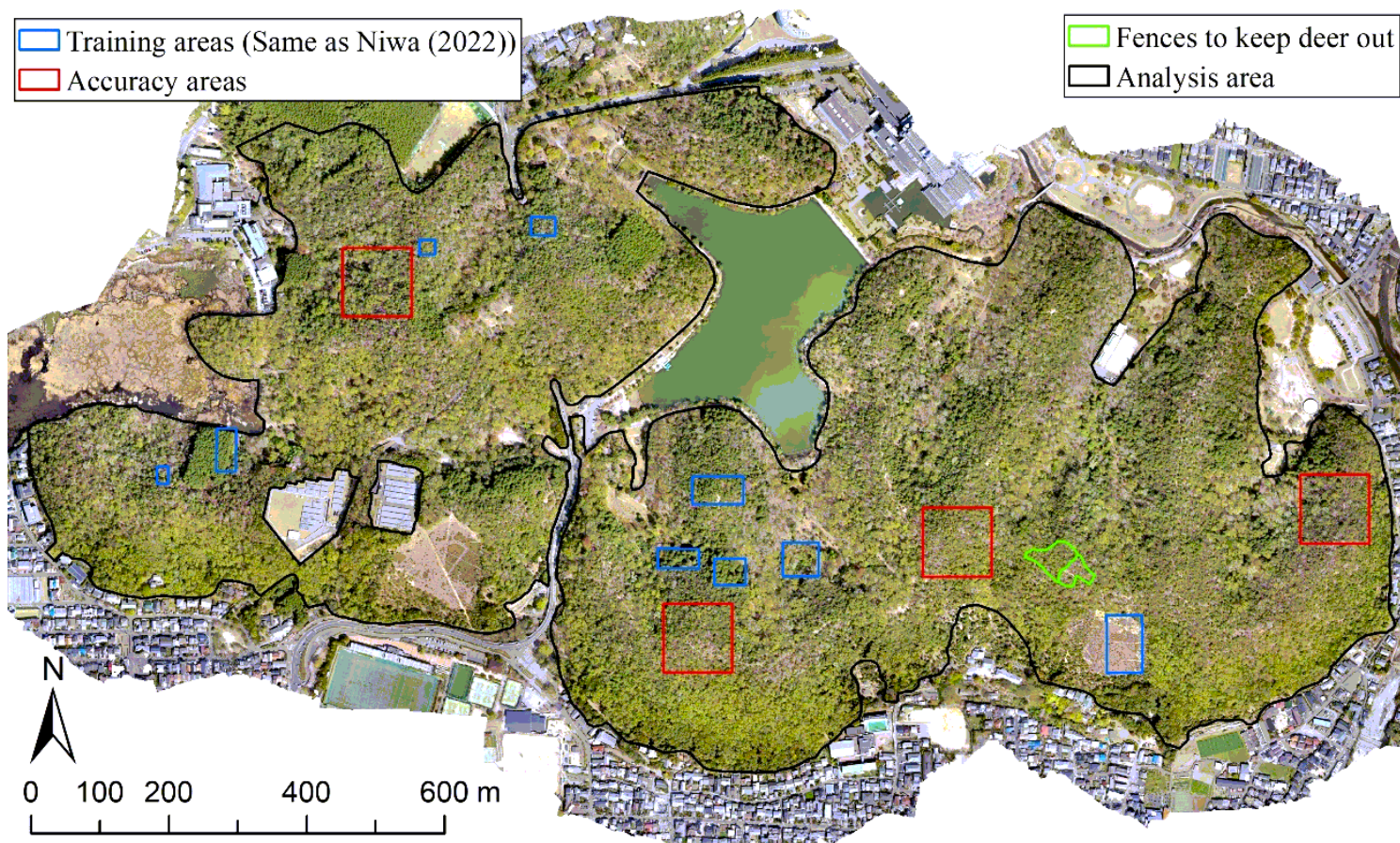


Figure 2

Training and accuracy areas in image recognition, including fences to keep deer out.



Figure 3

Vegetation map. Translated into English from Niwa et al. (2020).

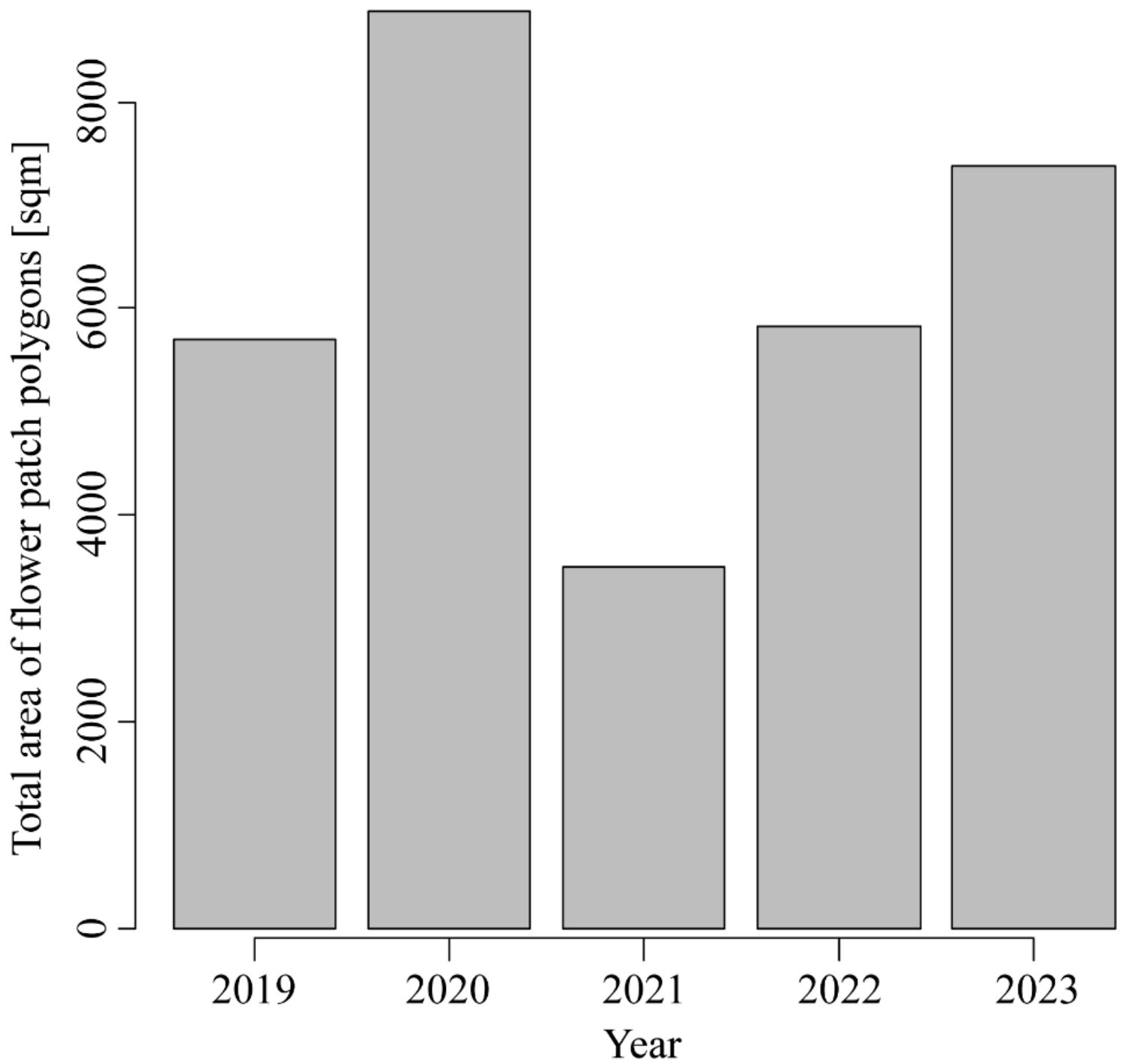


Figure 4

Vegetation map. Translated into English from Niwa et al. (2020).

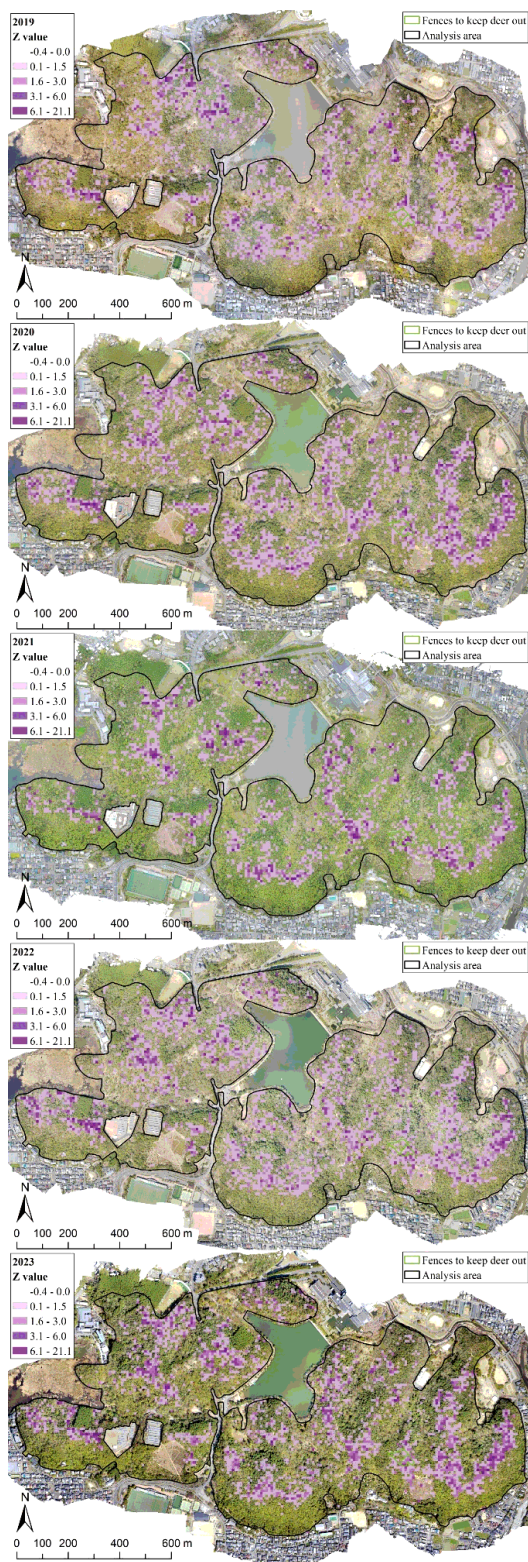


Figure 5

Patch polygon area of *Rhododendron reticulatum* flowers calculated for each mesh (10 m × 10 m) standardized by year and shown as Z values.

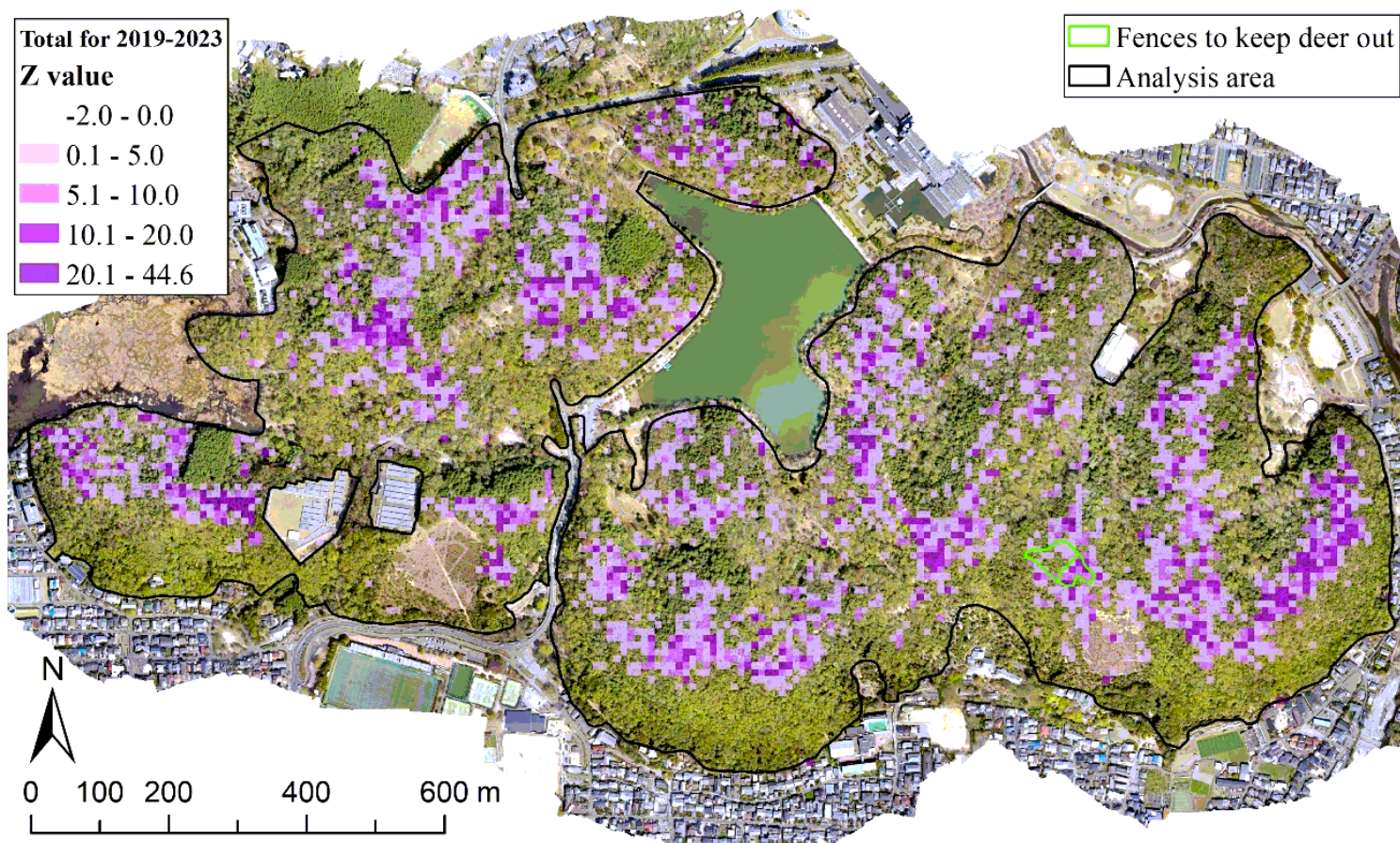


Figure 6

Total Z values from 2019 to 2023.

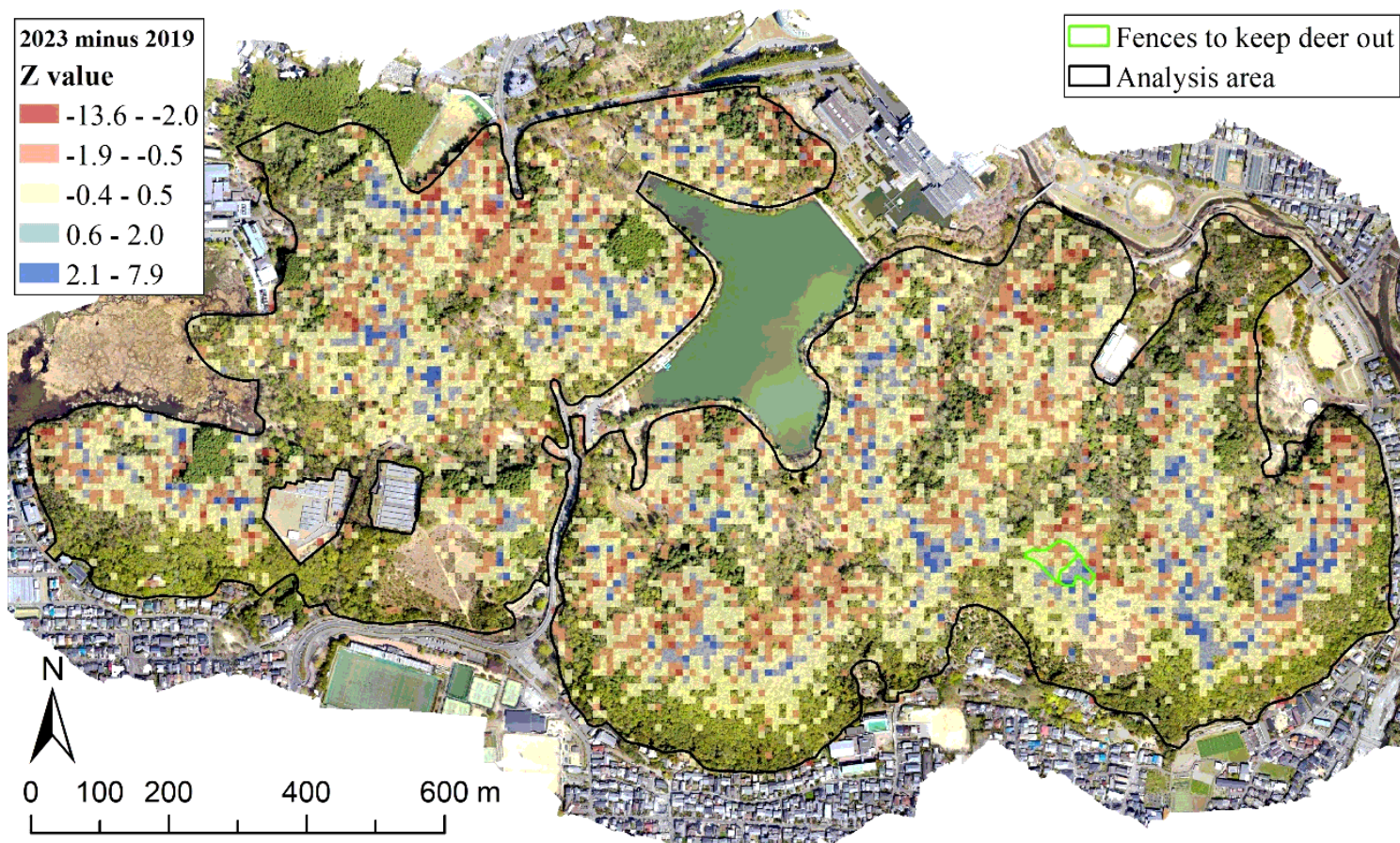


Figure 7

2023 z value minus 2019 z value

Supplementary Files

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- [Table14.docx](#)