https://doi.org/10.20965/ijat.2021.p0268

Paper:

Classification of Grass and Forb Species on Riverdike Using UAV LiDAR-Based Structural Indices

Naoko Miura[*1,†], **Tomoyo F. Koyanagi**[*2], **Susumu Yamada**[*3], **and Shigehiro Yokota**[*4]

[*1]Graduate School of Agricultural and Life Sciences, The University of Tokyo
1-1-1 Yayoi, Bunkyo-ku, Tokyo 113-8657, Japan
[†]Corresponding author, E-mail: miura@uf.a.u-tokyo.ac.jp
[*2]Field Studies Institute for Environmental Education, Tokyo Gakugei University, Koganei, Japan
[*3]Faculty of Agriculture, Tokyo University of Agriculture, Atsugi, Japan
[*4]Faculty of Environmental Studies, Tokyo City University, Yokohama, Japan

[Received October 30, 2020; accepted March 2, 2021]

Herbaceous vegetation on riverdikes plays an important role in preventing soil erosion, which, otherwise, may lead to the collapse of riverdikes and consequently, severe flooding. It is crucial for managers to keep suitable vegetation conditions, which include native grass species such as *Imperata cylindrica*, and to secure visibility of riverdikes for inspection. If managers can efficiently find where suitable grass and unsuitable forb species grow on vast riverdikes, it would help in vegetation management on riverdikes. Classification and quantification of herbaceous vegetation is a challenging task. It requires spatial resolution and accuracy high enough to recognize small, complex-shaped vegetation on riverdikes. Recent developments in unmanned aerial vehicle (UAV) technology combined with light detection and ranging (LiDAR) may offer the solution, since it can provide highly accurate, high-spatial resolution, and denser data than conventional systems. This paper aims to develop a model to classify grass and forb species using UAV LiDAR data alone. A combination of UAV LiDAR-based structural indices, V-bottom (presence of vegetation up to 50 cm from the ground) and V-middle (presence of vegetation 50–100 cm from the ground), was tested and validated in 94 plots owing to its ability to classify grass and forb species on riverdikes. The proposed method successfully classified the "upright" grass species and "falling" grass species / forb species with an accuracy of approximately 83%. Managers can efficiently prioritize the inspection areas on the riverdikes by using this method. The method is versatile and adjustable in other grassland environments.

Keywords: UAV, LiDAR, herbaceous vegetation, grass, riverdike

1. Introduction

Frequent and severe flooding has been recently reported in Japan. Riverdikes are extremely large and long river facilities that are built to protect human life and assets from flooding. River offices, which are locally set up throughout Japan by the Ministry of Land, Infrastructure, Transport and Tourism, are in charge of the management of riverdikes. Herbaceous vegetation on riverdikes plays an important role in preventing soil erosion, which can lead to the collapse of riverdikes and, consequently, severe flooding. It is crucial for managers to maintain suitable vegetation conditions, such as the native grass species *Imperata cylindrica*, and to secure the visibility of riverdikes for safety inspections. However, a recent reduction in the management budget makes this difficult and has resulted in the spread of the invasive forb species, such as *Solidago altissima*, which grow to more than 1 m in height with broad leaves and physically block the visibility of riverdikes [1]. If managers could efficiently determine the areas on vast riverdikes where suitable grass and unsuitable forb species grow, it would help simplify vegetation management on riverdikes.

Classification and quantification of herbaceous vegetation on riverdikes using remote sensing is a challenging task. It requires a spatial resolution and accuracy high enough to recognize small, complex-shaped vegetation on the steep slopes of riverdikes. Recent developments in unmanned aerial vehicle (UAV) technology may have the potential of solving this problem. Data can be acquired more frequently and flexibly using UAVs and with a higher spatial resolution (of the order of centimeters) in a cost-effective manner compared with conventional airborne data acquisition using manned aircrafts (e.g., [2]). It is also a non-destructive method for deriving plant parameters over large areas, unlike traditional destructive field measurement techniques [3].

For example, Sandino et al. [4] detected invasive grasses on arid lands using UAV RGB imagery and gradient-boosted decision trees. Buffel grass and spinifex were successfully classified, with a detection rate higher than 96%. However, the study site was flat and arid, with relatively sparse vegetation. It would be difficult to apply this method to herbaceous vegetation on riverdikes, where thick, tall, and various vegetation grows on a more complex topography. Based on a combination of structure from motion and multiview stereo techniques, passively acquired UAV imagery can generate 3D information. It has been reported that the sward height derived from UAV imagery is a promising parameter for estimating grassland biomass [5–11]. Most of these studies were conducted in a relatively flat environment, and the difficulty in application to riverdikes remains because topography affects the accuracy of determining the height from UAV imagery [12].

UAV combined with light detection and ranging (LiDAR) is another emerging technique. LiDAR is an active sensing technology that emits laser pulses and measures the distance between the sensor and the illuminated target. This technology provides 3D information regarding the target. Conventional airborne LiDAR, which uses manned aircrafts as a platform, is well documented for its utility in forestry applications (e.g., [13–17]). Use of UAV LiDAR is relatively new in airborne laser scanning. The innovative feature of this system is the acquisition of data from a relatively low flying altitude (< 100 m) with a more customized flight plan and lower cost. It provides highly accurate and denser data than the conventional system, which can be used for herbaceous vegetation analysis. Wang et al. [18] developed a model for the canopy height and fractional cover of a cattle-grazing grassland to estimate above-ground biomass using UAV discrete LiDAR (Velodyne HDL-32E). The authors pointed out that the LiDAR-derived indices are not very accurate for grassland ecosystems, but can be calibrated using field data to estimate the actual canopy height and fractional cover. In their study, the average point density was not very high (26 points/m^2), which might explain why the indices did not work very well. With a denser point cloud (460 points/m^2), Miura et al. [19, 20] utilized UAV waveform LiDAR (RIEGL VUX-1) to produce a herbaceous vegetation height map of a riverdike with a spatial (vertical and horizontal) resolution of 5 cm and revealed the vertical structure of the herbaceous vegetation using UAV LiDAR-based structural indices. The indices could be used for distinguishing between the “upright” grass species and “fallen” grass or forb species by using this process.

Therefore, in this paper, we evaluate and validate the utility of UAV LiDAR-based indices for classifying grass and forb species on riverdikes. A model is developed to classify grass and forb species and validated by comparing it with the classifications by a vegetation specialist.

2. Methods

2.1. Study Area

The study area is located in the high-water channel of the Tone River, 30 km northeast of Tokyo, Japan (**Fig. 1**). The mean annual precipitation and temperature are 1344 mm and 14.1°C, respectively, at the nearby Ryugasaki Meteorological Station. The section of the riverdike selected for the study was approximately 1 km long with a width of 40 m and a height of 7 m. The herbaceous vegetation covers both slopes of the riverdike. Tall herbaceous vegetation, such as *Imperata cylindrica* (grass species) and *Solidago altissima* (forb species), which grow to more than 1 m in height, is dominant in this area. Mowing was carried out twice a year, in mid-spring and late summer, during our study period as part of the vegetation management by the Tonegawa-Joryu River Office, Ministry of Land, Infrastructure, Transport and Tourism.

Fig. 1. Studied section of the riverdike.

Table 1. Specifications for LiDAR data acquisition.

Sensor	RIEGL VUX-1
Pulse repetition frequency	5 kHz
Scan angle	330°
Platform altitude	30 m
Flying speed	15 km/h
Overlap between courses	50%–60%
Average point density	460 points/m^2
Acquisition date	August and October 2017

2.2. UAV LiDAR Data

LiDAR data were acquired using an UAV system of Nakanihon AirService and Kohata Inc., TOKI, and it consists of a Gryphon Dynamics GD-X8-SP platform, RIEGL VUX-1 laser scanner, and Nikon Trimble AP20 GNSS/IMU system. This is a waveform system. The data of the area were collected twice, in August and October 2017, immediately before and after mowing. **Table 1** lists the specifications for laser data acquisition. Ground control points were surveyed using the RTK-GNSS network for height validation. The vertical accuracy of the acquisition was RMSE of 2.1 cm (August) and 3.4 cm (October).

2.3. Classification of Grass and Forb Species

Miura et al. [20] showed the potential of UAV LiDAR-based indices, V-bottom (presence of vegetation up to 50 cm from the ground) and V-middle (presence of vegetation 50–100 cm from the ground) in classifying grass

Fig. 2. Plots dominated by (a) forb species, (b) "fallen" grass species, and (c) "upright" grass species.

and forb species. Therefore, we used the same indices in this study for verification. This method is based on the following idea. In an herbaceous vegetation environment, when some vegetation is present in the middle vegetation layer, there should be a similar amount or more vegetation present in below layer, which is the bottom vegetation. One exception is that flowers or ears of grasses can dominate the middle layer and exceed the amount of vegetation in the bottom layer. However, we confirmed that there were no such cases in the data. In our analysis, some plots showed too few UAV LiDAR returns in the bottom vegetation layer compared with the number of returns in the middle vegetation layer. The authors found that the plots with this anomaly were dominated by the forb species (**Fig. 2(a)**) and "falling" grass species (**Fig. 2(b)**), whereas plots without this anomaly were dominated by the "upright" grass species (**Fig. 2(c)**). This suggests that, in the plots with this anomaly, the broad leaves of the forb species or the sides of leaves of the "falling" grass species physically prevent UAV LiDAR penetration into the bottom vegetation layer when they are abundantly present in the middle vegetation layer. Therefore, if V-middle is greater than V-bottom, the dominant species of the plot can be classified as a "falling" grass species or forb species. In contrast, if V-middle is the same or lower than V-bottom, the dominant species can be classified as the "upright" grass species.

In order to test this hypothesis, a circular plot with a radius of 50 cm was set up on a riverdike point cloud. A total of 94 test plots were randomly established using the ESRI's GIS software, ArcGIS (**Fig. 3**). For each plot, the UAV LiDAR-based indices, V-bottom and V-middle, were calculated in accordance with Miura et al. [20]. In this method, four types of LiDAR returns are defined. Type 1 is a singular return, which means that only one re-

Fig. 3. Randomly established 94 test plots (circular dot) on the riverdike.

turn is recorded from each emitted pulse of energy. Type 2 is the first of many returns, that is, part of the pulse of the incident energy interacts with a plant facet and is reflected back to the sensor; however, most of the energy passes through the plant and interacts with other facets along its path. Type 3 is intermediate returns, which are the subsequent interactions of the pulse described in Type 2. Type 4 is the last of many returns, which is the last pulse returned to the sensor from an incident pulse. The total number of returns, T, is expressed as

$$T = \sum_{i=1}^{4} \sum_{j=1}^{4} R_{ij}, \quad (1)$$

where R = UAV LiDAR returns, i = classified layers (1 = top vegetation, 2 = middle vegetation, 3 = bottom vegetation, and 4 = ground), and j = return types (1 = Type 1, 2 = Type 2, 3 = Type 3, and 4 = Type 4).

V-bottom comprises all return types (Types 1–4) from the bottom vegetation layer; this represents the presence of bottom vegetation.

$$V\text{-}bottom = \frac{R_{31}+R_{32}+R_{33}+R_{34}}{T} = \frac{\sum_{j=1}^{4} R_{3j}}{T} \quad . (2)$$

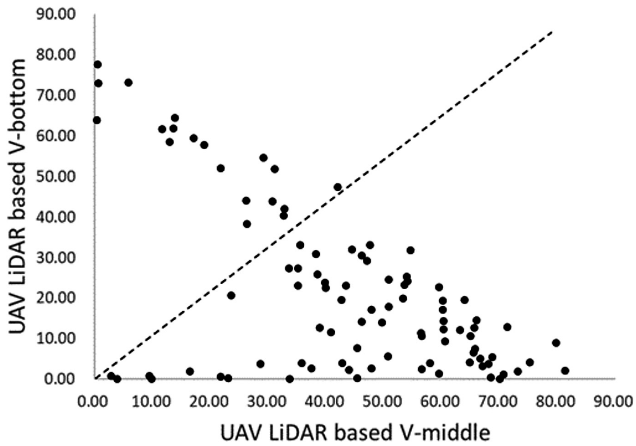

Fig. 4. Comparison between UAV LiDAR-based V-bottom and V-middle of 94 test plots. The value of the indices is expressed as a percentage.

V-middle contains all return types (Types 1–4) from the middle vegetation layer; this indicates the presence of middle vegetation.

$$V\text{-}middle = \frac{R_{21}+R_{22}+R_{23}+R_{24}}{T} = \frac{\sum_{j=1}^{4} R_{2j}}{T} \quad . \quad (3)$$

The "upright" grass species is expressed as follows:

$$\frac{V\text{-}bottom}{V\text{-}middle} \geq 1 \quad \ldots \ldots \ldots \ldots \quad (4)$$

The "fallen" grass and forb species are expressed as follows:

$$\frac{V\text{-}bottom}{V\text{-}middle} < 1 \quad \ldots \ldots \ldots \ldots \quad (5)$$

These are validated using the groundtruth data.

2.4. Groundtruth

The composition of vegetation species changes seasonally, and we could not collect the groundtruth on-site for LiDAR data acquired in 2017. As an alternative method, vegetation species in the test plots were visually classified by a vegetation specialist using orthoimage data captured by using a UAV RGB camera on the same day as the UAV LiDAR acquired in 2017.

3. Results

Figure 4 shows the results of the comparison between the LiDAR-based V-bottom and V-middle of 94 test plots. The model classified the "upright" grass species to be dominant in 19 plots and the "falling" grass species or forb species dominant in 75 plots. **Table 2** presents the confusion matrix. The true positive rate of the model is approximately 0.71 for the "upright" grass and 0.84 for the "falling" grass or forb species. The accuracy of the model is approximately 83%.

Table 2. Confusion matrix of classification for 94 test plots.

		Model classification	
		"Upright" grass	"Falling" grass/forb
Specialist	"Upright" grass	5	2
	"Falling" grass/forb	14	73

Fig. 5. Example of plots classified as creeper dominant (plot 64: creeper 90% and *Solidago altissima* 10%) by vegetation specialist using orthoimage. The area around plot 64 is shadowed, which means herbaceous vegetation is shorter than in the surroundings. Plot 31 is dominated by *Solidago altissima*.

4. Discussion

The proposed model successfully classified the "upright" grass species and "falling" grass species / forb species using UAV LiDAR data alone. Managers can efficiently prioritize the inspection areas on the riverdikes. Only 16 plots were misclassified. For 14 plots, the model misclassified the "upright" grass species as being dominant, because V-bottom was greater than V-middle. Three plots were classified as creeper (forb species) dominant by the specialist (**Fig. 5**). The specialist could not identify the vertical structure of the vegetation based on the orthoimage; however, in conjunction with the LiDAR data analysis, it is assumed that the creeper was thick in the bottom vegetation layer for these three plots. If small forb species, such as creeper, are present more in the bottom vegetation layer than in the middle vegetation layer, the model can misclassify the dominant species. A source other than LiDAR data, such as RGB and multispectral images, may be able to assist in the classification of creepers. This clearly needs further study. Other reasons for misclassification may be the orthoimage that we used to collect the groundtruth. In some plots, the image was not clear, as they were in the shadow on the slope. The specialist could have misclassified some. Because we used an orthoimage with a ground sampling distance of 2 cm for visual classification, images with a higher spatial resolution might solve this problem. However, a vegetation survey on site would be the ideal approach for gathering groundtruth.

5. Conclusion

The proposed method using a combination of UAV LiDAR-based structural indices successfully classified the "upright" grass species and "falling" grass species / forb species with high accuracy. This method is versatile and adjustable in other grassland environments. A combination with spectral imaging might improve the classification accuracy; however, this clearly needs further study.

Acknowledgements

This research was funded by JSPS KAKENHI (Grant Number 17H03958). We thank the Tonegawa-Joryu River Office, Ministry of Land, Infrastructure, Transport and Tourism for their support. We also acknowledge Yoshiko Kitagawa for her assistance during the vegetation survey.

References:

[1] S. Yamada and M. Nemoto, "Effects of Bare-Ground Revegetation Techniques Using *Imperata cylindrica* on Changes in the Plant Cover and Species Richness during Early Succession," Open J. of Ecology, Vol.6, No.8, pp. 471-483, 2016.

[2] T. Suzuki, Y. Amano, T. Hashizume, S. Suzuki, and A. Yamaba, "Generation of Large Mosaic Images for Vegetation Monitoring Using a Small Unmanned Aerial Vehicle," J. Robot. Mechatron., Vol.22, No.2, pp. 212-220, 2010.

[3] W. R. Catchpole and C. J. Wheeler, "Estimating plant biomass: A review of techniques," Australian J. of Ecology, Vol.17, Issue 2, pp. 121-131, 1992.

[4] J. Sandino, F. Gonzalez, K. Mengersen, and K. J. Gaston, "UAVs and Machine Learning Revolutionising Invasive Grass and Vegetation Surveys in Remote Arid Lands," Sensors, Vol.18, Issue 2, 605, 2018.

[5] J. Bendig, A. Bolten, S. Bennertz, J. Broscheit, S. Eichfuss, and G. Bareth, "Estimating Biomass of Barley Using Crop Surface Models (CSMs) Derived from UAV-Based RGB Imaging," Remote Sensing, Vol.6, Issue 11, pp. 10395-10412, 2014.

[6] J. Forsmoo, K. Anderson, C. J. A. Macleod, M. E. Wilkinson, and R. Brazier, "Drone based structure from motion photogrammetry captures grassland sward height variability," J. of Applied Ecology, Vol.55, Issue 6, pp. 2587-2599, 2018.

[7] E. Grüner, T. Astor, and M. Wachendorf, "Biomass Prediction of Heterogeneous Temperate Grasslands Using an SfM Approach Based on UAV Imaging," Agronomy, Vol.9, Issue 2, 54, 2019.

[8] U. Lussem, A. Bolten, J. Menne, M. L. Gnyp, J. Schellberg, and G. Bareth, "Estimating biomass in temperate grassland with high resolution canopy surface models from UAV-based RGB images and vegetation indices," J. of Applied Remote Sensing, Vol.13, Issue 3, 034525, 2019.

[9] H. Zhang, Y. Sun, L. Chang, Y. Qin, J. Chen, Y. Qin, J. Du, S. Yi, and Y. Wang, "Estimation of Grassland Canopy Height and Aboveground Biomass at the Quadrat Scale Using Unmanned Aerial Vehicle," Remote Sensing, Vol.10, 851, 2018.

[10] N. Viljanen, E. Honkavaara, R. Nasi, T. Hakala, O. Niemelainen, and J. Kaivosoja, "A Novel Machine Learning Method for Estimating Biomass of Grass Swards Using a Photogrammetric Canopy Height Model, Images and Vegetation Indices Captured by a Drone," Agriculture-Basel, Vol.8, Issue 5, 70, 2018.

[11] R. Nasi, N. Viljanen, J. Kaivosoja, K. Alhonoja, T. Hakala, L. Markelin, and E. Honkavaara, "Estimating Biomass and Nitrogen Amount of Barley and Grass Using UAV and Aircraft Based Spectral and Photogrammetric 3D Features," Remote Sensing, Vol.10, Issue 7, 1082, 2018.

[12] N. Miura, S. Yamada, and Y. Niwa, "Estimation of canopy height and biomass of *Miscanthus sinensis* in semi-natural grassland using time-series UAV data," ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., Vol.V-3-2020, pp. 497-503, 2020.

[13] J. Hyyppä, H. Hyyppä, D. Leckie, F. Gougeon, X. Yu, and M. Maltamo, "Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests," Int. J. of Remote Sensing, Vol.29, Issue 5, pp. 1339-1366, 2008.

[14] M. Maltamo, P. Packalen, X. Yu, K. Eerikainen, J. Hyyppa, and J. Pitkanen, "Identifying and quantifying structural characteristics of heterogeneous boreal forests using laser scanner data," Forest Ecology and Management, Vol.216, Issues 1-3, pp. 41-50, 2005.

[15] E. Naesset and R. Nelson, "Using airborne laser scanning to monitor tree migration in the boreal-alpine transition zone," Remote Sensing of Environment, Vol.110, Issue 3, pp. 357-369, 2007.

[16] F. Morsdorf, C. Nichol, T. Malthus, and I. H. Woodhouse, "Assessing forest structural and physiological information content of multi-spectral LiDAR waveforms by radiative transfer modelling," Remote Sensing of Environment, Vol.113, Issue 10, pp. 2152-2163, 2009.

[17] S. Solberg, A. Brunner, K. H. Hanssen, H. Lange, E. Naesset, M. Rautiainen, and P. Stenberg, "Mapping LAI in a Norway spruce forest using airborne laser scanning," Remote Sensing of Environment, Vol.113, Issue 11, pp. 2317-2327, 2009.

[18] D. Wang, X. Xin, Q. Shao, M. Brolly, Z. Zhu, and J. Chen, "Modeling Aboveground Biomass in Hulunber Grassland Ecosystem by Using Unmanned Aerial Vehicle Discrete Lidar," Sensors, Vol.17, Issue 1, 180, 2017.

[19] N. Miura, S. Yokota, Y. F. Koyanagi, and S. Yamada, "Herbaceous vegetation height map on riverdike from UAV LiDAR data," Proc. of the 2018 IEEE Int. Geoscience and Remote Sensing Symp. (IGARSS 2018), pp. 5469-5472, 2018.

[20] N. Miura, T. F. Koyanagi, S. Yokota, and S. Yamada, "Can UAV LiDAR derive vertical structure of herbaceous vegetation on riverdike?," ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., Vol.IV-2/W5, pp. 127-132, 2019.

Name:
Naoko Miura

Affiliation:
Assistant Professor, Graduate School of Agricultural and Life Sciences, The University of Tokyo

Address:
1-1-1 Yayoi, Bunkyo-ku, Tokyo 113-8657, Japan

Brief Biographical History:
2011- Graduate School of Agricultural and Life Sciences, The University of Tokyo

Main Works:
- N. Miura and Y. Asano, "Effective Acquisition Protocol of Terrestrial Laser Scanning for Underwater Topography in a Steep Mountain Channel," River Research and Applications, Vol.32, No.7, pp. 1621-1631, 2016.

Membership in Academic Societies:
- Japan Society for Precision Engineering (JSPE), Technical Committee on 3D Scanning, Recognition, and Modeling of Large Scale Environments

Name:
Tomoyo F. Koyanagi

Affiliation:
Associate Professor, Tokyo Gakugei University

Address:
4-1-1 Nukuikitamachi, Koganei, Tokyo 184-8501, Japan

Brief Biographical History:
2010-2012 National Institute for Agro-Environmental Sciences
2012-2014 Waseda University
2014- Field Studies Institute for Environmental Education, Tokyo Gakugei University

Main Works:
• "Impacts of previous maintenance of river embankments on the grassland communities by changing soil," Ecological Engineering, Vol.131, pp. 73-80, 2019.

Membership in Academic Societies:
• Ecological Society of Japan (ESJ)
• Japanese Institute of Landscape Architecture (JILA)
• Japanese Society for Environmental Education (JSFEE)

Name:
Susumu Yamada

Affiliation:
Associate Professor, Faculty of Agriculture, Tokyo University of Agriculture

Address:
1737 Funako, Atsugi, Kanagawa 243-0034, Japan

Brief Biographical History:
2008-2017 The University of Tokyo
2018- Tokyo University of Agriculture

Main Works:
• S. Yamada, M. Nemoto, and T. Okuro, "Season and plant life history stage in revegetation influence competition of foundation species, subordinate species, and weeds in a reclaimed grassland," Ecological Engineering, Vol.162, 2021.

Membership in Academic Societies:
• Japan Institute of Landscape Architecture (JILA)
• Ecological Society of Japan (ESJ)
• Japanese Society of Revegetation Technology (JSRT)

Name:
Shigehiro Yokota

Affiliation:
Associate Professor, Faculty of Environmental Studies, Tokyo City University

Address:
3-3-1 Ushikubo-Nishi, Tsuzuki-ku, Yokohama, Kanagawa 224-8551, Japan

Brief Biographical History:
2001-2015 Shimizu Institute of Technology, Shimizu Corp.
2015- Tokyo City University

Main Works:
• "Land Use Transition and Possibility of Climate Change Adaptation by Rice Farmers around the Industrial Estate in Bangkok's Urban Fringe," Urban and Regional Planning Review, Vol.7, pp. 22-42, 2020.

Membership in Academic Societies:
• City Planning Institute of Japan (CPIJ)
• Japan Institute of Landscape Architecture (JILA)
• Center for Environmental Information Science (CEIS)