Investigation of the potential of drone observations for detection of forest disturbance caused by heavy snow damage in a Japanese cedar (Cryptomeria japonica) forest

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Abstract

Forest disturbance by heavy snow seriously affects ecosystem functions and provision of ecosystem services. To evaluate the spatial distribution of this disturbance over large areas, it is necessary to develop a flexible, inexpensive, and generalizable method based on remote sensing. Here, we examined the ability of an unmanned drone to detect the disturbance caused by heavy snow in a Japanese cedar (Cryptomeria japonica) forest, which is a typical landscape species in Japan’s mountainous areas. We obtained aerial photographs in late October 2016 using the drone in a research plot where many individuals were damaged by moist, heavy snow in mid-December 2014. The forest disturbance rate was estimated by visually inspecting the structure from motion (SfM) point clouds generated from the drone’s aerial photographs. We detected 90 to 96% of healthy individuals, but many tilted trees and trees with broken stems but an intact canopy were misidentified as healthy individuals. The estimated forest disturbance rate (33%) obtained from the SfM point clouds coincided well with the actual forest disturbance rate (35%) obtained from tree surveys. Consequently, this approach can potentially be used to detect narrow and patchy disturbances in Japanese cedar forest, although further observations at multiple points will be required to develop the accuracy of this approach.

Key words: Drone, Forest disturbance, Japanese cedar, Photogrammetry, Snow damage

1. Introduction

Extreme meteorological events such as concentrated heavy rainfall, typhoons, and heavy snowfall threaten forest ecosystems, particularly in the mountainous areas that account for about 70% of Japan’s total land area. Heavy snowfall can become a severe natural disaster because it damages many trees, thereby causing immense cumulative damage. In Japan, many forest disturbances caused by snow damage have been reported, especially in Japanese cedar (Cryptomeria japonica) forests, which account for 18% of the total forest area in Japan (Suzuki et al., 2009). These disturbances result from breakage of the main stem, with or without loss of the canopy, and from tilting of the stem. Forest disturbance caused by snow damage affects the ecosystem functions and services they provide, such as tree productivity, carbon sequestration, evapotranspiration, water storage, provision of downstream flows of water, and preservation of river water quality in a river basin. In addition, recent supercomputer simulations predicted that even though the amount of snowfall will decrease throughout most of Japan as a result of ongoing climate change, the frequency of heavy snowfall will increase, especially in mountainous areas in central Japan (Kawase et al., 2016).

The development of flexible, inexpensive, and generalizable methods for assessing these impacts is, therefore, expected to support evaluations of the spatial distribution of forest disturbance caused by snow damage in Japanese forests. To support this goal, close-range remote-sensing is a promising tool, particularly at locations where access is difficult. Recently, researchers have investigated the potential of drone-based observations, since drones are less expensive than other types of aircraft, and preliminary results have shown their potential to accurately observe forest structures (Tang and Shao, 2015), gaps in the forest (Getzin et al., 2014), and biodiversity (Getzin et al., 2012). In particular, observation using a small drone equipped with a GPS-based autopilot flight system and digital camera would be a flexible, inexpensive, and generalizable method. For instance, Lisin et al. (2015) were able to distinguish among tree species by analyzing phenological images taken by an unmanned aerial system. In addition, the damage caused by a bark beetle in Norway spruce stands was evaluated by analyzing hyperspectral and digital camera images from drone-mounted sensors (Näsi et al., 2015).

One of the characteristics of forest disturbance caused by snow damage is that the damage happens in relatively narrow patches, in contrast with the larger and wider damaged areas caused by landslides and earthquakes. Although large and expensive drones have been used successfully for mapping and surveillance (e.g., for military purposes), and although techniques for processing
the data obtained by such drones have advanced greatly, such an approach is too expensive for most researchers and forest managers. Remote sensing using small drones equipped with GPS navigation and a digital camera might allow affordable and flexible detection of such narrow disturbance patches. In particular, structure from motion (SfM) photogrammetry using data obtained from drone observations would allow evaluation of the structural characteristics of the forest canopy from three-dimensional images such as tree height (Guerra-Hernández et al., 2016; Wallace et al., 2016; Panagiotidis et al., 2017), crown diameter (Guerra-Hernández et al., 2016; Panagiotidis et al., 2017), and individual trees (Mohan et al., 2017).

The purpose of the present study was to clarify the possible usability of observations obtained from a small drone equipped with a GPS autopilot flight system and a digital camera to detect forest disturbance caused by heavy snow. To achieve this aim, we conducted drone observations in a long-term ecological research plot in a Japanese cedar forest in Japan, in which heavy forest disturbance was caused by snow damage in mid-December 2014. We then estimated the forest disturbance rate by visually inspecting individual trees using SfM photogrammetry obtained from the drone observations, and compared this rate with the actual rate determined by means of a tree census.

2. Materials and Methods

2.1 Study site

Our study was conducted at a Japanese cedar plantation in Takayama, Gifu Prefecture, central Japan (36°08′24″N, 137°22′15″E; 800 m a.s.l.). This site belongs to the AsiaFlux network (http://asiaflux.net) and the JaLTER network (http://www.jalter.org/). The topography includes horizontal plateaus and steep south-facing slopes. The forest canopy was mostly closed (Fig. 1a). The tree density was 1153 trees ha⁻¹ in this study plot. The height of the forest canopy was 20 to 25 m. The mean diameter at breast height (DBH) was 32 cm (June 2014). In this study forest, many individuals were damaged by moist, heavy snow that covered the forest canopy in mid-December 2014. Many stems and branches were broken, and many stems developed a large degree of lean (tilt) under the weight of the snow.

2.2 Tree census

We established a 0.15-ha permanent sample plot (30 m × 50 m) in the middle of a south-facing slope in November 2004. The plot was divided into 15 subplots (each 10 m × 10 m). The DBH of each tree was measured before 14 June 2014 and after 12 May 2015 the snow damage; thus, all changes in the trees could be attributed to the snow damage. We measured all living individuals greater than 5 cm in DBH. In addition, before and after the snow damage, we visually confirmed the condition of each individual. We divided the trees into six condition categories to let us identify possible sources of error in our classification of the cause of disturbance: healthy tree (no visible signs of damage), broken stem (but canopy still intact), broken stem (with no canopy), tilted tree, uprooted (fallen) tree, and dead standing tree.

2.3 Photographs obtained by the drone-mounted camera

We photographed the canopy surface at 1-second intervals using an ILCE-6000 α6000 digital camera (Sony, Tokyo, Japan) mounted on the six-blade model of the SPIDER drone (Luce Search, Hiroshima, Japan; http://luce-s.net/services/spider/overview) on

Fig. 1. (a) Orthoimage created from the structure from motion (SfM) point clouds. The dashed white line shows the boundary of the sample plot. The numbers and arrows represent the location and direction, respectively, of the in situ photographs in (b). (b) In situ photographs taken on 11 June 2015.
21 October 2016. It was a cloudy but windless day. The overlaps of the photographs were more than 90% in the direction of flight and 60% to the sides. The digital camera was mounted on a gimbal for stabilization. Table 1 summarizes the digital camera’s specifications. We set the flight route by using the control software on a laptop computer. The drone flew automatically at about 2 m s\(^{-1}\) along this route at 140 m above the ground using GPS information to control its path. Table 2 summarizes the photographic conditions. The landing pad was located about 200 m from the 0.15-ha plot.

**Table 1.** Summary of the digital camera’s specifications.

| Property       | Description                        |
|----------------|------------------------------------|
| Camera model   | ILCE-6000                          |
| Lens           | Fixed-focus 35-mm lens             |
| Sensor size    | 23.5 mm × 15.6 mm                  |
| Resolution     | 6000 pixel × 4000 pixel            |
| Pixel size     | 4.04 μm × 4.04 μm                  |

**Table 2.** Summary of photographic conditions.

| Conditions   | Description                      |
|--------------|----------------------------------|
| Weather      | Overcast sky, windless           |
| f-value      | 6.3                              |
| Shutter speed| 1/250 s or 1/500 s               |
| Film speed   | ISO640 equivalent                |
| Exposure     | Auto                             |
| White balance| Auto                             |

2.4 Structure from motion (SfM) analysis and visual inspection

Structure from motion (SfM) point clouds and orthophotographs were obtained from 462 images using version 1.2.6 of the Photoscan Professional software (http://www.agisoft.com/). The SfM point clouds and orthophotographs covered about 5 ha (about 340 m × 140 m), including the 0.15-ha plot. We identified individual trees in the 0.15-ha plot by visual inspection using a screenshot of the nadir-view SfM point clouds displayed in version 1.3.3 of the MeshLab software (http://www.meshlab.net/; Fig. 2) and the original aerial photographs. To reduce the uncertainty of visual inspection, three investigators (i.e., three of the authors) identified individual trees. Here, we defined detected individuals as healthy individuals. One of the investigators also performed a ground survey to determine the relationship between the SfM point clouds and standing trees in the eastern part of the plot on 12 and 17 April 2017.

2.5 Estimation of the forest disturbance rate

For the 0.15-ha permanent plot and each subplot, we defined the actual rate of forest disturbance obtained from the ground survey of trees (\(D_{\text{actual}}\)) and the estimated rate of forest disturbance obtained from drone observations (\(D_{\text{drone}}\)) as follows:

\[
D_{\text{actual}} = 1 - \left( \frac{N_{H_{\text{2014}}} / N_{H_{\text{2015}}}}{100} \right) \times 100\% (1)
\]

\[
D_{\text{drone}} = 1 - \left( \frac{N_{H_{\text{drone}}}}{N_{H_{\text{2015}}}} \right) \times 100\% (2)
\]

where \(N_{H_{\text{2014}}}\), \(N_{H_{\text{2015}}}\), and \(N_{H_{\text{drone}}}\) indicate the number of healthy individuals obtained from a tree survey before the snow damage (14 June 2014), the number of healthy individuals obtained from a tree survey after the snow damage (12 May 2015), and the number of healthy individuals obtained from visual inspection using the SfM point clouds, respectively. We averaged three \(D_{\text{drone}}\) values (one for each of the three investigators who identified healthy trees) to provide a comparison with the single value of \(D_{\text{actual}}\).

3. Results

3.1 Forest disturbance

We counted 152 individuals in the 0.15-ha plot both before (14 June 2014) and after (12 May 2015) the snow damage. Of these, 150 were healthy individuals and 2 were dead standing trees on 14 June 2014. In contrast, on 12 May 2015, after the snow damage, 97 (65%) were healthy, 8 (5%) had a broken stem (but with the canopy still intact), 20 (13%) had a broken stem (with no canopy), 5 (3%) were uprooted (fallen), and 2 (1%) were dead standing trees. As a result, \(D_{\text{actual}}\) in the 0.15-ha plot was 35%. \(D_{\text{actual}}\) in each subplot ranged from 0% to 100%. Subplots with \(D_{\text{actual}} < 23\%\) were located in the western part of the permanent plot, which was a horizontal plateau (Fig. 3). In contrast, subplots with \(D_{\text{actual}} > 59\%\) were mainly located in the eastern part of the plot, which contained steep south-facing slopes.

3.2 Structure from motion (SfM) point clouds

We manually detected an average of 101 healthy individuals (98, 103, and 101 individuals detected by the three investigators) in the permanent plot from the SfM point clouds (Fig. 3). These included 87 to 93 healthy trees, 5 to 7 trees with a broken stem (but with the canopy still intact), and 3 to 4 tilted trees. Only 4 to 10% of the healthy individuals were not detected, whereas most of the trees with a broken stem (but with the canopy still intact) and most of the tilted trees were misidentified as healthy trees during visual inspection of the SfM point clouds. In the permanent plot, \(D_{\text{drone}} (33\%)\) coincided well with \(D_{\text{actual}} (35\%)\). However, clear differences between \(D_{\text{drone}}\) and \(D_{\text{actual}}\) occurred in subplots 12, 14, and 15, which included many broken stems with the canopy still intact and many tilted trees (Fig. 4). We summarized the relationship between the number of individuals with six...
4. Discussion

The forest disturbance rate estimated from the visual observation from 3D point clouds coincided well with the actual rate obtained from a tree survey, though overestimation and underestimation occurred in some subplots. The estimation errors in the drone observations were caused by failing to detect some healthy individuals and by incorrectly classifying trees with a broken stem but with the canopy still intact or trees with a tilt as healthy individuals. The average height and DBH of the 6 healthy individuals (the average of 4 to 10 individuals per

**Fig. 3.** Summary of the tree census results. T and S indicate a tower and shed, respectively, that have been installed to support field observations.

**Table 3.** Summary of the number of individuals with six condition categories obtained from a tree survey and the number of individuals obtained from drone observations.

| Condition categories                                      | Tree survey | Drone |
|------------------------------------------------------------|-------------|-------|
| Healthy tree                                               | 97          | 87–93 |
| Broken stem tree (but canopy still intact)                  | 8           | 5–7   |
| Broken stem tree (with no canopy)                          | 20          | 0     |
| Tilted tree                                                | 5           | 3–4   |
| Uprooted tree                                              | 20          | 0     |
| Dead standing tree                                         | 2           | 0     |
| Total                                                      | 152         | 98–103|

condition categories obtained from a tree survey and the number of individuals obtained from drone observations in Table 3.

**Fig. 4.** Relationship between the forest disturbance rate based on drone observations ($D_{\text{drone}}$) and the rate based on a tree survey in the field ($D_{\text{actual}}$). The thick black line and thin black line indicate the linear regression line and a line with a slope of 1, respectively. Vertical range bars indicate the maximum and minimum values detected by the three investigators. The numbers in the white circles indicate the subplot location IDs shown at the top of the graph.
investigator) that were not detected (18.2 m in 2005 and 27.7 cm in 2014, respectively) were shorter and smaller than those of the 91 healthy individuals (the average of 87 to 93 individuals per investigator) that were detected (21.3 m in 2005 and 33.4 cm in 2014, respectively); thus, the SfM point clouds may fail to display some shorter and smaller but healthy individuals. On the other hand, broken stems with a nearly intact canopy and trees with a tilt may have large enough canopies that visual inspection incorrectly classifies them as healthy individuals.

The limitations and accuracy of our approach would also depend on the spatial distribution of species and the canopy’s structural characteristics. The single species (which can be simulated as a pyramid) and the homogeneous canopy structure in the Japanese cedar stand that we studied facilitated generation of the SfM point clouds and orthophotographs within the 0.15-ha plot. Shadows created by the tree crowns helped to visually distinguish individual Japanese cedar. Although we could visually distinguish individuals of Japanese cedar from those of Japanese cypress (Chamaecyparis obtusa) located adjacent to the sample plot (on the right side of Fig. 1a), it was difficult to distinguish individuals of Japanese cypress from each other. One of the main reasons might be that the cypress tree crowns were less clearly bounded than those of Japanese cedar. This suggests that it may be difficult to distinguish individual trees that lack distinctive structural characteristics by examining SfM point clouds.

Observation of stands by using a three-dimensional laser scanner can reveal the spatial characteristics of a forest’s structure (Wallace et al., 2016; White et al., 2016) and the forest biomass (Ota et al., 2015). A recently developed laser scanner mounted on a drone (VUX-1UAV, RIEGL, Horn, Austria) can detect details of the structural characteristics of individuals such as the differences among healthy trees, trees with a broken stem but a nearly intact canopy, and trees with a tilt. However, use of the aircraft-mounted scanner is currently limited by its high cost.

The present results suggest that observations obtained by using a small drone with a GPS-based autopilot flight system and a digital camera has high potential for detecting forest disturbance (rates of 33% using the drone versus 35% in the field survey), but the method could be improved by more accurate detection of the structural characteristics of snow-damaged trees, such as the presence of a broken stem with a nearly intact canopy, of tilted trees, and of uprooted (fallen) trees. On the other hand, it allows inexpensive detection of the approximate condition of relatively narrow and patchy forest disturbances in Japanese cedar, and in other species with similar characteristics. If the accuracy of the estimated forest disturbance rate can be confirmed in further observations at multiple points and with different species, this data will be available as basic data for ecosystem process and dynamic vegetation models that can be used to reproduce forest carbon, water, nitrogen, and heat cycles.

Acknowledgments

We thank H. Miyama (Chiba Skytech) for operating the drone. The present study was conducted with funding from a Joint Usage/Research Grant from the River Basin Research Center (2016-F-0011, Gifu University. TMS thanks Prof. Koh Yasue (Shinshu University) and his students for their assistance in the ecological field observations. We thank the journal’s editor and two anonymous reviewers for their kind and constructive comments.

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