Forest Damage Detection Using High Resolution Remotely Sensed Data

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Abstract: Abandoned forests are increasing in Japan. In abandoned forest, falling and withering of trees may occur easily. Increase of these damaging of forests are troubling the forest administrators who have to keep identifying these damaged areas. However, identification is now implemented by means of direct ground surveying, which is difficult to grasp the damaged areas in the wide forest. Therefore, high spatial resolution remotely sensed imagery and digital surface models (DSM) are anticipated as a cutting-edge solution for supporting the field of forestry. In this study, we develop a forest damage detection method using high resolution remotely sensed imagery and DSM. Multinomial logit model is introduced for classifying the fallen areas and withered tree areas. The logit model is a simple statistical technique that is designed to analyze categorical data. Multinomial logit model can classify multiple categories (more than 3 categories). Explaining variables are (1) Gap areas extracted by DSM and (2) Spectral radiances of remotely sensed imagery. Dependent variables are no damage and damaged area (i.e. fallen area and withered tree area). Forest of Gifu prefecture is chosen as the test site, where a number of forest damages caused by deep snow and Pine beetle are observed every year. IKONOS imagery and LiDAR DSM are used for evaluation. It is confirmed that the multinomial logit model generates higher accuracies for 3 categories. Moreover not only large but also scattered damaged areas are detected.

Keywords: Remotely Sensed Imagery, Digital Surface Model, Forest Damage, Multinomial Logit Model, High Resolution Data

1. Introduction

Conventionally, Japanese forest has been managed precisely by administrations using forest inventory data and Forest Geographic Information System. Forest damage surveying kept as an important work for forest administrators to keep the forest inventory up to date. However, the conventional survey method was field survey, which is time consuming to identify scattered damaged areas of the whole administrating areas. In addition, the change of the circumstances surrounding the forestry (e.g. decrease of working population, increase of imported wood) in Japan is causing degradation in value of lumbers and devastation of forest. Still there is an important role for the forest, and record keeping of its condition is inevitable. Hence, an effective survey method is urged in the field of forestry. Especially, forest administrators are requiring for objective forest damage detecting method which can be adapted equally to large forest areas.

Various forest damage types can be categorized into fallen damage and withered damage. Fallen damage is mostly caused by snow and windstorm. Especially, snow damage is observed in non-thinning forest. Withered damage is caused by disease and harmful insects (e.g. pine beetle has revealed as a reason of mass mortality of oak trees). Later survey and action, and abandoned forest make forest areas to be easily damaged.

High resolution remotely sensed data (obtained by either satellite or aircrafts) and Digital Surface Model (DSM) generated from LiDAR has adequate resolution for detecting forest damage areas. These data are expected to have potential for supporting effective fallen and withered areas detection. There are many forests remote sensing studies using medium resolution remotely sensed data [1] [2]. Recently, studies focusing on the forest damage detection using high resolution remotely sensed data [3] are increasing. However these study's methods are site specific methods. Hence based on the assumption that administrators detect forest damaged areas, the generated method which can objectively detect categorized damage on training data must be developed.

The method developed in this study aims to detect the forest damage from both fallen and withered damages by utilizing high resolution remotely sensed imagery and DSM.

2. Method

2.1 Effectiveness of data combination

Detection based on single data (i.e. remotely sensed image or DSM) has a difficulty in classifying the fallen areas from withered areas. Remotely sensed imagery is capable of dividing land cover into forest class and non-forest class. But the various reflective properties of non-forest class make the further classification difficult. On the other hand, DSM directly represents the shape of the target, which can draw distinctions between areas of Non-fallen tree with areas of fallen trees. Nonetheless withered areas cannot be determined definitely because of the lack of land cover information.

Combining these data can complement the lack of information needed for forest damage detection. Withered areas can be detected from remotely sensed data after Non-fallen area (tree canopy) is detected by DSM. Thus, combining different types of data can improve the robustness of the detection method for forest damages.

2.2 Multinomial Logit Model

Forest damage detection (fallen, withered and no damage) conforms to a discrete category choice. In this study, the discrete choice model, which is a statistical model for discrete data analysis, is applied. The advantage of the discrete choice model is in its capability of combining continuous data and categorical data as explaining variables.

Effectiveness of applying the discrete choice model to remotely sensed imagery is suggested by [4]. The study of [4] showed that the logit model, which is one of the simplest discrete choice models, could be effectively applied to Landsat Thematic Mapper for landcover classification / landcover change. In this study, multinomial logit model is applied to classify multiple categories (more than 3 categories) to detect fallen, withered and no damaged areas because the logit model is simple and easy to apply. The category which has highest utility (U) calculated from observed data is applied to each pixel during the processing. The logit model estimates probability $P(y_{in})$ between 1 and 0. Dependent variables of pixel N can take three categories, which are non damaged area ($Y_{in}=0$), fallen area ($Y_{in}=1$), and withered area ($Y_{in}=2$). The each category's utility (U_0, U_1, U_2) is defined as [eq. (1)]

$$U_{in} = \beta_1 x_{1in} + \beta_2 x_{2in} + \Lambda + \beta_k x_{kin} + \varepsilon_{in} \tag{1}$$

where $x_{1in} \Lambda\ x_{kin}$ = observed variables that represents a pixel value; in = categories (i.e.0,1,2); and $\beta_1 \Lambda\ \beta_K$ = estimated parameters. [eq. (1)] is divided into fixed term (V_{in}) which can be observed and error term (E_{in}) that is oscillating probability. Error term (E_{in}) represents the distribution of unobservable factor. The distribution of the error term is represented by gumbel distribution which resembles normal probability distribution. These utility function parameters are estimated individually for each category. Each probability (P) to select the category is defined as [eq. (2)]

$$P(y_{in}) = \frac{e^{U_{in}}}{e^{U_0} + e^{U_1} + e^{U_2}} \tag{2}$$

where $e^{U_0} = 1$. Each pixel is classified into the category that possesses the highest probability. Parameters are estimated by Maximum Likelihood Estimation. Accuracy of the estimated model can be evaluated by several ways, which are (1) Wald statistics as interpretable parameters, (2) accuracy assessment by training data. Both tests were applied to the model.

2.3 Detection flow

Figure.1 shows the forest damage detection flow of the method. In the first step, correction of remotely sensed imagery and gap extraction using DSM are implemented. Correction of remotely sensed imagery includes both geometric and radiometric correction. The gap extraction method, which was developed by [5], is applied in this study. In this gap extraction method, gap areas are extracted based on certain threshold (i.e. DSM - DEM ≦ 3m [5]). In the second step, training data for multinomial logit model was settled by interpreting the damaged areas manually. Training data must contain both non damaged areas and damaged areas. The multinomial logit model is estimated from the training data. After the evaluation of the model, it is applied to the whole image. Finally, a forest damaged map is generated.

3. Evaluations

3.1 Test site and materials

In this section, a result of the forest damage detection method is evaluated. The test site “Minami” is situated in center of Gifu Prefecture, Japan (Figure 2). The site experienced a record snowfall in January 2002 which caused serious forest damages by weight of snow. There are still withered areas existing in the site. IKONOS multispectral imagery (spatial resolution: 4m), DSM and DEM generated from LiDAR data are used in the processing. IKONOS imagery was taken on May 2003; LiDAR data (footprint: 2.5m) was taken in early summer of 2004.

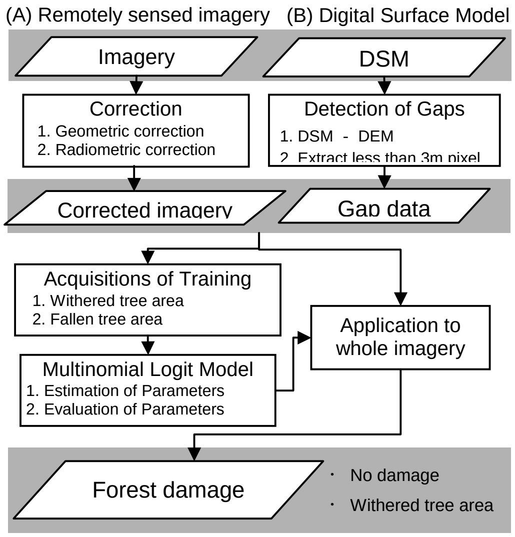

Figure 1. Flow of forest damage detection.

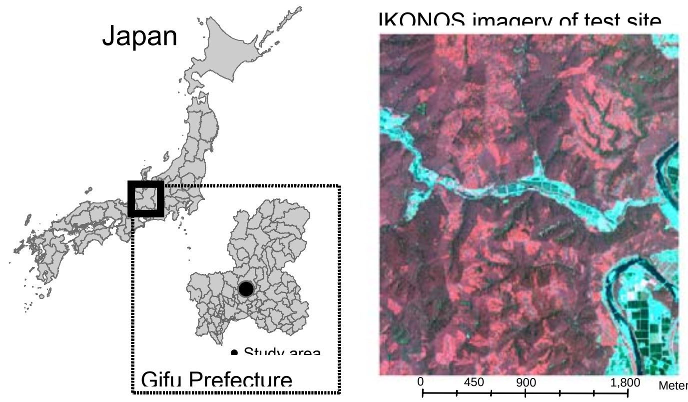

Figure 2. Test site and IKONOS imagery

The IKONOS imagery is radiometrically corrected to radiance using equations and coefficients recommended by Space Imaging document. However, significant difference was not observed among withered, fallen and no damaged area in band 1 and 2. Band 3 and 4, which showed apparent difference were used instead. Image mask was generated from features in GIS database to exclude the known irrelevant areas. The image mask excludes features such as road, farming areas and constructed areas.

There is a difference of spatial resolution between IKONOS imagery and DSM. In this study, the resolution of IKONOS imagery is used as a base for forest damage detection. When the extracted gap (calculated from LIDAR based data) is located in the center of the IKONOS imagery pixel, the pixel is decided as a gap area.

3.2 Results and accuracy assessment

First, training data for the multinomial logit model are obtained by field surveys data and orthorectified aerial photographs. Second, coefficients are estimated (Table 1). A reflectance of band 3 is increasing in damaged pixels including both fallen and withered area, while band 4 is decreasing. Hence, estimated coefficients of IKONOS imagery are pertinence. As coefficients of gap at fallen area are positive, estimated coefficients of gap are pertinence too. The Wald test indicates that the gap coefficient of withered is 10% significance level and the other coefficients are 0.01% significance level. The application of gap coefficient of withered is no problem because withered areas are 0 in gap data.

The accuracy assessment is directed using training data own. The result is shown in Table 2. Large damaged areas are detected correctly. However, there are some non-detected areas where small damaged areas are seen. As severe damage areas are detected, therefore this estimated model is determined to apply the whole imagery.

Table 1. Estimated coefficients

Coefficients	Intercept	Band 3	Band 4	Gap
Fallen	-39.37	192.75	-28.96	3.17
(Wald Statistics)	(-10.597***)	(12.853***)	(-12.466***)	(9.265***)
Withered	-57.49	254.56	-26.99	-1.75
(Wald Statistics)	(-16.794***)	(18.459***)	(-16.502***)	(-3.722*)

*** 0.01% significance level, * 10% significance level

Table 2. Accuracy assessment by training data

		Choice Result			
		No damage	Fallen	Withered	Sum
Training	No damage	2737	27	38	2802
	Fallen	36	167	6	209
	Withered	77	12	156	245
	Sum	2850	206	200	3256

Figure 3 shows three subsets of result detected by the method which is developed in this study. Scene #1 is an area where concentrated fallen and withered areas (pine beetle) are observed in an aerial photograph and IKONOS imagery.

This shows the separation of withered and fallen damaged areas resulted in a success. Scene #2 is an area where concentrated fallen areas and small withered areas are observed by an aerial photograph and IKONOS imagery. The areas with low tree height are detected as gap area in the gap extraction; however the area is not detected as non-forest areas in IKONOS imagery. Therefore the areas are not detected as fallen areas. Scene #3 is an area where scattered fallen areas are observed in aerial photograph and IKONOS imagery. Most of the scattered fallen areas are detected correctly; however areas which are detected as withered areas incorrectly are seen slightly. Therefore an improvement of data combination is needed.

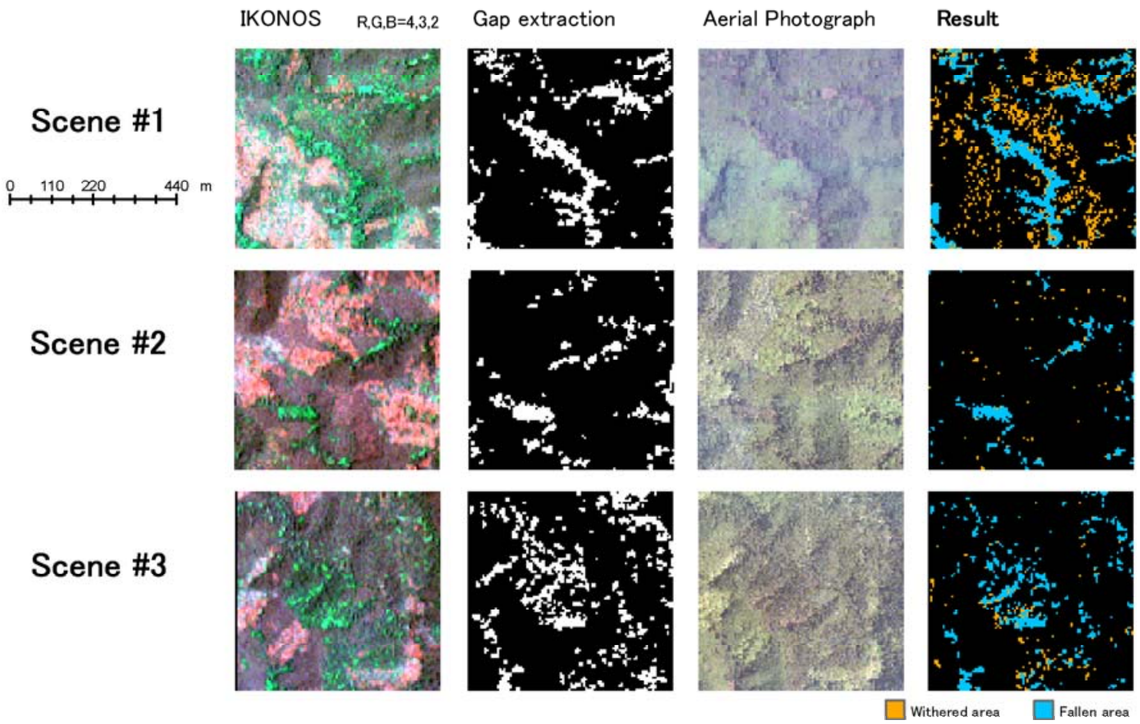

Figure 3. Results of forest damage detection (subset)

4. Conclusions and future works

This study, we developed a forest damage detection method using high resolution remotely sensed imagery and DSM. The multinomial logit model was employed to combine the data effectively. In Minami in Gifu prefecture, this method is applied using IKONOS imagery and gap data extracted by LiDAR DSM. The method succeeded in (1) detecting fallen and withered areas separately, and (2) detecting concentrated damaged areas. Although, several problems were left to be solved in the future work, which are (1) an improvement of the model which can consider for a geographical distribution, and (2) an estimation of a model using other explaining variables by the remotely sensed imagery.

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