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Relationship between Vegetation and Landslide Depth Using Statistical Methods: Aso Region, Kumamoto Prefecture, Japan

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Abstract **-** In recent years, climate change has led to an increased frequency and scale of heavy rainfall events, and subsequently, a rise in the occurrence of landslide induced by these rainfall events has been observed. Vegetation enhances slope stability by increasing soil strength through root systems. It is essential to quantitatively assess the influences that vegetation exerts on the occurrence of landslides and their depth to utilize vegetation to reduce disaster risk. Hence, in this study, we aimed to quantitatively evaluate the effects of vegetation diversity on the depth of landslides in the Aso region of Kumamoto Prefecture using statistical methods. We collected necessary data on topography, geology, vegetation, and rainfall and analysed them using a random forest. As a result of constructing the RF, the factors importance was the slope angle was the largest, followed by the landslide area, and the importance of vegetation was not large. As a result of creating partial dependence plots of the average landslide depth for each geology and vegetation type, the average landslide depth of secondary grasslands was approximately 20 cm smaller than that of broadleaf forests in all geological categories. This study could contribute substantially to future disaster mitigation efforts.

Keywords**:** landslide, disaster risk reduction, ecosystem, random forest

1. Introduction

In recent years, climate change has led to an increased frequency and scale of heavy rainfall events, and subsequently, a rise in the occurrence of landslides induced by these rainfall events has been observed. Landslides are triggered by various factors, including topography, geology, and vegetation [1]. Among these factors, vegetation has been reported to have a significant influence on the occurrence of landslides [2]. Vegetation enhances slope stability by increasing soil strength through root systems. [3][4]. The concept of utilising functions provided by ecosystems, such as vegetation, for disaster prevention and mitigation is known as ecosystem-based disaster risk reduction (Eco-DRR). The introduction of this approach has been under discussion in recent years [5]. It is essential to quantitatively assess the influences that vegetation exerts on the occurrence of landslides and their depth to utilize vegetation to reduce disaster risk. However, to the best of our knowledge, no study has quantitatively evaluated the impact of vegetation on the depth of landslides, considering factors such as topography, geology, and rainfall. Hence, in this study, we aimed to quantitatively assess the impact of differences in vegetation on the depth of landslides in the Aso region of Kumamoto Prefecture using statistical methods.

2. Study Area

The Aso region is located in the Kumamoto Prefecture, in Japan (Fig. 1). The total study area was approximately 376 km², with maximum and minimum elevations of 1591 m and 232 m, respectively. The Aso volcano, located almost in the centre of the study area, is situated roughly in the middle of Kyushu and possesses a caldera measuring approximately 25 km from north to south and 18 km from east to west. This caldera is one of the largest in the world and attracting many tourists each year. Extensive grasslands exist near the caldera, and numerous valuable flora and fauna that depend on these grasslands inhabit this area. The disaster targeted in this study was heavy rain disaster that occurred in the northern part of Kyushu in 2012.

During this heavy rain disaster in northern Kyushu from July 11 to 14, 2012, heavy rainfall exceeding 100 mm /h and 800 mm /24 h was observed mainly in Kumamoto, Oita, and Fukuoka Prefectures (Fig. 2). This resulted in flooding and landslide disasters at various locations.

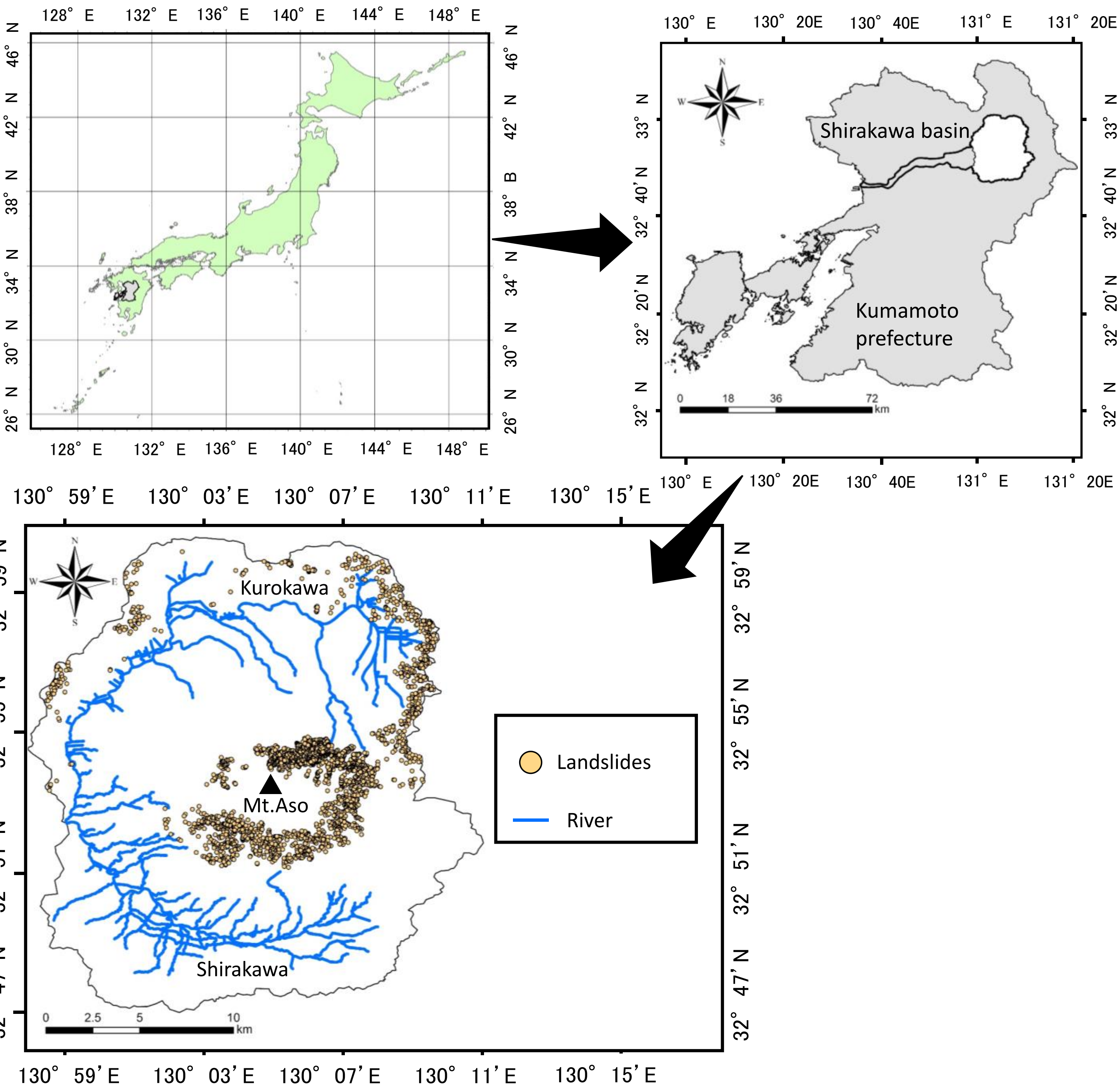

Fig. 1: Location of the study area

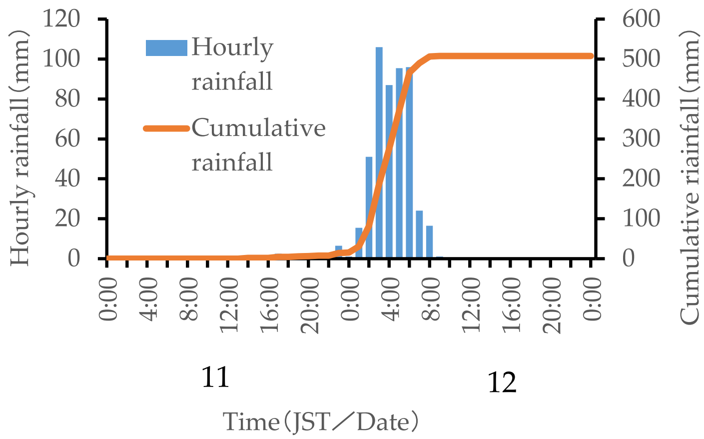

Fig. 2: Hourly rainfall and cumulative rainfall from July 11 to 12, 2012, at the Aso Otohime Observatory, Kumamoto Prefecture, Japan

3. Materials and Methods

3.1 Extraction of Landslide Sites

To identify landslide sites, we utilised the "Distribution Map of Sediment Movement Associated with the Heavy Rain in Northern Kyushu in July 2012" [6]. We conducted our analysis using on the method proposed by Asada et al. [7]. The identified landslide sites include bank erosion-type failures, where the foot of a hillside loses support and collapses. Therefore, we created first-order catchment areas according to the method by Asada et al. and targeted the landslide sites located within these catchment areas. A total of 1855 landslide sites were identified for the study (Fig. 3).

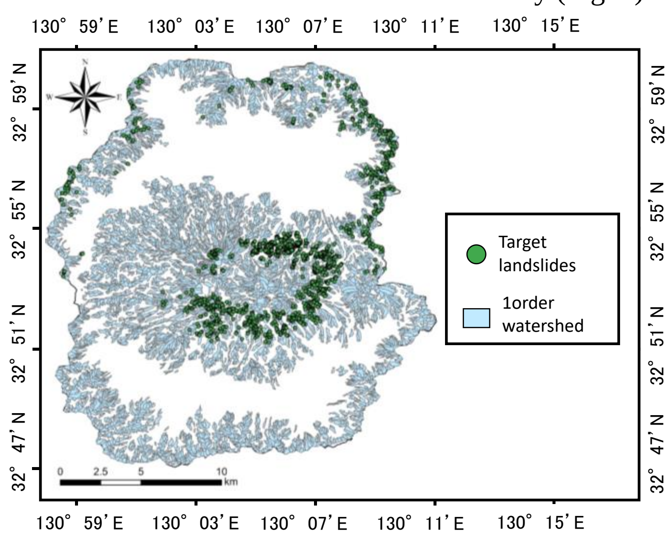

Fig. 3: Distribution of the target landslide areas

3.2 Data Collection

We collected data on factors considered to influence the occurrence of landslides, including elevation [8], slope [9], aspect [10], stream power index (SPI) [11] [12], topographic wetness index (TWI) [11] [12], surface geology [13], vegetation [14], and short-duration rainfall [15]. Elevation, slope, aspect, relief, SPI, and TWI were generated using pre-disaster laser profiler data for the digital elevation model. The surface geology was created by referencing the Aso Volcano Geological Map from the National Institute of Advanced Industrial Science and Technology [16]. The vegetation data was obtained from the Natural Environment Conservation Basic GIS data published by the Nature Conservation Bureau of the Ministry of the Environment [17]. The maximum hourly rainfall was derived from the 1km mesh analysis rainfall data provided by the Japan Meteorological Agency [18].

3.3 Statistical Analysis

Although Pearson's correlation coefficient was used for multicollinearity, the variance inflation factor (VIF) could be used to observe one-to-many correlations; therefore, it was adopted as an indicator to confirm multicollinearity in this analysis. The VIF was calculated using the following formula.

$$VIF = 1/(1 - R'^2) \tag{1}$$

R' denotes the multiple correlation coefficient. Multicollinearity may be present when the VIF is $\geqq 5$ [19]. Therefore, in this study, the VIF threshold was set to 5. If a value exceeded this threshold, the corresponding factor was excluded, and the VIF calculation was repeated until all VIFs were below 5.

The random forest (RF) was adopted as a statistical analysis method to evaluate the impact of factors including vegetation on the landslide depth. Random forest (RF) is a type of ensemble learning that levels out overfitting of decision trees by constructing a large number of decision trees and taking a majority vote on the results of each decision tree [20]. The explanatory variables were elevation, slope, direction, SPI, TWI, surface geology, vegetation, and maximum hourly rainfall. The response variable was the average failure depth at the slope failure site. Variable importance was calculated based on MSE (IncMSE). IncMSE is calculated as an index of how much the mean squared error increases when making predictions excluding the relevant explanatory variable. In order to quantitatively evaluate the influence of vegetation on the average collapse depth, partial dependency plots were created for each vegetation item. A partial dependence plot is a method for visualizing the relationship between an explanatory variable and a response variable when other explanatory variables are constant (average values). All analyses were performed using R -version 4.3.1.

4. Results

As a result of constructing the RF, the factors importance was the slope angle was the largest, followed by the landslide area, and the importance of vegetation was not large. As a result of creating partial dependence plots of the average landslide depth for each geology and vegetation type, the average landslide depth of secondary grasslands was approximately 20 cm smaller than that of broadleaf forests in all geological categories. In addition, using partial dependence plots, we showed the relationship between slope angle and average landslide depth for each vegetation, and the relationship between hourly rainfall and average landslide depth. For the slope angle up to 50 degrees, the average landslide depth of secondary grasslands is approximately 25 cm smaller than that of broadleaf forests. However, when the slope angle exceeded 50 degrees, the average collapse depth of secondary grasslands was similar to that of broad-leaf and coniferous forests. When the maximum hourly rainfall is less than 80 mm, the average landslide depth of secondary grasslands is about 30 cm smaller than that of broad-leaved forests. However, when the maximum hourly rainfall exceeded 120 mm, the average landslide depth of secondary grasslands was similar to that of broadleaf and coniferous forests.

5. Discussion

Statistical analysis revealed that secondary grasslands have smaller collapse depths than coniferous forests and broadleaf forests. Previous studies have also reported that grasslands have smaller landslide depths and sediment yield compared to forests [14]; the current study supports these findings. Moreover, while previous studies did not consider factors such as topography, geology, and rainfall during analysis, the present study quantitatively showed that secondary grasslands reduce the depth of collapse even when these factors are considered.

The smaller average landslide depth in secondary grasslands compared with that in coniferous forests and broadleaf forests can be attributed to differences in root distribution and volume. The root systems of herbaceous plants are generally distributed closer to the surface than those of woody plants [21] and do not penetrate deeply. Therefore, when landslides occur, much of the soil is not bound, and only the landslides. Thus, the landslide depth is also expected to be small. Soil thickness is another factor. Forest soil is thicker than grassland soil owing the accumulation of litter and other materials [22].

In this analysis, we could not obtain spatial data on soil thickness and, therefore, did not incorporate it into the model. model. However, future discussions on the influence of vegetation differences on landslide depth should consider soil thickness.

6. Conclusion

To gain insight into the impact of vegetation differences on landslide depth, we constructed and analysed a RF targeting landslides that occurred in the Aso region due to the July 2012 heavy rain in northern Kyushu. As a result of constructing the RF, the factors importance was the slope angle was the largest, followed by the landslide area, and the importance of vegetation was not large. As a result of creating partial dependence plots of the average landslide depth for each geology and vegetation type, the average landslide depth of secondary grasslands was approximately 20 cm smaller than that of broadleaf forests in all geological categories.This study could contribute substantially to future disaster mitigation efforts.

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