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Prediction of rainfall induced shallow landslide hazard: a dynamic approach

Prédiction des glissements de terrain superficiels induits par la pluie : Approche dynamique

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ABSTRACT: Korea is one of the countries suffering from landslide problem due to heavy rainfall. Many people had loss their life and their casualties every year. The estimated value of economic loss is more than expectation. In general, main causal factors of landslide contain static factors such as topographic, hydrologic, forest, soil and geology and they can be combined with dynamic factors related to rainfall. This research presents the method of landslide prediction from spatial and temporal probabilities and a simple statistical approach was proposed to find dynamic variability of hillslope condition. The landslide prediction on target area is the probability of landslide which calculated from relationship between probability of landslide under the rainfall and corresponding hillslope properties.

RÉSUMÉ : La Corée du Sud est un des pays souffrant des glissements de terrains dus aux fortes précipitations. Plusieurs pertes humaines et matérielles sont causées et leurs estimations sont supérieures aux prévisions. En général, les principales causes des glissements de terrains contiennent des facteurs statiques tels que la topographie, l'hydrologie, la forêt, le sol et la géologie. Ces derniers peuvent être combinés aux facteurs dynamiques liés aux précipitations. Cette recherche présente une méthode de prévision des glissements de terrains à partir de probabilités spatiales et temporelle. Aussi, une approche statistique simple a été proposée pour trouver la variabilité dynamique de l'état des pentes des collines. La prévision des glissements de terrains dans la zone ciblée est la probabilité de glissement de terrain qui est obtenue à partir de la relation entre la probabilité d'un glissement de terrain sous la pluie et les propriétés des versants des collines correspondantes.

KEYWORDS: Landslide susceptibility, GIS, Korean mountain.

Mots Clés: Glissement de terrain, SIG (Système d'Information Géographique), Montagnes coréennes.

1 INTRODUCTION

In Korea, mountains cover approximately 70% of the total landscape and the annual precipitation ranges from 1100 to 1400 mm, mainly during the rainny season from June through September. Most shallow translation landslides occur during summer rainy season (Pradhan and Kim 2015) and econoic loss is more than expectiona. The slope statibiliy is varied depend on water content in soil mass from rainfall.

Assessment of landslide hazard is usually stated as the probability of a landslide in a specified period of time and in a given area (Van Westen et al. 2006). Thus the estimation of hazard usually needs a spatial probability definition of "where" it occurs using predisposition factors, and a temporal probability definition for "when" or how frequently it occurs, considering the trigger factors. Temporal probability highly depends on the determinants of rainfall which have seasonality and regional differences (Crozier 1999). The landslide hazard can be predicted from rainfall measuring data. Thus the estimation of hazard usually needs a spatial probability definition of "where" it occurs using predisposition factors, and a temporal probability definition for "when" or how frequently it occurs, considering the trigger factors. Temporal probability highly depends on the determinants of rainfall which have seasonality and regional differences (Crozier 1999). The landslide hazard can be predicted from rainfall measuring data.

Temporal probability assesses the time and frequency in which slope materials are transported downhill and the role played by the factors that trigger them (Calvello et al. 2008; Capecchi and Focardi 1988). Temporal probability therefore is usually focused on the role of triggering factors since their mastery improve our understanding of the slope's behavior during different conditions.

This research presents the method of landslide prediction from spatial and temporal probabilities and a simple statistical approach was proposed to find dynamic variability of hillslope condition. Two different approaches are presented for estimating hazard for natural terrain in the catchment level. First is modeling of spatial landslide susceptibility using landslide inventory and different geospatial causative factors for landslide and second is temporal landslide hazard analysis using rainfall pattern and corresponding behavior of soil in the hillslope under the rainfall condition. Then probabilities of landslide related to triggered rainfall will be presented by dynamic map which probability can be recalculated and changed automatically from real-time rainfall data input. In short, the landslide prediction on target area is the probability of landslide which calculated from relationship between probability of landslide under the rainfall and corresponding hillslope properties.

2 STUDY AREA

The Onsan catchment in the northern part of Yongin and southern part of Seongnam district was selected as a study area (Figure 1) for following reasons: i) Government of Korea is planning to develop Yongin city as an information city, ii) this area was suffered a great deal of landslide damage following heavy rain during July 25–28, 2011. During this event, eight were killed, while seven went missing in Yongin District. The catchment occupies approximately 4.8 km^2 and the elevation of study area ranges from 48 m to 495 m. Study area is dominated by gneiss and recent deposits. The soils at the sites are principally weathered residual soil and colluvium soil. The monthly precipitation in July 2011 was 2.15 times greater than the average monthly rainfall. On July 27, the rain gauge station recorded 206 mm of rain in 24 h (53% of the mean monthly amount).

Geology has significant role in slope instability. Different lithological units have different characteristics such as composition, strength and structure (Carrara et al. 1991; Chauhan et al. 2010). The bedrock geology of the study area consists mainly of biotite gneiss. The lithological map is obtained from KIGAM.

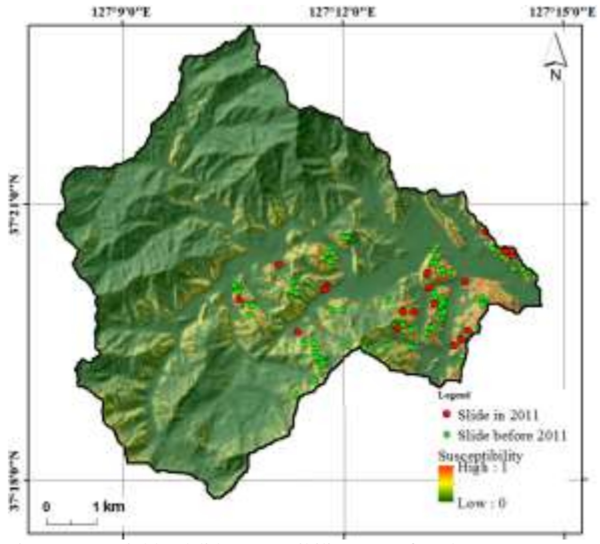

Figure 2. Spatial landslide susceptibility map of study area.

3 MATERIALS AND METHOD

In this study 14 representative landslide causative factors (CF) were used to find spatial probability. The 14 factors i.e. aspect, elevation, slope, internal relief, plan curvature, profile curvature, drainage proximity, stream power index (SPI), sediment transport index (STI), topographic wetness index (TWI), forest type, soil type, soil depth and geology data were used in 20 m resolution in ArcGIS 10.2. The explanatory factor for forest type considered in this study was extracted from a forestry map (1:25,000) developed by Korea Forest Service.

Landslide occurrence areas were detected by aerial photograph and Kompsat satellite image interpretation obtained from Korea aerospace research institute. To produce a detailed and reliable landslide inventory map, landslide locations obtained from remote sensing technique was verified by extensive field survey in 2014 August. All the landslide locations were identified and relocated by means of GPS.

These landslides were mostly distributed in the middle part and lower reach of the catchment. The study area also had much landslide damage following heavy rain in 1991. In the catchment 69 landslide were identified as landslides before 2011 July. Those landslide locations were used as model building data for spatial landslide susceptibility map. Whereas 18 landslides were identified as landslides in July 2011, that were used as validation of the model. Now this study has an advantage with two events data.

For spatial landslide susceptibility mapping a machine learning model, a maximum entropy (MaxEnt) was used, which is increasingly being regarded in various earth science studies (Phillips et al. 2006) and it has proven to be a very powerful statistical prediction tool. MaxEnt represents as the conditional density function of covariates π at presence, a random site x from the set X in the study area, and records 1 if the landslide is present at x, and 0 if it is absent.

For spatial landslide susceptibility modeling landslide before 2011 was considered as training data and landslide in 2011 July was considered as validation data.

The temporal probability was determined by using temporal variables like hourly cumulative rainfall, effective contributing area and infiltration rate.

The hazard is usually stated as the probability of a landslide in a specified period of time and in a given area (Van Westen 2000) (See Eq. 1).

$$\textit{Hazard} = (\textit{Spatial} \times \textit{Temporal})\ \textit{probability} \qquad (1)$$

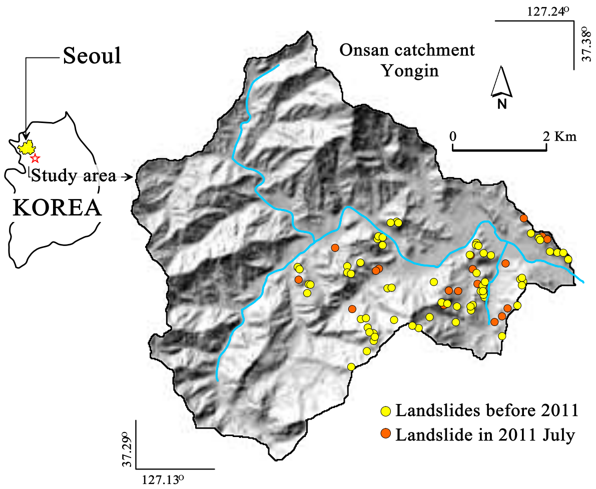

Figure 1. Location of study area and landslide distribution.

4 RESULTS AND DISCUSSION

4 .1 *Spatial landslide probability*

Spatial landslide susceptibility of Onsan catchment was obtained from machine learning presence data, Maxent model as shown in Figure 2. The probability value ranges of 0 to 1. In this analysis aspect, forest type, soil type, soil depth and geology are categorical data which remaining are continuous data. In total 10,000 pixels were used as background data, which are defined as random samples. The Jackknife test was performed to investigate which CF has the strongest effect on the prediction result. This test showed slope has the highest effect on the model while geology has the lowest.

4 .2 *Temporal landslide probability*

For temporal probability, rainfall parameter and hillslope behavior corresponding to rainfall such as cumulative rainfall, effective contributing area (ECA) and rainfall infiltration rate were selected. Cumulative rainfall maps were prepared by hourly rainfall that recorded in three rain gauge stations nearby catchment, and IDW algorithm was used. The modeling was done for 11h i.e. from 3 AM 27th July to 13:00 PM. Barling et al. (1994) stated that ECA is the fraction of the total specific contributing area that contributes subsurface flow to the contour segment within a specified drainage period d, corresponding to a rainfall duration. In this study, a D8 single flow direction algorithm was applied to calculate the contributing area. ECAs of the Onsan catchment were simulated for continuous 11 h duration as shown in Figure 3.

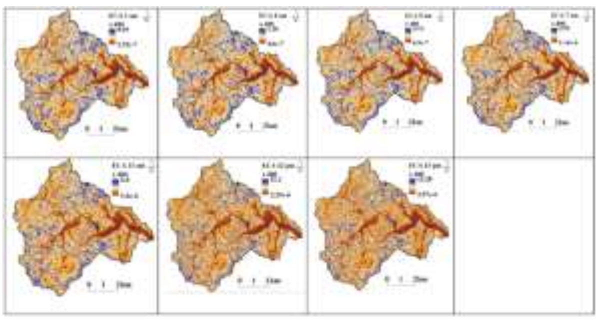
Figure 3. ECA simulation for 11h.

A transient rainfall infiltration model was used to obtain infiltration rate of the study area, which represents spatiotemporal changes in pore water pressure caused by rainfall infiltration. The transient infiltration model estimates transient pore pressure changes by considering changes in rain infiltration over time, while assuming that the initial groundwater level is a steady state. In this study, we adopted the hydrogeological model implemented as transient rainfall infiltration and grid-based regional slope stability (TRIGRS), which is coded in FORTRAN.

A simple logistic regression analysis was done to find the relationship between landslide presence and temporal. The accuracy of temporal probability was calculated using AUROC. It showed 89.77% accuracy for the model as shown in Figure 4.

4 .3 *Dynamic hazard modeling*

The temporal probability was (using LR) calculated for 11h i.e. 3AM, 4AM, 5AM, 7AM, 11AM, 12PM and 13PM of 27th July, 2011. The distribution of temporal probability was mainly due to soil properties i.e. hydraulic conductivity. Dynamic hazard means change of spatial landslide susceptibility with time variable. In this study, dynamic model was prepared for 11h before landslide event. It was simply performed by using equation (1). A series of maps from 3AM to 13PM were obtained from calculation (Figure. 5). This model shows the hillslope behavior during rainfall scenario. This kind of research is a novel in dynamic landslide hazard assessment. Generally previous studies used physically based model.

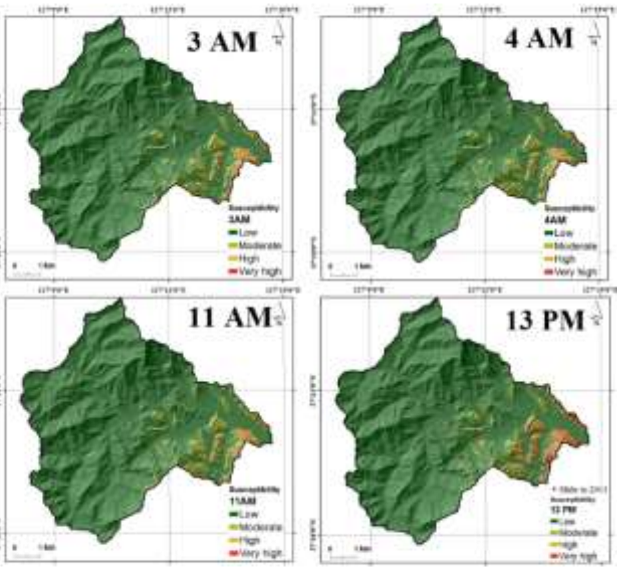

Figure 5. Dynamic landslide hazard.

5 CONCLUSIONS

Onsan catchment was selected to evaluate dynamic landslide hazard model. In this study, 14 spatial data and machine learning Maxent was used to make landslide susceptibility map. The hourly cumulative rainfall, effective catchment area and infiltration rate were used as spatiotemporal data. Landslide inventory map was used to make both spatial and temporal probability maps. A logistic regression model was used to find temporal probability. From this model, a rainfall scenario based dynamic landslide hazard was evaluated.

6 ACKNOWLEDGEMENTS

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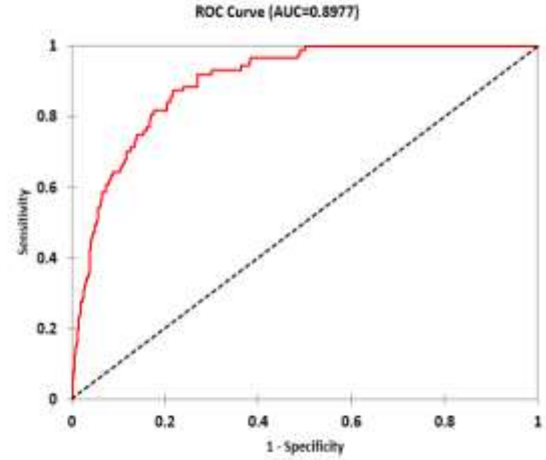

Figure 4. Model performance of temporal probability.

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