LOGISTIC REGRESSION MODEL FOR PREDICTING THE FAILURE PROBABILITY OF A LANDSLIDE DAM

Jia-Jyun Dong¹*, Yu-Hsiang Tung², Chien-Chih Chen³, Jyh-Jong Liao⁴, Yii-Wen Pan⁴

ABSTRACT

This research utilized logistic regression method and Jack-knife technique to screen out the significant geomorphic variables, including peak flow (or catchment area), dam height, width and length in sequence, affected the stability of landslide dam. The derived high overall prediction power demonstrates the robustness of the proposed statistical models. Accordingly, the failure probability of a landslide dam can be evaluated based on the proposed logistic regression models soon after the stream blocked. Two large landslide dams formed after 1999 Chi-Chi earthquake and 2008 Wenchuan earthquake are adopted as examples for calculating the failure probability. The stable Tsao-Ling landslide dam has a failure probability of 27.68%. On the contrary, the Tangjiashan landslide dam, which was artificially breached soon after the formation, has a failure probability as high as 99.53%. It appears that the proposed logistic regression model can be used as an evaluation tool for decision making on the respect of hazard mitigation soon after the formation of a landslide dam.

Key Words: Landslide dam, Stability, Logistic regression analysis, Geomorphic variables

INTRODUCTION

The occurrence of landslide dam and followed breach which sometimes accompanies with outburst floods and debris flow causes catastrophic disaster. Schuster and Costa (1986) reported that half of the landslide dam failed within 10 days. It is always a great challenge for hazard mitigation since the actions must be accomplished within a limited time.

Rapid assessment of the landslide-dam stability is one of the crucial steps for decision-making. Geomorphic approach is widely used to correlate the dam, river, and impoundment characteristics and landslide dam stability (Costa and Schuster, 1988; Ermini and Casagli, 2003; Korup, 2004). Among them, Ermini and Casagli (2003) utilized relevant geomorphic index DBI combining three important variables (dam height $H_d$, dam volume $V_d$, watershed area $A_d$) to evaluate the stability of a landslide dam, where $DBI = \log[(H_d \cdot A_d)/V_d]$. Incorporating these simplistic geomorphologic analyses, GIS-based modelling could be followed to evaluate the hazards of dam-break (Clerici and Perego, 2000).

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1 Associate Professor, Graduate Institute of Applied Geology, National Central University, Jungli, 32001, Taiwan. (*Corresponding Author; Tel.: +886-3-422-4114; Fax: +886-3-422-4114; Email: jjdong@geo.ncu.edu.tw)
2 Master student Graduate Institute of Applied Geology, National Central University, Jungli, 32001, Taiwan.
3 Professor, Institute of Geophysics, National Central University, Jhongli 32001, Taiwan.
4 Professor, Department of Civil Engineering and Hazard Mitigation Research Center, National Chiao-Tung University

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Recently, Dong et al. (2009) proposed a rigorous discriminant model with high overall success rate to evaluate the stability of landslide dams. The results also provide a ranking of the relevant variables contributing to the stability of a landslide dam, which are not considered in the current graphic approach adopted worldwide. In general, the existing methodology cannot evaluate the failure probability of landslide dam, which is always required for risk assessment. Alternatively, logistic regression could be used for statistically estimating the probability of an event occurring (Dai et al., 2002).

Together with the 84 worldwide dataset, Dong et al. (2009) compiled the Tabata’s inventory (Tabata et al., 2002) of Japanese landslide dams (Supplementary Table S1 and Table S2), which has complete geomorphology information. Based on these data, the main objectives of the present work are: (1) to propose a logistic regression model for predicting the failure probability of a landslide dam; (2) to compare the performance of the logistic regression models with the existing discriminant models; and (3) to evaluate the significance of the relevant variables.

LANDSLIDE–DAM DATA SETS

Tabata et al. (2002) studied 79 landslide–dam events that occurred in Japan. The triggering factor, geological and geomorphic characteristics of these landslide dams (Tabata’s inventory) and their longevity were well documented. In Tabata’s inventory (79 cases), there were 43 landslide dams (9 stable and 34 unstable ones) for which complete records of all 16 geomorphic variables are available. The detail information and the statistics of variables in Tabata’s landslide dam inventory are reported by Dong et al. (2009).

To compare the performance of the prediction between the DBI index–based graphic model, discriminant models and the logistic regression models, we use the 84 worldwide dataset (with complete records of $Ac$, $Hd$, and $Vd$) of landslide dams collected by Ermini and Casagli (2003) (Supplementary Table S2 of Dong et al., 2009) to build the logistic regression model with three log–transformed variables ($\log(Ac)$, $\log(Hd)$, and $\log(Vd)$) which are identical to the ones used for building the DBI index–based graphic model. Thereafter, we take the remained 37 Japanese cases for model verification.

METHODOLOGY

Logistic regression are wildly used statistical tools (Baeza and Corominas, 2001; Ohlmacher and Davis, 2003; Can et al., 2005; Ayalew and Yamagishi, 2005; Chang et al., 2007; Greco et al., 2007). First, we try to classify the landslide dams into two groups: (1) stable group, and (2) unstable group, on the basis of a non-linear function (logistic regression function) of a set of variable. In addition, the failure probability of landslide dam is calculated based on the logistic regression models. Secondly, the importance of the contributed variables is evaluated by a Jack-knife technique. The methodology adopted in this study is described as follows.

Categorizing the dataset using logistic regression analysis

Logistic regression is useful when the dependent variable is categorical (e.g., presence or absence) and the explanatory (independent) variables are categorical, numerical, or both
An “odds ratio” \( P \), which represented as the probability of a landslide dam remain stable, is defined as:

\[
P = \frac{1}{1 + e^{-L}},
\]

where \( L \) is the lineal combination of influencing variables as follows:

\[
L = b_0 + b_1x_1 + b_2x_2 + ... + b_nx_n = \ln\left(\frac{P}{1-P}\right)
\]

where \( x_i (i=1~n) \) is the independent variable, \( b_i (i=0~n) \) is the regression coefficient for sample data, \( n \) is the number of independent variables. \( \ln\left(\frac{P}{1-P}\right) \) is the log odds ratio or “logit”. If a dam with variables \( x_i \) results \( L > 0 \) (or \( P > 50\% \)), it would be divided into stable group. Otherwise, it would be divided into unstable group. A failure probability of landslide dam is defined as follows:

\[
P_{f} = 1 - P = \frac{e^{-L}}{1 + e^{-L}}.
\]

After testing the normality of the variables, analyzing the correlation between the variables, and checking the significance and performance of the predictive models composed of different combination of variables, Dong et al. (2009) proposed two predictive models with four variables (PHWL and AHWL). The variables in PSLW model (herein we renamed as PHWL_Dis) including log--transformed peak flow, dam height, dam width, and dam length. Since the peak flow is not always available for not too many dammed rivers in mountain area are gauged. Thereafter, a replacement of the peak flow by catchments area in the discriminant model is proposed (Dong et al., 2009). That is, an AHWL model (herein we renamed as AHWL_Dis) containing log--transformed catchment area, dam height, dam width, and dam length could be used at the first time for hazard evaluating. In this study, we adopted the identical variables as used in the two discriminant models proposed by Dong et al. (2009).

**Evaluating the performance of logistic regression model**

A confusion matrix (Table 1) was used to demonstrate the performance of the prediction models. The proportion of correctly classified observations \(( (a+b)/N ) \) was calculated to illustrate the prediction ability of the proposed statistical models. Cross-validation was also used to test the reliability and robustness of the proposed models (Carrara, et al., 2008). We split the dataset (43 cases) randomly into: (1) the training set (17 unstable and 5 stable); and (2) the target set (17 unstable and 4 stable). We next evaluate the predictive success of the model, built on the training set, by using the target set. The proportion of correctly classified observations is calculated to illustrate the prediction ability of the proposed statistical models. Alternatively, the prediction performance of a predictive model can be evaluated via a Relative Operating Characteristic (ROC) diagram, which has been widely used to measure prediction potential of landslide susceptibility models (e.g., Chung and Fabbri, 2003; Chen et al., 2007; Carrara et al., 2008; Lee et al., 2008a,b). In the ROC graph the false alarm rate (FAR) is plotted on the horizontal axis and the hit rate (HR) on the vertical axis. HR is the fraction of positive occurrences of dam failure that have been correctly predicted, while FAR is the fraction of incorrectly predicted cases that did not occur (Swets, 1988). A larger area under the ROC curve (AUC) indicates better model prediction (AUC index ranges from 0.5 for models with no predictive capability to 1.0 for models with perfect predictive power).
Table 1 Confusion matrix. \( a \): true positives; \( b \): false positives (error type I); \( c \): false negative (error type II); \( d \): true negatives. \( N = a + b + c + d \) is the total number of data sets.

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Observed</th>
<th>( a )</th>
<th>( b )</th>
<th>( c )</th>
<th>( d )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stable</td>
<td>Stable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unstable</td>
<td>Unstable</td>
<td></td>
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</tbody>
</table>

Jack-knife technique to identify the relevant variables

A jack-knife technique (Swan and Sandilands, 1995) was used to sort the importance of the relevant variables in the logistic regression model. We pick-out the variables in the logistic regression model one by one. M sub-models would be created if the logistic regression model has M variables. The more the prediction ability of the sub-model dropped, the more important of the picked-out variable is. Consequently, the significance of each variable could be determined.

RESULTS

Logistic regression models and performance for predicting the stability of landslide dam

Two predictive models with four variables (PHWL_Log and AHWL_Log) were proposed by Dong et al. (2009). The variables in PSWL_Dis including log–transformed peak flow, dam height, dam width, and dam length \( (LX_4, LX_{11}, LX_{12}, LX_{13}) \). Meanwhile, AHWL_Log containing parameters \( LX_1, LX_{11}, LX_{12}, \) and \( LX_{13} \) (log–transformed catchment area, dam height, dam width, and dam length). Logistic regression models (PHWL_Log and AHWL_Log) were built using 34 unstable dams and 9 stable dams as follows:

\[
L = -2.55LX_4 - 3.64LX_{11} + 2.99LX_{12} + 2.73LX_{13} - 3.87
\]

\[
L = -2.22LX_1 - 3.76LX_{11} + 3.17LX_{12} + 2.85LX_{13} + 5.93.
\]

The overall prediction power for models PHWL_Log and AHWL_Log are 88.4% and 90.7%, respectively. The cross-validation accuracy for models PHWL_Log and AHWL_Log is 85.7% and 77.3%. The confusion matrix of the logistic regression models are illustrated in Table 2.

Table 2 Confusion matrix of the logistic regression models

<table>
<thead>
<tr>
<th>Model</th>
<th>Actual groups</th>
<th>Number of landslide dams</th>
<th>Predicted group membership</th>
<th>Group 1 (stable)</th>
<th>Group 2 (unstable)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHWL_Log</td>
<td>Group 1 (stable)</td>
<td>9</td>
<td>66.7%</td>
<td>33.3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Group 2 (unstable)</td>
<td>34</td>
<td>94.1%</td>
<td>5.9%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Percentage of landslide dams correctly classified: 88.4 (Whole dataset; 43 cases)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>85.7 (Cross-validation)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AHWL_Log</td>
<td>Group 1 (stable)</td>
<td>9</td>
<td>66.7%</td>
<td>33.3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Group 2 (unstable)</td>
<td>34</td>
<td>97.1%</td>
<td>2.9%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Percentage of landslide dams correctly classified: 90.7 (Whole dataset; 43 cases)</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>77.3 (Cross-validation)</td>
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</tr>
</tbody>
</table>

The ROC plot is proposed as a convenient tool for decision-taking in a risk management context (Begueria, 2006). The ROC curves of tested models were plotted in Fig. 1. The logistic regression models PHWL_Log (AUC=94.8%) and AHWL_Log (AUC=92.5%) are proved to be the powerful for categorize the stability of a landslide dam.
Importance of the factors affects the stability of landslide dams

A jack-knife technique was utilized to test the importance of each variable in a predictive model. We eliminating four variables one by one and establishing four logistic regression sub-models. The Relative Operating Characteristic (ROC) curves were derived and the AUCs were calculated. Fig. 2 (a) shows the ROC curves of model PHWL_Log and 4 sub-models with one of the four variables was eliminated. The AUC of green line (peak flow picked-out) is 0.703 which is the lowest among all of the 5 models. The result reveals that the peak flow is the most significant variable in model PHWL_Log. The significance of the variables, in sequence, are dam high (AUC of the sub-model is 0.889 with dam height are picked-out), dam width (AUC of the sub-model is 0.908 with dam length are picked-out), and dam length (AUC=0.914). This result is identical to the one deriving from the SCDC of variables in discriminant model (Dong et al., 2009).

For model PHWL_Log, the catchment area and dam height are still evaluated as the most and second influencing variables from jack-knife technique (Fig. 2(b)). Fig. 2(b) indicates the dam width and dam length have less significance effect on the landslide dam stability. The result is also similar to the one deriving from the SCDC of variables in discriminant model (Dong et al., 2009), with the exception of the dam length is evaluated to have stronger effect on landslide dam stability than dam width from the SCDC of variables in discriminant model.
The failure probability of landslide dam

Fig. 3 (a) and (b) shows the failure probability of landslide dam calculated by the logistic regression models (PHWL_Log and AHWL_Log). 6 of the 9 stable landslide dams (with failure probability smaller than 50% which indicates the dam is stable) and 32 of the 34 unstable landslide dams (with failure probability greater than 50% which indicates the dam is unstable) were correctly classified by the PHWL_Log model. 6 of the 9 stable landslide dams and 33 of the 34 unstable landslide dams were correctly classified of the AHWL_Log model. It is worthy to mention that the calculated failure probability is greater than 80% for most of the failure landslide dam.

![Graph showing failure probability of landslide dams](image)  
**Fig. 3** Failure probability of 43 landslide dams predicted by (a) model PHWL_Log; and (b) model AHWL_Log.

DISCUSSION

The overall prediction power of the logistic regression models and the discriminant models (Dong *et al*., 2009) are listed in Table 3. The proposed logistic regression models PHWL_Log (AUC=94.8%) and AHWL_Log (AUC=92.5%) are capable for categorizing the landslide dams into stable and unstable groups with high success rates. Relatively, the logistic regression models are superior to the discriminant models with slightly higher AUCs (Table 3). Meanwhile, the models PHWL are superior to the models AHWL, both for the discriminant and logistic regression models. It is suggested that if the variable P (peak flow) is available, PHWL_Log should be used to evaluate the stability of a landslide dam. Since the peak flow is not easy obtained, especially when the dam stability required to be evaluated soon after the formation, model AHWL_Log is more useful in practice.

Notably, the proportion of correctly classified observations ($(a + b)/N$) of the proposed logistic regression models derived from cross-validation is lower than that of discriminant models. However, the error of type II “c” (false negative; model fail to predict the landslide dam instability) is also lower than discriminant models (Table 3). Begueria (2006) indicated that the sense of false negatives “c” and false positives “b” (error of types I) respect to the risk assessment could be significantly different. The logistic regression analysis has a lower error of type II “c” (5.9% and 2.9%) indicating its’ higher correctly classify ability of unstable landslide dam (94.1% and 97.1%, in Table 1). It means that the logistic regression models are conserve in predicting the stability of landslide dam compare to the discriminant models proposed by Dong *et al.* (2009). For catastrophic hazard frequently induced by the collapse of landslide dams, the ability to classify an unstable landslide dam correctly is more crucial than to classify a stable landslide dam.
Regarding the importance of the variables affect the stability of landslide dam, Jack-knife technique identified the peak flow and the catchment area to be the most significant one in the PHWL_Log and AHWL_Log models. The dam height is the second important variable contributes to the stability of landslide dam in the proposed logistic regression models. The peak flow, catchment area, and the dam height are negative factors contributed to the stability of landslide dam. The dam width and dam length are positive factors. In model PHWL_Log, the importance of the dam width is larger than the dam length. In model PHWL_Log, the importance of the dam length is larger than the dam width. The significance of the variables contributed to the stability of landslide dam for the proposed models are listed in Table 3. The result is almost identical to the one deriving from the SCDC of variables in discriminant model (Dong et al., 2009), only with the exception of the dam length is evaluated have a stronger effect on landslide dam stability than dam width for the model AHWL_Log.

Table 3 Comparison between the performance of the logistic regression models and the discriminant models (Dong et al., 2009)

<table>
<thead>
<tr>
<th>Model</th>
<th>Predicted</th>
<th>Observed</th>
<th>proportion of correctly classified observations</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Stable</td>
<td>Unstable</td>
<td>Whole data set</td>
</tr>
<tr>
<td>PHWL_Log</td>
<td>Stable</td>
<td>66.7%</td>
<td>33.3%</td>
<td>88.4%</td>
</tr>
<tr>
<td></td>
<td>Unstable</td>
<td>5.9%</td>
<td>94.1%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Significance of the variables contributed to the stability of landslide dam: P&gt;H&gt;W&gt;L</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AHWL_Log</td>
<td>Stable</td>
<td>66.7%</td>
<td>33.3%</td>
<td>90.7%</td>
</tr>
<tr>
<td></td>
<td>Unstable</td>
<td>2.9%</td>
<td>97.1%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Significance of the variables contributed to the stability of landslide dam: P&gt;H&gt;W&gt;L</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PHWL_Dis</td>
<td>Stable</td>
<td>77.8%</td>
<td>22.2%</td>
<td>88.4%</td>
</tr>
<tr>
<td></td>
<td>Unstable</td>
<td>8.8%</td>
<td>91.2%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Significance of the variables contributed to the stability of landslide dam: P&gt;H&gt;W&gt;L</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AHWL_Dis</td>
<td>Stable</td>
<td>77.8%</td>
<td>22.2%</td>
<td>88.4%</td>
</tr>
<tr>
<td></td>
<td>Unstable</td>
<td>8.8%</td>
<td>91.2%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Significance of the variables contributed to the stability of landslide dam: P&gt;H&gt;W&gt;L</td>
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</tr>
</tbody>
</table>

In addition to the conservativeness for categorizing the landslide dam into the unstable group, logistic regression models are superior to the discriminant models and index-based graphic method (e.g. DBI index) for the failure probability could be derived. To demonstrate the capability of the logistic regression model, we further reduced the variables into three, namely: catchment area, dam height, and dam volume, which is identical to the variables used by the DBI index (DBI<2.75 stable; DBI>3.08 unstable) proposed by Ermini and Casagli (2003) and AHV model (herein we renamed as AHV_Dis) proposed by Dong et al. (2009). We adopted the same 84 worldwide dataset (training set) to build the logistic regression Model AHV_Log as follows:

\[ L = -4.48LX_1 - 9.31LX_{11} + 6.61LX_{16} + 6.39 \]  

(6)

The overall prediction power of AHV_Log is 89.3%. The cross-validation accuracy is 85.7%. Besides, the AUC of the AHV_Log model is 95.1%. Using Eq. (6), the 39 Japanese landslide dams (target set) collected by Tabata et al. (2002) could be classified into stable or unstable landslide dams. The overall prediction power is 76.9% for model AHV_Log. The AUC of the AHV_Log model is 71.0%. Accordingly, the logistic regression model has an accepted ability to categorize a landslide dam into stable and unstable. More important, the failure probability of the landslide dam could be evaluated by the logistic regression model. Fig. 4 shows the contour surfaces for 50%, 90%, and 98% of failure probability of a landslide dam. Compare to the DBI and discriminant model AHV_Dis, the logistic regression model can offer the failure probability of landslide dam (other than just separating all the landslide dam cases into stable and unstable groups).
Two large landslide dams, one in Taiwan (Tsao-Ling landslide dam) and one in China (Tangjiashan landslide dam), were used to demonstrate the ability for calculating the failure probability. The Tsao-Ling landslide dam, formed after the 1999 Chi-Chi earthquake, is filled with sediments and still stable. The Tangjiashan landslide dam, formed after the 2008 Wenchuan earthquake, is artificially breached, due to its high risk to the downstream town. These two landslide dams attracted big attention about how to mitigate the related hazards. One of the key issues is how to determine the failure susceptibility of these two landslide dams quickly. The geomorphologic characteristics required in the index-based graphic method (DBI-index), discriminant models, and logistic models are listed in Table 3. The Tsao-Ling landslide dam and Tangjiashan landslide dam are categorized as stable and unstable dams, respectively, according to the DBI-index and the discriminant models (AHWL_Dis and AHV_Dis). The proposed logistic regression models obtained the identical results (Table 4). The failure probabilities of Tsao-Ling landslide dam are 27.68% and 0.07% (Fig. 4), respectively, according to the logistic regression models AHWL_Log and AHV_Log. On the other hand, a failure probability greater than 99% is derived for the Tangjiashan landslide dam. It appears that the proposed logistic regression model could be used as an evaluation tool for the decision makers on the respect of hazard mitigation, especially when the decision time is limited.

### Table 4 Geomorphologic characteristics of Tangjiashan and Tsao-Ling landslide dams (Li et al., 2002; Xu et al., 2009) and the failure probabilities predicted by logistic regression models

<table>
<thead>
<tr>
<th></th>
<th>Tangjiashan</th>
<th>Tsao-Ling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geomorphologic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>characteristics</td>
<td>catchment area (km²)</td>
<td>3550</td>
</tr>
<tr>
<td></td>
<td>dam height (m)</td>
<td>82 (lowest height)</td>
</tr>
<tr>
<td></td>
<td>dam width (m)</td>
<td>800</td>
</tr>
<tr>
<td></td>
<td>and dam length (m)</td>
<td>600</td>
</tr>
<tr>
<td></td>
<td>Dam Volume (10⁶m³)</td>
<td>20.4</td>
</tr>
<tr>
<td>Statistic model for predicting</td>
<td></td>
<td></td>
</tr>
<tr>
<td>the stability and failure</td>
<td>DBI</td>
<td>4.15 (&gt;3.08; Unstable)</td>
</tr>
<tr>
<td>probability of landslide dam</td>
<td>AHWL_Dis: D</td>
<td>-5.01 (Unstable)</td>
</tr>
<tr>
<td></td>
<td>AHV_Dis: D</td>
<td>-2.57 (Unstable)</td>
</tr>
<tr>
<td></td>
<td>AHWL_Log: L(Pf)</td>
<td>-5.35 (99.53%)</td>
</tr>
<tr>
<td></td>
<td>AHV_Log: L(Pf)</td>
<td>-5.90 (99.73%)</td>
</tr>
</tbody>
</table>

Three failure mechanisms are identified as dominating the instability of landslide dams: overtopping, piping, and slope failure (Schuster and Costa, 1986). Of these, overtopping is the most important one. Ermini and Casagli (2003) concluded that most collapses in their inventory coincide with the first dam overtopping. It is logical to select the peak flow or catchment area of
The volume of a landslide dam, which reflecting a resisting force, plays an important positive role in the stability of landslide dams. The dam height, however, has a negative effect on the stability of a landslide dam, for the higher the dam is, the larger the seepage driving force. The proposed predictive model which incorporating the catchment Area and dam geometry accounts for the above mentioned failure mechanisms reasonably. The detailed discussion regarding to the causative factors selected in the proposed models could be found in Dong *et al.* (2009).

**CONCLUSIONS**

Based on 43 Japanese training cases, logistic regression analysis for the quantitatively prediction of landslide-dam stability was presented. The proposed models PHWL_Log and AHWL_Log are able to categorize the landslide dams into stable and unstable groups with high success rates. The model PHWL_Log (AUC=94.8%) is slightly superior to the model AHWL_Log (AUC=92.5%). However, AHWL_Log may be more useful for practice since the peak flow information is difficult to be obtained soon after the dam formation.

The log-transformed peak flows (or alternatively, the catchment area) are identified as the most significant geomorphic variables influencing the stability of a landslide dam. The log-transformed dam height, with a negative contribution to the stability of a landslide dam, is the second most significant variable. The log-transformed dam width and length have a similar positive effect on a dam's stability; this is agreeable well with the results derived from discriminant analysis.

Compare to the discriminant models proposed by Dong *et al.* (2009), the logistic regression models have a slightly better ability to categorize the landslide dams into stable and unstable groups. Furthermore, the lower false negative (error type II; model fail to predict the landslide dam instability) predicted by the logistic regression models indicated their conservativeness in nature for categorizing a landslide dam into unstable group. Most importantly, a failure probability can be derived based on the proposed logistic regression models. This research used two large landslide dams (Tsao-Ling landslide dam in Taiwan and Tangjiashan landslide dam in China) to demonstrate the ability for calculating the failure probability. The stable Tsao-Ling landslide dam, formed after the 1999 Chi-Chi earthquake, has a failure probability 27.68% based on the logistic regression model AHWL_Log. On the other hand, the artificially breached Tangjiashan landslide dam, formed after the 2008 Wenchuan earthquake, has a failure probability as high as 99.53%. It appears the proposed logistic regression model can be used as an evaluation tool for decision making on the respect of hazard mitigation, especially when the decision time is limited.

**REFERENCES**


