AN INVERSE AND DECOMPOSITIONAL ANALYSIS OF CHAIN TRIGGER FACTORS FOR SLOPE FAILURE HAZARD ZONATION

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ABSTRACT:

This paper presents an inverse- and decompositional-analysis of unobserved "chain-trigger factors" according to slope failure, based on Structural Equation Modeling (SEM). Quantitative prediction models for slope failures generally elucidate the relationship between past slope failures and causal factors (e.g. geology, soil, slope, aspect, etc.). Due to the difficulties of obtaining pixel-based observations on the trigger factors (e.g. rainfall, earthquake, weathering, etc.), the trigger factors as explanatory variables are substituted for some of the causal factors in constructing prediction models, on the assumption that there are some correlations between causal and trigger factors. As a measure, we had tackled to construct a Trigger Factor Inverse analysis model (TFI model) in which the relationship between past slope failures (i.e. endogenous variables), causal factors (i.e. explanatory variables), and trigger factors (i.e. unobserved variables) are delineated on the path diagram in SEM approach. In the TFI model, through the "measurement equation" defined between the causal factors (i.e. observed variables) and the trigger factors (i.e. unobserved latent variable), the trigger factor can be inversely estimated. As the subsequent subjects for the previous studies, in this contribution, we have tried to decompose trigger factors into the "1st trigger factor" and the "2nd trigger factor" with respect to slope failures, which had been induced by Niigata Heavy Rainfall (Jul. 13, 2004:Case1) and Niigata Chuetsu Earthquake (Oct. 23, 2004:Case 2).

The analytical procedure consists of the following steps.

- **Step 1:** The 1st and the 2nd Trigger Factor Influence maps (TFI map) are produced according to Case1 and Case 2, respectively.
- **Step 2:** The differences in these TFI maps are delineated on a "difference (DIF) maps," which are also summarized on the "pair-wise comparative table."
- **Step 3:** Through the Hayashi's quantification method of the fourth type, the scatter-diagram is delineated with respect to items corresponding to each TFI map.

By using those scatter-diagram jointly with the pair-wise comparative table, the effective and efficient analysis on the "chain-trigger factors" can be achieved with respect to slope failures, simultaneously.

1. INTRODUCTION

A spatial data integration approaches applying the satellite remotely sensed data and the various kinds of geographical information (termed "causal factor") are highly expected for identifying the hazardous area affected by the slope failures. Quantitative prediction models for slope failures occurrences generally elucidate the relationship between past slope failures and causal factors (e.g. geology, soil, slope, aspect, etc.). Due to the difficulties of obtaining pixel-based observations on the trigger factors (e.g. rainfall, earthquake, weathering, etc.), the trigger factors as explanatory variables are substituted for some of the causal factors in constructing prediction models, on the assumption that there are some correlations between causal and trigger factors (Chung et al., 1999, 2002; Crozier et al., 2004;).

As a measure, we had tackled to construct a Trigger Factor Inverse analysis model (TFI model) of unobserved trigger factor, in which the relationship between past slope failures (i.e., endogenous variables), causal factors (i.e., explanatory variables), and trigger factors (i.e., unobserved variables) are delineated on the path diagram in the Structural Equation Modeling (SEM) (Joreskog, et al., 1968; Hoyle et al., 1995). In the TFI model, through the "measurement equation" defined between the causal factors and the trigger factor (i.e., unobserved latent variable), the trigger factor can be inversely estimated (Kojima et al., 2006).

In the TFI model, the pixels corresponding to past slope failures are generally used as the input data of endogenous variable (i.e., training data sets). The inverse estimated values on trigger factor are delineated on a Trigger Factor Influence map (termed "TFI map"), which depends on the distribution of the past slope failures used as the training data sets. Also, in our previous experiments, as for the structure of path diagram used in SEM, a "single exogenous variable" had been considered as main trigger factor of rainfall or earthquake.

However, slope failures are induced by various trigger factors, the modified path model with several exogenous variables as trigger factors should be investigated to improve the identification of path model in SEM approach. This inevitable subject corresponds to an inverse and decompositional analysis of unobserved trigger factors according to slope failures induced by different trigger factors. As a crucial subsequent subject, the "chain trigger factors" in particular should be estimated, that is the investigation on the time robustness of the TFI model. With those issues as background, our efforts in this contribution are to:

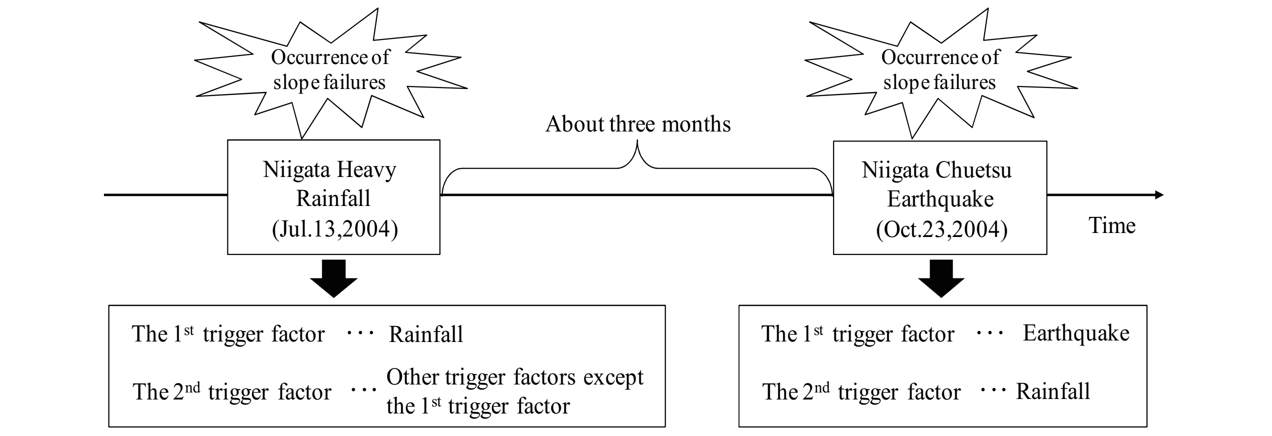

Figure 1. Definition of "chain trigger factors" with respect to slope failures in the study area.

- construct an inverse- and decompositional analysis algorithm of unobserved "chain-trigger factors" with respect to the slope failures; and
- provide a pair-wise comparative strategy of the 1st and the 2nd trigger factor influence maps according to the slope failures, which had been induced by different and chain trigger factors.

2. STUDY AREA AND INPUT DATA SETS, DEFINITION OF CHAIN-TRIGGER FACTORS

2.1 Study Area and Spatial Input Data Set

The study area is located on Mitsuke in Niigata prefecture, Japan, where the slope failures had caused by the different trigger factors of Niigata Heavy Rainfall (Jul. 13, 2004) and Niigata Chuetsu Earthquake (Oct. 23, 2004). Through the field investigation and the aerial photographs, those occurrences were precisely plotted on the topographical map as the training data sets for constructing the prediction model.

In this study, the inverse and decompositional analysis model of unobserved chain trigger factors has been constructed the relationship between those past slope failures and the following nine "causal factors": (1) Soil, (2) Surface geology, (3) Topography, (4) Land cover, (5) Vegetation index, (6) Slope, (7) Aspect, (8) Elevation, (9) Relief, and (10) Drainage. Each map consists of 100×70 pixels (3.0 Km×2.1 Km, 30m/pixels). The latter five factors were produced based on the Digital Elevation Model (DEM). The experts in each research field have made the Soil-, Surface geology- and the Topography-map. The land cover map is made through the maximum likelihood classification for the QuickBird data. The vegetation-index map is also produced by calculating the Normalized Difference Vegetation Index (NDVI) given by

$$NVI = (B4 - B3) / (B4 + B3) \quad (1)$$

where $B3$ and $B4$ are the digital numbers in each pixel corresponding to QuickBird Bands 3 and 4, respectively.

2.2 Definition of chain trigger factors with respect to slope failures

Figure 1 shows the definition of the "chain trigger factors" with respect to slope failures in the study. As mentioned above, the Niigata Heavy rainfall (Jul. 13, 2004) and the Niigata Chuetsu Earthquake (Oct. 23, 2004) had caused the slope failures in the study area. In particular, note that, the occurrence interval of these different trigger factors which had caused slope failures is too short. So, it is possible to say that the influence of the Niigata Heavy rainfall was indirectly reflected in the slope failures caused by the Niigata Chuetsu Earthquake.

To evaluate the influence of such "chain trigger factors," in this study, we have tried to decompose trigger factors into the "1st trigger factor" and the "2nd trigger factor" with respect to slope failures, which had been induced by Niigata Heavy Rainfall and Niigata Chuetsu Earthquake. The 1st and 2nd trigger factors with respect to each above-mentioned disaster are as follows.

- In case of the Niigata Heavy rainfall (Jul. 13, 2004), the 1st trigger factor and the 2nd trigger factor correspond to "rainfall" and "other trigger factors except the 1st trigger factor", respectively.
- In case of the Niigata Chuetsu Earthquake (Oct. 23, 2004), the 1st trigger factor and the 2nd trigger factor correspond to "earthquake" and "rainfall," respectively.

The inverse and decompositional analysis of such "chain trigger factors" is a requisite function of quantitative models for the better assessments of slope failure hazard. Through this procedure, the Trigger Factor Influence (TFI) maps with respect to the 1st and the 2nd trigger factor are produced in each examination cases, respectively. Furthermore, a pair-wise comparative analysis for these TFI maps has been carried out based on the Hayashi's quantification method of the fourth type, which is well known as one of the multivariate statistical analysis (Kojima et al., 2009).

3. INVERSE AND DECOMPOSITIONAL ANALYSIS OF UNOBSERVED CHAIN TRIGGER FACTORS

Figure 2 shows the inverse and decompositional analysis algorithm of the chain trigger factors, which consists of the following steps:

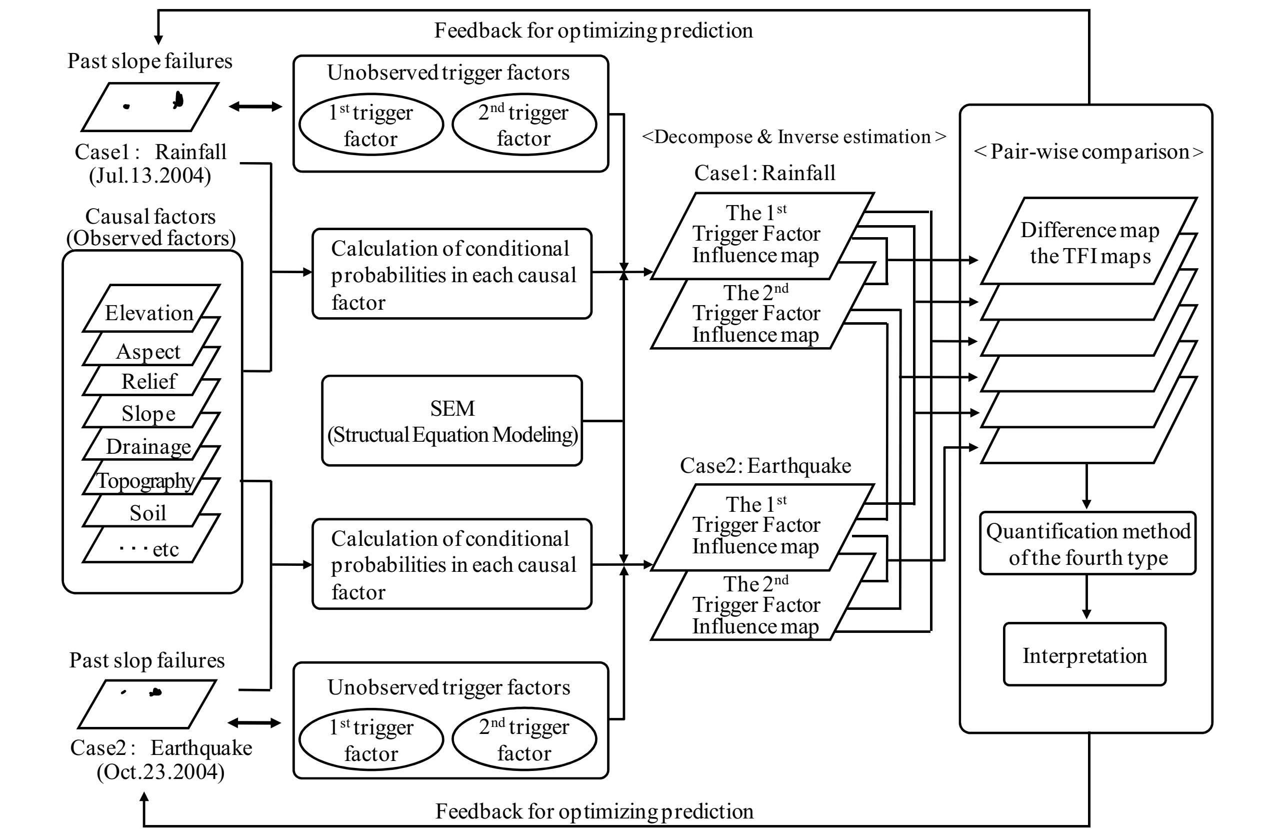

Figure 2. An inverse- and decompositional- analysis algorithm of "chain trigger factors" with respect to the slope failures

3.1 Conditional Probabilities as the Input Data

To evaluate the hazardous area affected by slope failure at each pixel with respect to slope failures, let us consider the following proposition:

F_p : " a pixel p will be affected by a future slope failure of a given type."

The conditional probabilities in each causal factor given by

$$P(Tq \mid Cij) = \frac{Tij}{Nij} \tag{2}$$

where C_{ij} is the i^{th} category of the j^{th} causal factor; N_{ij} is the number of pixels of C_{ij}; and T_{ij} is number of pixels of the past slope failures that had occurred in the area corresponding to C_{ij}. ***Prob***($F_p|C_{ij}$) are used as the input data for the SEM-based analysis (Kojima et al., 2006) .

3.2 Path Diagrams

To construct a quantitative prediction model, the relationship between the past slope failures (i.e., endogenous variables), the causal and trigger factors (i.e., exogenous variables) should be delineated on the path diagram used in the SEM. Let us consider the path diagram as shown in Figure 2 that is called a recursive mode. *Prob*($F_p \mid C_{ij}$) of Equation 2 are the input data as the exogenous variables, while the pixels corresponding to occurrences and non-occurrences of the slope failures are assigned to the value "1" or "0", respectively, that are used as the endogenous variables. To exclude a multi-collinearity between causal factors, among a pair of causal factors with high correlation (e.g., above 0.7), one of a pair with high partial correlation was selected. Figures 2 shows the path diagrams composed of selected causal factors. The training data sets (i.e., endogenous variables) of these models are as follows:

- Case1: using training data sets of slope failure affected by "Niigata Heavy Rainfall" ;
- Case2: using training data sets of slope failure affected by "Niigata Chuetsu Earthquake"

3.3 Evaluating model fit

Not knowing the trigger factors, the program is how to estimate the path weights of $\{a_1 , ... , a_n , b_1 , ... , b_n , c_1 , ... , c_n\}$ in Figure 2. Through the estimation procedure in SEM, those are estimated by minimizing the errors between the observed variance-covariance matrix and the reemerged one. Among various estimation procedures, i.e., maximum likelihood estimation, asymptotically distribution-free estimation, generalized least squares estimation, 'scale free' least squares estimation, unweighted least squares estimation, etc., Maximum likelihood estimation procedure is selected in this study, which is generally reported as a better estimator for the large population. For evaluating model fit, the Goodness of Fit Index (GFI), the Adjusted Goodness of Fit Index (AGFI), and the Root Mean Square Error Approximation (RMSEA) are applied as the generally employed statistical measures of fit. Details on these fit measurements are available for the references (Hoyle

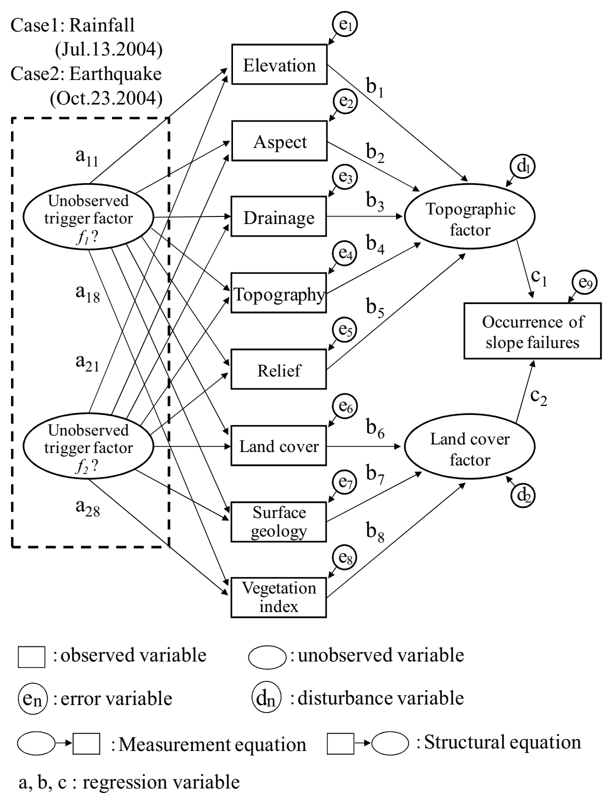

Figure 3. Path diagram for the SEM-based analysis .

et al., 1995). Table 1 shows the results of calculating these fit measures. By rule of thumb, GIF and AGFI need to be more than 0.9, conversely, RMSEA should be less than 0.08 for selecting reasonable model. Based on these criterions, Table 1 gives us an indication of which all models can be accepted as a model. These results imply the significance of adding the plural unobserved trigger factors (i.e., latent variables) to the path diagram.

3.4 Inverse and decompositional analysis of unobserved trigger factors

Note that the path components connecting "unobserved variables to each other" and "observed variables to unobserved variables" are often called the "structural equation" and "measurement equation," respectively. In this study, through the measurement equation, the influences of the trigger factors are inversely estimated pixel-by-pixel, and they are delineated on a "Trigger Factor Influence map (termed TFI map)." In the path diagram shown in Figure 3, the measurement equation between the trigger factors (i.e., unobserved variables) and the causal factors (i.e., observed variables) is given by

$$z_{ji} = a_{1j} f_{1i} + a_{2j} f_{2i} + e_{ji} \tag{3}$$

where z_{ji} is the input value of the i^{th} pixel in the j^{th} causal factor as shown in equation 3; f_{1i} and f_{2i} are the unobserved trigger factor corresponding to the 1st and the 2nd trigger factor, respectively (see Figure 2); a_{1j} and a_{2j} are the path parameters that are linked the j^{th} causal factor with the 1st and the 2nd trigger factor; and e_{ji} is the error term of the the i^{th} pixel in the j^{th} causal factor. The objective is to inversely calculate the

Table 1. Evaluation of model fit.

measure of fit	Case1	Case2
GFI	0.994	0.988
AGFI	0.980	0.965
RMSEA	0.042	0.061

Notes
Case1: using training data sets of slope failure affected by "Niigata Heavy Rainfall"
Case2: using training data sets of slope failure affected by "Niigata Chuetsu Earthquake"

estimates for f_{1i} and f_{2i} of the unobserved trigger factors. Suppose $\hat{f}_{1i}$ and $\hat{f}_{2i}$ are the estimates of f_{1i} and f_{2i}, respectively, then the inverse functions are given by

$$\hat{f}_{1i} = \sum_{j=1}^{p} h_{1j} z_{ji} \tag{4}$$

$$\hat{f}_{2i} = \sum_{j=1}^{p} h_{2j} z_{ji} \tag{5}$$

where h_{1j} and h_{2j} are the inverse parameters; and p is the number of the causal factors. h_{1j} and h_{2j} are determined by minimizing the following square error:

$$Q = \sum_{i=1}^{n} (f_{1i} - \hat{f}_{1i})^2 + \sum_{i=1}^{n} (f_{2i} - \hat{f}_{2i})^2 \rightarrow minimizing \tag{6}$$

$$\therefore \quad \frac{\partial Q}{\partial h_{1j'}} = -2\sum_{i=1}^{n} z_{j'i}(f_{1i} - \sum_{j=1}^{p} h_{1j} z_{ji}) = 0 \tag{7}$$

$$\frac{\partial Q}{\partial h_{2j'}} = -2\sum_{i=1}^{n} z_{j'i}(f_{2i} - \sum_{j=1}^{p} h_{2j} z_{ji}) = 0 \tag{8}$$

where n is the number of pixels in the study area. To solve equations 7 and 8, note that the average and variance of z_{ji} are standardized to "0" and "1", respectively. Also, assuming that there is no correlation between the 1st and the 2nd trigger factor, h_{1j} and h_{2j} can be simply given by

$$h_{1j} = \sum_{j'=1}^{p} a_{1j'} r^{jj'} \tag{9}$$

$$h_{2j} = \sum_{j'=1}^{p} a_{2j'} r^{jj'} \tag{10}$$

where $r^{jj'}$ is the element (j , j') of inverse matrix for the correlation matrix between causal factors. Using equations 4 and 5, $\hat{f}_{1i}$ and $\hat{f}_{2i}$ can be calculated and delineated on the 1st and the 2nd trigger factor influence maps (TFI maps), respectively.

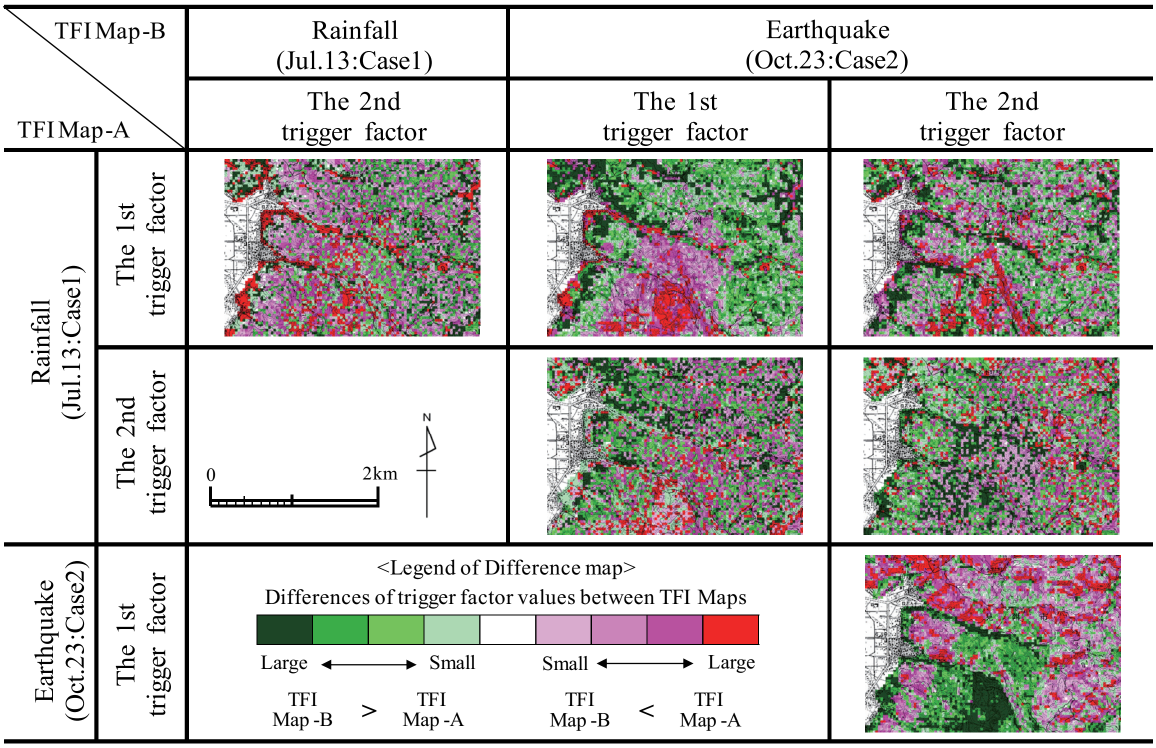

Figure 4. Difference maps (DIF maps) between Trigger Factor Influence maps (TFI maps).

3.5 Pair-wise comparison of trigger factor influence maps

As a final product of the inverse and decompositional analysis of trigger factors, the estimated values of $\hat{f}_{1i}$ and $\hat{f}_{2i}$ are delineated on the "Trigger Factor Influence map (termed TFI map)." Figure 4 indicates the difference maps (termed "DIF map") with all combination cases of TFI maps, with respect to two kinds of trigger factors that are "Niigata Heavy Rainfall (Case1)" and "Niigata Chuetsu Earthquake (Case2)," respectively. Note that the legend for these DIF maps lead to the following interpretation on the difference of trigger factor influence:

- **Shade of red:** The estimated values in each pixel of TFI map-A (see Figure 4) are larger than that of TFI map-B;
- **White:** The estimated values in each pixel of TFI map-A are almost equivalent to that of TFI map-B; and
- **Shade of green:** The estimated values in each pixel of TFI map-A are lower than that of TFI map-B.

Such "heuristic information" would be useful not only for assessing the hazardous area affected by the trigger factors in terms of the slope failures, but also for improving the cost-effectiveness in locating the places for setting the field measuring systems, i.e. the tensiometer, the rain gage, etc.

3.6 Exploratory analysis of decomposed trigger factors

The pair-wise comparative strategy as shown in Figure 5 are useful for clarifying the spatial differences between the TFI maps, however, there are limitations in analyzing the mutual relationships between decomposed trigger factors according to slope failures. As a measure, in this study, the Hayashi's quantification method of the fourth type is introduced, which is a set of related multivariate analysis method (e.g., multi-dimensional scaling) often used in data visualization for exploring similarities or dissimilarities in multivariate data. The dissimilarity measure (DI) used in this study is as follows (Kojima et al., 2009):

$$DI = \frac{1}{n}\sum_{i=1}^{n}\left|x_i - y_i\right| \tag{11}$$

where n is the number of pixels in the study area, x_i and y_i are the estimated values in each pixel of TFI map-A and TFI map-B, respectively.

Based on a matrix consisted of the dissimilarity measures (DI) between all pairs of items, a location of each item is plotted on the N-dimensional space. The items correspond to the 1st and the 2nd trigger factors according to the Case1 and Case2. Figure 5 illustrates a scatter diagram with respect to these items, in which the axis X and Y correspond to the 1st and 2nd eigenvalues, respectively. From those scatter diagrams, the following points could be indicated:

- Focusing on the X axis, the item of the 1st trigger factor with respect to Niigata Heavy Rainfall (Jul.13, 2004:Case1) and the items of the 1st and 2nd trigger factors with respect to Niigata Chuetsu Earthquake (Oct.23, 2004:Case2) are closely distributed. Such a scattered distribution suggests the Niigata Heavy Rainfall and the Niigata Chuetsu Earthquake that had caused slope failures has the relations on the "chain trigger factors."
- On the other hand, focusing on the Y axis, it is interesting to note that the two items of the trigger factors with respect to Niigata Heavy Rainfall (Jul.13, 2004:Case1) are distributed in a positive side and the two items of the trigger factors

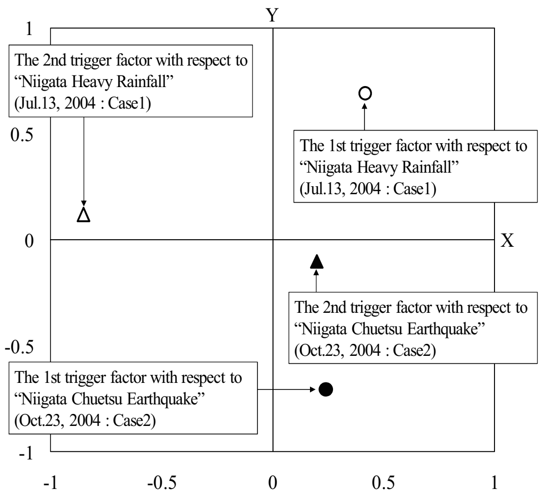

Figure 5. Scatter diagram with respect to decomposed trigger factors.

with respect to Niigata Chuetsu Earthquake (Oct.23, 2004:Case2) are distributed in a negative side. These results imply that the Y axis in the scatter diagram is applicable for analyzing the differences of trigger factor influences with respect to slope failures.

By using those scatter-diagram jointly with the pair-wise comparative table, the effective and efficient analysis on the "chain trigger factors" can be achieved with respect to slope failures, simultaneously.

4. CONCLUDING REMARKS

In this contribution, we have discussed inverse and decompositional analysis of unobserved chain trigger factors according to the slope failures, based on the SEM approach. The results of this study are summarized as follows:

- We strongly point out the necessity for evaluation of the "chain trigger factor" influences with respect to the slope failures, we tackle to construct an inverse- and decompositional- analysis algorithm of unobserved chain trigger factors with respect to the slope failures. As a measure, through the measurement equation (defined in SEM) between the causal factors (i.e., observed variables) and the trigger factors (i.e., unobserved variables), a "Trigger Factor Influence map (termed TFI map)" is produced;
- As a decompositional analysis of the trigger factors, the trigger factors are decomposed into the "1st trigger factor" and the "2nd trigger factor." The Trigger Factor Influence maps (TFI map) with respect to these trigger factors are also produced according to the slope failures, which had been induced by Niigata Heavy Rainfall (Jul. 13, 2004: Case1) and Niigata Chuetsu Earthquake (Oct. 23, 2004: Case 2), respectively; and
- As a final outcome, the differences in these TFI maps are delineated on a "difference (DIF) maps," which are also summarized on the pair-wise comparative table. Furthermore, a pair-wise comparative analysis for these TFI maps has been carried out based on the Hayashi's quantification method of the fourth type. Through the analytical procedure proposed in this study (**Figure2**), we can evolve the analysis on the "chain trigger factor influences," jointly with the expert's opinions, for the hazardous area affected by the slope failures.

In order to further proceed in the practical applications of inverse and decompositional analysis model, the subsequent subjects are as follows:

- As a decompositional analysis of trigger factors, we only considered the dual "exogenous variables" as shown in **Figure 3**. Slope failures, however, can be affected by various kinds of trigger factors. So, the modified path models with three or more exogenous variables should be investigated to improve the model identification in the SEM approach; and
- As occasion demands of investigators and specialists working on the slope failures, the training data sets of other types of slope failures or landslides should be added in the path model. In other words, we should investigate the sensitivity analysis of the model with respect to the different types of slope failures.

Note that the pixel-based estimation of unobserved trigger factors with respect to slope failures is the necessary condition for constructing the quantitative prediction models, but a difficult subject. As one of the supporting and heuristic information for slope failure hazard assessment, the difference maps in Figure 4 between the trigger factor influence maps would be useful for investigating the chain trigger factors induced slope failures. Furthermore, the conception on inverse and decompositional analysis of "chain trigger factors" presented in this study contributes to the future related research activities on the practical applications of quantitative prediction models, as well as to those expansions for slope failure hazard zonation.

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