6. SUMMARY AND CONCLUSIONS

This study integrates the Remote sensing and GIS techniques for identifying areas affected by landsliding, assessing landslide hazard, producing landslide hazard maps, and evaluating these maps. The potential of multitemporal Landsat Thematic Mapper (TM) data to identify landslide affected area was examined. The digital images obtained prior to, and following a disaster for the Kulekhani watershed (124 km^2) Nepal, were analyzed using five different kinds of change detection techniques. The techniques use the changes in spectral characteristics exhibited by land cover, to identify the landslide-affected areas in response to disturbances, in visible, infrared and mid infrared parts of the spectrum. The change detection techniques applied are 1) spectral image differencing, 2) vegetation index image differencing, 3) tasseled cap transformation image differencing, 4) spectral change vector analysis, and 5) principal component analysis. Different change detection techniques were then compared for their applicability in the assessment of affected areas associated with landsliding.

The landslide distribution data extracted by remote sensing means and brought into GIS (Geographic Information Systems) and thematic information stored in the GIS was then used for the landslide hazard assessment. The conventional aerial photographs, which are still the most important remote sensing means for landslide studies, were also used to produce the landslide distribution map. To determine the factors and classes influencing landsliding, layers of topographic factors derived from a digital elevation model, geology, and land use/cover were analyzed by quantification scaling type II (Q-S II) analysis and univariate statistical analysis (Failure rate: FR) analysis, and the results used for hazard mapping. In addition, in the Q-S II analysis, the effects of different samples of landslide and non-landslide groups on the critical factors and classes, and subsequently on hazard maps were evaluated. Simple random sampling was used to obtain samples of the landslide group and either an unaligned stratified random sampling or an aligned systematic sampling method generated the non-landslide group. For the analysis, one set of the landslide group was combined with each of five different sets of the non-landslide groups. Two FR analyses, based on area or frequency (number) of landslide were employed. The scores of the classes of the factors quantified by the five analyses in Q-S II and two analyses in FR were used for the hazard mapping with the GIS, with four levels of relative hazard classes: high, moderate, less, and least. In order to determine which sample combination best represents the population (in Q-S II analysis) the accuracy of hazard maps (i.e. evaluation of Q-S II results) was assessed. An evaluation method of the spatial agreement between the hazard maps was introduced, and the spatial agreements between the hazard maps were measured to comprehensively examine the effect of sampling on the final outcome of the analysis. The spatial agreements between the hazard maps produced from the FR analysis to that of the Q-S II analysis were evaluated to determine the effect of the method used, on the final outcome.

The results of using individual bands of multitemporal Landsat TM data show effectiveness of visible bands in the detection of landslide affected areas. The algorithms that use all the three visible bands perform better. For example the use of band 3 (red) alone was less effective but when it was combined with bands 1 and 2, the detection capacity is improved. The results of the analysis of multitemporal Landsat TM data show the spectral change vector analysis (using bands 1, 2 and 3) as the best method to detect the landslide affected areas, with overall and Khat accuracies of 88.3 percent and 75.4 percent, respectively. Band 2 spectral image differencing and principle component analysis were the next best. Band 7 (mid infrared) and tasseled Cap transformation (brightness) were shown to be the least accurate. NDVI performed the best among the four algorithms that were especially employed to examine the vegetation responses to landslides. The overall and Khat accuracies were 86.2 percent and 53.3 percent, respectively. The spectral change vector analysis, which used bands 3 and 4, was expected to give good results, but it did not perform well.

The change image of spectral change vector analysis (bands 1, 2 and 3) was further analyzed to detect the sediment deposition area, and landslides. NDVI was also evaluated for its capacity to detect landslides. Spectral change vector analysis shows higher accuracy for detecting sediment deposition class compared to landslides. The producer's and user's accuracies for sediment deposition class are 80.9 percent and 90.3 percent, respectively. The producer's and user's accuracies for landslide class are 56.7 percent and 73.6 percent, respectively. The producer's and user's accuracies for landslide class by NDVI are 52.8 and 73.5, respectively. Better results were obtained when the pixels interpreted as landslides from the multitemporal Landsat TM data were evaluated in terms of catchment area.

This study clearly shows that multitemporal Landsat TM data are a good tool to enable the assessment of landslide affected area, especially if the results are necessary for an early assessment. The sediment deposition area was more correctly determined than was possible for landslides. All the sediment depositions occurred in the same type of land use/cover (alluvial fan or river terraces) and their spatial sizes were larger, and this might be the reason for its higher accuracy. On the other hand, landslides were located in all the types of land use/cover, and the detection of changes due to landsliding in all kinds of land use/cover seem to be comparatively difficult by a single change detection method. In addition, large number of landslides in the study area were of single pixel size; consequently the accuracy in terms of pixel to pixel was critical, because of the errors that are introduced at each stage in this kind of analysis. For example, it is introduced during the preparation of a landslide distribution map from aerial photographs, digitization of landslides, transformation of landslide distribution map, GPS survey, and rectification of the image from the topographic map. For this reason, the pixels identified as landslides by analyzing multitemporal Landsat data was compared with the landslide and non-landslide catchment units, derived from the DEM and landslides interpreted from aerial photographs, the agreement was remarkably high. More than 80 percent landslide catchment units were identified. However, many non-landslide catchment units did also contain change pixels. Hence, classifying the change pixels to landslides was hence a difficult task than detecting the change. Though most of the landslides were included in the total change pixels, it was slightly difficult to extract (classify) only landslides from them.

The accuracy found for detecting landslides using multitemporal Landsat data in this study is better than previous studies, which used a single date image processing for detecting landslides. Considering the test area where these techniques were applied the multitemporal TM data can be a good means of data for the assessment of landslide affected area. In this part of the world aerial photographs are often unavailable.

The availability of continuous images from the satellite is hence very promising for the assessment of landslide affected areas and for detecting landslides in this part of the world. Though the cloud influences this kind of satellite data, and many times it is difficult to find cloud free data, the choice of many kinds of data available at present (such as Landsat TM, SPOT, IRS) and many more satellite plans of the future indicate that problems relating to the unavailability of data will gradually diminish. The theory behind the detection would be the same as described in this study irrespective of which data is used, as long as the bands have similar characteristics.

Landsat TM data taken at two different dates can be used to produce a landslide distribution map. The landslide identification from multitemporal Landsat TM data proved to be effective for the landslide hazard assessment based on the catchment units; however, it may not suitable for the grid-cell based hazard assessment. Hence the grid-cell based landslide hazard assessment method should produce landslide distribution map from the large scale aerial photographs.

The results of the grid-cell based landslide hazard assessment and mapping process, indicate that the map produced from Q-S II analysis to be more accurate when compared to FR analysis. Within the Q-S II analysis, a higher accuracy is found for the unaligned stratified random sampling method for generating non-landslide group. The methods described for the evaluation of landslide agreement in the landslide hazard map by measuring "overall spatial agreement" shows an agreement in the hazard maps of between 60 percent to 80 percent, depending on the number of hazard classes (two or four) used in a hazard map. The agreements in the hazard maps, produced from different sample combinations using unaligned stratified random sampling for selecting non-landslide group, are found to be acceptable for practical use in hazard mitigation and watershed management planning. These results are likely to indicate that although the outcome depends to some extent on the sampled data, the difference may be small enough for the practical use of a hazard map. As a result, when using unaligned stratified random sampling for a non-landslide group, one sample set would practically suffice for the analysis and hazard mapping. This finding is an important achievement in the field of landslide hazard assessment.

Landslide hazard assessment involves many different problems at various stages of analysis. For landslide hazard assessment of small grid-cells, it is essential to determine the smallest landslide as much as is possible. Though satellite data prior to and after heavy rainfall can detect landslides much more effectively than having data taken on a single date, it has a limited use in the grid-cell based hazard analysis. At present, conventional aerial photographs is still the most important remote sensing means for detailed landslide studies, allowing accurate mapping of landslides in large areas for the hazard assessment. However, many satellites have been planned in the next decade and many kinds of digital data will be available. This may improve the limitation of presently available data. GIS is helpful to landslide hazard assessment and mapping in many ways and can also facilitate a trial and error approach for assessment methods.

This study demonstrates the use of remote sensing and GIS in the application of landslide hazard assessment. The study determines the potential and appropriateness of using satellite remote sensing data and aerial photographs at different stages of landslide hazard assessment and mapping. Multitemporal satellite data such as Landsat TM was successfully used for the assessment of the areas affected by the landslides. They are highly capable of detecting areas affected by landslides. The landslide identification from multitemporal Landsat TM data proved to be effective for the analysis based on the catchment units. The landslide hazard assessment requires many critical decisions and this study provides a better understanding of different landslide hazard assessment methods in GIS for large areas. The application of remote sensing and GIS techniques described in this study helps in many ways to serve to hazard mitigation activities and watershed management planning.