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Developing Remote Sensing Methods to Assess the Effects of Large Floods at a Regional Scale

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Foreword

This project was initiated and funded by the Inventory and Monitoring Technology Development (IMTD) steering committee. This committee was chartered to identify emerging issues and provide oversight to the USDA Forest Service's Technology and Development (T&D) program. The Remote Sensing Applications Center wishes to acknowledge the committee and the San Dimas Technology and Development Center for guidance, direction, and oversight on the project reported in this document.

Abstract

Extreme precipitation events often result in landslides and other mass earth movement that can have a devastating impact on forests. The objective of this project was to investigate remote sensing analysis as a means to identify and map recent landslides over large areas with a focus on data and software that are readily available to most land management agencies. Multi-temporal, remotely-sensed imagery was used to detect changes between the pre- and post-event landscape conditions. Two sources of remote sensing data were investigated: multispectral Landsat Thematic Mapper (TM) imagery and panchromatic digital orthophoto quadrangles (DOQ). A Spectral Change Vector Analysis (SCVA) method was used with the Landsat TM, while simple image algebra was used to create a change layer for the DOQs.

Using either method, approximately seven out of ten landslides were detected. In addition to change due to landslides, changes in the landscape due to forest management, road construction, reservoir water levels, and fires were also detected. Manual editing of the draft landslide map was required to reduce these false positive errors. Variations in the aerial photographs used to produce the DOQs were problematic. Despite efforts to normalize the DOQ histograms, differences in tone between the 1998 and 1993 imagery caused both false positive and false negative errors. Vertical displacement and time of acquisition differences between photographs also caused false detection of changes. By re-sampling the DOQs to five-meter spatial resolution some of these problems were reduced. High resolution, space-borne imagery may have fewer problems with this because less mosaicking is involved and there are fewer problems with off-nadir displacement distortion.

Both methods were more successful at detecting larger landslides than smaller ones. Based on the results of this study, Landsat TM data is not sufficiently resolute to map landslide features less than an acre in size. DOQ data have some problems due to variation in the source data (aerial photography), and multispectral information is lacking. Future landslide mapping efforts should focus on multispectral data with a spatial resolution in the 5 to 10 meter range. Merging higher resolution panchromatic data with multispectral data should also be investigated. The new generation of high-resolution sensors produce imagery that is also promising, but these data sources are also prohibitively expensive across large areas.

Introduction

Figure 1—A Large debris flow along the Stanislaus River in California.

Extreme precipitation events often result in landslides and other related phenomena, such as earth flows, slumps, stream re-channeling, and sediment deposition. These geological processes can have a devastating impact on forested landscapes (figure 1). Following a heavy precipitation event, efficient detection and mapping methods are needed so managers can assess the damage over large areas and prioritize efforts to control and stabilize earth movement.

Typically, landslide inventories are conducted using post-event aerial photography, aerial survey, and field visits. Usually these inventory efforts are focused on small areas, do not cross administrative boundaries and are time-intensive. Differences in mapping methods between administrative units often do not allow adjacent datasets to be combined, so an all-encompassing map of the damage from a particular event is rarely compiled. This lack of a comprehensive inventory can lead to erroneous conclusions about the relationships between land management activities and flood effects. What is needed is a practical method for producing a comprehensive map of landslides and erosion damage across large areas.

The objective of this project is to develop a methodology to apply selected passive electro-optical satellite imagery to identify and map recent landslides and river channel changes over large areas pursuant to flooding. We focused on data and software that are readily available to most land management agencies.

The problem of mapping landslides efficiently across large areas has received considerable attention by the research community. Many of these studies are focused on hazard assessment and monitoring existing mass movement features. Mantovani, et al. (1996) provide an overview of the current (at that time) remote sensing research efforts on detection, monitoring, and risk assessment of landslides. They also provide an interesting table of minimum sizes of objects that can be resolved using various types of imagery. Dhakal, et al. (2002) evaluate a number of different change detection techniques with Landsat TM imagery. Their goal was to accurately detect areas affected by heavy rainfall (e.g., erosion, landslides, sedimentation, etc.). Sarkar and Kanungo (2001) obtained good results by visually interpreting landslides from a merged image product created from IRS-PAN and IRS-LISS-III data. Often, landslide features can be recognized by their shape and topographic characteristics as well as their spectral response. Barlow, et al. (2003) sought to map landslide scars in British Columbia's Cascade Mountains using image segmentation software (eCognition) that allowed them to select for features of a certain shape. These features were then classified using a system that incorporated spectral and topographical properties. Others have combined optical sensor data with Synthetic Aperture Radar (SAR) data (Singhroy, et al. 1998); the SAR data help to define small changes in elevation and slope.

Background and Study Area

In late December, 1996 and early January, 1997, a series of warm, wet storms produced heavy rain in the northern California/southern Oregon region. These storms resulted in heavy flooding and significant landslides. The Klamath, Siskiyou, Shasta-Trinity and Six Rivers National Forests (figure 2) are within this area.

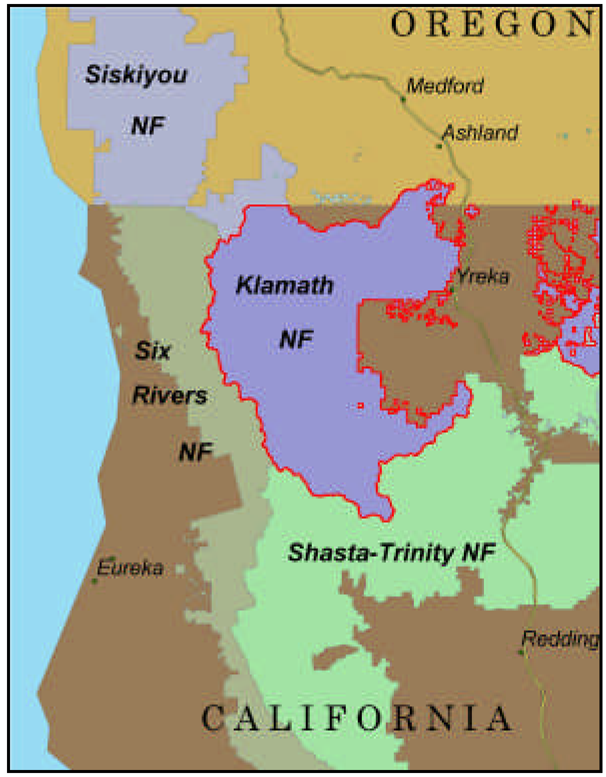
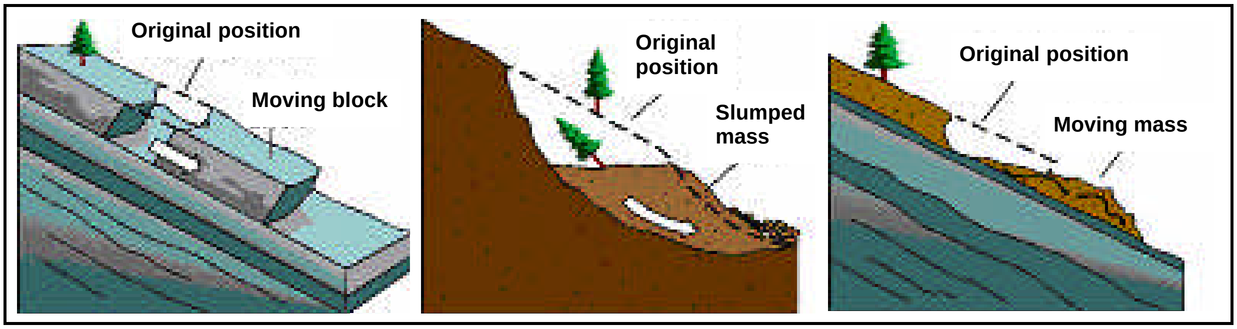


Figure 2—Klamath National Forest is located in northwest California.

Efforts to assess and map the damage from the 1997 flood were conducted by each of the National Forests in the region, and by the Oregon Department of Forestry. These studies are specific to each administrative area and are not easily combined into a comprehensive map of flood damage for the region.

The Klamath National Forest conducted a quick assessment of the flood damage using aerial photo interpretation and field observations. This effort produced a polygon coverage of landslides and stream channel damage for the Klamath National Forest. We will refer to this polygon layer as the 1997 Flood coverage. Landslides identified in this layer are categorized, three of the major types of landslides are presented in figure 3.

This pilot study was restricted to a single Landsat scene to avoid having to acquire adequate cloud-free pre- and post-flood imagery for more than one scene. Our study area for the Landsat TM data was that portion of the Klamath National Forest that lies within WRS Path 46 Row 31 (figure 4). For the methods that focused on the 7.5-minute DOQs, we chose the Grider Valley, Seiad Valley, and Scott Bar quads for the study area. All of these quads are within the Klamath National Forest (KNF). Based on the 1997 Flood coverage, there appeared to be substantial damage in these three quads.



Debris slide: Movement parallel to planes of weakness and occasionally parallel to slope.

Debris Slump: Complex movement of materials on a slope; includes rotational slump.

Debris flow: Viscous to fluid-like motion of debris.

Figure 3—Three basic types of landslides. (Courtesy of the Government of British Columbia, Ministry of Engineering and Mines).

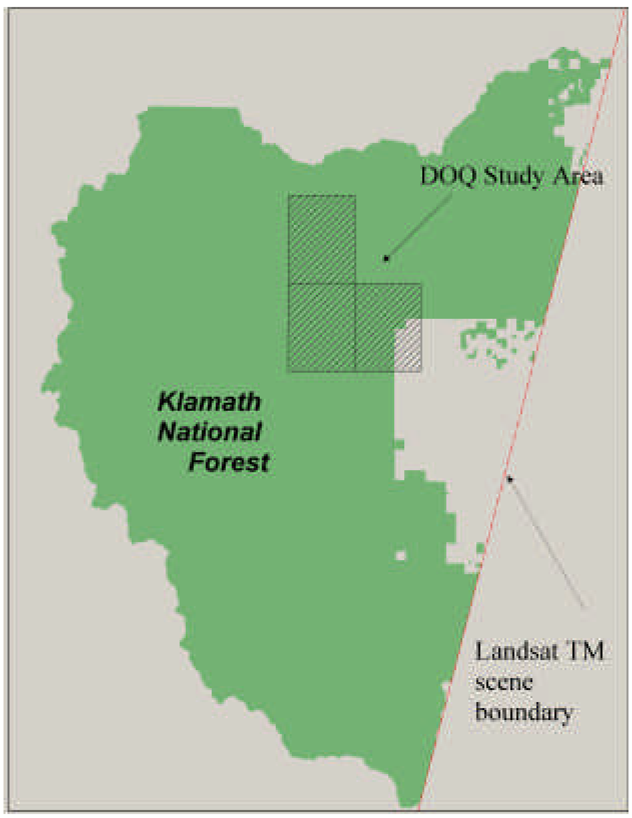


Figure 4—The study area for the TM method was That portion of the KNF that lies in Landsat scene Path 46 row 31.

Methods

The approach used to map the landslides used multi-temporal, remotely-sensed imagery to detect changes between the pre- and post-event landscape conditions. This type of remote sensing is known as change detection; a number of different algorithms have been developed to assess change in the landscape due to natural or human causes (Jensen, 1996). Change detection methods necessarily use imagery that was collected before the event and compare this imagery to that collected after the event. To minimize detecting landscape changes that are not due to the event, every effort should be made to obtain pre- and post-event imagery that is as close to the event date as possible.

Data Acquisition

As stated previously, the focus of this project was on methods that utilize data and software that are readily available to land management agencies. Data from the Landsat series of satellites is easily obtained and archive libraries contain the same scene captured on many different dates. We obtained a pre-event image collected on August 31, 1995, and a post-event image on July 23, 1997 (Path 46, Row 31). DOQs are commonly available for most land management agencies; they have been available for over a decade and are updated on a regular basis. Most agencies have access to archival DOQs that can be used for change detection. We obtained 1993 and 1998 DOQs for the three study area 7.5-minute quads. The Klamath National Forest provided ancillary GIS layers used to help develop and refine the methods, including the 1997 flood damage layer mentioned above, and a coverage of disturbance (fires, timber harvest) for the period 1994-1998. Digital elevation model (DEM) data were obtained from the archives at the Remote Sensing Applications Center. These data were used to develop slope and aspect layers used in the analysis.

Spectral Change Vector Analysis using Landsat TM

The two Landsat scenes were clipped to the project boundary and radiometrically normalized through histogram matching, and a pixel to pixel registration was conducted between the two (1995 and 1997) project area images. There was some difficulty adequately registering the two images, so a second order polynomial transformation was performed on the 1997 image. Following this processing step, registration was improved. The Normalized Differential Vegetation Index (NDVI) is a band ratio using Bands 3 and 4; it is a well-recognized index of vegetation biomass and water content. The NDVI was calculated for each image.

The 1997 Flood coverage contains 810 polygons representing landslides that occurred or were active as a result of the 1997 Flood. A subset of these polygons (152 polygons) were greater than or equal to one acre in size. Because the spatial resolution of Landsat data is 30 meters by 30 meters, we decided to use only those polygons that were one acre or more in size for training and accuracy assessment. Resolving features smaller than one acre would be difficult due to spectral mixing within pixels and relatively small registration errors. A training dataset of 25 polygons was randomly selected for use in developing the models and methods. The remaining 127 polygons were set aside for later use in accuracy assessment.

The Spectral Change Vector Analysis (SCVA) change detection model was used for our first attempt at mapping the 1997 landslides using TM data (based upon the results of Dhakal, et al., 2002). SCVA uses three bands in the two source images (pre-event and post-event) and calculates a change vector layer (direction of change — increase or decrease — for each of the three bands) and a change magnitude layer (overall amount of change). We created a SCVA model using the Spatial Modeler in ERDAS Imagine 8.6, using Bands 1, 2 and the calculated NDVI band as inputs.

Zonal statistics were then calculated to provide information on the range of values for the change layers of the training sites. This helped us begin the process of determining the threshold for what is change and what is not. Thresholds were established by interactive examination of the change layers and the training site polygons. SCVA is discussed in detail in Jensen (1996) and by Michaelak, et al. (1993).

Once the thresholds were established, these settings were used to create a draft GIS layer of landslides. This layer contained all changes to the landscape for the period between the image dates, so the next step was to edit out changes that were not landslides. Examination of the draft landslides layer showed a significant amount of scattered pixels classified as change in the upper elevations. Closer inspection of these areas showed that change detected in these areas is probably attributed to differences in snow pack, shadowing, and vegetation phenology. Also, an analysis of zonal statistics for the 1997 Flood coverage with the elevation layer showed that none of the landslide polygons (of at least one acre) were in the high elevation areas. Therefore, we removed any change detected above 1850 meters in elevation.

Further inspection of the draft landslide layer revealed many areas where change pixels appeared to be the result of shadows, urban and agricultural areas, and vegetation changes in brush/grassland cover types. These areas, along with areas identified using the disturbance layer provided by the KNF, were manually edited out.

We evaluated the final TM-derived landslide layer by looking at each of the polygons in the 1997 Flood layer that were designated for accuracy assessment and determining how many pixels within those polygons were classified as landslides. A designation was placed on each polygon based on the following decision rules:

1. If 40 percent or more of the polygon is classified as landslide, then the landslide is "accurately detected."

2. If a polygon is adjacent (within one pixel) to an area of landslide pixels that is at least 40 percent of the polygon area, then the landslide is tagged as "accurately detected - adjacent."

3. If neither 1 or 2 above is met, then the landslide is considered "not detected."

Criterion 2 was created to account for apparent registration differences between the polygons in the 1997 Flood coverage and the TM source imagery.

DOQs

DOQ data for each of the study quads were imported, mosaicked, and histogram-matched. The raw DOQ files have a spatial resolution of one meter. At this resolution, details such as individual tree crowns can be recognized. This level of detail can produce a great deal of false change detection, given that DOQs are composed of many orthorectified aerial photographs with inconsistent shadows, brightness values, and vertical displacement.

To minimize the false change detection, the DOQs were resampled to five meters. These data are single-band panchromatic images, so multispectral change detection methods such as SCVA are not possible. Simple image algebra was used to create a change layer for each quad. This method simply creates a GIS layer of the difference in brightness values (BV) between the pre-event and post-event images. The draft landslide layers output by the image algebra model were then analyzed to establish the change threshold by using the training sites, and by examining obvious landslide areas on the raw one-meter imagery (figure 5).

Once the change threshold was established, the draft landslide layers were edited to remove obvious spurious change pixels that were caused by shadows, timber harvest, road construction, and urban or agricultural areas.

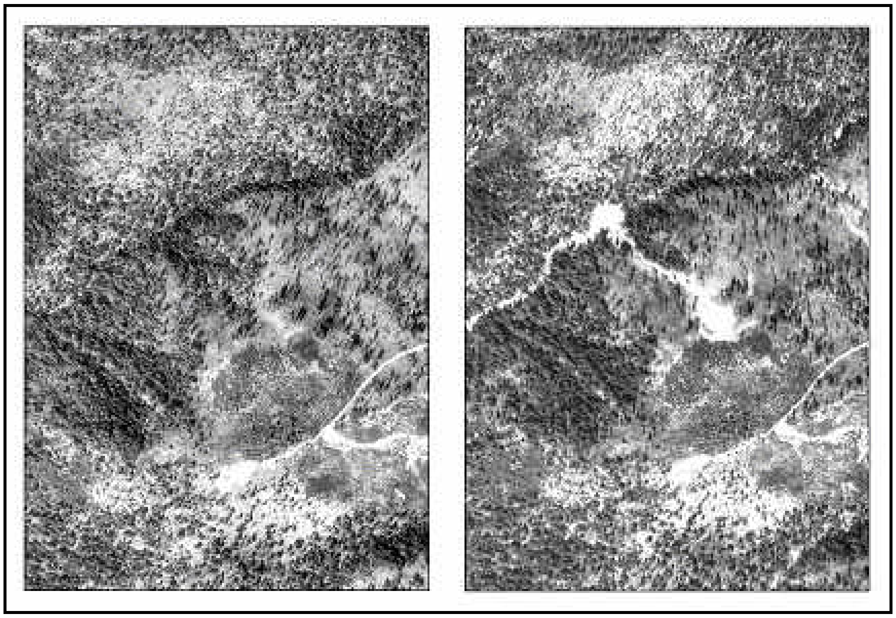


Figure 5—Slide and earth flow types of landslides tend to scour vegetation and leave a scar. The 1993 DOQ is on the left and the 1998 DOQ on the right.

The draft DOQ landslide layers were evaluated by visually inspecting each of the polygons that were within the extents of the three DOQs and assigning one of the following:

1. If 40 percent or more of the polygon is classified as a landslide, then the landslide is “accurately detected.”

2. If a polygon is adjacent (within five pixels) to an area of landslide pixels that is at least 40 percent of the polygon area , then the landslide is tagged as “accurately detected - adjacent.”

3. If neither 1 nor 2 above is met, then the landslide is considered “not detected.”

Criterion 2 was created to account for poor registration between the landslide polygons and the draft DOQ landslide layers. These evaluation criteria are similar to those used to evaluate the SCVA technique. Because of the higher spatial resolution of the DOQs, we decided to use all of the polygons in the three quad study area for accuracy assessment regardless of size.

Results

Because of the imperfect geolocation of the 1997 Flood coverage in relation to the DOQ and TM derived landslide layers, we decided to combine those landslide polygons designated as “accurately detected – adjacent” with those designated as “accurately detected”. This seems logical considering that most of the “adjacent” polygons were within 30 meters of a block of pixels that were similar in size and shape. Data for both “accurately detected” and “accurately detected – adjacent” polygons are presented in Table 1.

The SCVA analysis method successfully detected 70% of the polygons in the 1997 Flood coverage, whereas the DOQ method detected 41% of the landslides successfully.

Certain landslide types may be easier to detect with remote sensing than other types, mostly because some types (slumps) do not disturb vegetation as drastically and therefore exhibit much less spectral change. Slides and flows have a tendency to scour away vegetation and the subsequent scar is easier to detect with the imagery (figure 5). This is somewhat supported by the results: the SCVA method detected slides and flows (debris slide, debris slide/slump, debris flow, slump/earth flow) more effectively than slumps (table 2). However, the results for the DOQ method show no difference in the ability to detect slides versus slumps (39% and 40%, respectively).

Not surprisingly, larger landslides were easier to detect than smaller ones. The two methods detected landslides between .5 acre and 1 acre in size at nearly identical proportions (52% and 56%), and larger slides (greater than one acre) were more effectively detected (70% and 67%, as shown in table 3).

Table 1— Accuracy of change detection methods in detecting the 1997 landslides

Criteria	**SCVA***	**DOQ****
Successful detection	63 (49%)	91 (25%)
Adjacent detection	26 (21%)	60 (17%)
Not Detected	38 (30%)	213 (59%)
	n = 127	*n* = 364

* Polygons one acre in size and greater. **All polygons within the extent of the study quads.

Table 2—Accuracy of the change detection methods by landslide type

Method	**Debris slide**	**Debris slide/ slump**	**Debris Flow**	**Slump**	**Slump /Earthflow**
SCVA**	**68%**	**77%**	**100%***	**53%**	**100%***
DOQ***	**39%**	**57%**	**71%**	**40%**	**0%**

* *n* = 2. ** Polygons one acre in size and greater (*n* = 127).
***All polygons within the extent of the study quads (*n* = 364).

Table 3—Accuracy of the change detection methods by size of landslide

Method	**< .5 acre (*n* = 582)**	**.5 – 1.0 acre (*n* = 125)**	**> 1 acre (*n* = 129)**
SCVA	**35%**	**52%**	**70%**
DOQ	**30%**	**56%**	**67%**

Discussion

The accuracy presented give insight into false negative errors (i.e., failure to classify a landslide polygon in the 1997 Flood coverage as landslide). For both methods, approximately seven out of ten landslides were detected if they were greater than one acre in size. False positives (i.e., classifying areas as landslide when in reality they were not) were not analyzed quantitatively. Reducing false positives was the primary goal of manual editing of the draft landslide layers.

Our intent was to minimize subjective manual editing of the landslide GIS layers, but it was obvious that the initial landslide layers produced by both methods substantially overestimated landslides. In addition to changes detected due to forest management, road construction, reservoir water levels, and fires, there were many areas where shadows cast by trees and topographic features were different enough to be classified as landslides. Correct interpretation of these areas was not always easy, especially using the 30-meter resolution TM data. Setting the threshold beyond which change would be determined to be a landslide was also a subjective process; we balanced the need to represent the landslides as closely as possible in our training datasets, while also trying to minimize the number of false positives that would need to be edited out.

In a perfect world, change detection studies would be performed with images collected just before and just after the event in question. All changes detected would be the result of the event being studied. In reality, we usually work with imagery that is available or that we can easily acquire. We used TM imagery acquired 8/31/95 (pre-event) and 7/23/97 (post-event), and 1993 (pre-event) and 1998 (post-event) DOQs. Many landscape changes may have occurred in the interval between image dates, and not all of these changes are the result of the 1997 flood.

In developing and testing our methods, we benefited from having a training dataset of known landslides. This training dataset was used to establish thresholds and evaluate model output. In most situations, land managers would not have access to such a dataset. Training data could be created by photo interpreting landslides in representative sub-regions of the larger area to be mapped.

Variation in the aerial photographs used to produce the DOQs was problematic. These images are single-band panchromatic, so the change detection was based on simple differences in brightness values – areas where a slide occurred were much brighter in 1998 than in 1993. Despite efforts to normalize histograms, differences in tone between the 1998 and 1993 imagery caused false change detection and also false negatives, especially in brushy areas.

Vertical displacement and time of acquisition differences between photographs caused variation in shadows. Re-sampling the DOQs to five-meter spatial resolution was our effort to reduce the effect of this variation, while still preserving spatial resolution sufficient to map the smaller landslides. The added information in multispectral bands is undoubtedly important in landslide detection in forested landscapes; there simply is not enough information in single-band panchromatic imagery to adequately detect landslides. Space-borne imagery may have fewer problems with variation because less mosaicking is involved and there are fewer problems with off-nadir displacement distortion.

The minimum size of a feature that can be resolved using remotely-sensed imagery is largely a function of the spatial resolution of the source imagery. A general rule of thumb to calculate the minimum size of resolvable features is to multiply the spatial resolution of the imagery by ten for high-contrast features and by forty for low-contrast features (Mantovani et al., 1996). Thus, the minimum feature size that is resolvable for 30-meter TM data is 2.2 acres for high-contrast features and 8.8 acres for low-contrast features. Following this logic, Barlow et al. (2003) attempted to detect only landslides larger than one hectare (approximately 2.5 acres).

Our results replicate the finding that the size of the landslide is significant in the ability to detect it. Both methods were much more successful at detecting larger slides (table 3). Over two-thirds of the landslides in the 1997 landslides coverage are less than 0.5 acres in size; high resolution imagery is needed to resolve these small features. The impact of spatial resolution is depicted graphically in figure 6.

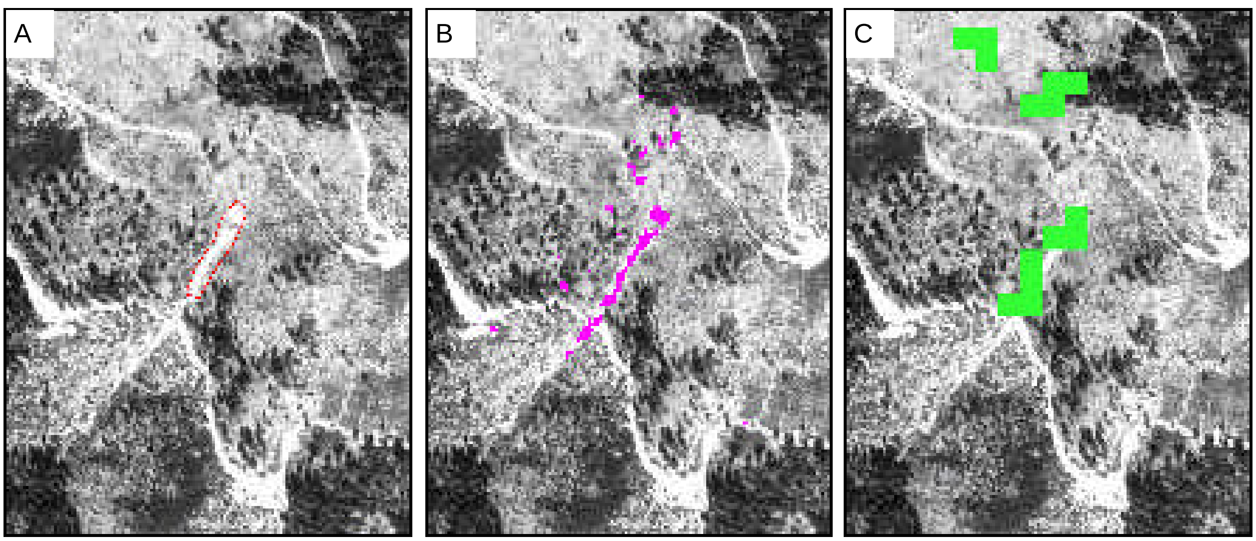


Figure 6—A 1.3 acre landslide as detected *(A)* by the aerial survey analysis, *(B)* with the DOQ method and (*C*) using SCVA with the 30m Landsat TM data.

We attempted to develop a model that would remove changes due to forest management; we hypothesized that the shape and slope angle of forest management units would allow us to separate them from landslide features. We found that we were unable to separate these features based on these criteria. In addition to mapping slope failures, we also sought to map changes in stream channels and removal of riparian vegetation. These features could be any shape and could occur on shallow slopes.

Conclusions

We attempted to map a broad range of erosion features across a forested landscape using two different types of commonly available imagery. The accuracy of both methods is sufficient to provide an overview of the damage across large landscapes, especially for large (at least one acre) landslide scars.

The methods we present here could be used in conjunction with a more detailed photo-interpretive effort. Areas of significant change could be identified using a TM based change detection and those areas could be mapped in detail using large-scale aerial photography.

Based on our experience in this study, TM data is not sufficiently resolute to map landslide features less than one acre in size. DOQ data have some problems due to variation in the source data (aerial photography), and multispectral information is lacking. Future landslide mapping efforts should focus on multispectral data with a spatial resolution in the 5-10 meter range (e.g., IRS, SPOT satellites). Merging higher resolution panchromatic data with multispectral data should also be investigated. The new generation of high-resolution sensors produce imagery that is promising (i.e., IKONOS, QuikBird, OrbImage) but is also prohibitively expensive for use over large areas.

Remote sensing and GIS will continue to be critical tools in the assessment of erosion damage from heavy rainfall events. The work presented here is intended to lead to a refined process by which land managers can effectively map landslides across large areas.

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