Detection of land cover changes using MODIS 250 m data

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Abstract

The Vegetative Cover Conversion (VCC) product is designed to serve as a global alarm for land cover change caused by anthropogenic activities and extreme natural events. MODIS 250 m surface reflectance data availability was limited both spatially and temporally in the first year after launch due to processing system constraints. To address this situation, the VCC algorithms were applied to available MODIS 250 m Level 1B radiance data to test the VCC change detection algorithms presented in this paper. Five data sets of MODIS Level 1B 250 m data were collected for the year 2000, representing: (1) Idaho–Montana wildfires; (2) the Cerro Grande prescribed fire in New Mexico; (3) flood in Cambodia; (4) Thailand–Laos flood retreat; and (5) deforestation in southern Brazil. Decision trees are developed for each of the VCC change detection methods for each of these six cases. These decision trees are to be used for updating the look-up tables required by the VCC production code. For these change detection cases, the VCC change detection methods worked reasonably well. In the Idaho–Montana wildfire case, a fire perimeter polygon data set compiled by the USDA Forest Service was used to validate the output of the VCC change detection methods. Although the VCC output identified only 32% of the burned pixels within the ground observed Idaho–Montana fire perimeter polygons, the detection accuracy of the VCC output did reach 99% when the VCC product is considered as an alarm system identifying the occurrence of the change in an area. For other cases, the detection accuracy in per-pixel terms of the VCC output ranges from 55% to 90% against reference change bitmaps that were created by image interpretation. Look-up tables created with AVHRR and Landsat Thematic Mapper data require modifications for the MODIS data due to differences in radiometric response between MODIS and the heritage instruments. The applications presented in this paper also evaluate the relative performance of each of the five change detection methods used as VCC algorithms. Conclusions reached in this paper will be used for future refinement of the VCC product.

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1. Introduction

Human activities combined with natural events are increasingly altering the Earth’s land cover. These land cover changes alter the land surface roughness and albedo, which affect the exchanges of sensible heat, latent heat (water vapor) and carbon dioxide and other greenhouse gases between the land surface and the atmosphere (Sellers et al., 1996) and consequently cause regional and even global climatic changes (Dickinson & Henderson-Sellers, 1988; Nobre, Sellers, & Shukla, 1991; O’Brien, 1996; Xue, 1996). Therefore, more reliable land cover change information and data sets are needed in global change studies, especially in increasingly sophisticated Earth system models (Townshend, Justice, Li, Gurney, & McManus, 1991; Townshend et al., 1994).

The Moderate Resolution Imaging Spectroradiometer (MODIS) is one of the remote sensing instruments onboard the first NASA Earth Observing System (EOS) satellite, Terra. As one of the efforts of the MODIS Science Team, a 250 m resolution land cover change data product, Vegetative Cover Conversion (VCC), is being generated from MODIS data. Zhan et al. (2000) have described the generation of prototype products using data from NOAA’s Advanced Very High Resolution Radiometer (AVHRR) and Landsat’s Thematic Mapper (TM). This paper reports some early results of VCC products generated using 250 m
Table 1
Critical dates in MODIS 250 m Level 2G surface reflectance production for year 2000

<table>
<thead>
<tr>
<th>Day of year</th>
<th>Date</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>055, 2000</td>
<td>24 February 2000</td>
<td>Nadir door opens</td>
</tr>
<tr>
<td>110, 2000</td>
<td>19 April 2000</td>
<td>First geolocation update (500 m RMS)</td>
</tr>
<tr>
<td>153, 2000</td>
<td>1 June 2000</td>
<td>First calibration update</td>
</tr>
<tr>
<td>178, 2000</td>
<td>26 June 2000</td>
<td>Mirror wedge angle correction to geolocation (100 m RMS)</td>
</tr>
<tr>
<td>217, 2000</td>
<td>4 August 2000</td>
<td>Instrument operation suspended</td>
</tr>
<tr>
<td>231, 2000</td>
<td>18 August 2000</td>
<td>Instrument operation resumes</td>
</tr>
<tr>
<td>241, 2000</td>
<td>28 August 2000</td>
<td>Initial processing stabilizes on 5% production</td>
</tr>
<tr>
<td>301, 2000</td>
<td>27 October 2000</td>
<td>One day instrument formatter outage</td>
</tr>
<tr>
<td>305, 2000</td>
<td>31 October 2000</td>
<td>Switch to B-side electronics; MODAPS assumes 10% production</td>
</tr>
<tr>
<td>335, 2000</td>
<td>30 November 2000</td>
<td>One pixel geolocation offset corrected in L1B data</td>
</tr>
</tbody>
</table>

Table 2
Types of land cover change to be detected by the MODIS 250 m land cover change product

<table>
<thead>
<tr>
<th>Time 1 cover type</th>
<th>Time 2 cover type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>Nonforest</td>
</tr>
<tr>
<td>Nonforest</td>
<td>Regrowth</td>
</tr>
<tr>
<td>Bare</td>
<td>Regrowth</td>
</tr>
<tr>
<td>Water</td>
<td>Flood retreat</td>
</tr>
<tr>
<td>Burn</td>
<td>Regrowth</td>
</tr>
<tr>
<td>Deforestation</td>
<td>bare</td>
</tr>
<tr>
<td>Deforestation</td>
<td>Urbanization</td>
</tr>
<tr>
<td>Flooding</td>
<td>Flood retreat</td>
</tr>
<tr>
<td>Burn</td>
<td>Regrowth</td>
</tr>
<tr>
<td>Burn</td>
<td>Regrowth</td>
</tr>
</tbody>
</table>

The empty boxes indicate that the conversion is not of interest or is not likely to occur.

resolution MODIS data. Specifically, this paper first reports on the status of MODIS 250 m data production, then presents our early results for detecting land cover changes using the VCC algorithms, and finally discusses the main issues and the lessons learned in the VCC product generation.

2. MODIS 250 m resolution data situation

The MODIS instrument onboard NASA’s Terra satellite is a scanning radiometer system with 36 spectral bands extending from the visible to the thermal infrared wavelengths (Running et al., 1994). The first seven bands are designed primarily for remote sensing of the land surface with spatial resolutions of 250 m for band 1 (red, 620–670 nm), and band 2 (near infrared, 841–876 nm), and 500 m for bands 3 to 7 (459–479, 545–565, 1230–1250, 1628–1652, 2105–2155 nm, respectively). Note that while the bands are commonly referred to as 250 and 500 m, the actual resolution of the grids is 7.5” and 15”, which equates to 236 and 472 m at the equator. The Terra orbital configuration and MODIS viewing geometry produce full global coverage every day for all but the equatorial zone, where the repeat frequency is approximately 1.2 days. Because many land cover changes due to human activities occur at spatial scales near 250 m (Townshend & Justice, 1988), the land cover change product described in this paper is derived from the two MODIS bands available at 250 m resolution. Although the number of bands is limited, the two bands are in the red and near-infrared wavelength intervals, which are among the most important spectral regions for remote sensing of vegetation (Townshend et al., 1991).

The Terra satellite was successfully launched on December 18, 1999. However, several factors have limited 250 m MODIS data production and the generation of the VCC product. First, a decision reached by NASA’s EOS Investigator Working Group (IWG) limited MODIS 250 m Level 2+ data production to a 10% sample of the globe in favor of providing better resources for producing the 500 m and 1 km products at full global coverage. The selected 10% sample includes the conterminous United States, southern Canada, and several regions where intensive EOS field and validation activities were planned—primarily in South America and southern Africa. Furthermore, actual production of 250 m data fell far short of this 10% goal in the early post-launch period. The 250 m data production system was hindered by hardware failures limiting production to a 5% sample including only North America. This 5% sample was not produced consistently until day 241 (August 28th) of 2000, due in part to upstream data feed problems with the EOS Data and Operations System (EDOS), computing problems at the Goddard Distributed Active Archive Center (GDAAC), hardware failures on the 250 m data production system, and limited band width on the NASA Goddard Space Flight Centre computer network.

Second, sufficient calibration and geometric rectification were not achieved for Level 1B radiance data, the input for Level 2G surface reflectance, until day 153 (June 1st) of 2000. See Table 1 for a summary of important dates in 250 m data production. Note that a large portion of the 2000 growing season for the Northern Hemisphere is not part of the available record. This will be corrected during the first reprocessing (Collection 3), with processing beginning during the summer of 2001.

Given this situation, Level 1B 250 m radiance data have been utilized for detection of vegetative cover conversion caused by recent significant natural events (burning and flooding) and human activities (deforestation). With these data, we have used the VCC change detection algorithms to produce land cover change products. The data situation, while still limited to a 10% global sample at present, is now functioning dependably. Planned production will also
extend the spatial sample, ultimately to full global production in the second reprocessing (Collection 4) slated to begin in early fall of 2002.

3. Application of the VCC algorithms to MODIS Level 1B data

The MODIS VCC product identifies locations where land cover changes attributable to human activities and extreme natural events occur. The product is designed to serve as an alarm, where rapid land cover conversion, once detected, can subsequently be analyzed with data from higher resolution sensors such as Landsat 7, Ikonos, and Quickbird. Toward this end, automation of product generation and reduction of commission errors are the highest priority in the design of the algorithms. With these considerations, interest is limited to changes between five categories of land cover: forest, nonforest vegetation, bare ground, water surface and burned areas. Table 2 shows the change types the MODIS VCC product will depict. For detecting these types of land cover change, multiple change detection algorithms are utilized. Three methods utilize the spectral domain, while the remaining two are based on texture. Specifically, these methods are: (1) the red-NIR space partitioning method; (2) the red-NIR space change vector method; (3) the modified delta space thresholding method; (4) changes in spatial textures; and (5) changes in linear features. Details of these methods are given in Zhan et al. (1998, 2000). Table 3 summarizes each of the methods, the criteria used, and implementation.

The operational implementation of the MODIS Vegetative Cover Conversion algorithms will use composite images of MODIS Level 2G 250 m resolution surface reflectance data (Vermote & Vermeulen, 1999) optimized for cloud-free, near nadir observations. In this early work, we have used selected pairs of single date cloud-free images. The associated look-up tables were generated with surface reflectance data from AVHRR or Landsat TM.

While the global composited data required for the VCC production code were not yet available, we adapted these algorithms to run with the currently available MODIS Level 1B data to dete specic types of vegetative cover conversions. For each of these applications, the following procedure is followed, which is similar to that which will be used operationally.

(1) Select pixels in the Level 1B images for training data for each of the five cover type categories using image interpretation. If there are clouds in the images, some cloud and cloud shadow pixels are selected as an additional class. If the images lack one or more of the five land cover type categories, there will be no training pixels for the missing type or types.

(2) Prepare the following training data for each of the five change detection methods summarized in the previous section: (i) MODIS band 1 and band 2 reflectance for each

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Table 3
Change detection procedures (for further details see Zhan et al., 2000)

<table>
<thead>
<tr>
<th>Name of method</th>
<th>Criteria used</th>
<th>Implementation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red-NIR space partitioning</td>
<td>Based on partitioning of red-NIR space between cover types at a given time of year and latitude. Identification of whether pixel value changes from subspace of one cover type to a second.</td>
<td>Implemented using LUTs depicting cover type for a given pair of red and NIR reflectance values for each month and latitudinal zone at times 1 and 2.</td>
</tr>
</tbody>
</table>
| Red-NIR space change vector        | Using the Red-NIR space, based on the angle and magnitude of the vector defined by the pixel value at time 1 to that at time 2. The direction and magnitude of change are defined as: \[
\Theta = \arctan\left(\frac{\Delta p_{\text{red}}}{\Delta p_{\text{NIR}}}\right)
\]
\[
A = \sqrt{\left(\Delta p_{\text{red}}\right)^2 + \left(\Delta p_{\text{NIR}}\right)^2}
\]
where \(\Theta\) = change angle; \(A\) = change magnitude; \(p_{\text{red}}\) = red reflectance; and \(p_{\text{NIR}}\) = NIR reflectance. | Implemented using LUTs depicting the angle and magnitude couplets associated with all possible land cover changes for each pair of months and latitudinal zone. |
| Modified delta space thresholding  | Uses space defined by differences in pixel values for times 1 and 2 for the red and NIR values of each pixel (no change occurs at the origin). Type of conversion defined by angle and distance from origin and the initial state of the pixel. | Implemented using LUTs defining the initial cover type at time 1 and the sector of the delta space in which the pixel lies at time 2 for each latitudinal zone. |
| Texture                            | Uses coefficient of variation of the NDVI within a \(3 \times 3\) kernel at times 1 and 2. Conversion flagged when change exceeds a threshold. | Implemented using LUTs defining threshold value for change between each pair of cover types for each month, latitudinal zone, and initial state of the pixel. |
| Linear feature                     | Compute the mean of the absolute difference of the pixel value for each neighbor pixel in a \(3 \times 3\) kernel. A threshold determines whether a linear feature is present. | Implemented using rule identifying whether linear feature exists in time 2 when absent in time 1. |
| Integrated measure of change       | Voting method: conversion confirmed where three out of five methods flag conversion. | |
of the five cover type categories in Table 2 for the red-NIR space partitioning method for both time 1 and time 2; (ii) Time 2 MODIS band 1 and band 2 reflectance and magnitude and angle of the red-NIR space change vector for burned pixels and all unburned pixels for the red-NIR space change vector method; (iii) the magnitude and angle of the red-NIR space change vector modified with the reflectance differences between time 1 and time 2 for the modified delta space thresholding method; (iv) time 1 and time 2 values of the coefficient of variation of the Normalized Difference Vegetation Index (NDVI) values of a 3 × 3 pixel kernel for the texture change detection method; and (v) time 1 and time 2 linear feature measure based on band 1 (red band) reflectance for the linear feature change detection method.

(3) Generate a decision tree with these training data, one for each of the five methods and each of the change processes listed in Table 2, to distinguish changed pixels from all other pixels including cloud and cloud shadow pixels. The use of decision tree techniques to conduct land cover classification or land cover change detection is introduced in Hansen, Dubayah, and DeFries (1996) and Zhan et al. (2000). The computer software used for decision tree induction is introduced in Murthy, Kasif, and Salzberg (1994).

(4) Apply the decision tree to the entire area of interest to label changed pixels for each of the five methods and integrate the five results to generate the final labeling of the VCC algorithms.

(5) Evaluate the labeling results from each of the five methods and their integration with available ground observation data.

(6) When the ground observation data are not available, generate a reference bitmap of changes for method evaluation using more comprehensive change detection method and more intensive human involvement. For this paper, the following steps are used to generate reference bitmap of change if needed:

(i) use all the available training data of band reflectance, change vector, texture and linear feature measures and develop a comprehensive decision tree to distinguish the changed pixels and other training pixels;
(ii) preliminarily label all pixels of the image as changed or not changed using the decision tree;
(iii) visually inspect the labeling and correct any significant error according to expert knowledge. The result is then used as the reference bitmap for the change process being evaluated.

4. Evaluation measures of change detection results

The above procedure of applying the MODIS VCC algorithms to MODIS Level 1B 250 m data produces two sets of results. One is the set of threshold values for each of the five change detection methods generated from the training data using the decision tree techniques. These threshold values can be used to update the look-up tables required for VCC production. The other results are bitmaps of the areas where the changes are detected by the VCC methods and the integrated result of the five VCC algorithms. To limit the length of this paper, the first type of results will be presented in another paper. In this paper, we present the detected change maps and their comparisons with the ground observations or reference change bitmap.

To quantitatively evaluate the results of the comparisons between the ground “truth” and the results from each change detection method, the following measures, that is, error and accuracy rates, are computed for each change detection cases:

(1) Commission error (\%)=(number of changed pixels identified by a method but NOT included in the ground “truth” polygons)/(total number of changed pixels identified by a method) × 100%.
(2) Omission error (\%)=(number of changed pixels included in the ground “truth” polygons but NOT identified by the method)/(total number of changed pixels included in the ground “truth” polygons) × 100%.
(3) Detection accuracy (\%)=(number of changed pixels included in the ground “truth” polygons AND identified by the method)/(total number of changed pixels included in the ground “truth” polygons) × 100%.
(4) Overall accuracy (\%)=(number of changed pixels included in the ground “truth” polygons AND identified by the method)/(total number of pixels within the whole area of the image) × 100%.

The MODIS VCC algorithms have then been applied to the detection of areas burnt, flooded, and deforested using the MODIS Level 1B 250 m data and the procedure described in Section 3. With the above evaluation measures, results are presented in the following three sections.

5. Detection of burned areas

Burning is one of the most important types of vegetative cover conversion. Burning destroys forest and land resources, releases land surface carbon stocks to the atmosphere (Sellers et al., 1995), and alters biosphere–atmosphere interactions (Levine, Cofer, Cahoon, & Winstead, 1995; Scholes, 1995) via changes in surface roughness, leaf area index and other biophysical parameters associated with land cover. Burning is also an important agent in the succession and rejuvenation of forests and savanna. Therefore, quantitative information about the spatial and temporal distribution of burning events and burned areas is important not only for forest and land resource management, but also for atmospheric chemistry and climatic change studies. This
section reports the capability of the VCC change detection algorithms to identify burned areas using Idaho–Montana and Cerro Grande fire events in year 2000 as examples.

5.1. The year 2000 Idaho–Montana wildfires

Year 2000 was a year of numerous wildfire events in both Idaho and Montana. MODIS Level 1B 250 m resolution images clearly show these fires. Fig. 1 is a comparison of two MODIS Level 1B images of the Idaho–Montana area: one was acquired immediately before and the other shortly after the wildfires.

Following the procedure described in Section 3, the VCC algorithms were applied to the images shown in Fig. 1 for assessing the area burned by the Idaho–Montana wildfires. The cover types considered for the two images are forest, herbaceous vegetation, bare ground, and burn scar. The white clouds in the time 1 image were treated as bare and dark speckles as water since these two types are not of concern for the forest-to-burn conversion.

Fig. 2 shows the fire perimeter polygons generated by the United States Department of Agriculture Forest Service (USFS)—from ground observations, helicopter GPS flights, and airborne infrared imaging—for the area displayed in Fig. 1. This data set was used as ground reference data to evaluate the burned area detection results from the VCC algorithms. One interesting aspect of the polygons shown in Fig. 2 is the comparison of the occurrence of year 2000 fires in “roadless” areas (United States, 2001) within the federal and state forest lands versus those areas with existing transportation infrastructure. Analysis showed that 23.82% of the fires were within roadless areas, the latter comprising 23.17% of total forest area. Thus, for these particular events, roadless (presumably undisturbed) areas were no more likely to burn than was forest with road infrastructure.

There are two ways to use these polygons to evaluate the burned area detection results. The fire perimeter polygons used as “truth” are the maximum extent that the fires are believed to have reached. Within the polygons, there are areas that were not burned, as found through visual inspection of the images and from their spectral values. Burning within wildfires is quite heterogeneous and depends upon factors such as fuel load, soil moisture, stand age, stand...
species, topography and wind direction. Therefore, the perimeter data are not accurate on a per-pixel basis (pixels within the polygons are mislabeled when all pixels are labeled burned). The VCC product is designed as an alarm that will serve as an indicator of places where vegetative cover conversion may have taken place (Zhan et al., 2000). Therefore, if a change detection method identifies one or more burned pixels within a polygon, the method identified the land cover change associated with the polygon. From this point of view, the change detection results from the each of the five methods and their integration were evaluated in a polygon-wise fashion. The burned area detection results are shown in Fig. 3 where green pixels are correctly identified burned areas, blue are incorrectly labeled burned areas and red are undetected burned areas. The computed error and accuracy rates appear in the upper part of Table 4. The polygon-wise analysis demonstrates that most of the five change detection methods and the integrated measure of change identified burned areas very well. For details where VCC indicates changes, high-resolution satellite data may be acquired to conduct further assessment.

According to the USFS fire perimeter polygon, the acreage of the burned areas is 73,790 MODIS 250 m pixels, that is 1,139,579 acres. The acreage of the burned areas identified by the integration of the five methods, which serves as the output of the VCC algorithms, is about 1,208,101 acres. The commission error pixels are mostly topographic shadows. These shadows have very similar spectral and textual characteristics to the burned areas. This indicates that more information is needed to distinguish shadows when using satellite data to survey burned areas.

An alternative evaluation method is to consider all pixels in the polygons as burned and compare the result from each of the five methods with the reference data set in a pixel-wise fashion. The burned area detection results are depicted in this way in Fig. 4. The error and accuracy rates corresponding to the results in Fig. 4 are listed in the lower part of Table 4. As expected, the pixel-wise evaluation is apparently much less favorable. Three of the five methods and the integration of the five methods performed reasonably well, but many more omission errors are indicated due to unburned pixels within the USFS fire perimeter polygons. It seems likely that many of the omission errors are not true errors but represent areas that are partially burned or unburned. The use of remote sensing allows a representation of burning at a far more
spatially detailed level than traditional USFS methods. The poorly performing modified-delta space thresholding method identified more burned pixels (low omission error rate) than other methods, but its commission error exceeds 80%. The high commission error may result from the lack of consideration to the starting or ending position of the change vectors. This is because there are other types of changes that have similar change magnitude and angle as forest burning. The linear feature method missed nearly all burned pixels. The implication of this result is that the linear feature method may not be helpful for burned area detection. It is intended primarily for detection of change in areas with anthropogenic structures such as roads and fence lines.

5.2. The Cerro Grande prescribed fires

The Cerro Grande prescribed fire was initiated by fire personnel of the National Park Service in Cerro Grande, New Mexico on May 4, 2000. Because of unexpected weather conditions and critical mistakes of fire management, the prescribed fire became a wildfire on May 7 and burned into the town of Los Alamos on May 10, 2000. The fires were controlled by late May, but not before 235 homes were destroyed and approximately 18,000 residents were evacuated.

Fig. 5 shows the MODIS Level 1B images before and after the Cerro Grande prescribed fire and a reference bitmap of the areas burned by the fire. To apply the VCC

<table>
<thead>
<tr>
<th>Method</th>
<th>Space partitioning</th>
<th>Change vector</th>
<th>Modified delta</th>
<th>CV change</th>
<th>Linear feature</th>
<th>Integration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polygon-wise</td>
<td>Commission error</td>
<td>16.59</td>
<td>28.41</td>
<td>67.77</td>
<td>27.02</td>
<td>2.65</td>
</tr>
<tr>
<td></td>
<td>Omission error</td>
<td>0.76</td>
<td>0.62</td>
<td>0.11</td>
<td>0.31</td>
<td>62.66</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy</td>
<td>98.49</td>
<td>97.04</td>
<td>84.49</td>
<td>97.25</td>
<td>95.3</td>
</tr>
<tr>
<td>Pixel-wise</td>
<td>Commission error</td>
<td>32.2</td>
<td>46.44</td>
<td>82.17</td>
<td>43.16</td>
<td>90.47</td>
</tr>
<tr>
<td></td>
<td>Omission error</td>
<td>58.45</td>
<td>54.52</td>
<td>54.43</td>
<td>51.39</td>
<td>99.89</td>
</tr>
<tr>
<td></td>
<td>Detection accuracy</td>
<td>41.55</td>
<td>45.48</td>
<td>45.57</td>
<td>48.61</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy</td>
<td>94.23</td>
<td>93.07</td>
<td>80.49</td>
<td>93.48</td>
<td>92.55</td>
</tr>
</tbody>
</table>
algorithms to these images with the procedure in Section 3, only four cover types are considered. They are forest, short vegetation, bare ground, and burn scar.

To evaluate the results from each of the five methods and their integration, a reference burned area bitmap was generated following the procedure described in step (6) of Section 3. The reference bitmap is overlaid in red on the time 2 MODIS image of the Cerro Grande area in Fig. 5. The estimated burned area is 2132 MODIS 250 m resolution pixels, that is, about 133 km$^2$ or 32,925 acres. The acreage of burned areas estimated by the National Park Service (NPS) is 46,000 acres (http://www.nps.gov/cerrogrande/). When considering that the total acreage reported by the NPS is based on fire perimeter polygons, this includes areas

![Fig. 5. MODIS 250 m natural color images before and after the Cerro Grande prescribed fire in New Mexico and the reference bitmap of burned areas used to evaluate the output of the VCC algorithms. In these images, MODIS L1B band 1 (red) reflectance is shown in red and blue colors, and band 2 (NIR) in green. The dark areas clearly show the burned areas.](image)

![Fig. 6. Results from the VCC change detection algorithms evaluated against the reference burned area bitmap generated for the Cerro Grande prescribed fire. The color legend and VCC method numbering are the same as in Fig. 3.](image)
inside the polygons that were not burned as well as areas where only the understory was back-burned as part of the fire suppression activities. Thus, the acreage of the reference bitmap may be closer to reality.

Fig. 6 demonstrates the burned area detection results from each of the five VCC methods and their integration against the reference bitmap. As in Fig. 4, the green color indicates where the method correctly identified burned pixels. The blue color is commission error and the red color is omission error. The error and accuracy rates for each result are listed in Table 5. The three spectral methods performed significantly better than the two texture methods. One reason for the poor performance of the Coefficient of Variation change detection method may be that the image acquired in early May had greater heterogeneity in the drier season. In later May, the warmer weather melts mountain snow, providing better moisture conditions and causing changes similar to those texture changes associated with the burning. The linear feature method missed all burned pixels again. The lack of linear feature changes in the area is one of the reasons. The result for the integrated measure change described in Table 3 is reasonably good. The relatively larger commission errors of the modified delta method and the CV change method are not transferred to the integration results. This indicates that the methods are indeed complementary to each other and that the integration procedure helps improve change detection results.

6. Detection of flooding/flood retreat

Flooding is another natural hazard that can cause significant vegetative cover conversions. Flooding causes damage to human structures such as roads, buildings, and agricultural fields. Its impact on land cover is also significant (Baldwin & Mitchell, 2000). Satellite remote sensing is the most effective approach to monitoring flooding extent, damages and flood frequency (Islam & Sado, 2000; Zhou, Luo, Yang, Li, & Wang, 2000). MODIS has daily global coverage and should be the most useful satellite sensor for flood monitoring. This section assesses the flooding extent of the Southeast Asia floods of September 2000 and the water surface area changes in the Paraguay–Argentina border region.

6.1. The year 2000 Cambodia flood

A major Southeast Asia flood occurred in early September 2000. Cambodia was one of the nations impacted by the flood. Fig. 7 displays two MODIS Level 1B 250 m images of Tonle Sap Lake and Phnom-Penh City (Cambodian capital) area and the reference flooded area bitmap. The MODIS images were acquired before and during the floods. The Mekong River flows westward into the image from the east side and then southward through Phnom-Penh. Under the white or pink clouds, the dark or deep purple areas are water bodies or flooded areas. The extent of the flooding is extensive considering that the image covers more than half of Cambodia.

Following the procedure described in Section 3, the VCC algorithms were applied to the two images in Fig. 7.

![Fig. 7. MODIS 250 m natural color images acquired before and after the year 2000 Southeast Asia floods and the reference flooded area bitmap used for evaluating the output of the VCC algorithms. The images cover most of western Cambodia. The color composition is the same as in Fig. 1.](image-url)
with consideration of five cover types: forest, short vegetation, bare ground, water, and cloud and cloud shadow. Only changes of forest, vegetation or bare ground converting to water are of interest for this VCC application. Since there are no ground observation data available for the flood, a reference bitmap of the flooded areas is generated following step (6) of the procedure in Section 3. The resultant reference bitmap is overlaid in red on the time 2 MODIS image in Fig. 8. Since it is difficult to judge whether the surface is land or water under the clouds, the cloud or cloud shadowed areas are excluded from consideration. Therefore, there are some data missing within the flooded areas in the reference bitmap. Additional temporal coverage in VCC 250 m composite images will eliminate such effects.

Results of the VCC algorithm’s performance measured against the reference bitmap are demonstrated in Fig. 8. The color legend is the same as in Fig. 3. The error and accuracy rates are listed in Table 6. As Fig. 8 and Table 6 show, the red-NIR space partitioning method, the change-vector method and the integration of the five methods performed reasonably well against the reference bitmap. The two texture change detection methods did not work for flood detection. This may result from the homogeneity of water surfaces and highly vegetated surfaces in the area. The poor performance of the modified delta method is due to the insignificance of the differences between the change vectors associated with flooded pixels and non-flooded versus vegetated pixels. Differences in method performance indicate that only the change vector method, the space partitioning method or their integration is useful for detecting flooded areas in highly vegetated areas like Cambodia.

According to the reference bitmap of flood area in the region shown in Fig. 8, the area flooded by September 15, 2000 is about 12,500 km². Cambodia’s national area is approximately 181,000 km². Thus, the flooded area

<table>
<thead>
<tr>
<th>Method</th>
<th>Space partitioning</th>
<th>Change vector</th>
<th>Modified CV change</th>
<th>Linear feature</th>
<th>Integration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commission error</td>
<td>14.2</td>
<td>8.8</td>
<td>18.2</td>
<td>0.5</td>
<td>6.7</td>
</tr>
<tr>
<td>Omission error</td>
<td>35.4</td>
<td>23.6</td>
<td>78.9</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Detection accuracy</td>
<td>64.6</td>
<td>76.4</td>
<td>21.1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Overall accuracy</td>
<td>95.4</td>
<td>97</td>
<td>91</td>
<td>91.1</td>
<td>91.1</td>
</tr>
</tbody>
</table>

Fig. 8. Results from the VCC change detection algorithms evaluated against the flooded area reference bitmap in Fig. 7 for the Year 2000 Cambodia floods. The color legend and VCC method numbering are the same as in Fig. 3.
accounts for 7% of the nation, discounting the possibly flooded areas outside the images shown in Fig. 8.

6.2. Retreat of the Thailand flood

The year 2000 floods in Southeast Asia also affected Thailand and Laos. Monsoonal rains that caused the flood ceased in mid-September 2000. To assess flood areas after the flood retreated, two MODIS 250 m images of the Thailand–Laos border area were selected as shown in Fig. 9. The time 2 image not only displays the flood retreat, but also shows a considerable decrease in greenness for the areas that were affected. The greenness decrease of the Mekong river basin may be crop harvest or flood damage.

Fig. 9. MODIS 250 m natural color images showing the retreat of the year 2000 monsoonal floods in the Thailand–Laos border area and the reference bitmap of the retreated floods used for evaluating the output of the VCC change detection algorithms. The color composition is the same as in Fig. 1. The decrease in greenness of some areas in the images from time 1 to time 2 may be associated with flood damage or crop harvest that is not of interest to flood area assessment and is not addressed in this paper.

Fig. 10. Results from the VCC change detection algorithms evaluated against the flooded area reference bitmap in Fig. 9 for the year 2000 floods in the Thailand–Laos border area. The color legend and VCC method numbering are the same as in Fig. 3.
Since current ground data about the vegetation of the Mekong river basin are unavailable, only flooded area in the September 15, 2000 image is of interest.

Using the same procedure in Section 3 to assess the flooded areas in the September 15 image of Fig. 9, the following five cover types were considered: forest, herbaceous vegetation, bare ground, water, and cloud and cloud shadows. Only the conversion between the images of water to bare ground, herbaceous or forest is of interest for this case. Since there are no ground observation data available to us for the flooded area, step (6) of the procedure described in Section 3 was used to generate a reference bitmap of flooded areas. The reference bitmap is overlaid in red on the September 15 MODIS image in Fig. 9. Since only the retreated flood areas are of interest, the areas where the surface greenness decreased significantly from September 15 to November 4 are not mapped.

In Fig. 10, the retreated flood areas identified by each of the five VCC methods and their integration are evaluated against the reference bitmap, and the error rates and accuracy rates are listed in Table 7. For detecting areas from which floods have retreated, the space partitioning method and the change vector method perform better than other methods as the results show, but the linear feature method did not work. The CV texture method worked better for this case than for the Cambodia flood case, which is probably because the scale of the flooded areas in this case is much smaller than the Cambodia case.

According to the reference bitmap, the area of the retreated flood is 30,614 MODIS 250 m pixels, that is, about 1913 km². The area identified by the integration of the VCC methods is 1966 km². This 90% detection accuracy confirms that integrating the output from multiple methods can produce acceptable results even when some of the methods do not perform well.

### Table 7

<table>
<thead>
<tr>
<th>Method</th>
<th>Space partitioning</th>
<th>Change vector</th>
<th>Modified delta</th>
<th>CV change</th>
<th>Linear feature</th>
<th>Integration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commission error</td>
<td>23.5</td>
<td>9.9</td>
<td>7.8</td>
<td>24.2</td>
<td>0</td>
<td>11.6</td>
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<tr>
<td>Omission error</td>
<td>37</td>
<td>1.9</td>
<td>48.8</td>
<td>64.5</td>
<td>100</td>
<td>10.4</td>
</tr>
<tr>
<td>Detection accuracy</td>
<td>63</td>
<td>98.1</td>
<td>51.2</td>
<td>35.5</td>
<td>0</td>
<td>89.6</td>
</tr>
<tr>
<td>Overall accuracy</td>
<td>97.8</td>
<td>99.5</td>
<td>98.1</td>
<td>96.9</td>
<td>96.8</td>
<td>99.2</td>
</tr>
</tbody>
</table>

7. Detection of deforestation

In the last two decades, a significant portion of the tropical forests have been lost to deforestation as a result of agricultural expansion (Myers, 1991; Tucker & Townsend, 2000). Although many means have been employed to assess the extent of tropical deforestation, the range of current estimates of the areas and rates of deforestation is still wide (Skole & Tucker, 1993). In this section, the VCC algorithms are applied to two MODIS 250 m images collected for an area in southern Brazil where forest lost due to agricultural expansion is evident and significant. Fig. 11 displays the two MODIS Level 1B images and a reference bitmap of newly deforested areas (in red color) overlaid on the time 1 image.

To apply the VCC algorithms with the procedures described in Section 3 to these two images, training pixels are selected from the images for five cover types: forest, crop, bare ground, water, and cloud and cloud shadows. With these training data and the derived decision trees, a map of the areas was generated where forest was newly
changed to crop or bare within the three months from June to September 2000, from each of the five VCC methods and their integration. The reference bitmap (in red) overlaid on the June image is generated following the step (6) of the procedure in Section 3 and is used to evaluate the differences among the deforested areas indicated by the VCC methods. The evaluation results are shown in Fig. 12 and their corresponding error and accuracy rates are listed in Table 8.

These results demonstrate that detection of small-scale deforested areas is relatively difficult compared to the detection of large-scale flooding or burning. The detection accuracy of the integrated VCC results is only 74% with relatively high commission (68%) and omission (26%) errors. The performance intercomparison of the five VCC change detection methods shows the relative strength of the change vector method, which is similar to the results for the cases of flood and burning detection. The performance of the integration of the five methods is not as good as the change vector method alone (see Table 8 higher omission error and lower detection accuracy), as shown for the change detection cases presented in the previous cases. This confirms the usefulness of the change vector method.

According to the reference bitmap of deforested areas, the area of new deforestation is 145 MODIS 250 m pixels, that is, approximately 9 km². Operational VCC results will provide estimates for the previous 96-day and 1-year periods, which will allow the tracking of small-scale deforestation through time.

8. Discussion and conclusions

The algorithms for change detection developed for the MODIS Vegetative Cover Conversion (VCC) product require a time series of MODIS 250 m Level 2G daily data composited into monthly data sets. Look-up tables created with AVHRR and TM data need to be modified for the MODIS data due to differences in radiometric response between the instruments. Toward this end, the VCC algo-
rithms have been applied to available MODIS 250 m Level 1B data. The cases presented include the detection of flooded areas, burned areas and deforested areas. From the results presented in previous sections of this paper, the following conclusions have been reached:

1. Four of the five change detection methods for the MODIS VCC product worked satisfactorily for the detection of flooded area, burned area and deforestation as long as the threshold values are modified for real MODIS retrievals. These methods are the red-NIR space partitioning method, the red-NIR space change vector method, the modified-delta space thresholding method, and the coefficient of variation change detection method. The linear feature method did not work for any of the six cases of change detection presented in this paper. It will have more value in areas with active road building.

2. Among the different types of land cover changes, the VCC change detection methods performed better for the detection of large scale flooding and burning. For detection of patchy deforestation, these methods can produce large commission errors.

3. Among the four workable change detection methods, the red-NIR space change vector method performed satisfactorily for all six cases and is the best for four of the six cases.

4. The Coefficient of Variation (CV) change detection methods worked very well for the Idaho–Montana burn case. Forest fire causes significant changes of surface homogeneity in terms of spectral reflectance. CV characterizes this homogeneity. If the areas other than the burned area do not have significant homogeneity change, then the CV changes can separate burned area from unchanged areas very well.

5. The red-NIR space partitioning method worked very well for the two burned area detection cases. For detecting water surface changes in a wet region and small patchy deforestation, this method may have a high commission error.

6. The strategy of integrating multiple methods for the VCC product proved to be effective. For all cases presented in this paper, the performance of the integration is generally satisfactory. This indicates that the methods selected are indeed complementary to each other, at least for the red-NIR space partitioning method, the change vector method and the CV change detection method.

With the experience gained applying the VCC algorithms to MODIS Level 1B data, we anticipate that the MODIS VCC product generated from MODIS Level 2G composited data may need to address the following issues:

1. Composite data may have larger misregistration errors than the data used in this paper. This is because the misregistration error of individual images may propagate into the composite image (Roy, 2000). Larger misregistration errors will cause larger commission errors and/or omission errors.

2. The look-up tables (LUTs) required for the VCC change detection methods were generated with AVHRR and TM data. They must be updated with MODIS 250 m data because the reflectance values of MODIS for the same cover type are different from those of the AVHRR. This is due to the narrower spectral bands on the MODIS instrument. The decision trees developed for change detection cases in this paper will be used to update these LUTs.

3. The decision trees used for detecting similar burned areas for the Idaho–Montana case and for the Cerro Grande case are different. This indicates that stratification of the LUTs may need to be redefined.

The results presented here are promising for these applications and demonstrate how a suite of integrated results provide a more robust detection scheme than can be provided by a single algorithm.

For additional information on VCC, please see http://www.glcf.umiacs.umd.edu/MODIS.

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References


