A New Multi-Temporal Transform for the Broad-Scale Analysis and Visualization of Landscape Dynamics

Jennifer N. Hird[1], Guillermo Castilla[2], Greg McDermid[3], and Inacio T. Bueno[4]

1 Foothills Facility for Remote Sensing and GIScience, Department of Geography, University of Calgary, jennifer.hird@ucalgary.ca
2 Foothills Facility for Remote Sensing and GIScience, Department of Geography, University of Calgary, gcastill@ucalgary.ca
3 Foothills Facility for Remote Sensing and GIScience, Department of Geography, University of Calgary, mcdermid@ucalgary.ca
4 Department of Forest Sciences, Federal University of Lavras, Lavras, Minas Gerais, Brazil, inaciotbueno@gmail.com

Abstract

The current ease of access to satellite data sets with high temporal resolutions has greatly expanded our abilities within the remote sensing community for the multi-temporal analysis of Earth's dynamic surface. The full potential of these data sets is not yet fully realized in the remote sensing of landscape dynamics and change however, as many analyses still rely on bi-temporal rather than multi-temporal approaches. Here we describe a new transform for analyzing and visualizing both short- and long-term landscape changes and trends. The CAT (Change, Aftereffect and Trend) Transform converts a multi-annual, satellite vegetation index data set possessing a high temporal resolution into three new variables, which are calculated from annual peak greenness derived from the vegetation index time series. We demonstrate this new transform using a MODIS 16-day 250 m Normalized Difference Vegetation Index (NDVI) time series covering the province of Alberta, Canada, for the years 2001 through 2011. Our results show that not only do the three CAT Transform variables capture much of the non-seasonal change occurring over the Alberta landscape during this period, they also produce a striking and informative false-colour visualization of these landscape dynamics, and in addition, were shown to out-perform an image differencing approach when applied to the detection of new urban developments around the city of Calgary during this period.

Background and Relevance

Change detection and analysis have been an important focus in satellite remote sensing since the first public availability of Earth Observation data sets. Our need to observe, understand, and monitor Earth's dynamic environments is constant, as both natural and anthropogenic changes in these environments can have enormous impacts at local to global scales. Drought, fire, deforestation, urban expansion, and mining are just some examples of the types of changes or events about which any type of spatially-distributed, timely, and meaningful information is of great importance. Indeed, as landscape change appears to be occurring at ever-increasing rates, the value of this information continues to grow. The ability of Earth Observation satellites to fulfill some of this need was very quickly recognized, and thus fostered decades of research into various change detection methods and techniques (Coppin, Jonckheere, Nackaerts, Muys, & Lambin, 2004; Lu, Mausel, Brondízio, & Moran, 2004; Singh, 1989). Well-known approaches include image differencing and ratioing, post-classification comparisons, regression-based and vector-change analyses, and more recently, object-based techniques.

The majority of change detection techniques found in the literature involve two-date comparisons – most are bi-temporal in nature, and can thus be somewhat limited in their ability to detect particular types of landscape change. For instance, subtle shifts in land cover due to vegetative growth, changing climatic conditions, etc., could be confused with radiometric or geometric differences between a 'before' and 'after' image or may not be clearly identifiable as a gradual change versus a sudden, drastic change. Conversely, less-common multi-temporal approaches incorporate satellite images from multiple dates within the period of interest, thereby enabling the study of more subtle, gradual landscape dynamics. Ideally, such approaches should be better able to track both gradual and sudden, drastic changes than bi-temporal techniques because of their greater temporal sensitivity. Not only are long-term trends (e.g., 5-, 10-year or longer) or shifts in landscape composition more easily identified and separated from other types of changes using a multi-temporal time series, but more sudden changes and their time of occurrence can be detected at any point within the time series, rendering their capture and identification more accurate. This would be particularly true of features such as forest cutblocks or wildfires, which experience vegetative regrowth and succession over the long-term and which, therefore, may be less easy to detect using a bi-temporal approach where the initial and final state images are separated by several years.

We present a new multi-temporal approach to longer-term landscape change analysis and visualization that converts a multi-annual (generally 5 or more years), satellite vegetation index data set with a high temporal resolution (i.e., one or more observation per month) into a set of three variables that capture a variety of landscape dynamics covering the period. Our goals were: i) to develop a method of simple, effective compression for multi-temporal time series as a means of capturing landscape changes; ii) to evaluate the application of the transformed results to the visualization of landscape dynamics; and iii) to test the ability of our results to support quantitative change analysis.

Methods and Data

Our method involves a set of simple calculations applied to a multi-temporal, remote sensing vegetation index (VI) data set that spans five or more years and contains a minimum of one observation per month, to produce three new variables labeled *Change*, *Aftereffect*, and *Trend*. The approach is named for these three variables – the CAT Transform. First, a multi-year VI time series is simplified, and the effects of seasonality removed by extracting per-pixel, annual peak-greenness. From this the three variables are calculated as follows: i) maximum inter-annual absolute difference (i.e., Change); ii) mean peak-greenness for the period following this maximum inter-annual change (i.e., Aftereffect); and iii) the slope of a linear regression applied to the entire peak-greenness time series (i.e., Trend). The Change variable reflects the largest change in maximum greenness – either positive or negative – that occurs between consecutive years within the period of observation. Aftereffect indicates the average amount of maximum annual greenness following the largest inter-annual change occurring in the time series, indicating the state of surface vegetative land cover following this greatest change. Trend, meanwhile, relates to the overall direction and magnitude of longer-term vegetative changes observable over the period.

We applied the CAT Transform to a MODIS 16-day 250 m Normalized Difference Vegetation Index (NDVI) time series that covers the province of Alberta, Canada from 2001 through 2011. Alberta encompasses 660,000 km^2 of varying landscapes, topographies, and vegetative communities. The more populous south is dominated by semi-arid prairie environments, and by rangeland and agriculture in particular. Foothill and alpine ecosystems are seen along the southern- and central-western portions of the province along the Rock Mountains, while mixed forests and various wetlands combine to form the northern Boreal forest. We extracted yearly second-highest NDVI (shNDVI) as a measure of annual peak greenness from our 11-year MODIS NDVI time series because we observed improbably high values and unrealistic instability in our resulting time series when maximum NDVI was used. These are likely the results of the combined effects of temporal compositing, mis-registration errors, and varying sun-sensor-surface geometries. When shNDVI was used many of these anomalies disappeared, and where they did not exist, the difference between maximum and shNDVI was negligible. Once calculated, the shNDVI time series was then processed to produce the three CAT Transform variables described above: Change, Aftereffect, and Trend.

We evaluated the change visualization capabilities of the CAT Transform variables by combining them into a single, false-colour composite image (labeled the CAT Image or CATI). Change, Aftereffect, and Trend were placed in the Red, Green, and Blue colour channels, respectively. A qualitative, visual evaluation examined the ability and efficacy of the CATI to capture a variety of different landscape changes, both sudden and gradual, and from subtle to drastic.

In addition to evaluating its visualization potential, we also tested the applicability of the CAT Transform variables in quantitative change analysis. The city of Calgary, Alberta has experienced a dramatic population increase in recent decades (Government of Alberta, 2000, 2001), as has the province of Alberta, due to its growing, resource-based economy which has encouraged high levels of immigration into the province. This growth in population is reflected by the notable expansion in the urban footprints of all of Alberta's main urban centers, including Calgary. We used the city of Calgary as a case study for testing the ability of the CAT Transform variables to map new urban sprawl within the administrative boundaries of the city. The CAT variables were employed within a simple decision-tree classification to create a change/no change binary classification of the city of Calgary, wherein the change category reflects newly-developed urban areas that were formerly natural or agricultural landscapes. This was compared with a bi-temporal, image-differencing and thresholding change detection technique that employed the same MODIS NDVI data that was used in the CAT Transform – we chose a peak summer composite period (mid-July), and compared the corresponding NDVI imagery from 2001 and 2011. Both classifications were performed on a 75-km by 75-km study area surrounding the city of Calgary, but the results of each were clipped to the city's administrative boundary so that we could assume that any major land cover changes reflecting a sudden, lasting decrease in NDVI represented urban development.

Accuracy assessment of the two binary change classifications comprised their comparison with a set of reference data compiled through the manual digitization of new urban developments within Calgary from a set of high resolution ortho-photos that covered the area between 2001 and 2011. Error matrices and Kappa statistics were produced from this comparison.

Results

The false-colour CATI is shown in Figure 1. A histogram stretch, provided in Table 1, was applied to the image, followed by its conversion into a set of known, labeled colours. These enhancements were designed to provide a standard means of visualizing CAT Transform output that could be applied anywhere outside our study area. In other words, the link between the colours found in the final visualization and the corresponding variables values stored in each colour channel would be consistent across applications.

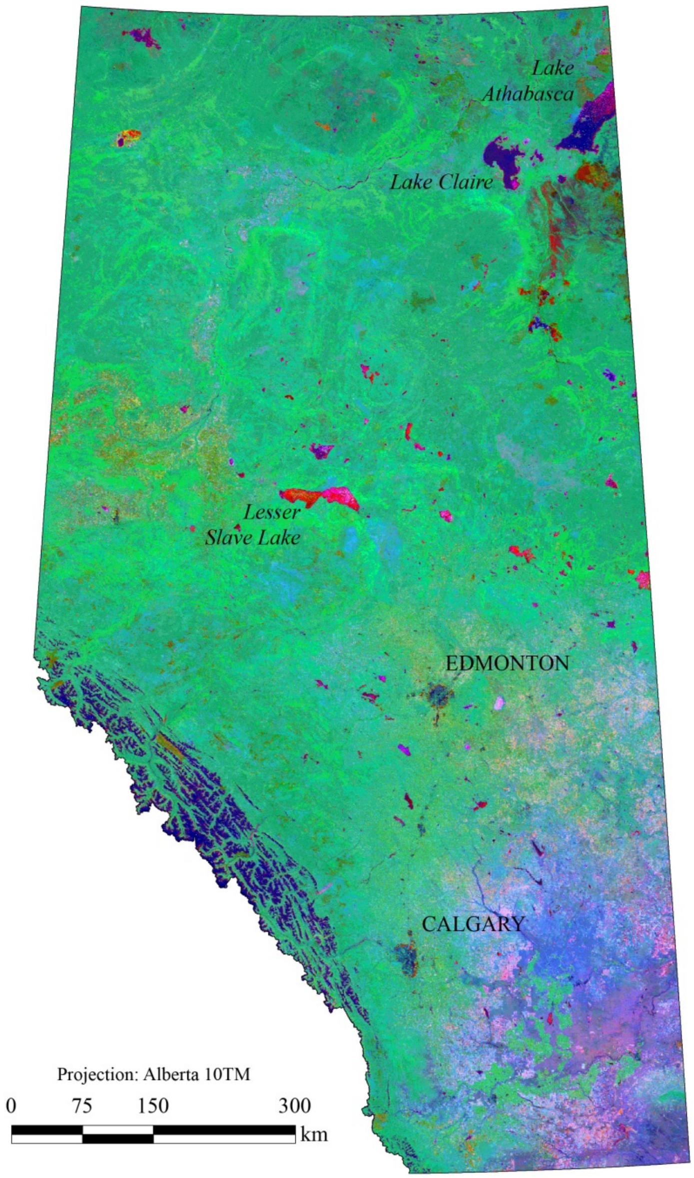

Figure 1. False-colour composite combining the Change, Aftereffect, and Trend variables produced by the CAT Transform in the Red, Green and Blue colour channels, respectively. Alberta's two largest urban centres (capital letters), and three largest lakes (italics) are also shown.

Table 1. Parameters used for the false-colour CAT image stretch.

CAT Variable	Channel	Input Value for Min. Output (0)	Input Value for Max. Output (255)
Change	Red	0.00	0.50
Aftereffect	Green	0.20	1.00
Trend	Blue	-0.02 (-2%/yr)	0.02 (+2%/yr)

The visualization found in Figure 1 presents an incredibly comprehensive view of Albertan landscape change, and the landscape itself from 2001 through 2011. Both sudden, often drastic land cover changes and longer-term shifts in surficial vegetation are clearly visible. Reds and oranges depict a rapid decrease in vegetation, as seen in new mining activity, urban expansion, wildfires, and forestry cutblocks. Conversely, sudden gains in levels of vegetative greenness appear in near-white, as found in a number of new pivot-irrigation fields in Alberta's southeast. Gradual vegetation gain is observed as light blues, and is reflected in recovering wildfires and cutblocks where defoliation occurred before 2001, and in reclaimed mined areas. Dark blues, on the other hand, indicate stable, mostly non-vegetated surfaces such as bare rock, urban landscapes with little to no vegetation, very dry scrub- or rangeland, and in some cases, deep water bodies. Most water bodies within Alberta, which are generally relatively shallow, display a speckled combination of magentas and reds however, which could be due to a combination of known reflectance artifacts in this MODIS NDVI product (Shao, Taff, & Lunetta, 2012), algae blooms, varying water levels, and/or changing growth of emergent vegetation. Agricultural croplands within the province are often found in tones of light pink, where they undergo fallow crop practices, or in bright greens, where they are irrigated. Outside of Alberta's agricultural zone, the bright greens that cover much of the province reflect stable, densely-vegetated land covers (i.e., forests).

Table 2 presents the error matrices for the multi-temporal and bi-temporal binary change classifications generated for the city of Calgary case study area. The overall accuracies of both classifications were high, while the Kappa statistics were notably lower. This is not unexpected, given the binary nature of the classifications. In both cases, however, our multi-temporal CAT Transform variables out-performed the image differencing bi-temporal approach to change detection. Significance testing at the 95% confidence level supported this conclusion. The superior performance of the multi-temporal classification was also reflected in both the producer's and user's accuracies (Table 2).

Table 2. Error matrices and accuracies calculated for (a) the multi-temporal, CAT Transform change classification, and (b) the bi-temporal, image differencing change classification.

a) CAT Transform-based Change Classification			
	Reference		
Classification	Change	No Change	**Total**
Change	1025	576	1601
No Change	438	11518	11956
Total	1463	12094	13557
Producer's Accuracies:		Change	70.06%
		No Change	95.24%
User's Accuracies:		Change	64.02%
		No Change	96.34%
Overall Accuracy:			92.52%
Kappa:			62.70%

b) Bi-temporal, Image Differencing Change Classification			
	Reference		
Classification	Change	No Change	**Total**
Change	892	571	1463
No Change	700	11394	12094
Total	1592	11965	13557
Producer's Accuracies:		Change	56.03%
		No Change	95.23%
User's Accuracies:		Change	60.97%
		No Change	94.21%
Overall Accuracy:			90.62%
Kappa:			53.12%

Conclusions

The novel, multi-temporal approach to landscape dynamic analysis we present here is shown to offer considerable potential not only as a tool for visualization, but also as a means of quantitatively analyzing various types of change over multi-year periods. The CAT Transform, labeled for the three variables it produces – Change, Aftereffect, and Trend – enables the exploitation of currently-available, temporally-dense, Earth-observation satellite data sets in a way that existing techniques do not. By compressing several years of bi-monthly MODIS NDVI observations over the province of Alberta into these three variables while maintaining much of the non-seasonal vegetative dynamics occurring during the period of interest, the transform provides a simple yet effective approach to regional-scale change detection. A false-colour composite of the CAT variables covering our Alberta study area revealed a complex, yet comprehensive perspective on the wide diversity of landscape changes occurring over the province. Our case study over the city of Calgary successfully demonstrated the applicability of these same variables to the quantitative extraction of new urban development areas around Calgary between 2001 and 2011. This new approach to change analysis using multi-temporal VI data sets presents a first step toward the greater realization of the full potential of current Earth-observation data sets, opening the doors to numerous possibilities for this type of analysis.

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