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Article

Bi-temporal Change Detection, Change Trajectories and Time Series Analysis for Forest Monitoring

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Summary: Traditional change detection refers to bi-temporal approaches. With the recent open access policy of several data providers, the use of multi- to hyper-temporal data for change detection and monitoring applications becomes feasible. Dense time series with several hundreds of Landsat-like satellite images are rarely used to date. This study exemplifies opportunities of three approaches with respect to forest monitoring on a local study area on Vancouver Island (Canada). Each of the approaches has advantages and disadvantages that make it particularly powerful for certain purposes. The more datasets are involved the more complex the analysis becomes. At the same time, complex processes such as forest structural development can only be resolved with multi- to hyper-temporal datasets. Dense time series are an adequate means to account for the dominant temporal dimensions of forest development and change including phenological or seasonal variation, structural or long-term trends, as well as abrupt changes and changes in forest dynamics. Exploration of dense time series is the key to efficient use of upcoming high temporal resolution sensors such as Sentinel-2.

Zusammenfassung: *Bi-temporale Veränderungsdetektion, Veränderungstrajektorien und Zeitreihenanalyse sowie deren Anwendung im Waldmonitoring.* Traditionelle Veränderungsdetektion bezieht sich meist auf bi-temporale Ansätze. Durch die derzeitige offene Datenpolitik verschiedener Datenanbieter wird die Anwendung von multi- und hyper-temporalen Datensätzen für die Veränderungsdetektion und das Monitoring zunehmend praktikabel. Dichte Zeitreihen von mehreren Hundert Landsat-ähnlichen Satellitendaten werden aktuell nur wenig genutzt. Diese Studie zeigt beispielhaft die Möglichkeiten dreier verschiedener Ansätze in Bezug auf das Waldmonitoring an einem Untersuchungsgebiet auf Vancouver Island (Kanada). Jeder der drei Ansätze hat Vor- und Nachteile, die sie besonders leistungsstark für bestimmte Anwendungen machen. Je mehr Daten in die Analyse einbezogen werden, desto komplexer wird die Analyse. Gleichzeitig können komplexe Prozesse wie die Waldstrukturentwicklung nur mit multi- und hyper-temporalen Daten entschlüsselt werden. Dichte Zeitreihen sind ein geeignetes Mittel, um die dominanten zeitlichen Dimensionen der Waldentwicklung und -veränderung zu erfassen, darunter phänologische oder saisonale Schwankungen, strukturelle oder Langzeittrends sowie abrupte Veränderungen und Veränderungen in der Walddynamik. Die Analyse dichter Zeitreihen ist essenziell für den effizienten Einsatz zukünftiger Satelliten mit hoher zeitlicher Auflösung wie Sentinel-2.

1 Introduction

Change detection is a key remote sensing application. Many state-of-the-art methods were developed as early as in the 1970s and 1980s, e.g., image differencing (Weismiller et al. 1977), post-classification comparison (PCC) (Jensen et al. 1987), or change vector analysis (CVA) (Malila 1980). From a technical perspective, remote sensing change detection is the identification of differences between two or more images. Generally, these changes can be measured in terms of intensity, frequency, spatial and temporal extent, spatial and temporal stability, rates and speed. Estimating change with remote sensing data of only one

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acquisition requires detailed knowledge of the study site so that the features on the image can be related to processes on the ground. For long time, remote sensing analysts were mainly interested in what is known as conversion, i.e., the replacement of one land use class by another (Coppin et al. 2004). Changes due to phenological changes of vegetation were frequently undesired, and it was seen as a prerequisite to avoid such changes by carefully selecting the images used for change detection. According to Singh's (1989) definition change detection is "the process of identifying differences in the state of an object or phenomenon by observing it at different times". Many comprehensive change detection reviews have been published (e.g., Coppin et al. 2004, Lu et al. 2004, Singh 1989), most of them reflecting the long history of bi-temporal methods. Recent reviews include time series analysis (Hecheltjen et al. 2014) but do not refer to forestry. Forest managers and climate modellers are not only interested in forest loss due to land use change. They also need detailed information about structural changes of the land cover including forest management, e.g., harvesting, replantation, and natural processes, e.g., forest growth, biomass accumulation, insect infestation, fire, and recovery. The opening of the Landsat archive in 2008 triggered the use of multi- to hyper-temporal datasets rather than bi-temporal data. However, to date there is no study examining potential and limits of each category. In the present paper, we compare bi-temporal change detection, change trajectory analysis and time series analysis and their implications for forest monitoring. We focus on a demonstration of specific advantages and disadvantages that complement the current understanding of change detection rather than rating each category according to achieved accuracies.

2 Data and Study Site

The study site is located on southern Vancouver Island, British Columbia, Canada (Fig. 1). Most of the area is composed of forested land. The Vancouver Island forests are a major resource for the Canadian timber and paper industry. Thus, there is a long history of forest use and management. Dominant tree species in the southern part of Vancouver Island are western hemlock (*Tsuga heterophylla*), western redcedar (*Thuja plicata*), Amabilis fir (*Abies amabilis*), Douglas-fir (*Pseudotsuga menziesii*), yellow-cedar (*Chamaecyparis nootkatensis*), lodgepole pine (*Pinus contorta*), grand fir (*Abies grandis*), and Sitka spruce (*Picea sitchensis*) (Pojar et al. 1991). Red alder (*Alnus rubra*) is a widespread species on logged or otherwise disturbed sites (Pojar et al. 1991).

The area has a strong climatic gradient, pronounced topography, and complex ecosystem dynamics. Rainfall varies between about 700 mm per year in Victoria and more than 3500 mm per year at the west coast of Vancouver Island (Government of Canada 2011). Precipitation falls mainly as rain predominantly in autumn and winter. The study site (Fig. 1) was chosen in the overlapping part of two world reference system (WRS-2) tiles with path/row indices p048r026 and p047r026. The study site has an area of 1000 × 1000 pixels (i.e., 30 × 30 km^2) with elevation ranging from about sea level to heights of about 1.135 m. In the present study, we processed all available Landsat images taken between 1984 and end of 2012 available from the USGS Global Visualization Viewer (http://glovis.usgs.gov/). They amount in 1.550 scenes including cloudy images as well as Landsat ETM+ SLC-off data. In the eighties and nineties, winter acquisitions were rarely taken. With the start of Landsat 7 in 1999 and Landsat 5 working simultaneously

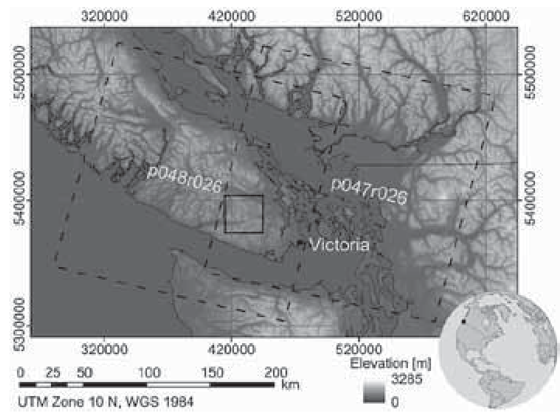

Fig. 1: Study site (black solid quadrangle) in the overlapping part of two neighbouring WRS-2 tiles (black dashed line).

the number of acquisitions was increased up to eight per month. The Scan Line Corrector (SLC) of Landsat 7 ETM+ failed in May 2003 resulting in data gaps whose extent increases towards the far edges of each scan resulting in a loss of about 22% per scene whilst the precise location of the missing scan lines varies from scene to scene (Chen et al. 2011). From late 2011, no Landsat 5 TM data are available for the study area. Thus, only Landsat 7 ETM+ SLC-Off images are available for 2012. One additional cloud free image from Landsat 8 OLI from July 2013 was processed as a reference image at the end of the observation period. All Landsat data have been processed consistently in order to allow for automated time series analysis. The datasets used for the bi-temporal change detection and trajectory analysis have been selected from the cloud and gap free datasets.

3 Methods

3.1 *Pre-processing*

Pre-processing included geometric and radiometric processing as well as cloud detection. The latter becomes relevant when all data of a time series are to be analyzed (Zhu & Woodcock 2014) or compositing techniques are chosen to create cloud free composites (Griffiths et al. 2013).

The majority of the established change detection methods require high geometric registration accuracy at subpixel level as image misregistration may cause image object properties to be evaluated at incorrect locations. This can lead to the identification of spurious changes as well as the failure to identify genuine changes due to even slight dislocations of image objects (Townshend et al. 1992). Very good geometric quality is reported for Landsat data processed with the Landsat Product Generation System (LPGS) which processes all Landsat scenes to Standard Terrain Correction Level 1T if the required ground control and elevation data are available. We removed all images exceeding 80% cloud cover to assure good geometric quality. The resultant number of images is lowered from 1.550 to 778.

Atmospheric correction was applied to all images using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospheric correction tool (Masek et al. 2006, Vermote et al. 1997).

Cloud cover is a severe problem when using optical data. This becomes even more evident when using time series of many images. For bi-temporal change detection and trajectory analysis cloud free images have been selected. The dataset used for time series analysis disregards the choice of cloud-free images. Instead, we made use of all cloud-free pixels. All pixels that are not contaminated by clouds, cloud shadows or snow are referred to as "clear". Clear land pixels are clear pixels that do not show water bodies. Masking of clouds, cloud shadow, snow and water is essential. A sophisticated method was presented by Zhu & Woodcock (2012) with the object-based function of mask (Fmask) algorithm. It provides masks for clouds, cloud shadows, snow, and water. Recent advances extended the Fmask algorithm to reduce errors based on multi-temporal analysis of Landsat data (Zhu et al. 2012, Zhu & Woodcock 2014). In this study, we applied Fmask with standard configuration to all images and used the resultant mask to exclude contaminated pixels from time series analysis. Accordingly, each pixel has an individual time series. The number of observations varies over the image.

3.2 *Bi-temporal Forest Change Detection*

Relatively few of the numerous change detection methods that have been developed go beyond the discrimination of changed and unchanged features (Hecheltjen et al. 2014). Valuable information is added when additional information about the nature of change is provided. Change vector analysis (CVA) (Malila 1980) is a widely used and robust method which produces two quantities of change information: 1) change magnitude which represents the intensity of change; and, 2) change direction which provides information about the spectral behaviour of the change vector. Bovolo & Bruzzone (2007) provided a comprehensive theoretical framework for CVA.

CVA performs change detection by differencing the spectral vectors of identical pixels in two co-registered multispectral images. The difference vector of all spectral bands can be described by its magnitude and its direction. Change magnitude is expressed as the Euclidean distance in the multidimensional feature space, calculated from the differences in each spectral band (1), (2):

$$x_{diff_i} = x_{2_i} - x_{1_i}\,, \tag{1}$$

$$m = \sqrt{\sum_{i=1}^{n} {x_{diff_i}}^2}\,,\ m \in \left[0, \max(m)\right], \tag{2}$$

where x_{1i} and x_{2i} are the reflectances of band i in images 1 and 2, respectively; x_{diffi} is the difference of each band i; m is the change magnitude; and n is number of bands.

Change direction indicates the spectral direction of change rather than providing from/to classes, e.g., increase or decrease in a given image band over time. It can be calculated in several ways. We adopt the methodology described by Bovolo et al. (2010), who extended the polar domain approach (Allen & Kupfer 2000) to represent higher dimensional feature spaces in two dimensions (3):

$$\alpha = \cos^{-1}\left[\frac{1}{\sqrt{n}}\left(\frac{\sum_{i=1}^{n} x_{diff_i}}{\sqrt{\sum_{i=1}^{n} {x_{diff_i}}^2}}\right)\right], \alpha \in \left[0, \pi\right], \tag{3}$$

where α is the direction expressed as multidimensional angle.

To show the performance of the bi-temporal approach we used data taken virtually at the same day of the year but six years apart. The data are from 2004-07-24 and 2010-07-25. Both datasets are from the identical WRS-2 tile and from Landsat 5. Image noise that remains after atmospheric correction or results from sensor degradation was reduced by relative radiometric normalization using the iteratively re-weighted multivariate alteration detection (IR-MAD, Canty & Nielsen 2008). The T-point thresholding (Coudray et al. 2010) was applied to the magnitude component to separate change from no-change. The final change detection map was derived by unsupervised clustering using the expectation maximization (EM) algorithm (Bazi et al. 2007). The map indicates vegetation losses, vegetation increases and unchanged vegetation. The study site does not cover urban areas. Thus, all occuring changes can be attributed to forest gain or loss.

3.3 *Forest Change Trajectories*

Trajectory analysis and time series analysis are often not clearly defined and the use of the terms is often confused. Time series in remote sensing simply describe a dataset consisting of a sequence of images taken from the same area at different times. Time series analysis, however, is related to the composition of a time series. Time series decomposition into trend, seasonal and remainder (noise) components is a common technique to characterize time series and describe their temporal behaviour. An example is the seasonal-trend decomposition procedure (STL) based on a locally weighted regression smoother (LOESS) (Cleveland et al. 1990). A well-established method for time series analysis of remote sensing data is breaks for additive season and trend (BFAST) (Verbesselt et al. 2010a, Verbesselt et al. 2010b) which allows for the detection of long-term trends and of abrupt breaks in the trend and seasonal components. Whereas many recent studies use time series they do not apply time series analysis in terms of decomposition (e.g., Griffiths et al. 2012, Kennedy et al. 2007). Since most of these approachs aim at fitting trend models and deriving trends from the data (Lawrence & Ripple 1999, Kennedy et al. 2007, Kennedy et al. 2010) they can be seen as a combination of time series analysis and trajectory analysis. As all of these studies focus on annual or less data, seasonal patterns cannot be explored.

Trajectory analysis in the present study is understood as analyzing multi-temporal datasets that have one observation per year or less. In the present case study, the trajectory is a compostition of multiple bi-temporal change detection results. Trends have to be interpreted from the derived map rather than calculated from observed physical properties such

Tab. 1: Data used for change trajectories.

Dates	Path/Row	Sensor
1984-07-17	048/026	Landsat 5 TM
1986-08-08	048/026	Landsat 5 TM
1989-10-03	048/026	Landsat 5 TM
1992-08-17	047/026	Landsat 5 TM
1995-09-02	048/026	Landsat 5 TM
1998-09-26	048/026	Landsat 5 TM
2001-09-10	048/026	Landsat 7 ETM+
2004-07-24	048/026	Landsat 5 TM
2007-09-12	047/026	Landsat 5 TM
2010-07-25	048/026	Landsat 5 TM
2013-07-26	047/026	Landsat 8 OLI

as the normalized difference vegetation index (NDVI) or other spectral indices.

We take advantage of the CVA approach and perform bi-temporal change detection on consecutive image pairs instead of individually classifying them. Lunetta et al. (2004) used CVA to assess land cover changes in a forested area in North Carolina in a similar approach. Their findings indicate that a repetition rate of 3 − 5 years is required to monitor forest cover change. Higher temporal resolution is recommended, however. For the 29-year observation period in our study we chose a time intervall of about three years. The first time step is only two years (Tab. 1). Consequently, a dataset with 11 time steps was created. Ten individual bi-temporal change detection tasks have been performed as described in section 3.2. The individual results were subsequently combined in a way that allows to visualize the time span where the most intense changes have happened. These can be attributed to forest clearings.

3.4 *Time Series Analysis for Forest Monitoring*

Recent advances in medium and high resolution remote sensing focus on time series, i.e., trend analysis (Dubovyk et al. 2013) or time series reconstruction by segmented regression modeling (Kennedy et al. 2010). Most of these methods focus on trends or abrupt changes (e.g., Griffiths et al. 2012). The combined analysis of trends, seasonal cycles, and abrupt changes is rarely applied (Verbesselt et al. 2010a, Verbesselt et al. 2010b). A problem with Landsat data may be its irregular time spacing since many time series methods require regular time spacing.

Interpolation is a commonly applied technique in time series analysis to fill gaps (Verbesselt et al. 2006). The average gap length in our time series varies between less than 20 days and more than 70 days in less favoured areas. The real gap length varies between 1 day (cross-sensor Landsat 5/7 and adjacent tiles) and more than 1000 days in the high altitude regions and along shorelines. As the time series contain outliers in spite of masking clouds and missing observations, filtering was applied to reduce noise. An adequate state-of the art method is the Savitzky-Golay filtering (Savitzky & Golay 1964) which is also used in other time series approaches (Jönsson & Eklundh 2004). As indicated previously great benefit of time series is expected in understanding additional process dimensions such as seasonal pattern and their changes over time, long-term trend direction and intensity, timing and intensity of abrupt changes, and subtle changes that might be lost when looking only on trends. These processes are usually not directly related to spectral responses. Some indices, however, are suitable to characterize at least some of the processes to a certain degree although additional information is often required for better characterization, e.g., lidar to quantify biomass accumulation (Duncanson et al. 2010). The selection of appropriate spectral indices is essential to understand forest development. An index that is closely related to the structure of coniferous forests is the normalized difference moisture index (NDMI) (Hardisky et al. 1983). It is calculated from near-infrared (NIR) and shortwave-infrared (SWIR) bands as follows (4). The numbers in brackets indicate the respective Landsat TM/ETM+ bands:

$$\mathrm{NDMI} = \frac{\mathrm{NIR}(4) - \mathrm{SWIR}(5)}{\mathrm{NIR}(4) + \mathrm{SWIR}(5)} \quad (4).$$

As the SWIR band is sensitive to foliage water content and the fraction of dead leaf material, NDMI is promising in forest monitoring (GOODWIN et al. 2008). The pre-processing of the dense time series did not include radiometric normalization because IR-MAD obscures seasonal variation. Whereas this is appreciated in many bi-temporal studies where seasonal variation is considered as noise, it is important to keep the seasonal variation pattern in time series because of its additional information content.

As our main focus is on abrupt changes and recovery we used a robust method to detect breaks in the Landsat time series and estimate recovery trends subsequently. The interpolated and filtered NDMI time series was analyzed for discontinuities by applying the Webster measure (WEBSTER 1973). This measure is calculated with a pixel-based temporal moving window that is divided in two parts. For each part the mean is calculated, and the difference of the left hand and right hand means is plotted. The timing of change is assumed at the point with the biggest difference, i.e., the minimum value. The size of the moving window was defined with a width of 365 days. Hence, the time period considered in the moving window is always one full year, ensuring that seasonality is leveled out. This means that in a time series without change the Webster measure will be zero. To ensure the presence of real changes rather than outliers in the time series and at the same time preventing fixed thresholds, a statistical non-parametric Kolmogorov-Smirnov test was performed. Once the break point is detected several properties of the time series may be analyzed, e.g., magnitude of change or recovery rate following the disturbance. The recovery trends are not linear but for ease of interpretation we calculated linear trends for the periods directly following the clearcut event. The time series based change detection method follows the workflow presented in THONFELD et al. (2014):

a) Construction of individual NDMI time series for each pixel
b) Linear interpolation between all observations to create equally-spaced time series
c) Filtering the time series using Savitzky-Golay filter (window = 365)
d) Application of Webster discontinuity measure on the filtered time series
e) Determination of the minimum in the Webster measure as the indicator of the break date
f) Performing the statistical non-parametric Kolmogorov-Smirnov test
g) Calculation of change properties, e.g., timing of change, intensity of change, recovery rates after change event

From dense time series of forests several features can be calculated that describe the temporal behaviour of the index including date, duration and intensity of abrupt changes, shifts in seasonality, trends before and after major change events, date, duration and intensity of secondary changes, long-term anomalies, and regrowth rates.

3.5 *Accuracy Assessment*

The validation of change detection results is particularly challenging due to the very common lack of reference data for all time steps. Frequently, available ground information is of different date than the image data. The detection of clearcuts in Landsat images by means of visual interpretation is feasible because their size is often several hectares, and the spectral change signal is usually very clear. However, analysts often apply minimum mapping units or spatial filters to get rid of small change areas which are often difficult to validate visually. Our validation procedure is based on the time series analysis. Studies exploring annual time series refer to the year of disturbance onset or the first year with detected disturbance (GRIFFITHS et al. 2012). We derived reference data from the dense Landsat time series itself since this dataset provides most comprehensive temporal information. Bi-temporal datasets (as well as annual time series) allow indicating a period of change rather than an exact year. We applied stratified random sampling on the time series results to select 30 pixels per disturbance year plus 30 pixels from the undisturbed pixels. For each of the resulting 900 locations we extracted the NDMI time series, plotted and manually checked them. For some of the reference points the labels had to be revised. This was mainly because the changes happened in late fall of the previous year rather than in spring of the next year. For

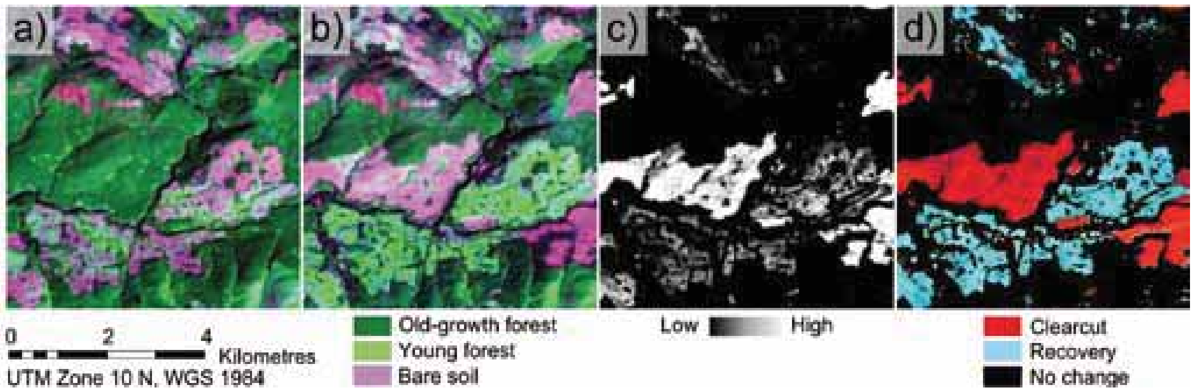

Fig. 2: Subset of the study site (6 × 6 km^2), a) Landsat from 2004-07-24, b) Landsat from 2010-07-25 (RGB = 7-4-2), c) masked change magnitude, and d) masked change directions.

each of the 900 locations we checked if change and no-change pixels were detected correctly. For the trajectory and the time series we also evaluated if the year of change was specified correctly. The reference dataset was adjusted to the bi-temporal study and the trajectory, respectively. If there was a clearcut before the time covered by two observations, it was labeled as regrowth in the reference map.

4 Results and Discussion

The results of the bi-temporal change detection based on CVA are shown in Fig. 2. It can be seen that the two major changes, i.e., forest loss due to clearcut harvesting (red) and forest recovery due to the establishment of new forest cohorts (blue), are well displayed in the direction component (Fig. 2d). Change intensity, i.e., magnitude, is shown in Fig. 2c in grey levels with bright colours indicating strong changes and dark areas indicating small or no changes. Since forest regrowth is rather slow compared to forest clearcut harvest, the change magnitude is higher for forest loss where the spectral signature has completely changed. Detectability of regrowth depends on the time-lag between the two images and the growth rate of the forest. The forests of the study site grow rather slowly. The overall accuracy of the final map indicating clearcuts, recovery, and unchanged areas was only 51.9%. The main reason is that recovery is a long-term process that causes only gentle spectral changes compared to the strong changes of clearcuts. Thus, the selection of appropriate thresholds is challenging. The accuracy of clearcut detection, i.e., ignoring recovery, was 93.4%.

Results of the change trajectory analysis are shown in Fig. 3. The major changes, i.e., clearcuts, are displayed with the colours indicating the time span where the harvest happened. A specific date of the harvest events cannot be derived. The detected change patches retrace the clearcuts well. Some groups of trees left standing inside the clearcuts show up as well as small-scale change patches that have been rendered to install new forest roads. In the southern part of the study site, some mapped elongated clearcut patches are a result of topographic effects rather than real changes. It can be seen in Tab. 1 that it was not possible to establish a time series of annual data. Some off-season data had to be used. The results confirm that off-annual data should

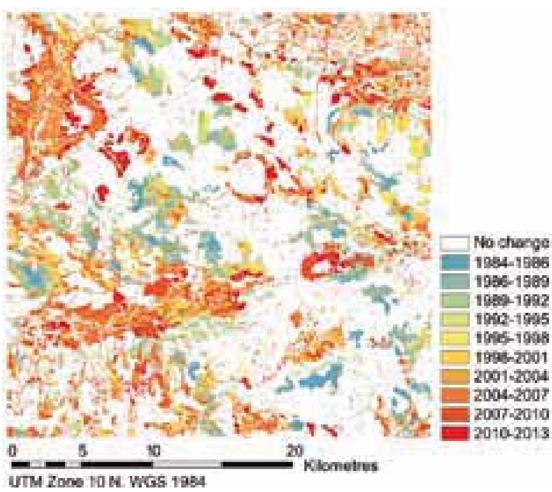

Fig. 3: Time span of clearcut events as result of change trajectory analysis.

be preferred over off-seasonal data. Assessing the regrowth rates is rather challenging with the data used for this experiment whereas clearcuts can be well detected even after a time lag of one or two years. The overall accuracy was 69.6%. However, the visual inspection of the dense time series revealed that there was often more than one change event in a time series. The trajectory analysis did only account for the first strong change signal. However, that one is sometimes not the most pronounced in a time series. In other words, changes are often well detected but at wrong dates. The analysis if change was correctly seen as change, and thereby ignoring the correctness of the date, revealed an overall accuracy of 91.4%.

Results of the time series analysis are shown in Fig. 4. The break date can be identified accurately. Besides the precise year of change, even the month of the clearcut can be derived (Fig. 4a, b). As the forest harvest within a clearcut area takes several weeks until all trees, branches, and woody debris are removed, there is some bias in this information. However, start, end and duration of the clearcut can be derived, e.g., break duration in Fig. 4c. A combined map of clearcut events detected during the observation period and trends is shown in Fig. 4d. The trends refer to those areas that have been harvested before the start of the observation period and regrow since that time. White areas refer to mature and old-growth forests or to non-forest areas. Years of change were detected with an accuracy of 93.1%. The overall accuracy of correctly identified changes was 95.4%.

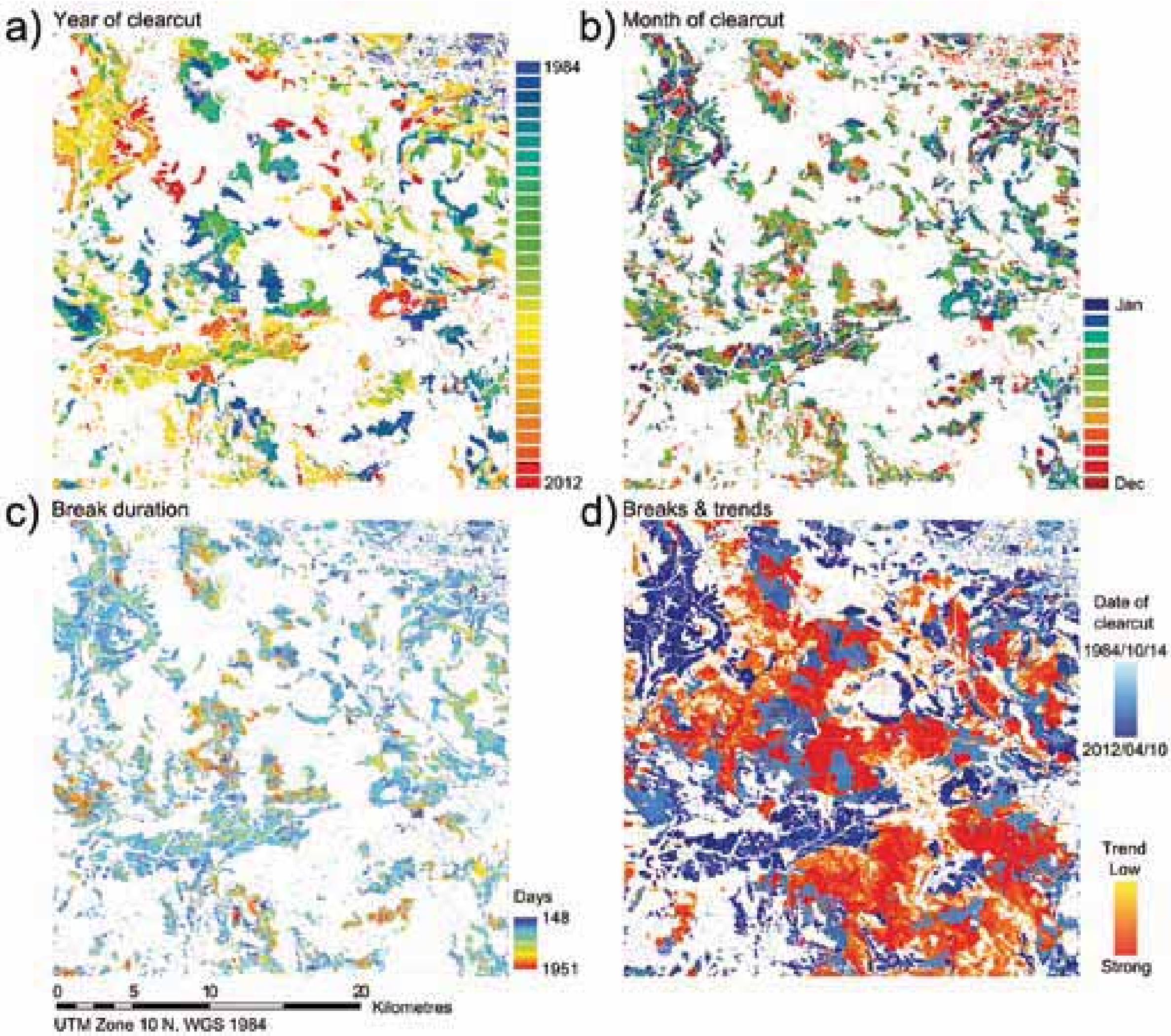

Fig. 4: Results of time series analysis: a) year of clearcut, b) month of clearcut, c) break duration, and d) combined break date and trend map.

Tab. 2: Comparison of bi-temporal change detection, multi-temporal change detection, and time series analysis.

	Bi-temporal change detection	**Multi-temporal change detection (including trajectories of annual observations)**	**Time series analysis (more than one observation per year)**
Suitable to detect abrupt changes?	yes	yes	yes
Suitable to detect long-term trends?	no, trends cannot be clearly separated from noise or phenological differences	yes	yes
Suitable to detect seasonal variation, e.g. phenology?	no	no, inter-annual changes that fall below a certain threshold are considered noise, those above are seen as abrupt change	yes
Date of change detectable?	no, it is only known that the change happened between two observations	a rather coarse indication of the date of abrupt changes can be estimated	changes can be detected with good temporal precision
Major preprocessing steps	co-registration; atmospheric correction or radiometric normalization; (manual) scene selection	geometric & radiometric processing (atmospheric correction, radiometric normalization); cloud detection; scene selection; compositing	geometric & radiometric processing (atmospheric correction); cloud detection
Requirements	cloudfree scenes; ideally equal phenological conditions & equal sun position	cloudfree pixels; each observation must be chosen with respect to rainfall, phenology, and sun illumination	cloudfree observations
Option to label changes?	yes, several methods exists (Hecheltjen et al. 2014)	yes, if multi-temporal classifications are compared; usually, the change itself can be related to a certain class	yes (Zhu & Woodcock 2014); usually, the change itself can be related to a certain class
Advantages	small data volume; many algorithms (see Coppin et al. 2004, Hecheltjen et al. 2014)	moderate data volume; good balance of outcome and effort; trends and abrupt changes detectable	seasonal effects, inter- & intra-annual dynamics detectable; all observations used; no scene selection or compositing required; almost gapless process characterization; option of time series decomposition; no thresholding required
Limitations	processes and their spatio-temporal characteristics are not detectable; thresholding required to separate change from no-change	data selection and/or compositing required; areas of frequent cloud coverage; seasonal variation & dynamics are not detectable; data availability in some regions	big data volume; comprehensive preprocessing requires automation; data availability in some regions
Application	various, e.g., emergency response, flood detection, urban expansion	various, e.g., forest cover change, mining	various, e.g., forest cover change, continuous map update
Examples of methods	CVA , Post Classification Comparison	LandTrendr	BFAST, time series approach used here

Some of the most relevant characteristics of the three approaches demonstrated in this study are listed in Tab. 2. The information content that can be derived with bi-temporal datasets, trajectories of triennial data, and dense time series with gaps in the range of few days to several weeks increases with the number of available observations (cf. rows 1-3 in Tab. 2). Secondary changes, information on seasonal variation and changes therein are not displayed in Fig. 4. However, this information can be derived from the dense time series as well.

Although bi-temporal change detection (cf. column 2 of Tab. 2) is very powerful in forest change detection it is rarely used in operational monitoring projects. Methods such as the land-cover change mapper (LCM) (Castilla et al. 2009) are efficient tools but require knowledge of the study site for the interpretation of changes. The bi-temporal example shown here based on CVA provides additional information about the nature of change. The link to processes, however, is challenging. Any quantification needs well adjusted images that do not only account for illumination differences but also for phenological differences and weather impacts such as rainfall, drought, and wind. Even annual data do not guarantee identical phenological conditions. Radiometric normalization may reduce noise but does not eliminate illumination differences that occur when off-season data are used. The problem of finding data taken under comparable conditions becomes even more critical when time series are used. Although the summers on Vancouver Island are relatively dry, the time suitable for cloud free acquisitions is rather limited. Recently, compositing techniques have been developed (Griffiths et al. 2013) to avoid the laborious and sometime misleading task of seeking cloud free images. Those techniques aim at finding clear land pixels that are as close to a predefined reference date as possible. Off-year acquisitions are preferred over off-seasonal images (Wulder et al. 2004). Compositing is promising when annual data are sufficient or when several tiles have to be combined to seemless image mosaics. In a way compositing can be seen as a data reduction which may also be regarded as a disadvantage. Data reduction also means information loss. To date only a very small portion of the Landsat archive has been explored (Wulder et al. 2012). Exploring all datasets may improve our understanding of processes on the ground rather than disregarding the vaste majority of datasets.

The trajectory analysis presented here is suitable to detect major changes, i.e., timber extraction and forest regrowth. The detection of insect infestation and other subtle changes is difficult with such datasets or even annual time series because they are often too weak to exceed the noise level that is included in these time series. Consequently, subtle changes are often identified as noise. The quantification of the forest recovery is also challenging because the timing of each acquisition has enormous impact on the shape of the recovery curve. Change trajectories of classified images are thus of limited use in forest studies. Trends can be derived from trajectories (cf. column 3 of Tab. 2) with appropriate methods such as Landsat-based detection of trends in disturbance and recovery (LandTrendr) (Kennedy et al. 2010). This time series segmentation techniques calculates trend curves based on any spectral index. It is very powerful in detecting strong changes. The accuracy of the recovery trends, however, is hard to estimate. Divergence from idealized time series models is considered noise. Compositing techniques are an appropriate means to reduce spurious changes that result from imperfect data. Noise is reduced as well. Seasonal dynamics, interannual variation and non-linear dynamics, however, are neither displayed in annual time series nor in trajectories of categorized data.

A more comprehensive way towards better understanding of ecosystem processes, landscape dynamics, and their relationship to driving forces is using all available information. This can be achieved by using Moderate Resolution Imaging Spectroradiometer (MODIS)-like standardised products such as the 16-day-NDVI product (Roy et al. 2010), the multitemporal multispectral modeling of land cover classes based on all observations (Zhu & Woodcock 2014) or the time series analysis approach used here. Future satellite missions such as Sentinel-2 will deliver data at high temporal resolution. Comprehensive ecosystem process understanding requires the efficient exploration of as many observations as possible – including multi-sensor approaches.

5 Conclusion

The study presented here revealed that each of the three different change detection strategies has advantages and disadvantages that make it suitable for different applications in forest management. The most comprehensive information can be derived from dense time series. The superiority in information detail is at the expense of high computational efforts. With the launch of recent, e.g., Landsat 8, and upcoming, e.g., Sentinel-2, sensors the processing of dense time series is likely to become more feasible also in regions that have been less covered to date. When processes are in the scope of a study, remote sensing based time series are a good means for improved understanding. Forest monitoring and forest change detection requires high spatial and temporal resolution for comprehensive structural characterization and process understanding which can be achieved with dense time series. The use of dense time series does not only deliver more information about ongoing processes; changes can also be detected with higher temporal precision and higher accuracy.

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