Forest monitoring using Landsat time-series data- A review

Review paper

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Abstract:

Unique among earth observation programs, the Landsat program has provided continuous earth observation data for the past 41 years. Landsat data are systematically collected and archived following a global acquisition strategy. The provision of robust data products for free since 2008 has spurred a renaissance of interest in Landsat and resulted in an increasingly widespread use of Landsat time series (LTS) for multi-temporal characterizations. The science and applications capacity has developed steadily since 1972, with the increase in sophistication offered over time incorporated into Landsat processing and analysis practices. With the successful launch of Landsat-8, the continuity of measures at scales of particular relevance to management and scientific activities is ensured in the short term. In particular, forest monitoring benefits from LTS, whereby a baseline of conditions can be interrogated for both abrupt and gradual changes and attributed to different drivers. Such benefits are enabled by data availability, analysis-ready image products, increased computing power and storage, as well as sophisticated image processing approaches. In this review, we present the status of remote sensing of forests and forest dynamics using LTS, including issues related to the sensors, data availability, data preprocessing, variables used in LTS, analysis approaches, and validation issues.

Introduction

Forests are the most widely distributed terrestrial vegetation type, and thus play an important role in providing the environmental context and shaping the dynamics of regional and global ecosystem processes (Wulder, 1998; Westoby, 1989). Forests are important globally for provision of fiber to meet a range of needs, from local uses such as cooking fuel through to industrial utilization for construction materials. As such, forests play a role in the lives of most people on the planet. It is increasingly understood that forests store large quantities of carbon in both vegetation and soil and also exchange carbon with the atmosphere. The ability to mitigate the impacts of climate change through enhancement of carbon sequestration has been identified (Brown, 1996). Forests also sustain important functions for a variety of biological processes by cycling nutrients through processes such as decay and tree regeneration (Boring et al., 1981), provide multiple ecosystem services (e.g., filtration of water, provision of habitat, among others), and protect biodiversity.

Forests can be characterized by both their current state and temporal dynamics. Several attributes such as structure and composition describe the state of the forest (Graetz, 1990), whilst the manner in which they change over time define their temporal dynamics (Hobbs, 1990). These dynamics can result from any combination of short-term events (such as droughts), longer-term variability attributable to climate change, and human activities. Indeed, there is an increasing sense of urgency to understand temporal dynamics and resiliency of forest ecosystems in the context of rapid global change (Manning et al., 2009). Understanding these temporal dynamics can aid both forest management and policy development (Cohen et al., 2010). For example, one of the major challenges for successful implementation of the international forest carbon policy, reducing emissions from deforestation and forest degradation, and through conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries (REDD+), is to estimate national-level net changes in carbon stocks that would occur without policy implementation (De Sy et al., 2012). Remotely sensed data can potentially address this challenge by providing a means to estimate baseline forest conditions in a spatially explicit manner, departures from which can be employed to assess current and historical trends of deforestation and forest degradation (Baker et al., 2010)

Earth observation (EO) instruments play an important role in the assessment and monitoring of forest dynamics in a spatially and temporally continuous fashion. Among the current and historic constellation of EO satellites, the Landsat series of satellites stands out for three primary reasons. First, the Landsat program offers the richest and longest running historical archive (40 years) of systematically collected remotely sensed data (Goward et al., 2006), providing otherwise unavailable opportunities for improved understanding of mechanisms and extents of past forest changes and recovery. Second, the unique combination of imagery with a 30 m or similar spatial resolution collected with temporal repeat frequency of 16 days makes Landsat data well suited for detecting changes on the Earth's surface across relatively short time intervals (Coppin and Bauer, 1996; Gillanders et al., 2008; Wulder et al., 2008). Third, due to a new data policy implemented in 2008, all new and archived Landsat data held by the United States Geological Survey (USGS) are available free-of-charge in a pre-preprocessed ready for analysis standard format (Woodcock et al., 2008; Wulder et al., 2012), ultimately increasing the opportunity to utilize multi-temporal images representing a period of time, a large spatial area, or both (Hansen and Loveland, 2012).

The availability of large volumes of free Landsat imagery, coupled with advances in image processing methods and computational capacity have stimulated widespread use of Landsat time series (LTS) in many applications including classification and assessment of changes in forested ecosystems (e.g., Kennedy et al., 2007), prediction of forest biophysical parameters (e.g., Main-Knorn et al., 2013), and assessment of vegetation phenology (e.g., Melaas et al., 2013). To effectively understand how disturbance impacts composition, structure, and function of forests, it is beneficial to quantify disturbances at a time step relevant to the affected processes (for example, annually, Masek et al., 2013) and using long-term data sets to, as possible, capture instances and trends related to forest disturbances and recovery (Frolking et al., 2009). Hence, time series data comprised of image stacks over a longer duration and greater temporal frequency can provide a more comprehensive understanding of the complexity of forest disturbance and dynamics than a pair of Landsat images used in a bi-temporal change detection approach (Cohen et al., 2010; Wulder et al., 2012). Whilst image pairs can inform on a change in state, image stacks and LTS provide information on trends, and can relate continuous and discontinuous changes in both positive (accrual) and negative (depletions) directions (Kennedy et al., 2014). Data from daily viewing sensors such as MODIS and AVHRR are well suited for time series analyses at regional and global scales, but are less equipped to capture and analyze finer-scale disturbances that are relevant from management and monitoring perspectives (Walker et al., 2012). The key advantages of Landsat are a spatial resolution that is appropriate for capturing anthropogenic impacts (Townshend and Justice, 1988), and a temporal dimension that spans more than 40 years and enables retrospective analyses and long-term characterization of change (Wulder et al., 2012). LTS data can capture and characterize abrupt, stochastic events as well as subtle changes, while potentially revealing new patterns or processes occurring across forested landscapes (Cohen et al., 2010). Indeed, Hansen and Loveland (2012) state that past approaches relying on bi-temporal image comparisons will soon be replaced by more exhaustive and data intensive methods employing LTS datasets (e.g., Kennedy et al., 2007; Huang et al., 2009). Such replacement hinges upon the broader availability of accurately pre-processed LTS data and further development and improvement of automated algorithms for extracting information characterizing a wide range of forest dynamics.

The needs and challenges of assessing forest dynamics with LTS data are varied and have not been articulated in a comprehensive manner. LTS data analysis differs from traditional analysis using single or bi-temporal imagery in many respects, from dataset assembly through to creation and validation of a final product. While resources for traditional forest dynamic assessment approaches using EO data are generally known and widely discussed in textbooks and review articles (e.g., Coppin and Bauer, 1996; Coppin et al., 2004; Lu et al., 2004), corresponding resources for time-series based approaches have not matured to the same level. Several aspects of LTS data analysis such as preprocessing requirements, criteria for selecting spectral variables (original bands or derived indices), and analysis approaches have not been the subject of extensive review. Hence, the primary goal of this paper is to review the current status and recent advances in LTS tools and data processing techniques, specifically from the perspective of monitoring forests and forest dynamics. In doing so, we provide (i) a brief history of the Landsat program, as well as insights into issues related to (ii) image selection, (iii) image pre-processing techniques, (iv) information extraction techniques, as well as (v) issues pertinent to the validation of products derived from LTS data. We focus this review on forestry related articles; however, many of the issues discussed are equally relevant for monitoring dynamics in a wide range of ecosystems.

Landsat data and related issues

Current and past Landsat missions have used four different types of sensors for the collection of earth observation (EO) data. The characteristics of each sensor are provided in Table 1. Landsats 1–5 had a multispectral scanner system (MSS), which acquired data from 1972 through late 1992, and again briefly in 2012. The spatial resolution of the MSS sensor was approximately 80 m with radiometric coverage in four spectral bands from the visible green to the near-infrared (NIR) wavelengths. The MSS sensor on Landsat 3 had a fifth band in the thermal infrared. Landsats 4 and 5, which were launched in 1982 and 1984 respectively, had the Thematic Mapper (TM) sensor in addition to the MSS. The TM sensor collected data in seven bands with three in the visible region of the spectrum (blue, green and red), one in the NIR region, two in the shortwave infrared (SWIR1 and SWIR2) region, and one in the thermal region. The spatial resolution of the TM sensor was 120 m for the thermal band and 30 m for the other bands. Landsat 5 continued to acquire data until February, 2012, far exceeding its 3-year design life. Landsat 7 was launched in 1999 with the Enhanced Thematic Mapper Plus (ETM+) sensor, which has similar spectral and spatial properties as TM, with a 60 m spatial resolution thermal band and with the addition of a 15 m panchromatic band. Landsat-7 has also well surpassed its 5-year design life and continues to acquire data; however, the Scan Line Corrector (SLC) of the ETM+ sensor has been inoperable since May 31, 2003, resulting in gaps in ETM+ scenes that range in size from two pixels at the scene center, to 14 pixels at the western and eastern scene edges (Markham et al., 2004; Maxwell, 2004). While long deactivated to preserve instrument power and aid in longevity of the favored TM instrument, the dormant MSS sensor on-board Landsat 5 was briefly reactivated in 2012 to compensate for the difficulties and predicted loss of the TM instrument.

On February 11, 2013, termed the Landsat Data Continuity Mission (LDCM), Landsat 8 was launched with the Operational Land Imager (OLI) and thermal infrared sensor (TIRS). In addition to the bands present on the Landsat 7 ETM+ sensor, Landsat 8 OLI collects data in two new bands; a blue band (0.433–0.453 μm) designed principally for ocean color observations in coastal zones, and a shortwave infrared band (1.360–1.390 μm) that is located in a strong water vapor absorption feature, facilitating the detection of cirrus clouds. The widths of several OLI bands have been refined relative to ETM+ bands to avoid atmospheric absorption features (Irons et al., 2012). The data quality (signal to noise ratio) and radiometric quantization (12-bits) of the OLI and TIRS instruments are higher than previous Landsat instruments (8-bit for TM and ETM+). From Landsats 4 to 8, consistency in both sensor and image characteristics have been maintained through a rigorous process of calibration and quality assurance (Markham et al., 2004). As a result, Landsat observations from the TM, ETM+, and OLI sensors are amenable to time series analysis. LTS studies that seek to incorporate MSS data into LTS have additional radiometric and geometric considerations, due principally to differing spatial resolutions and spectral band widths compared to the later sensors (e.g., Powell et al., 2010; Pflugmacher et al., 2012).

As previously noted, the Landsat satellite sensor series has been continually observing the earth surface to meet a wide range of information needs for more than four decades (Wulder et al., 2008). The continuity of the Landsat mission, however, does not entail uninterrupted collection or complete recording of the data in the archives. Data recording at the sensor is limited by some physical and technological considerations, including the size of on-board data storage and data downlink capacity. Optimization of data collection, via implementation of the long term acquisition plan (LTAP), provides for seasonally refreshed global terrestrial coverage mating with the system capabilities for image capture, storage, downlink, processing, and archiving (Arvidson et al., 2006). While variable by sensor, Landsat 7 currently obtains approximately 400 scenes per day (Ju and Roy, 2008), which is well above the 250 images specified by system design (Arvidson et al., 2006). The LTAP implemented for Landsat 8 builds upon previous lessons learned and is augmented by additional spatial information, such as incorporation of historic expectation and current maps of cloud cover (Irons et al., 2012). Locations known to have a history of persistent cloud cover that may require additional acquisition opportunities are given increased priority. Mission control operations have scheduled objectives for the collection of 400 Landsat 8 OLI and TIRS terrestrial images per day. Based upon previous experience, the specified number of scenes per day is likely to be exceeded. Currently, the specified collection level has been well exceeded with nearly all possible sunlit, continental scenes imaged each overpass, resulting in over 700 images collected per day (Wulder and Coops 2014). Potential impacts upon satellite longevity and ground system costs are to be revisited to determine if this acquisition rate can be maintained. Investigation of the Landsat archive for a given location and / or time period will show variability in the number of images available. This spatial and temporal variability in image availability in the global collection is related to historic implementation of collection (e.g., government vs. commercial), technology available (e.g., on-satellite and ground storage capacity), and the nature of the downlink of data (e.g., to international cooperators) (see Wulder et al., 2008 for details). Regarding the last item, there is an ongoing program focused on collecting unique images from the global international cooperator network to add these images to the USGS archive (Wulder et al., 2012). Landsat 8 has sufficient onboard recording and downlink capacity to downlink all images collected directly to the USGS for ingest, processing, archiving, and sharing (Wulder et al., 2012).

Image selection

Assembling an appropriate set of images for time series stacks may be challenging in some locations due to the aforementioned spatial and temporal discontinuities in Landsat data archives. Furthermore, the reduced applicability of images due to clouds and the ETM+ scan-line-corrector (SLC) failure makes the search for adequate high-quality images more challenging. Ju and Roy, (2008) analyzed the likelihood of obtaining cloud free ETM+ pixels within and outside the conterminous United States. The authors report a high probability of obtaining at least one cloud free pixel during any given growing season within the United States and a moderate probability globally (i.e., summer = 0.78 and spring = 0.75). The reduced quality of image data due to clouds (and SLC gaps for Landsat ETM+), however, could be a lesser concern for a pixel based analysis using LTS with sufficient temporal density. If an individual pixel is treated independent of its neighbors, selecting the best pixel among all-available near-anniversary scenes in a time-series reduces the requirement of cloud free-imagery (Griffiths et al., 2012). Composites are created through a rule-based process to select the "best" pixel observations from among the candidate images available. The rules for selecting the best available pixel observation can be related to nearness to a target day of year and avoidance of atmospheric interference (be it cloud, haze, or resultant shadows), or prioritization of a particular sensor (see White et al. 2014 for conceptual summary). Those generating composites at high latitudes will likely encounter issues related to phenology, whereas those generating composites for locations closer to the equator are more likely to encounter issues related to persistent cloud cover. Further, due to image overlap increase with latitude additional opportunities to obtain clear, cloud or snow free, pixels are enhanced. Notwithstanding, methods to monitor land cover in the presence of clouds, such as those developed by Zhu et al. (2012), combined with the advancement of techniques to fill temporal gaps in LTS by Helmer and Ruefenacht (2005), and Goodwin et al. (2013), and Landsat-MODIS image fusion techniques by Gao et al. (2006), Hansen et al. (2008), and Brooks et al. (2012) offer additional opportunities to obtain or generate cloud-free imagery.

Besides image quality, selection of an appropriate set of Landsat data in a time series requires careful consideration of image acquisition dates. Optimal temporal resolution is difficult to assess as requirements are often application specific (Wulder et al., 2008). For example, applications focused on vegetation phenology require images spanning all seasons over the period of interest; whereas, annual or near annual imagery during the same season (often summer) may suffice for many applications. For certain applications, it is critical that annual images with near-anniversary dates are selected in order to minimize spectral differences caused by intra-annual variation in phenology and sun angle differences. Image selection should consider both image quality (cloud cover) and acquisition date. Landsat metadata are refreshed daily (http://landsat.usgs.gov/metadatalist.php) and provides details on the presence of cloud, both overall for the entire image and by image quadrant. A visual inspection can help to determine if an image is cloud-free over a particular area of interest.

Brazil set an important precedent in early 2008 when the National Institute of Space Research (INPE) began making satellite data holdings available free of charge[1]. Encouraged by the Brazilian precedent, the USGS moved later in 2008 to "web enable" contents of the Landsat data archive. The policy change to free and open access by the USGS resulted in a sharp increase in imagery downloads (Wulder et al., 2012) as well as a change in how Landsat data are used (Hansen and Loveland, 2012). As described in Wulder et al. (2012), all Landsat images available within USGS archives can be downloaded in a standard analysis-ready terrain corrected format (referred to as Level 1T). However, the USGS Landsat holdings represent only a portion of the Landsat scenes acquired since 1972 (Loveland and Dwyer, 2012). Almost 3 million unique Landsat images are currently held by international agencies with ground receiving stations that directly downlink Landsat data. An effort is underway to consolidate the Landsat archives of all stations worldwide and make all Landsat scenes available to users under Landsat Global Archive Consolidation (LGAC). This effort was started in 2010 and is estimated to last up to six years. More information on the status of image repatriation to the USGS archive can be found under the auspices of the LGAC project (http://landsat.usgs.gov/Landsat_Global_Archive_Consolidation.php). Based upon archive consolidation efforts, users can go to what is effectively a centralized global archive at the USGS EROS data center to obtain systematically and consistently processed analysis ready imagery.

[1] 1. http://www.nature.com/nature/journal/v452/n7184/pdf/452127b.pdf

Preprocessing of LTS images

An individual image in an LTS may suffer from different levels of geometric errors and atmospheric effects. A robust correction for these effects is an important precursor to LTS analyses. Historically, pre-processing for multi-temporal images required considerable computational cost and was a limiting factor in time series analysis (Hansen and Loveland, 2012). However, significant improvements in computational power and automated procedures have enabled efficient and rapid mass-processing of images. Moreover, emerging techniques for applications, such as land cover mapping from LTS (Gray and Song, 2013), are being designed to accommodate some degree of spectral variation or noise in LTS. In the future, such methods may negate the need for radiometric normalization of images in the time series; however the requirements for pre-processing of LTS images ultimately depend on the information need, the target (e.g., forests), and the environment being studied. Increasingly, standardized Landsat data products are being made available as calibrated surface reflectance products, delivered as Climate Data Records (Dwyer et al., 2011).

Radiometric correction

Radiometric correction procedures are normally specific to the nature of the radiometric distortions in a given image and typically involve calculating a series of sequential operations, including calibration to radiance or at-satellite reflectance, atmospheric correction or normalization, and may also involve applying bi-directional reflectance distribution (i.e., view angle) normalization, and terrain normalization (Wulder et al., 2012). Most of the approaches to time-series analysis require that the radiometric differences between images due to the atmosphere be minimal; however, some notable approaches such as those developed by Helmer et al. (2009) and Helmer et al. (2010) perform well without atmospheric correction.

Atmospheric correction

Incoming (downwelling) and outgoing (upwelling) radiation from the earth's surface can be significantly modified by the earth's atmosphere. As a consequence, the digital number (DN) recorded in a Landsat image pixel may not truly represent the reflective properties of the object in the pixel. Temporal variation in atmospheric properties can have varying effects on images taken at different dates, ultimately impacting the inter-comparability of images in the LTS. Atmospheric correction procedures for LTS images can be categorized into absolute correction and relative normalization (Schroeder et al., 2006). Table 2 lists different atmospheric correction techniques employed by various studies.

Absolute atmospheric correction procedures entail rectifying individual images in a time series either using empirical or radiative transfer based approaches. Empirical correction methods are mostly variants of the dark-object subtraction (DOS) method (Chavez, 1999; Song and Woodcock, 2003). DOS approaches apply a single correction to all pixels in an image without considering the pixel-to-pixel variation in atmospheric effects and are not capable of correcting for multiplicative effects of atmospheric scattering (Ju et al., 2012). Hence, despite their simplicity, these methods will provide only a rough adjustment for atmospheric effects and are generally not suitable for producing consistent results across images in the time series. Many different absolute atmospheric correction models exist, including: Simplified Method for Atmospheric Correction (SMAC) (Rahman and Dedieu, 1994), Second Simulation of the Satellite Signal in the Solar Spectrum (6S) code (Vermote et al., 1997), MODTRAN (Berk et al., 1998), and ATCOR (Richter, 1997). Among them, the 6S based approach is the most widely used absolute correction technique for LTS analysis. It enables accurate simulations of the sensor signal by modeling a realistic cloudless atmosphere described by the mixture of different gases and molecules. A limitation common to all absolute atmospheric correction procedures is the requirement for spatially and temporally explicit atmospheric data such as aerosol optical thickness (AOT) and water vapor that are rarely available at the location or time of satellite overpass in a routine manner.

Relative normalization procedures involve adjustments to the radiometric properties of image time series data to match that of a single reference image, via the relationship obtained between pseudo-invariant features (PIF) from different dated scenes (Song et al., 2001). Pseudo-invariant features are spatially well-defined objects that are presumed to have stable reflectance properties over the time series period. A variety of methods have been developed for the selection of PIFs (e.g., Hall et al., 1991; Schott et al., 1998; Canty et al., 2004; Paolini et al., 2006). These approaches range from manual selection of features to cover the range of bright, midrange and dark data values to automatic selection of invariant features using statistical methods such as multivariate alteration detection (MAD). For LTS, the reference image is normally corrected using the absolute atmospheric correction method and the other images in the time series are then normalized to the reference image using PIFs.

None of the existing methods can completely correct for atmospheric effects. Such absolute accuracy is, however, not essential as time series approaches are generally robust towards minor perturbations in reflectance due to atmospheric and other effects. However, some form of atmospheric correction is necessary for large area monitoring through time (Song et al., 2001). The user can also minimize the atmospheric effects by selecting spectral variables (e.g., Tasseled Cap Wetness (Section 5)) that are less sensitive to atmospheric effects (Song and Woodcock, 2003). A few studies have validated the surface reflectance derived from various atmospheric correction methods (Song et al., 2001;Schroeder et al., 2006; Vicente-Serrano et al., 2008; Ju et al., 2012; Feng et al., 2013) , and have found mixed results. While different methods have their own share of advantages and limitations, the method best suited for LTS must have minimum user interaction, and be robust, transparent, and consistent across all the images in the stack. Though relative normalization produces consistent results across images, the methods rely on the accuracy of PIF identification and the reference image correction. Nevertheless, the techniques are suitable for time series analysis in the absence of the detailed atmospheric data required by absolute correction methods.

Although radiative transfer based approaches are amenable to systematic large volume satellite processing, they do require temporally and spatially explicit atmospheric characterization data (Vermote et al., 2002). A notable advancement is offered by Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) software (Masek et al., 2006), which employs the 6S code. The program estimates per-pixel AOT using the Dense Dark vegetation (DDV) method (Kaufman et al., 1997) and retrieves other ancillary data from various sources that include gridded TOMS (Total Ozone Mapping Spectrometer) data, column water vapor from the NOAA NCEP reanalysis data, digital topography and NCEP surface pressure data (Ganguly et al., 2012). The LEDAPS approach can be applied to the historic Landsat Thematic Mapper archive (available since 1982). The recent trend suggests that the Landsat community is converging towards LEDAPS for generating surface reflectance products from the historical Landsat archive. The USGS EarthExplorer interface surface (http://earthexplorer.usgs.gov) and EROS Science Processing Architecture (ESPA) now provide surface reflectance products for Landsat TM and ETM+ generated from LEDAPS (http://landsat.usgs.gov/PLSRP.php), which will likely further increase the use of LEDAPS-processed product in LTS analysis. Furthermore, the USGS is openly sharing and maintaining the LEDAPS code, further enabling users to implement the software within their own processing environments. As a physical value, the calculation (or utilization) of surface reflectance is recommended to offer year-on-year consistency of measures mitigating the possible impacts and processing requirements of normalization based correction approaches.

Topographic correction

Topographic effects are observed brightness variations in a single image from the same cover types as a result of undulating or complex terrain. Topographic effects are often notable in mountainous regions, and are primarily caused by differential terrain illumination due to the change in incidence angle between the sun and the surface normal. In addition to modifying the incident radiation on surface, topography alters the viewing geometry and introduces BRDF effects (Song and Woodcock, 2003). For time series and change detection studies the movement of shadows in crevices and north facing slopes through the growing season can result in erroneous identification of change. Topographic correction of remotely sensed imagery over mountainous regions is at least as important as atmospheric correction (Liang, 2005) particularly for time series analysis (Wu et al., 2004). Richter et al. (2009) provide a useful summary of topographic correction methods. The simplest way of minimizing topographic influence is to use ratio based indices as spectral variables. If illumination effects due to topography are proportional across two different bands, the ratio of the two bands can reduce topographic effects. However, topographic effects generally vary among different bands, and hence ratio indices may not provide satisfactory results (Liang, 2005). The cosine correction method converts the surface reflectance observed over sloped terrain to the equivalent value of the horizontal surface by modeling illumination characteristics of a horizontal surface using the local solar incident angle. The latter is calculated based upon solar geometry and a digital elevation model (DEM) with a spatial resolution comparable to the Landsat imagery. The cosine correction method assumes the earth's surface is a Lambertian reflector; i.e., reflecting incoming radiation equally in all directions. Under the Lambertian assumption, images tend to be over-corrected, with slopes facing away from the sun appearing brighter than sun-facing slopes (Teillet et al., 1982). The C-correction (Teillet et al., 1982; Meyer et al., 1993) method attempts to factor into the non-Lambertian behavior of earth's surface by incorporating a correction coefficient (C) to the cosine correction equation. The method is purely based on the correlation observed between reflectance and cosine of the incident illumination. The C-coefficient is estimated from the image as a ratio between slope and intercept of the linear regression between the local solar incident angle and surface reflectance of the sloped terrain. The C-correction has been found to be the most effective topographic correction method for Landsat (Wu et al., 2004), although it also suffers from overcorrection in regions with low illumination conditions (Tan et al., 2013). A model developed by Tan et al. (2010), which does not assume a Lambertian surface, overcomes such problem in low illumination condition and has been demonstrated to perform better than the C-correction in a consistent manner. Topographic normalization is typically ignored in LTS analysis, except in a few studies (e.g., Lehmann et al., 2013). Vicente-Serrano et al. (2008) demonstrated that the spatial comparability of images is not assured without the application of topographic corrections and highly recommended that this step be included in LTS processing protocols in areas with significant variation in terrain. Additional research is needed to determine the impact of topographic correction, or lack thereof, on LTS analysis focusing on different applications and geographical areas.

Geometric correction

Geometric correction of LTS involves accurate registration and correction of terrain related errors to maintain consistency between image geometry through time. The L1T Landsat product from the USGS archives is an orthorectified product with ≈30 m and ≈50 m geo-location accuracy for the US and Global dataset, respectively, depending upon availability of local ground control points (GCPs), as well as the resolution of the best available DEM (Loveland and Dwyer, 2012). Ground control points used for the L1T correction come from the GLS 2005 data set (Gutman et al., 2008). Such standard orthorectified products considerably reduce the amount of time and effort users need to create rectified time-series datasets. However, while explored in more detail elsewhere (Fisher, 1997), a particular pixel does not represent the exact same location on the ground in subsequent satellite over passes. Further, the geolocation of a given pixel, beyond the fact that differing contents are represented, can also be expected to vary especially as a function of the number and quality of GCPs used. Even with an average geolocation error of a half-pixel, some degradation of time series quality can be expected, including noisy trends in high variance environments (complexity in land cover or underlying terrain, for instance) or lack of distinction at or near the edges of features. Not all images in the USGS archives are L1T products as some scenes are processed to a Level 1 systematic correction (L1G) when insufficient ground control or elevation data necessary for precision or terrain correction are available (Potapov et al., 2011). These images and others acquired from different sources than USGS might need to be manually checked for geolocation accuracy. Hence, a precise co-registration of LTS images may be required especially for those collected outside the US to ensure a sub-pixel level geo-location accuracy. Such co-registration typically involves selecting a cloud free image as a base image to which other images are registered. The geometric relationship between the images is obtained through a transfer function modeled over a number of tie points. Standard image processing software provides the functionality for automatic generation of tie points and co-registration of images. The automated registration and orthorectification package (AROP) is a free software tool provided by NASA that can automatically produce sets of co-registered images (http://ledaps.nascom.nasa.gov/tools/tools.html). AROP uses precisely registered and orthorectified Landsat data (e.g., GeoCover or recently released free Landsat Level 1T data from the USGS EROS data center) as the base image to co-register and orthorectify additional images (Gao et al., 2009). Software such as AROP can be used to both evaluate the geometric fidelity and facilitate coregistration of images in the time series.

Time series analyses that integrate Landsat MSS data with TM and ETM+ data must address the difference in spatial resolution of the MSS sensor (60 m) with the TM and ETM+ sensors (30 m). Integration of Landsat MSS into the time series is especially important in establishing the long-term trend in forest dynamics as well as improving the time step of Landsat data in the time series. In 2010, the USGS released a new MSS data product with improved radiometric and geometric corrections (http://landsat.usgs.gov/NewMSSProduct.php). MSS data are now produced by the Level 1 Product Generation System (LPGS), similar to TM and ETM+, and are cross-calibrated to improve radiometric consistency across sensors (Pflugmacher et al., 2012). This can significantly increase the utility of MSS data in time series analysis. Very few studies have utilized MSS data in the LTS analysis (Powell et al., 2010; Gómez et al., 2011; Pflugmacher et al., 2012; Liu et al., 2013; Ahmed et al., 2013). The majority of these studies resampled MSS imagery to 30 m. Pflugmacher et al. (2012) found that, despite being terrain corrected, the geometric accuracy of MSS was not as high as TM and ETM+ and required further co-registration to a reference image. Landsat 8 OLI product specifications indicate that the geometric accuracy is within 12 m of previous Landsat sensors (Irons et al., 2012). The Landsat 8 L1T products have improved geometric accuracy due to the pushbroom sensor design and a fully operational onboard global positioning system (GPS) to measure the exterior orientation directly, rather than inferring it from ground control points (Roy et al., 2014).

Spectral variables used in LTS

In a forest monitoring context, the prime objective of a LTS is to characterize and summarize forest dynamics over time based upon the observed temporal trajectory of a spectral variable. The spectral variables (SV) range from single band reflectance to a host of indices calculated from different algebraic manipulations of the original spectral bands and their derivatives. Commonly used SVs are known for their maximum sensitivity towards forest structure or green leaf area, and can be broadly categorized into four groups according to how they are calculated: (1) spectral bands or summation of spectral bands, (2) ratio indices, (3) tasseled cap indices and (4) spectral mixture analysis (SMA) based indices (Table 3).

A single spectral band or summations of bands having similar responses to vegetation structure in a time series is frequently utilized for constructing LTS. The bands are chosen on the basis of their greatest sensitivity to changes in vegetation properties. Kennedy et al. (2007) used the SWIR1 band (band 5 in TM and ETM+) in LTS to detect disturbances in coniferous forest of Oregon, USA. Schroeder et al. (2011) obtained the highest overall accuracy with the SWIR1 band to map wildfire and clearcut harvest disturbances across a boreal forest in Saskatchewan, Canada. The SWIR1 band reflectance is useful because it is less impacted by atmospheric noise and usually has low values for forests but high values for soil and non-photosynthetic components of vegetation, such as bark and branches. Lehman et al. (2013) used an index based upon the summation of the red and SWIR1 bands, which is negatively correlated with vegetation density, to map forest cover trends in Australia. Huang et al. (2009) developed Vegetation Change Tracker (VCT) specifically for monitoring forest disturbance using LTS. VCT calculates a forestness index (a measure of a pixel's likelihood of being forested) via a summation of normalized values of the red, SWIR1, and SWIR2 (band 7) bands. The SWIR bands are of great importance for ecological applications using Landsat (Cohen et al., 2004). Landsat MSS data lack a SWIR channel, thereby confounding LTS analyses that seek to integrate MSS and TM/ETM+ data (Pflugmacher et al., 2012). Ratio indices utilize band combinations in the form of a ratio to maximize contrast between vegetation greenness and background spectral components. The most common ratio index is the normalized difference vegetation index (NDVI), which is calculated as:

$$\frac{NIR-Red}{NIR+Red} \qquad (1)$$

NDVI is sensitive to the vigor and density of green vegetation as well as leaf area but is also strongly impacted by soil and atmospheric noise (Schroeder et al., 2011). Some variants of NDVI that are more resistant to soil effects (e.g., soil adjusted vegetation index, SAVI)) or atmospheric noise (e.g., atmospheric resistant vegetation index, ARVI) are rarely utilized in LTS. However, the normalized difference moisture index (NDMI) and the normalized burn ratio (NBR) indices, which contrast the reflectance difference between the NIR and SWIR in an equation from similar to NDVI, are frequently used. The NDMI has demonstrated utility for detecting forest harvests of varying intensities (Jin and Sader, 2005) and for characterizing insect infestation dynamics (Goodwin et al., 2008). Kennedy et al. (2010), Cohen et al. (2010), and Hais et al. (2009) found NBR more responsive to different disturbance types (e.g., clear-cuts, fire, bark beetle outbreak etc.) as compared to NDVI.

The Tasseled Cap Transformation (TCT) is an orthogonal transformation that converts Landsat bands into three components related to the brightness (TCB), greenness (TCG), and wetness (TCW) of the surface (Kauth et al., 1976). TCT components correspond to the physical characteristics of vegetation and have been widely used for studying forest change (Cohen et al., 2002; Wulder et al., 2004; Healey et al., 2005; Jin and Sader, 2005; Kayastha et al., 2012). From an LTS perspective, TCB and TCG serve as in important bridge between MSS and TM or ETM+ imagery (Powell et al., 2008). Among the three TCT components, the TCW has been found to be the least sensitive to topography (Cohen et al., 1995; Song and Woodcock, 2003) and atmospheric correction (Song and Woodcock, 2003) as compared to

TCB and TCG, and thus has been frequently used in LTS (Jin and Sader, 2005; Kennedy et al., 2010; Griffiths et al., 2012). The TCW contrasts the sum of the visible and NIR bands with the sum of the SWIR bands. It has been shown to be an important indicator of forest maturity and structure in closed canopy forest stands (Cohen et al., 1995) and works equally well in both coniferous and deciduous forests (Griffiths et al., 2012) across various disturbance types (Hais et al., 2009). Other derivatives of TCT indices have also been recently developed, including the Disturbance Index (Healey et al., 2005; Hais et al., 2009), which contrasts between TCG and TCB, and the TC angle (TCA) (defined as the arc tan of ratio between TCG and TCB) (Asner et al., 2009; Powell et al., 2010; Schroeder et al., 2011; White et al., 2011; Gómez et al., 2012). The rationale for developing these indices is that canopy removal has the opposite spectral response in TCG and TCB, which can be enhanced in a ratio or difference form to help identify both disturbance type and intensity.

The fraction of canopy cover (CF) calculated from spectral mixture analysis (SMA) has been found useful for monitoring disturbance in semi-arid and dryland forests (Röder et al., 2008; Yang et al., 2012) as well as mapping canopy damage due to understory fires (Morton et al., 2011) and forest degradation in tropical environments (Souza et al., 2005; Alencar et al., 2011). SMA assumes that the spectrum of each pixel is a linear combination of a few pure spectra, called endmembers (Roberts et al., 1998). The major challenge working with SMA is difficulty associated with finding pure endmembers. This because the size of a pure object is often smaller than the Landsat pixel size, and endmember variability can greatly increase with the size of the study region (Röder et al., 2008). Asner et al. (2009) developed an automated method for mapping tropical deforestation and forest degradation, which employs a large spectral endmember library derived from extensive field measurements and hyperspectral satellite imagery. Similarly, in a study of the Brazilian Amazon, Souza and Siqueira (2013) developed an image-based approach for obtaining generic endmembers from Landsat n-dimensional spectral space (following Small (2004)) to generate fraction images.

There are multiple classes of SVs to choose from to create a LTS; the decision to select a particular SV is, however, not straightforward. One approach might involve using all spectral bands and potentially useful vegetation indices such as those adopted by Helmer et al. (2010). Several studies have compared the performance of selecting SVs for different applications, finding some to outperform others. However, as evidenced by these studies, the superiority of one SV over others is purely empirical; they have not been routinely tested across different vegetation types, soil conditions as well as disturbance types or intensities. In addition to vegetation structure, SVs are sensitive to many factors related to illumination, atmosphere, topography, and soil background. Song et al. (2002) used a forest succession model (ZELIG) and a canopy reflectance model (GORT) to produce spectral trajectories of forest succession from young to old-growth stages and demonstrated that TCW and TCG are much better predictors of forest successional stage as compared to TCB. They found that the wetness component has a higher signal to noise ratio, making wetness patterns less sensitive to atmospheric and topographic noise. Cohen et al. (2010) presented similar results for disturbance monitoring demonstrating that TCW performed best for detecting recovering or persistent forests. Similarly, Sonnenschein et al. (2011) found little difference in sensitivity among four SVs (NDVI, SAVI, TCG, and SMA fractions) for analyzing trends of gradual changes in dryland ecosystems whereas the response of the indices differed markedly for abrupt events such as fires. Rogan et al. (2002) found SMA outperforming TC components in monitoring multitemporal vegetation change in California. According to Roy et al. (2006), NBR, which was found most useful by Kennedy et al. (2010) for disturbance mapping, was far from optimal for burn severity mapping. One goal in the mapping of forest dynamics using LTS is to create a reliable method that is extendable across different sites. Such broader applicability requires simultaneous testing of all common SVs in empirical studies supported by rigorous evaluation of their sensitivities to vegetation dynamics across different sites and atmospheric conditions.

Finally, as shown in Table 1, Landsat sensors are characterized by slightly different spectral responses and can introduce sensor-induced differences in SVs values. The potential error caused by such differences is generally greater for a single band than vegetation indices (Vogelmann et al., 2001). Until recently, these sensors were not consistently calibrated and the ability to perform time series analysis was limited. Recent work has placed all Landsat radiometers (MSS, TM, and ETM +) onto a consistent radiometric scale, and radiometric uncertainties have been quantified. These calibration updates have been instituted at the USGS EROS archive and all data currently being distributed contain the most accurate radiometric calibration available (Markham and Hedler, 2012). Teillet et al. (2001) compared Landsat 7 ETM+ and Landsat 5 TM and found top-of-atmosphere NDVI differences of 1 – 4%. Li et al. (2014) compared SVs derived from ETM+ and OLI sensors and found high degree of similarity (coefficient of determination greater than 99.9%) between vegetation indices derived from different sensors even though individual band values varied slightly. They found that NBR values had the greatest similarity among different vegetation indices. Based upon the comparison of NDVI values simulated for different sensor systems, Stevan et al. (2003) found that the NDVI values computed from the Landsat-ETM+ sensor can differ as much by 2% from the TM sensor. The effect of such inconsistencies in the cross-calibrated USGS level-1 product has not been studied in detail in the context of LTS application, and the users need to be aware of these limitations. The analysis of long-term trends and variation in the time series are central to the majority of the LTS approaches reviewed in this paper, thus being more robust to slight spectral variation attributable to sensor differences and other uncertainties than single or bi-temporal images based analysis.

Approaches for analyzing LTS

Conventional methods for analyzing remote sensing data that include one or a small set of imagery are not readily extendable to LTS analysis. Over the past two decades, the remote sensing community has been using time series analysis for studying long-term vegetation dynamics with different global coverage products from daily viewing sensors such as MODIS and AVHRR. These sensors have a high temporal resolution, a low spatial resolution, and a large image footprint. Daily acquisitions from these sensors result in high data densities and concomitant analysis approaches that aim to characterize seasonal and intra- and inter-annual trends (e.g., Eastman and Fulk, 1993). These types of analyses are generally not well suited to the less dense time series constructed from Landsat, which are constrained by the temporal revisit and historic acquisition characteristics of the Landsat program.

Similarly, the analysis method most suited for one LTS application does not necessarily lend itself to other applications. In studies focused on phenology, analysis methods typically concentrate on accurately capturing different seasonal events such as the date of the onset of greenness, the date of leaf senescence, and duration of the growing season from LTS data, whereas the analysis of disturbance dynamics focuses on a set of attributes such as disturbance year, magnitude, and types of disturbance events. Table 3 lists examples of commonly applied LTS analysis methods by specific applications. To date, LTS analysis techniques have been mainly developed for disturbance analysis and mapping with few exceptions such as the Threshold Age Mapping Algorithm (TAMA), which is an automated procedure for mapping forest age using LTS data (Helmer et al., 2009). Techniques used for disturbance analysis have also been proven useful in other applications such as characterizing current forest structure (Deel et al., 2012; Pflugmacher et al., 2012). Changes in forested ecosystems can be categorized into three types: (i) abrupt changes caused by stand replacing disturbances (e.g., clear-cutting, crown fire, large scale insect defoliation etc.), (ii) changes related to partial removal of canopies (e.g., partial harvest, understory fire, insects and diseases), and (ii) subtle changes occurring gradually through time (e.g., forest degradation, tree mortality, and forest successional dynamics). The ability of any system to detect changes in forested ecosystems is dependent upon the method's ability to discriminate real changes, or changes of interest, from apparent changes caused by variations in background signal and noise (e.g., phenological variation, Bidirectional Reflectance Distribution Function (BRDF) effects, image artifacts etc.) (Kennedy et al., 2014).

Past studies using LTS have demonstrated that the effect of abrupt changes leading to stand clearance and subsequent recovery can be accurately distinguished from apparent change (e.g., Huang et al., 2009; Helmer et al., 2010; Kennedy et al., 2010). Such changes can also be accurately characterized based upon different attributes such as year of disturbance, disturbance types, and nature of forest regrowth or recovery depending upon the temporal density of the LTS. On the contrary, partial removal of canopies caused by disturbance agents such as understory fire, insects, diseases, and partial harvest are difficult to detect and monitor, although advances are ongoing and given appropriate support information an emerging capacity is evident (Cohen et al., 2010).

LTS approaches for change detection can be broadly categorized into two types: image classification and trajectory-based analysis.

Image classification based analysis

Classification based approaches for change detection mainly include post-classification comparison of independently produced results from each end of the time interval of interest, followed by a comparison to detect changes and disturbance types. Individual images are separately classified, thereby minimizing the problem of radiometric calibration between dates (Coppin et al., 2004). As such, availability of near anniversary images and stringent atmospheric correction are not strictly necessary for post classification comparison. However, the accuracy of the post-classification comparison is usually dependent upon the accuracy of the initial classifications as the misclassification and misregistration errors present in the original images are compounded in the final map. A similar classification approach has been widely used for change detection with bi-temporal images and has been reviewed in detail in the literature (Coppin et al., 2004; Lu et al., 2004). In a tropical forest environment, Helmer et al. (2010) created eight cloud-free Landsat composites spanning from 1984 to 2002 and classified each individual Landsat image into land cover and forest disturbance types using a supervised decision tree algorithm. Potapov et al. (2012) generated epochal Landsat composites representing 2000–2010) for the Democratic Republic of the Congo. The image composites were then classified using a decision tree based classifier for mapping forest change. The forest cover and monitoring results were then compared with results from Hansen et al. (2008) for the 1990–2000 interval and analyzed to reveal generic patterns in forest cover loss dynamics within the country. They estimated the total forest cover loss within the common area of analysis for 1990–2000 as 1.25% of study area, compared to 1.89% for the 2000–2010 interval, indicating a substantial decadal increase in forest loss (34%). One advantage of such classification approaches is that a broad suite of complementary information including Landsat bands, their derivatives, as well as auxiliary information from other data sources can be included as input variables to the classification. More importantly, such a classification scheme affords multitemporal disturbance analysis to be implemented over regions otherwise lacking in sufficient temporal frequency (e.g., annual or near annual) required for trajectory-based analysis. Souza et al. (2013) used fraction images calculated from SMA as input variables in a knowledge based decision tree classification. Their method performed well for mapping both deforestation and forest degradation due to selective logging and forest fire in Amazon forest. Asner et al. (2009) applied a similar approach in a fully automated system called CLASlite to identify deforestation and forest degradation in Brazil and Peru. The disturbance maps from CLASlite, however, require additional analysis in order to interpret them as specific types of disturbance (anthropogenic vs. natural; logged vs. fire scars). Rather than detecting changes between two classified images, Schroeder et al. (2011) employed all images in the LTS stack (from different years) as input into a supervised minimum distance to mean classifier to map fire and harvested areas in a boreal forest environment.

Trajectory-based change detection

Trajectory based approaches utilize the temporal patterns of spectral variables to detect disturbance types and magnitude. Unlike classification, it involves analysis of a time series of single spectral variables, and can be further divided into four categories: (1) Threshold based change detection, (2) single curve fitting, (3) hypothesized curve fitting, and (4) trajectory segmentation. Threshold based change detection requires a prerequisite threshold value to determine forest disturbances. The curve fitting and trajectory segmentation based approaches capture the trend and disturbance events based upon information derived from the time-series without the need for estimating thresholds. Trajectory-based approaches allow for insights to be based upon, often subtle, trends that can become evident when many years of imagery are considered in sequence. Change detection based upon image pairs informs on change in state, whereas, trajectory based approaches can inform on the nature of the change in state, such as via rates or magnitudes of change. Utilizing trajectory-based approaches allows analysts to understand change in more than a binary fashion and does not require an additional analytical stage to produce sets of image classifications. Post-classification change approaches are limited by the accuracy of the classifications being differenced, limiting the effectiveness and reliability of the approach. Trajectory-based approaches, however, call for robust radiometric correction and availability of near anniversary images to minimize false detection of changes due to phenology (although, noting that algorithms such as LandTrendr compensate for this), BRDF, and atmospheric effects. Ideally, trajectory-based approaches also require creation of time series with sufficient image density to capture the disturbances of interest, with complications arising due to cloud cover and sparse historic image coverage for some regions.

Threshold-based change detection methods

Threshold based change detection methods employ a predetermined threshold value for identifying forested pixels in a time series. A year marked by significant deviation from this threshold value as compared to the preceding year is identified as the year of disturbance. Additional information gathered from the pattern of deviation in subsequent years can then be used to identify the magnitude of disturbance and recovery times. The VCT developed by Huang et al. (2010) is a threshold based automated forest change mapping algorithm that utilizes a parameter called the Integrated Forest Z-score (IFZ) as spectral variable in LTS analysis. IFZ is an inverse measure of the likelihood of a pixel being forested (pixels below a threshold IFZ value are considered forested). The IFZ threshold value is calculated based upon the distribution of values from several pixels that are identified as pure forest pixels. Liu et al. (2013) modified the IFZ models by normalizing phenological differences in the images acquired at different times and growing seasons before calculating IFZ scores. Such normalization procedures are useful in regions where it is almost impossible to collect image time series during the peak forest growing season. Kayastha et al. (2012) used a similar threshold based approach to map changes in forested wetland ecosystems in northern

Virginia, USA via the forestness index calculated from tasseled cap images. The major limitation of threshold-based techniques is that the threshold is empirically determined and thus is not directly transferrable to other study areas characterized by different vegetation types and vegetation densities. Thus, the requirement of computing the threshold adds a significant cost to processing time (Verbesselt et al., 2010).

Stueve et al. (2011) found erroneous results with VCT that appeared to be associated with wetlands and agricultural fields in complex and highly fragmented forest landscapes. They found that significant improvements in the algorithm could be obtained by incorporating a non-forest mask derived from snow-covered, winter time series images. Thomas et al. (2011) evaluated forest disturbance history maps derived from VCT for six sample locations in the USA and found that the method performed reasonably well in dense forest and with stand-clearing disturbances, but performed poorly in sparsely vegetated canopies and for non-stand clearing disturbances, such as thinning and partial damage from natural disturbance events.

Single curve fitting

Within the framework of trajectory based change detection (trend analysis), univariate time series data are considered a mixture of a long-term movement or trend, cyclic seasonal fluctuation, and residual random movements (de Beurs and Henebry, 2005). Trend analysis for LTS usually involves suppressing seasonal effects by selecting near-anniversary date images corresponding to the timing of peak vegetation growth. A pixel-wise trend function generally based upon least squares regression (LSR) is fitted between a SV (integrated over a year) and time. The trend is expressed as the slope of the regression curve. The sign of the slope indicates either an increase or decrease in vegetation cover or density depending upon the type of spectral variables used. A slope that is significantly different from zero (at some significance level (critical *p*-value)) determines presence or absence of a trend (Vogelmann et al., 2012). The slope represents the rate at which change occurs over time. The difference in the value of the fitted function between the beginning and terminal date of the LTS is used to characterize the magnitude of change over time (e.g., Sonnenschein et al., 2011).

Various studies have demonstrated the utility of single curve fitting for analyzing forest dynamics. Röder et al. (2008) used a linear trend analysis to characterize spatiotemporal patterns of vegetation cover development in Northern Greece using a time series of fifteen Landsat images from 1984–2000. Lehmann et al. (2013) used linear and quadratic fitting to analyze forest cover trends from LTS for the whole Australian continent. They calculated different summary variables such as mean, slope, and quadratic coefficients from the temporal sequence of a woodness index dataset. In addition to slope for summarizing the linear trend, the coefficients of quadratic curvature were found to be important for understanding disturbance and recovery. McManus et al. (2012) analyzed a 24-year (1986–2010) LTS in a latitudinal transect across the boreal forest-tundra biome boundary in northern Quebec, Canada in an effort to understand tundra and boreal forest vegetation response to climate change. With linear trend analysis, they found that the area is experiencing a strong positive trend in the NDVI, which is indicative of significant increases in peak growing season leaf area. Vogelmann et al. (2012) used trend analysis to assess gradual changes occurring in four different natural ecosystems. Their general rule for trend analysis was that regression models with high positive or negative slope values are more likely to be statistically significant and thus the pixel locations where p values are at 0.01 and 0.05 levels of confidence can effectively depict spatial trends. With this approach, they found that high elevation understory conifers showed range increases towards lower elevations in the White Mountains of New Hampshire, USA.

A known shortcoming of the trend analysis approach is that standard underlying statistical assumptions made by least squares regression such as data normality and equal variance is generally difficult to meet (de Beurs and Henebry, 2005). Violation of the assumptions results in an inadequate representation of the data by the fitted function (Chandler, 2011). Similarly, the presence of autocorrelation in the data may provide incorrect estimates of standard errors at least in small samples, so that standard hypothesis tests and confidence intervals are invalid. Furthermore, statistical outliers in the data pose a problem for trend estimation because the regression estimator can be overly sensitive to outlying observations, which ultimately influence the trend fitted (Muhlbauer et al., 2009). Indeed trends may be biased leading to a false interpretation of the data. Statistical outliers may also impact significance levels and have major implications for the reliability of confidence intervals and hypothesis tests.

Hypothesized curve fitting

Many phenomena associated with forest change may have distinct temporal progression both before and after the disturbance event, resulting in a characteristic spectro-temporal signature (Hayes et al., 2007; Kennedy et al., 2007). A forest experiencing gradual change might be represented by a linear trend, whereas, a forest in steady-state (i.e., no change) can be represented by a horizontal line with no slope. Similarly, disturbance agents causing abrupt changes may result in a sharp change in the trajectory followed by a stable, increasing or decreasing trend determined by the course of the forest recovery process. Thus, the trend of forested pixels may be better analyzed by fitting curves characteristic of certain disturbance types, rather than a single linear or polynomial function. This approach requires the definition of change trajectories based upon the expected behavior of the SV, given disturbance type, before and after disturbance events. Trajectory based change detection can be interpreted as a supervised change detection method with hypothesized trajectories representing training signatures specific to different disturbance types (Verbesselt et al., 2010). The major limitation of this approach is that the shape of the trajectory must be predefined, and the method will only function properly if the observed spectral trajectory matches one of the hypothesized trajectories. Kennedy et al. (2007) used such idealized trajectory fitting to detect and label disturbances in coniferous forests of western Oregon, U.S.A. Similarly, Gillanders et al. (2008) compared trajectories of each pixel to the four predefined disturbance curves hypothesized for mine development and rehabilitation in Boreal forests in Alberta, Canada.

Trajectory segmentation

The previously discussed long-term trend calculations show the overall trend across the entire time period, but provide little information on whether different sub-trends exists. Kennedy et al. (2010) recently developed a technique named LandTrendr to characterize distinct sub-trends within a trajectory based upon temporal segmentation. It employs an endogenous data-driven approach to decompose the trajectory into a series of straight-line segments to capture broad features of the trajectory as well as sub-trends. The result of the segmentation is a simplified representation of the spectral trajectory, where the time position and spectral value of vertices of segments provide the essential information needed to produce maps of change, or serve as predictor variables for informing on forest structure (e.g., Pflugmacher et al., 2012). The advantage of this approach is that the straight-line segments allow detection of abrupt events such as disturbances as well as longer-duration processes such as regrowth. Moreover, no predetermined model of change is required as the data themselves determine the shape of the trajectory. Cohen *et al.* (2010) found that the LandTrendr algorithm captures abrupt disturbances such as clear-cuts as well as or better than two-date change detection methods and detects subtle changes such as insect-related disturbance and growth with reasonable robustness.

The utility of LandTrendr has been demonstrated in different geographical regions for a wide range of dynamics related to different disturbance regimes (Kennedy et al., 2010; Meigs et al., 2011; Griffiths et al., 2012; Ohmann et al., 2012). In addition to the ability of detecting both abrupt events and trends in data, the strength of LandTrendr lies in its ability to compute a number of metrics that provide information on disturbance magnitude and regeneration. Furthermore, since the segmentation process distills an often-noisy yearly time series into a simplified series of segments avoiding most false changes (Kennedy et al., 2010), it provides flexibility for integrating many near-anniversary images to select cloudless pixels. One potential weakness of LandTrendr lies in its reliance on the p-values of F-statistics in deciding on a final number of segments, since the reliability of p-values diminishes in the presence of different noise and autocorrelation, especially for small-sized datasets.

Accuracy assessment

Accuracy assessment is an integral part of a mapping or spatial assessment process involving the evaluation of map quality against some known reference samples. Any validation method should be statistically rigorous and defensible in order for spatial products and information to be used in scientifically sound management and policy decisions (Stehman et al., 1998). In LTS analysis, validation may range in complexity depending upon the nature of the application and the related product. Validating thematic maps of continuous or categorical response variables is akin to the methods for evaluating similar products using single-date imagery, as reference samples are required only for the terminal year of the series for such analysis. A comparison of predictions with reference samples is the usual basis for validation. For continuous measurements, accuracy is typically expressed via metrics such as the root mean square error (RMSE), correlation coefficient (r), and the coefficient of variation (R^2) between predicted and observed values from reference samples. In thematic mapping with categorical data, accuracy is usually expressed as percentages of correctly classified cases for each mapped class by constructing an error or contingency matrix (Foody, 2002). Such accuracy measures are typically estimated from a sample and thus are subject to uncertainty (Olofsson et al., 2013). Hence, the error matrix is increasingly considered to be inadequate for full accuracy reporting, and new approaches for techniques for constructing inferences in the form of confidence intervals and equivalence tests are increasingly popular (McRoberts, 2010).

Validation of change maps requires collection of reference samples for different observation periods. Map accuracy is usually evaluated on the basis of whether a particular category of change has been correctly identified or not. In the case of LTS analysis, reference samples may need to be collected for each observation year in the series. In addition, a LTS change-map may contain different change categories such as disturbance types, change year, and residence time as compared to the bivariate change response (i.e., ‘change’ or ‘no change’) attained in conventional change-maps. Hence, the collection of a sufficient number of reference samples is a challenging task. Accuracy assessment is often avoided in studies concerned with disturbance mapping because historical reference datasets can be prohibitively expensive to compile and often times are rarely available. The lack of a statistically rigorous accuracy assessment reduces the credibility of derived change maps. Recent examples, such as Cohen et al. (2010), indicates that the importance of robust evaluation of the LTS change products is being gradually recognized and that innovative approaches to validation are being developed.

A sound validation technique requires that a proper sampling and response design be followed for selecting and labeling reference samples into change class. The sampling design should be based upon a probability based design such that the probability of selecting each sampling unit is known (Foody, 2002; Olofsson et al., 2014). The disturbed area usually represents a small portion of the map, and disturbance events may be sparsely represented in time. Hence, a sampling design for LTS should be sensitive to rare classes in both space and time. Among different probability based designs, a stratified random sampling design can make better use of smaller sample sizes and represent rare classes, ultimately providing adequate precision (Thomas et al., 2011). However, caution should be applied when allocating an equal or optimal number of samples instead of proportion samples because the inclusion probability for sampling units in different strata will vary. Unequal inclusion probabilities should be accounted for in the estimation formula used to generate the error matrix (Stehman et al., 1998).

The labeling of reference sample points may be based upon different information sources. Although field visits can be costly and may not accurately describe past disturbance events and their intensity (Cohen et al., 2010), they can potentially yield useful information about current and historical forest conditions. Other sources of information such as historical national forest inventories, aerial photographs, or high spatial resolution images can also act as proxies for ground reference data. Zimmerman et al. (2013) used reference disturbance classes obtained through photointerpretation of image sets from the National High Altitude Program (NHAP), National Aerial Photography Program (NAPP), and the National Agriculture Imagery Program (NAIP) for validating disturbance maps in the Western Great Lakes region of the US. Goodwin et al. (2008) used independent helicopter based survey data collected in three different years to validate maps of mountain pine beetle (*Dendroctonus ponderosae*) outbreak in western Canada.

Reference data from historic surveys or aerial photos may or may not exist and hence cannot always be relied upon for validation. Other manual approaches levering data in the existing time series can be used to support validation in such situations. For example, Helmer et al. (2009) manually inferred secondary forest age via viewers simultaneously displaying a series of image dates or date combinations in RGB color space for accuracy assessment. A similar technique was also adopted by Helmer et al. (2010) who used simultaneous sequential observations of tasseled cap wetness images to assign age classes and disturbance types. Cohen et al. (2010) developed a tool named TimeSync primarily to facilitate accuracy assessment of a LTS time series analysis. Using TimeSync, a trained interpreter can manually define different change classes by interpreting pixel trajectories, much in the same manner as the time series algorithm automatically does. TimeSync, however, allows the interpreter to account for spatial, spectral, and temporal context as well as ancillary high-resolution Google Earth images when labeling reference pixels. According to Kennedy et al. (2010), TimeSync is necessary as it is nearly impossible to find reference data with the same temporal frequency, depth and spatial coverage of Landsat data. It has been demonstrated to work well or even better as compared to other ancillary reference datasets such as from US Forest Service Forest Health Monitoring Program and the US Bureau of Land Management in evaluating the LandTrendr segmentation for a wide range of forest change process in Oregon, USA (Cohen et al., 2010). Hence, TimeSync provides a promising tool for accuracy assessment of LTS change maps, and a growing number of studies have recently incorporated it. However, performance is contingent upon the ability of a human LTS interpreter for accurately labeling disturbance event, types, and magnitudes. In the absence of high resolution Google Earth images, the method merely evaluates how well the algorithm fits the data rather than how well it predicts change. A spectral variable may be greatly sensitive to atmospheric noise, BRDF effects, phenology and background. Consequently, the signal due to real change or lack thereof may be completely masked in the temporal trajectory, and false agreement between the visual label and model prediction is likely. As such, the reference and the prediction dataset are not independent and may inflate accuracy as compared to conservative estimates provided by an independent reference dataset. Among the papers reviewed for this manuscript, six studies used TimeSync as a means for disturbance validation, seven used visual interpretation of the image in the time series, thirteen others used a combination of field data, high resolution imagery, and visual interpretation for validation, while eleven studies did not mention a validation procedure.

Conclusions

The Landsat series of satellite sensors represents the longest-running space-based earth observation program. The spatial, spectral, and temporal resolution offered by Landsat data is well suited and increasingly established and operational in usage for forest management and analysis. The change to a free and open Landsat data distribution policy in 2008 has accelerated the use of Landsat time series (LTS) for forestry research and applications. Interest in LTS has been further enhanced by the recent introduction of several novel automated data processing techniques suitable for multitemporal analysis. Moreover, the launch of Landsat 8 in February 2013 ensures the continuity of the Landsat mission—at least in the short-term. Nonetheless, as identified herein, challenges remain in order for the analysis of LTS to move into a more operational realm, especially in the global context.

The assembly of an LTS stack with sufficient temporal density is more challenging in jurisdictions outside of the United States. Repatriation of images held by International Cooperators into the United States Geological Survey (USGS) archive is actively being pursued to mitigate this (Wulder et al., 2012). User must also be mindful that historic storage and computing conditions are not the same that we enjoy today. In the early 1970s when the first Landsat was launched, satellite and ground systems had markedly slower satellite downlink rates and capacity, limited on-satellite storage, and ground storage largely on magnetic tapes, as well as no internet to facilitate data storage, archive, and transfer needs, among a myriad of other issues. Notwithstanding these limitations, the USGS and many other US and foreign governments worked in partnership to obtain and safe-keep the images we have access to today. Projects such as the Web-enabled Landsat Data (WELD), which provide Landsat Enhanced Thematic Mapper Plus (ETM+) data composites on a monthly, seasonal, and yearly basis over the conterminous United States (Roy et al., 2010), provide a model for a promising new era of globally available Landsat composite products that take advantage of the full Landsat archive. An expansion of such a project for broader geographical regions could help facilitate widespread use of LTS data. In the absence of composite products being readily available, operational large area LTS analyses would require substantial computational resources to compile and preprocess Landsat data. Centralized computing infrastructure that allows users to bring algorithms to the data offer an opportunity to reduce network, storage, and computation overheads, mitigating what could otherwise be a limitation to the analysis of long term, large area datasets, especially in developing countries (Wulder and Coops., 2004).

Accurate methods for correcting atmospheric, topographic and geometric errors are necessary for inter-comparison of images in the time series. Both relative and absolute atmospheric normalization techniques have been regularly used to correct radiometric errors. Although some studies have found relative normalization sufficient for LTS analysis, the comparative ease of implementation and fast processing offered by new tools such as LEDAPS have made absolute correction techniques viable in most situations. Unlike geometric and atmospheric correction, topographic correction was rarely applied in the LTS studies reviewed. The standard products delivered by the USGS are in a Level 1 terrain corrected (L1T) format, which is a top of atmosphere terrain corrected form. Beyond this first order topographic correction, the impact of topography – especially over mountainous terrain

– remains a topic requiring further research. It is worth noting that the USGS has expanded beyond the Landsat L1T to introduce a suite of Essential Climatic Variables, of which surface reflectance data, based upon the LEDAPS algorithm, can be ordered and downloaded for free.

A wide range of spectral variables (SVIs) have been employed in LTS analysis based upon their enhanced sensitivity to vegetation greenness. The performance of individual SVIs differs mostly due to their varied sensitivity to external factors such as topography and atmospheric conditions. The most appropriate SVI depends on the application, with Tasseled Cap components emerging as a popular choice in many applications, particularly for studies that are seeking to incorporate Multispectral Scanner System (MSS) and data from other sensors. Further research is needed into quantifying the uncertainties due to varying spectral response of different sensors on the time series analysis using Tasseled Cap and other indices.

Approaches for analyzing LTS are nascent and evolving, and ultimately expected to improve. It is worthwhile emphasizing that these novel and informative analytical techniques are using data from a satellite program this is over 40 years old. At the time of this review, there are mainly two change detection algorithms commonly used for LTS: classification or trajectory analysis. Classification based techniques are an extension of traditional change detection techniques based upon two images. Trajectory-based methods identify trends and breakpoints corresponding to disturbance events, stability, and recovery time, and have been found useful for characterizing different disturbance regimes. Users should understand the strength and limitations of each method prior to conducting an LTS analysis, ideally selecting a given method based upon their particular information needs. Although a comparative analysis is potentially useful when selecting an algorithm, it is ultimately more important that users understand the relative merits of a specific algorithm in light of their specific information needs, and the amount of resources and effort that they are willing to expend.

In summary, unprecedented advances in the assessment of forest conditions and dynamics have been realized in recent years using LTS data as an information source. Many issues and challenges still remain to harness the full capabilities offered by rich, freely available LTS datasets. In particular, issues associated with pre-processing, analysis, and validation of LTS all require further research, however best practices are beginning to emerge as approaches mature.

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Table 1. Landsat sensors and their characteristics

Sensors	Bands		Wavelength (micrometers)	Resolution (meters)	Acquisition years
	Landsat 1-3	*Landsat 4-5*			
Multispectral Scanner (MSS)	Band 4	Band 1	0.5-0.6	60	1972-2001*
	Band 5	Band 2	0.6-0.7	60	
	Band 6	Band 3	0.7-0.8	60	
	Band 7	Band 4	0.8-1.1	60	
	Landsat 4 -5				
Thematic Mapper (TM)		Band 1	0.45-0.52	30	1984 -2012
		Band 2	0.52-0.60	30	
		Band 3	0.63-0.69	30	
		Band 4	0.76-0.90	30	
		Band 5	1.55-1.75	30	
		Band 6	10.40-12.50	120	
		Band 7	2.08-2.35	30	
	Landsat 7				
Enhanced Thematic Mapper Plus (ETM+)		Band 1	0.45-0.52	30	1999- Ongoing
		Band 2	0.52-0.60	30	
		Band 3	0.63-0.69	30	
		Band 4	0.76-0.90	30	
		Band 5	1.55-1.75	30	
		Band 6	10.40-12.50	60	
		Band 7	2.08-2.35	30	
		Band 8	0.52-0.90	15	
	Landsat 8				
Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)		Band 1	0.43 - 0.45	30	2013 - Ongoing
		Band 2	0.45 - 0.51	30	
		Band 3	0.53 - 0.59	30	
		Band 4	0.64 - 0.67	30	
		Band 5	0.85 - 0.88	30	
		Band 6	0.85 - 0.88	30	
		Band 7	2.11 - 2.29	30	
		Band 8	0.50 - 0.68	15	
		Band 9	1.36 - 1.38	30	
		Band 10	10.60 - 11.19	100	
		Band 11	11.50 - 12.51	100	

*Following failure of the TM sensor on Landsat 5, the MSS sensor was reactivated for a short period of time prior to satellite decommissioning (Table source: http://landsat.usgs.gov).

Table 2. Most common atmospheric correction techniques used

Categories	Method	Description	References
1. Absolute	DOS	Assumes existence of features with near zero reflectance and the signal reported for these feature is attributed to atmosphere and subtracted from all the pixel	Neuenschwander and Crews, 2008 Deel et al., 2012 Mishra et al., 2012
	6S	A 6S radiative transfer based method calculates surface reflectance by modeling of a realistic atmosphere described by the mixture of different gases and molecules.	Asner et al., 2009 Li et al., 2009 Huang et al., 2010 Kayastha et al., 2012 McManus et al., 2012 Alencar et al., 2011 Masek et al., 2013
	MAD	Uses Canonical correlation analysis to identify pseudo-invariant pixels which are used to normalize the image using reduced major axis regression	Gómez et al., 2011 Lehmann et al., 2013
2. Relative	COST+MAD	One base image is corrected using COST method and other images are normalized to the base image using MAD approach (COST is based upon DOS method that deals with both additive and multiplicative effect of atmosphere using atmospheric transmittance calculated from cosine of solar zenith angle.)	Goodwin et al., 2008 Griffiths et al., 2012 Kennedy et al., 2012 Pflugmacher et al., 2012 Yang et al., 2012 Kennedy et al., 2012
	6S+MAD	One base image is corrected using 6S method and other images are normalized to the base image using MAD approach	Schroeder et al., 2006 Powell et al., 2010 Liu et al., 2013

Table 3. Examples of spectral variables and approaches used in LTS for different forest monitoring applications

Landsat	Method	Spectral Variables	References
*1. **Forest cover /species mapping***			
2000-2008 ETM+ 1984-1987 TM	Multitemporal classification using decision tree classifier	Tasseled cap and others	Helmer et al., 2012
2000 -2012 ETM+	Multidate compositing and decision tree classifier	Spectral bands	Potapov et al., 2012 Hansen et al., 2013
2000 -2005 ETM+	Multidate compositing and decision tree classifier	Spectral bands	Potapov et al., 2011
1989-2006 TM/ETM+	Joint multitemporal classification using a Bayesian rule	Single date probability image	Lehmann et al., 2013
1983-2006 TM/ETM+	Classification of exotic species using support vector machine	Stacks of image in 5 year increment	Gavier-Pizarro et al., 2012
2. Change Detection/Disturbance mapping			
1984-2004 TM/ETM	Curve Fitting	B5 reflectance	Kennedy et al., 2007
1988-2010 TM/ETM+	Linear trend analysis	NDVI and SWIR/NIR ratio	Vogelmann et al., 2009 Vogelmann et al., 2012
1984-2008 TM/ETM+	Temporal Segmentation (Landtrendr)		Kennedy et al., 2010
1973-2008 MSS/TM/ETM+	Object based – hierarchical spatial and temporal segmentation	Tasseled cap angle (TCA)	Gómez et al., 2011
1989-2006 TM/ETM+	Linear and quadratic polynomial fitting	Woodness Index	Lehmann et al., 2013
1984-2006 TM/ETM+	Threshold based (Vegetation Change Tracker)	Integrated Forestness Z-score (IFZ)	Huang et al., 2010 Stueve et al., 2011
2001-2003 (all available images for the years) TM/ETM+	Prediction of Landsat images and uses threshold for change identification	Disturbance index (DI)	Zhu et al., 2012

1984-2008 TM/ETM+	Subtraction between DI and minimum DI for all images	DI	Deel et al., 2012
1986-2010 TM/ETM+	Linear trend analysis	NDVI	McManus et al., 2012
TM/ETM+ 1986-2008	Threshold/decision tree	Mainly band-5 : other indifferent indices were also compared	Schroeder et al., 2011
TM/ETM+ 1992-2006	Threshold/decision	NDMI	Goodwin et al., 2008
TM/ETM+ 1984-2005	Decision tree classification	B1-5, B7, NDVI , NDMI, and TC indices	Helmer et al., 2010
3. Biophysical variables and canopy chemistry			
1972-2010 MSS/TM/ETM+	Forest structure woody /dead Biomass , basal area estimation using LTS metrics and lidar	TCA	Pflugmacher et al., 2012
1985-2006 TM/ETM+	Curve fitting (biomass estimation)	TCA, NDVI, DI	Powell et al., 2010
1984-2008 TM/ETM+	Canopy nitrogen/forest structure estimation using disturbance metrics from LTS and hyperspectral images	DI	Deel et al., 2012
1975 – 2003 MSS/TM/ETM+	Threshold based technique (forest age) and biomass (with lidar)	WBDI	Helmer et al., 2009
1984-2005 TM/ETM+	Decision tree classification (disturbance and age) and regression tree (height and percentage foliage cover)	B1-5, B7, NDVI , NDMI, and TC indices	Helmer et al., 2010
4. Phenology			
1984-2002 TM/ETM+	Logistic function used to derive phenological markers	Variable vegetation fraction derived from SMA	Fisher et al., 2006 Elmore et al., 2012
1982 -2011 TM/ETM+	Logistic function to derive phenological markers	EVI	Melaas et al., 2013

2006 TM and synthetic images using STARFM	Timing and magnitude of peak NDVI	NDVI	Souza et al., 2013