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Review

A review of large area monitoring of land cover change using Landsat data

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ABSTRACT

Landsat data constitute the longest record of global-scale medium spatial resolution earth observation data. As a result, the current methods for large area monitoring of land cover change using medium spatial resolution imagery (10–50 m) typically employ Landsat data. Most large area products quantify forest cover change. Forests are a comparatively easy cover type to map as well as a current focus of environmental monitoring concerning the global carbon cycle and biodiversity loss. Among existing change products, supervised or knowledge-based characterization methods predominate. Radiometric correction methods vary significantly, largely as a function of geographic/algorithmic scale. For instance, products created by mosaicking per scene characterizations do not require radiometric normalization. On the other hand, methods that employ a single index or classification model over an entire study area do require radiometric normalization. Temporal updating of cover change varies between existing products as a function of regional acquisition frequency, cloud cover and seasonality. With the Landsat archive opened for free access to terrain-corrected data, future product generation will be more data intensive. Per scene, interactive analyses will no longer be viable. Coupling free and open access to large data volumes with improved processing power will result in automated image pre-processing and land cover characterization methods. Such methods will need to leverage high-performance computing capabilities in advancing the land cover monitoring discipline. Robust validation efforts will be required to quantify product accuracies in determining the optimal change characterization methodologies.

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1. Introduction

With the opening of the United States Geological Survey's (USGS) Landsat data archive (Woodcock et al., 2008) and future plans for open access policies for follow-on missions, there is the possibility for documenting global land surface change both retrospectively and prospectively. With this increased data availability, there will be a corresponding demand in improving our capacity to mass-process Landsat data in support of large area monitoring objectives. Fortunately, co-incident with the new Landsat data policy are new high-performance computing capabilities that enable the mining of the archive in ways heretofore not yet realized. The need for timely, accurate observations documenting global land change is more pressing than ever, given the changing state of global climate, biodiversity, food and fiber demand, and other critical environmental/ecosystem services. The improved data availability, advanced processing methods, and pressing need for information on environmental change will dictate a commensurate increase in our quantification of global land change in the coming months and years. While each of these three aspects is necessary for realizing this improved monitoring capability, none is more critical than data availability. The expansion of land monitoring methods and systems to other regions of the world and to other themes of interest will be maximized best via a free and easy access data policy for global monitoring systems. There is an additional need to improve historical and annual global coverage of Landsat-class data, either through coordinated acquisitions to improve contemporary coverage, or through the consolidation of unique Landsat data held in international archives.

This paper will review a number of large area medium spatial resolution land cover monitoring products, all of which employ Landsat data as inputs. To date, forest change products dominate due to the topicality of forest change regarding carbon accounting, biodiversity monitoring, and other issues concerning forested landscapes. Another reason forests are the most common large area monitoring target using remotely sensed data is that forests are one of the most easily distinguished vegetation cover types when compared to other monitoring targets, such as croplands or urbanized landscapes. The forest monitoring methods included in this review all employ digital image processing algorithms to quantify forest extent and change. As such, products that use heritage photointerpretative mapping methods, such as the Global Forest Survey of India (2008) and Indonesia's forest land use mapping efforts (Government of Indonesia/World Bank, 2000), are not reviewed. The objective of the paper is to assess the state of the practice in large area Landsat monitoring of land cover change, which most commonly centers on forest monitoring products. A product on crop type mapping, produced annually by the U.S. Department of Agriculture, National Agricultural Statistical Service (NASS), is also included as an example of algorithm-driven monitoring of agriculture using medium spatial resolution observations (National Agricultural Statistics Service, 2011).

The review is divided into a series of methodological intercomparisons which include pre-processing, geographic/algorithmic and temporal scales, and the change detection algorithms themselves. Validation practices are not reviewed, but validation is recognized as the key to future determination of not only the quality of individual products, but as a way to assess the aforementioned methodological considerations in generating large area change products. Validation of static large area land cover products is difficult, but change products are even more of a challenge (Khorram, 1999; Strahler et al., 2006). With the advent of large area land cover change products, the development of rigorous validation protocols is essential. The following review illustrates the wide variety of methods and the lack of consensus in large area monitoring approaches. Validation will be required to quantify the various strengths and weaknesses as the land cover and land cover change mapping community moves forward.

Studies reviewed in this paper include land cover change products that employ digital image processing-based algorithms to quantify cover conversion at national scales or larger, typically greater than 1 Mkm^2 in area. As will be shown there is no consensus approach to large area monitoring using medium resolution input data sets. A wide range of methods exist and are outlined in Table 1 for reference. Some commonalities are worth mentioning at the outset. Landsat is the primary data source and is used in all studies; Indian Remote Sensing Advanced Wide Field Sensor (AWiFS) data are used as one of the inputs along with Landsat data in the NASS Cropland Data Layer (CDL) crop type maps. Forest cover and change is the primary thematic variable, excepting the NASS CDL crop type map (National Agricultural Statistics Service, 2011). Methods are often employed interactively or iteratively in deriving map outputs. Supervised learning algorithms are favored in most examples. Exceptions include the PRODES product of Brazil's National Institute for Space Research (INPE), which uses multiple algorithms, including an analyst-driven linear mixture model, a segmentation model and an unsupervised clustering model (Shimabukuro et al., 1998). The North American disturbance product employed the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), a knowledge-based approach that used indices to mask non-forest and to map forest disturbance (Masek et al., 2008). In addition to the North America disturbance product, the Australia National Carbon Accounting System (NCAS) method is an index-based forest/non-forest mapping approach (Caccetta et al., 2007), and INPE's PRODES relies primarily on a shade fraction index to map deforestation (Shimabukuro et al., 1998). Despite these general commonalities, there is a remarkable amount of methodological variation between the existing large area change products.

Table 1
General processing characteristics of products reviewed in this paper. LEDAPS — NASA Goddard Space Flight Center, University of Maryland and Oregon State University (Masek et al., 2008); SDSU — South Dakota State University (Broich, Hansen, Potapov, et al., 2011; Potapov et al., 2011, this issue); USDA NASS CDL — United States Department of Agriculture National Agricultural Statistical Service Cropland Data Layer (Johnson & Mueller, 2010; NASS Cropland Data Layer, 2010); CSIRO NCAS — *Commonwealth Scientific and Industrial Research Organisation National Carbon Accounting System* (Caccetta et al., 2007)*; INPE PRODES — National Institute for Space Research Amazon Deforestation Monitoring Project* (Instituto Nacional de Pesquisas Espaciais, INPE, 2010; Shimabukuro et al., 1998)*; USGS NLCD — United States Geological Survey National Land Cover Dataset* (Xian et al., 2009; Xian & Homer, 2010)*; CI — Conservation International* (Harper et al., 2007; Killeen et al., 2007; Leimgruber et al., 2005).

Product	Geographic/algorithmic scale	Radiometric processing	Image inputs per characterization	Change detection approach	Land cover theme(s)
LEDAPS — North America Forest Disturbance index	Continental	Normalized data	Single-date	Post-characterization comparison of disturbance index	Forest
SDSU — Congo/Indonesia/European Russia	National/regional	Normalized data	Multi-date	Classification of forest cover loss	Forest
USDA NASS CDL — Continental U.S.	State	Non-normalized data	Multi data	Annual classification of crop types	Crop type
CSIRO NCAS — Australia	Ecozone	Normalized data	Single-date	Time-series of forest classifications using joint probabilities	Forest
INPE PRODES — Legal Amazon	Per scene	Non-normalized data	Single-date	Classification of deforestation	Forest
USGS NLCD — Continental U.S.	Per scene	Normalized data	Single-date	Change vector thresholds	Forest and impervious surface
CI — Bolivia, Burma, Madagascar	Per scene	Non-normalized data	Single-date	Classification of deforestation	Forest

2. Product intercomparison

2.1. Operational versus experimental

The most important distinction between existing large area medium spatial resolution land cover change products is whether they are made in an operational or experimental setting. By definition, standards for product deliverables are more demanding for operational products than experimental ones. Operational products exist as decision support systems for broader policy objectives and this requires close attention to product consistency and accuracy, and a practical approach to mapping in meeting product delivery dates. Research-based products have a higher tolerance for uncertainty whereas operational ones need to meet quality and timeliness standards dictated by the administrative setting in which they operate. The PRODES product from INPE, the NCAS product from CSIRO, the NLCD from USGS, and the CDL from NASS represent operational products. The CI products are made in collaboration with national partners as monitoring priorities and opportunities are identified. The SDSU and LEDAPS methods are experimental in nature.

2.2. Pre-processing

2.2.1. Geometric corrections

In order to perform time-series analyses of land cover change, a consistent geometric image set is required. Historically, geometric rectification has been a limiting factor in mass-processing of Landsat data and costly in-house rectification procedures have been employed to ready imagery for analysis. For example, the operational PRODES and NCAS data products use a reference set of base images to match new image sequences to. The NASS CDL project has included the purchase of rectified imagery, including the commercial provision of geometrically corrected AWiFS data. As the discipline moves forward, the realization that large area monitoring is dependent on consistent geometric corrections has led to the development of standard orthorectified products, beginning with the Global Land Survey (Tucker et al., 2004) data set. The GLS data sets of orthorectified Landsat imagery were produced with global coverage for the 1990, 2000 and 2005 epochs. The North American LEDAPS disturbance mapping project of Masek et al. (2008) employed the GLS data sets for 1990 and 2000. Consistent image geometry of Landsat scenes across epochs is achieved through the use of an improved digital elevation model and ground control network. The resulting orthorectified, terrain corrected image base is now used for all USGS Landsat processing. The opening of the 2.6 million image USGS Landsat archive for no cost access to Landsat data (Woodcock et al., 2008) in late 2008 included automatically generated orthorectified data as the product deliverable, referred to as Level 1 Terrain-corrected data (L1T). The SDSU products employed this data product. The NASS CDL project has also integrated Landsat L1T data more recently into their data stream.

Standard orthorectified imagery produced by data providers will be the wave of the future. For example, all data from the forthcoming Landsat Data Continuity Mission (LDCM) will be generated as standard orthorectified imagery processed with the same inputs currently used to generate all other USGS Landsat products, reducing the amount of effort needed by separate projects to create rectified time-series datasets and ensuring geometric consistency. The automatic rectification of imagery is relatively new and will enhance the implementation of more data-intensive multi-temporal studies.

2.2.2. Radiometric corrections

A host of radiometric corrections are possible for pre-processing Landsat data. Table 2 outlines the corrections used by methods reviewed in this study. While other standard products such as albedo or net primary productivity require surface reflectance inputs, radiometric corrections are not required for land cover characterization. Radiometric corrections for land cover are only required when a given land cover characterization model is to be extrapolated beyond a single image, whether in space or time. This leads to an interesting mix of approaches, as shown in Table 2.

Table 2
Radiometric corrections applied per change product.

Product	Top of atmosphere reflectance	Surface reflectance	BRDF/view angle normalization	Terrain normalization
LEDAPS — North America Forest disturbance index	+	+		
SDSU — Congo/ Indonesia/European Russia	+		+	
USDA NASS CDL — Continental U.S.				
CSIRO NCAS — Australia	+		+	+
INPE PRODES — Legal Amazon				
USGS NLCD — Continental U.S.	+			
CI — Bolivia, Burma, Madagascar				

The radiometric corrections applied in these studies include top of atmosphere reflectance, surface reflectance, bi-directional reflectance distribution/view angle normalization, and terrain normalization. Top of atmosphere reflectance calculations are typically bulk corrections applied to all of the pixels in a given image to adjust primarily for sun angle and earth-sun distance. Since Landsat solar geometry is not provided per pixel, TOA adjustment within a given scene does not typically vary per pixel. In these cases, TOA corrections do not enhance within scene fidelity. TOA calibrations are principally employed as a step towards inter-scene normalization. From Table 2, only the CDL, PRODES and CI products do not employ TOA corrections. For PRODES, analysts work at the per-scene scale, and no algorithm is applied across scenes whether in space or time. For the CDL maps, near exhaustive training data overcomes the need for any radiometric correction. The NLCD change product employs a TOA adjusted input, but this correction is not necessary for the map characterizations (Xian, pers. comm.).

Surface reflectance is a robust and complicated correction that includes per pixel adjustments with the goal of creating consistent radiometric response both within and between images. The most mature approach is that of LEDAPS (Masek et al., 2006), which estimates per pixel surface reflectance. LEDAPS accounts for scene spectral variations caused by atmospheric effects including ozone concentration, column water vapor, elevation and surface pressure, and aerosol optical thickness. The LEDAPS North American forest disturbance map employs a full surface correction application based on the MODIS 6S radiative transfer approach (Masek et al., 2006; Vermote et al., 1997). The benefits of removing atmospheric effects from input imagery are obvious, as consistent surface reflectances enable the application of standard models to all scenes, as in the LEDAPS product.

Surface-related spectral variations that may require additional correction include bi-directional reflectance distribution function (BRDF) effects (Schaaf et al., 2002). For wide-view angle sensors, these effects can be pronounced and confound analyses. But, even narrower swath medium spatial resolution sensors such as Landsat evidence BRDF effects, largely a function of solar zenith and sensor view angles (Danaher et al., 2001; Toivonen et al., 2006). While BRDF effects are target-dependent, bulk empirical adjustments have been shown to improve radiometric response and cover characterizations (Hansen et al., 2008). Fig. 1 shows an example of this for a scene in the Congo Basin where a coarse scale forest mask is used along with a modeled view angle parameter to adjust spectral response

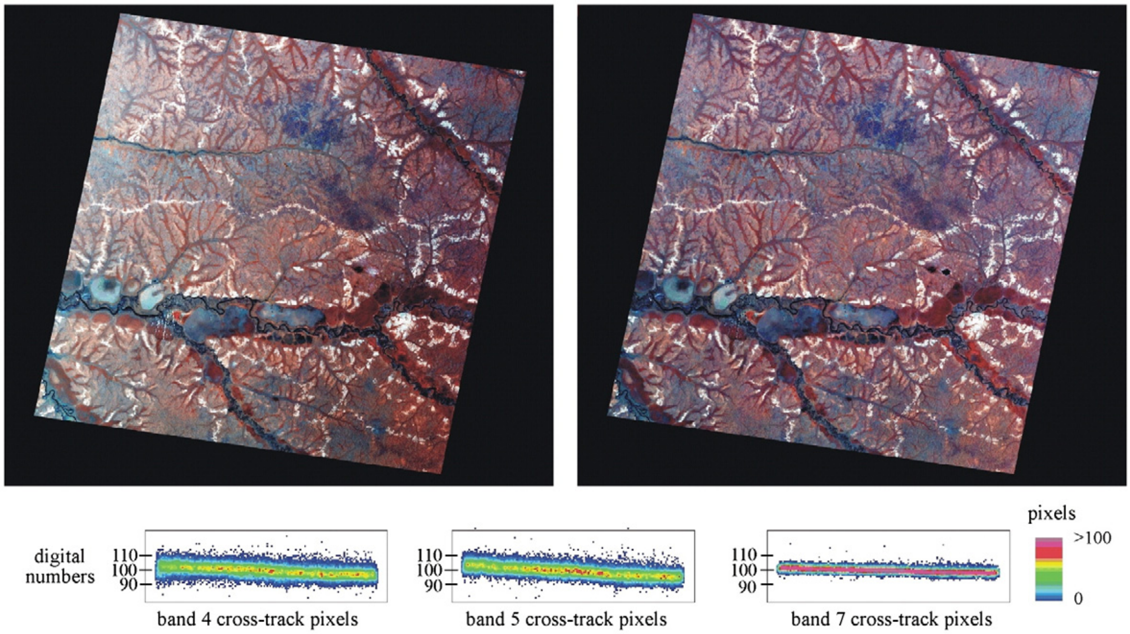

Fig. 1. Example per-scene BRDF normalization and cross-track radiometric responses for mature forests within the given Landsat scene from the Congo Basin (path/row 179/060, March 5, 2000, r-g-b of raw digital numbers for bands 4-5-7 on left and normalized bands 4-5-7 on right.). A mature forest mask is used to adjust per band radiometric response as a function of cross-track pixel location, resulting in a spectrally consistent depiction of forest cover on the right that improves forest characterization (Hansen et al., 2008).

per pixel. The SDSU and NCAS methods employ a per scene BRDF adjustment.

Topographic effects on radiometric response result from differences in illumination of and reflectance from sloped surfaces (Dymond & Shepherd, 1999). Removing this source of spectral variation can improve discrimination of land cover types and their change over time. However, a generic and robust approach to correcting such effects is not yet widely available (Lu et al., 2008). Models range from simple ratios to complex physical modeling (Civco, 1989; Holben & Justice, 1980; Sandmeier & Itten, 1997). The NCAS product employs a per scene correction using solar geometry, a digital elevation model, a C-factor correction (Teillet et al., 1982) and a ray-tracing algorithm to model and remove illumination variation due to terrain shading.

Absolute radiometric conversion of imagery to at least top of atmosphere reflectance values is preferred by a majority of applications. As methods increase their use of multi-temporal imagery, and extend studies to multi-decadal time scales, radiometric consistency will only become more important regarding land cover monitoring (Wulder et al., 2008). For methods using Landsat data from different missions (Landsats 1–7) and instruments (MSS, TM, and ETM+), it is necessary to cross-calibrate sensor radiometries (Chander et al., 2009). As of late-2010, the USGS has cross-calibrated all Landsat data to a consistent radiometric standard, enabling multi-decadal studies using the Landsat platform. Moving forward, the interoperability of other medium spatial resolution sensors with Landsat will largely be a function of consistent radiometric calibration.

2.2.3. Geographic/algorithmic scale

Algorithm implementation can be performed per scene, per stratified sub-unit, or over the entire study area. The ability to apply the same rule-base over the entire study area has advantages in ensuring consistency in the characterization across space. However, signature extrapolation limitations can result, deleteriously impacting the characterization (Cihlar, 2000). Additionally, spectral confusion between dissimilar cover types can result and similarly impact the quality of the characterization. A solution is to stratify the study area and apply per stratum algorithm runs. The drawback to this is potential inconsistency in the individual models and the creation of seams/inconsistencies at strata boundaries. Operational methods typically employ a stratified approach, whether per scene as with PRODES or per ecozone as with NCAS. The NLCD and CI change products were derived per scene. The CDL product employs a state-based stratification that allows for a sub-stratification based on the richness of the calibration data. The LEDAPS product performed a per scene characterization of non-forest before applying the disturbance index algorithm within forests.

The more experimental products (LEDAPS and SDSU) employ a single model/index over the entire study area in quantifying change. This variance reflects the fundamental difference between the operational and research-based products. Working within smaller geographic subsets provides greater control of outputs by the analysts, ensuring quality characterizations. From a research perspective, the ability to generically process data over large areas without analyst interference represents the ultimate evolution of processing methods in support of monitoring. Such a goal, if realized, may eventually translate to the operational domain and will be essential for global land change monitoring. Given that no operational systems function in this manner, the research community has additional work to do in demonstrating that such methods are ready for operational implementation.

The geographic/algorithmic scale is often tied to radiometric processing. Radiometric normalization is required to extrapolate signatures across multiple images, either through space or time. Given a stable radiometric feature space, for example a NDVI time-series, a standard model for mapping land cover and its change over time is enabled. An example of this type of application is found with the LEDAPS product, where a standardized disturbance algorithm was applied to a continental mosaic of surface reflectance-corrected Landsat data. Another example of this is from the SDSU projects, where a standard radiometric correction is applied to Landsat data in determining per pixel quality assessment and the subsequent development of a study area-wide multi-temporal feature space.

The PRODES, CDL and CI products do not have any radiometric corrections performed. In the case of PRODES and CI, analysts use digital numbers for annually collected cloud-free imagery; results are subsequently mosaicked together. For the Cropland Data Layer, an annual crop type map for the lower 48 United States, NASS analysts rely on extensive training data consisting of per field labels of crop type. These labels are submitted by farmers to the Farm Service Agency near the beginning of the growing season. For some states, the participation rate of farmers in labeling their fields is nearly 100%. Field extents are held in a geographic information system database and the labels assigned per polygon and used as training data. In this case, the analysts create image stacks of non-normalized Indian Remote Sensing AWiFS and Landsat data where each image is held in a different layer without mosaicking. In other words, a virtual stratification is made where the number of image inputs varies greatly from place to place. In this case, the extensive training data map the particular local context and no standard state-level model is applied or even needed. This is a rare case of nearly exhaustive training data. Without such training information, radiometric normalization is required for large area mapping.

Summarizing geographic/algorithmic scale, models either operate at the study area scale, or per a population of sub-units. In the first case, a reliance on standard radiometric responses is required. These signals are characterized using a fixed model applied to all pixels over space and through time. The second case relies on training data to model local to state-level radiometric responses in mapping large area land cover. The model tunes to local conditions and no standard rule relating spectral response to land cover exists; there are a host of models.

A method in between these two extremes is that of the Australian NCAS national land cover data set produced by CSIRO. In their approach, radiometric corrections, including surface reflectance, BRDF and topographic adjustments are made in a standardized manner. Thereafter, characterizations are performed in a stratified way per pre-defined ecozone with models tuned to each setting. The rationale is that the stratification identifies areas where landcover types within a zone have similar spectral properties (Caccetta et al., 2007). The same method is applied in the USGS NLCD tree cover base map of 2000, where ecoregions were the scale of algorithm implementation. However, change was quantified per path/row.

2.2.4. Temporal scale

To date, annual or multi-year epochal studies have been performed with medium spatial resolution imagery. Sub-annual change quantification has typically not been a reporting requirement for land cover change products. INPE's DETER product is an exception, employing MODIS data to provide a near-real time alarm product in monitoring Legal Amazon deforestation. No Landsat products to date operate in such a manner. For most monitoring objectives, annual change quantification is sufficient, and is in fact the goal of a number of global and national monitoring objectives (GCOS; U.S. Climate Change Science Program, 2003). However, for many other applications, such as pastureland or natural hazard monitoring, sub-annual monitoring is required and will likely be tested given the open Landsat archive.

Large area updating of land cover using medium spatial resolution data sets is largely limited by the frequency of temporal repeat visits (Wulder et al., 2009). Compared to coarse resolution data sources, such as MODIS that have nominally daily image capture globally, Landsat has a repeat cycle of 16 days. However, only the United States is acquired automatically each overpass. This lack of coverage impacts the ability to quantify annual land change for many regions. In addition to limited acquisitions, seasonality and cloud cover also reduce the viability of annual land cover updates. For example, persistent cloud cover over Indonesia has led to the use of MODIS to disaggregate 5-year aggregate Landsat-scale change to annual estimates (Broich, Hansen, Stolle, et al., 2011b). For the PRODES and NCAS data sets, a seasonal cloud-free window each dry season enables annual updating. This is not the case for many other countries and regions that require more data intensive methods to remove clouds, and that may face likely fundamental data limitations to synoptic annual monitoring.

Improved temporal updating at medium spatial resolutions will be solved only by more frequent image acquisitions. Ideas for improved acquisitions over tropical forests with persistent cloud cover include constellations of satellites with both polar and equatorial orbits to ensure that sufficient data are collected in tropical areas along the equator (Hansen et al., 2006). The Disaster Monitoring Constellation (da Silva Curie et al., 2002) has such a capability, but does not operate within the context of a continuing global acquisition strategy comparable to that of Landsat. Regardless, improving the temporal revisit rate of the land surface at medium spatial resolution is the most pressing need regarding large area land cover and change monitoring.

2.2.5. Algorithms

Physically-based modeling of land cover has not been demonstrated, and empirical methods are the rule. Traditionally, land cover characterization algorithms have been divided into supervised and unsupervised methods. In terms of the approaches used in large area land cover mapping using medium spatial resolution inputs, supervised methods, or slight variations of supervised approaches are favored. All example products reviewed here, except for the LEDAPS and NLCD change products, directly employ training data for model development. In the case of PRODES, an analyst defines the spectral endmembers principally for creating a shade fraction layer that is subsequently input to segmentation and unsupervised clustering algorithms. For NCAS, training data are used with a spectral index, derived by reducing the feature space using a canonical variate analysis. A thresholding approach is applied to discriminate forest from non-forest. The method used for the SDSU and CI products employs training data and a decision tree algorithm. The NASS CDL uses one of the richest training datasets, labeled agricultural field polygons, also with a decision tree algorithm. The North America Disturbance Index method employed a knowledge-based disturbance index empirically tuned to be a relative measure between mature forest and bare soil. An index for creating a non-forest mask was also developed.

2.2.6. Change detection methods

The most common approach to change detection is bi-temporal change analysis, the direct comparison of pairs of images or characterizations (Coppin et al., 2004). Change is quantified via spectral (image) or thematic (characterization) contrast. Such comparisons can often employ a thematic base map to better isolate or target the change dynamic of interest. Most of the large area mapping products reviewed here use some kind of variation of bi-temporal change detection. Another approach is multi-temporal change detection that employs more imagery to enhance the feature space beyond a time 1 to time 2 construct. Again, a variety of approaches and mixes of these basic constructs exist in current products. All methods rely on the use of a base map within which change is identified.

The direct comparison of individual characterizations through time, or post-characterization comparison, is used in the NCAS and LEDAPS products. Post-characterization methods are susceptible to the conflation of errors in the individual characterizations. The NCAS approach ameliorates this problem through the use of a time-series and spatial modeling of joint probabilities (Caccetta et al., 2007). The LEDAPS forest disturbance and NLCD impervious surface products use a continuous index as a basis of comparison. Such an approach reduces overall error when compared to a discrete post-characterization comparison of, for example, forest/non-forest classes.

The SDSU and CI methods directly characterize forest loss using all spectral inputs. In the case of CI and the SDSU European Russian product (Potapov et al., 2011), a combined time 1 and time 2 image feature space is used to map forest cover loss. The CI methods employs optimal single date imagery for both time 1 and time 2 periods. The SDSU European Russia derived composite time 1 and time 2 imagery from over 7000 image inputs. For the SDSU Congo and Indonesia products, a multi-temporal feature space derived from thousands of image inputs was used. This method exploits all available observations within the study period, and is drawn from experience mapping change with MODIS time-series data sets (Hansen et al., 2010).

A third approach is the use of spectral vectors or change indices from a reference state, a method employed in the NLCD land cover change layer. For this method, a set of indices, including NDVI, were interactively thresholded in identifying and mapping change (Xian et al., 2009). A fourth approach, that of the CDL layers, is in fact not a change detection approach. For this product, annual crop type extent is mapped independently and used in a regression estimator procedure to refine annual crop acreage estimates. In this manner, the CDL derives annual acreage estimates that are directly comparable from year to year.

3. Discussion and recommendations

3.1. Improving data policies

Landsat data dominate the field of national-scale land cover change monitoring to date. This is due to the value of Landsat observation continuity (Wulder et al., 2011) as well as the new free Landsat data access policy (Woodcock et al., 2008). It is imperative that other data providers develop similar, liberal data policies if additional data streams are to be widely used in the future. In the examples provided in this study, only the CDL employed data other than Landsat. INPE, for one, has provided medium spatial resolution CBERS (INPE, 2003) data free of charge since before the change in Landsat data policy. The planned Sentinel mission of the European Space Agency will also include an open and free data access policy (European Space Agency, 2009).

In addition to a free and accessible data policy, global acquisition strategies are needed to ensure consistent depictions of regional, continental, biome and global scale land cover extent and change. To date, Landsat ETM+ is the only medium spatial resolution sensor to have a global acquisition strategy (Arvidson et al., 2001). A global acquisition strategy also allows for the sharing of methods and experiences from using data from a common sensor. This is important for programs such as the UNFCCC's Reducing Emissions from Deforestation and degradation in Developing countries initiative (REDD+). However, it is incumbent that data policies do not backslide given the increased interest in, for example, carbon accounting (GOFC-GOLD, 2010), and the resulting possible policy initiatives to commoditize imagery.

3.2. The end of per scene analysis

Three of the more mature methods, all within operational settings, the PRODES, NCAS and NLCD forest or land change products, require significant per scene analyst interaction. This is made possible due to the viability of single-image updates per year, such as largely cloud-free imagery captured during the respective dry seasons within Brazil and Australia. For many other areas, cloud cover is a confounding factor and precludes the use of singe image updates of land cover per year. Per pixel processing methods using multi-date imagery are required for such areas, and are exhibited here in the Congo/Indonesia/European Russia and CDL examples.

Regardless of current approaches, the future will lie in mass-processing of Landsat or other like data. Single-date comparison methods are a legacy of prohibitive data costs and a lack of automation in geometric and radiometric pre-processing. For many, the capacity to process thousands of images from raw radiometric state to finished land cover extent and change product simply does not exist. The derivation of standard products, whether simply time-series imagery or derived cover extent and change maps is needed. One example of a pre-processed set of user-friendly Landsat data, based on the MODIS processing model (Justice et al., 2002), is the Web-Enabled Landsat Dataset (WELD), which exists for the continental United States and Alaska (Roy et al., 2010). With WELD, all cloud-free pixels are identified and processed into seamless weekly, monthly, and seasonal composites.

Pre-processed image time-series data sets will signal the death-knell for the per scene or path/row approach to mapping. While stratification will continue to be a favored approach for large area monitoring, the arbitrary division of land surfaces based on scene footprints will end. Processing methods will mimic those of the MODIS Land Science team (Justice et al., 2002), enabling a host of users the ability to characterize large area land cover extent and change. Stratification will be used based on ecological considerations, such as with the NCAS and NLCD tree cover layers.

An example change product based on WELD is shown in Fig. 2. This product is part of the WELD land cover product suite (Hansen et al., 2011), and depicts a post-characterization of WELD Vegetation Continuous Field layers of percent bare ground. The method employs the MODIS VCF approach (Hansen et al., 2003), where each 30 m pixel's fractional cover is estimated using sub-pixel training data and a regression tree algorithm. The advent of Landsat-resolution pre-processed time-series data sets will greatly reduce the costs and logistical complexity of mapping national scale and larger mapping efforts. Distributed and costly mapping models that require hosts of analysts will no longer be required.

3.3. Improving data processing and characterization

As illustrated in this review, there are a variety of methods currently in use in support of either operational or research-based large area monitoring of land cover change at medium spatial resolutions. The advent of both the open Landsat archive and improved high-performance computing capabilities will lead to dramatic changes in current methods. Past approaches that rely on bi-temporal image comparisons, i.e. single-date time 1and time 2 analyses, as per the PRODES, NCAS, NLCS, LEDAPS and CI methods, will be replaced by more exhaustive and data intensive methods that employ time-series data sets (Huang et al., 2009; Kennedy et al., 2009). Such methods will use all appropriate available data in characterizing change. The SDSU approach uses all available data in the Landsat EROS archive based on a cloud cover metadata threshold. The CDL product combines AWiFS and Landsat ETM+ and TM data in characterizing annual crop type extent. Once these methods are sufficiently mature and validated, their adoption for national monitoring purposes will follow. In effect, countries that have been limited by past data policies and processing limitations will be able to 'leapfrog' directly to more data intensive methods. The development of user-friendly versions of such methods is required, however. Efforts in support of initiatives such as REDD+ should include the creation of pre-processed inputs, such as the WELD data, as well as algorithmic interfaces that enable the appropriate country agencies to exploit image archives in more automated manners.

The generation of standard products as inputs will continue to evolve. The creation of input data sets that include geometric, atmospheric, BRDF and topographic corrections is an important objective. However, each step of processing should be evaluated in quantifying the proposed improvements to input data sets. Ju et al. (this issue) perform such a comparison of a proposed WELD atmospheric correction methodology with that of LEDAPS for Landsat processing. Additionally, multi-sensor cross-calibration will become an important focus of research as more data sets from more sensors are used in ensemble approaches.

Part of the evolution of processing will include cloud-computing, such as that currently being developed by NASA in the form of the NASA Earth Exchange (NEX) (Nemani et al., 2011) and by Google in the form of the Google Earth Engine (GEE) (http://earthengine.googlelabs.com). Both systems rely on parallel processing to reduce computing time in the derivation of remotely-sensed earth system science products. While none of the products reviewed here used

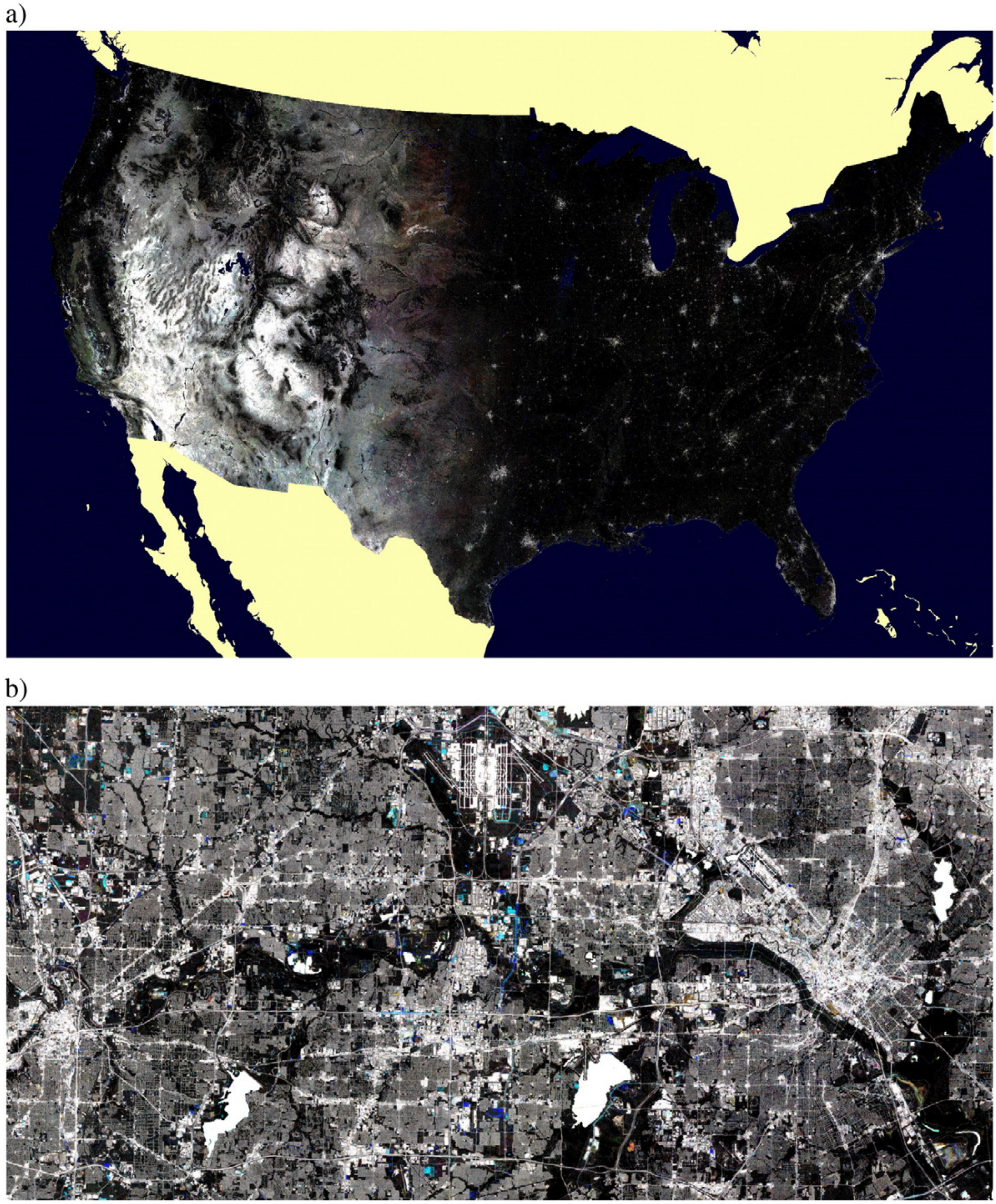

Fig. 2. a) Continental United States minimum annual percent bare ground layers for 2006, 2008 and 2010 in r-g-b derived from WELD data; b) Zoom of a) for the Dallas-Fort Worth metropolitan area. Gray-scale indicates no change, cyan — new bare ground after 2006, blue — new bare ground after 2008.

cloud computing, such processing systems will be more accessible to research and operational users in the future, improving product iteration/analysis capabilities and reducing the latency of product delivery. By partnering with these or other such computing facilities, agencies or research institutes interested in large area land cover and change mapping will be able to focus on characterization methods while avoiding the overhead associated with developing and maintaining high-performance computing infrastructures. Alternatively, computing costs will continue to decline, enabling users to build their own high-performance computing infrastructures.

3.4. Advancing thematic outputs

The large area land cover change products reviewed here capture land cover conversion processes, largely due to the comparative ease with which such dynamics can be detected and mapped. Other more subtle disturbance dynamics, such as within-cover modifications, are considerably more challenging to quantify. Forest recovery and degradation are two such examples. While selective logging has been quantified for the major logging states of the Brazilian Amazon by Asner et al. (2005) and such methods are being improved (Souza &

Roberts, 2005), the level of maturity for operational implementation at national scales and larger has not yet been realized. The admitted difficulty in capturing such subtle cover changes consistently through time and across space does not lessen their importance. Many land use dynamics occur in the context of cover modification, not conversion, and are critical to quantifying many earth system dynamics (Ramankutty et al., 2006). Moving these products into a more operational mode is required.

3.5. Completing the Landsat archive

Finally, for global studies, there is a significant need to improve the amount of Landsat coverage available for use in land change studies. For environment, technical, and programmatic reasons, the geographic and temporal coverage of global Landsat data is uneven. A significant amount of unique Landsat coverage dating from 1972 to the present is found in international archives and are either not accessible or are in formats inconsistent with those distributed by the USGS. The USGS is working with its network of International Cooperators to collect and consolidate unique historical Landsat coverage in the USGS Landsat archive. Preliminary analysis suggests that an additional 2.5–3.0 million unique Landsat scenes may be available. In the future, improved global coverage will come about through acquisition capacity improvements planned for Landsat Data Continuity Mission and other follow-on Landsat missions, and through international collaboration with other compatible medium resolution missions, such as the European Sentinel-2 mission.

4. Conclusion

Currently, there is a wide variety of methods employed in large area land cover change characterization. While much of the methodological variation described here will persist, future methods will evolve and adapt to greater data volumes and processing capabilities. The land cover change monitoring community is poised for a dramatic increase in characterization capabilities, due to the new Landsat data policy and concurrent advances in high-performance computing. Heritage change mapping methods relying on analyst interaction with individual scenes should decline over time given the improved ability to process and characterize rich time-series of medium spatial resolution data. However, such methods will be tested against institutional requirements for thematic accuracy. Near-term research objectives will require robust validation data sets in establishing which data-intensive methods are most appropriate in quantifying large area land cover change.

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