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Transitioning from change detection to monitoring with remote sensing: A paradigm shift

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ABSTRACT

The use of time series analysis with moderate resolution satellite imagery is increasingly common, particularly since the advent of freely available Landsat data. Dense time series analysis is providing new information on the timing of landscape changes, as well as improving the quality and accuracy of information being derived from remote sensing. Perhaps most importantly, time series analysis is expanding the kinds of land surface change that can be monitored using remote sensing. In particular, more subtle changes in ecosystem health and condition and related to land use dynamics are being monitored. The result is a paradigm shift away from change detection, typically using two points in time, to monitoring, or an attempt to track change continuously in time. This trend holds many benefits, including the promise of near real-time monitoring. Anticipated future trends include more use of multiple sensors in monitoring activities, increased focus on the temporal accuracy of results, applications over larger areas and operational usage of time series analysis.

1. Introduction

The use of time series of data in the analysis of remote sensing images, particularly at Landsat-like spatial resolutions and finer, is a relatively recent phenomenon that is leading to new and exciting capabilities for monitoring land surface change. It is important to note that change detection, in general, and use of time series data in remote sensing have a long history. An early and excellent review of methods for change detection dates back to 1989 (Singh, 1989) with other outstanding later reviews (Jensen, 2005; Coppin et al., 2010), The use of time series data started with early Advanced Very High Resolution Radiometers (AVHRR) – see, for example Viovy et al., 1992; DeFries and Hansen, 1995; Loveland et al., 1995, but has been more common with MODIS imagery (see Friedl et al., 2002; Boschetti et al., 2009; Verbesselt et al., 2010). That time series analysis with Landsat and finer resolution sensors lagged that of MODIS is understandable from several perspectives. First, MODIS produced datasets well organized for time series analysis, with acquisitions binned to common grids, and composited to remove the effects of clouds (Justice et al., 2002). Also, the data were freely available for download from the web. The use of time series analysis for Landsat data only came after the data were freely available and the processing of the imagery became standardized. Improvements in cloud and cloud shadow masking as well as automation of atmospheric correction also contributed (Wulder et al., 2012).

The publication of this special issue is a good time to take stock of where we are as a remote sending community and where we may be going with respect to time series analysis. This introductory paper to the special issue is an attempt to elucidate some of the larger trends and issues related to time series analysis. The articles (Table 1) in the special issue serve as the examples and guides to the discussion of the changes rippling through the community. The articles are diverse and include investigations of dynamic conditions at seasonal and annual scales, including long-term analyses, but many relate to significant shifts from time series-based change detection to continuous monitoring.

2. Background and context

A short history of remote sensing of the land surface suggests that the initial uses of remote sensing were for single-date mapping and then the focus switched to multi-date image analysis and systematic change detection (Hansen and Loveland, 2012; Zhu and Woodcock, 2014; Hermosilla et al., 2015). The questions originally were, for example, "where are the cities and how much of the landscape do they cover?" and then became "where are the cities and how much have they grown

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Table 1
Papers in time series analysis special issue.

Authors	Paper titles
Arévalo P., Woodcock, C.E., Olofsson, P.	Continuous monitoring of land change activities and post-disturbance dynamics from Landsat time series: a test methodology for REDD+ reporting.
Bayat, B., van der Tol, C., Verhoef, W.	Retrieval of land surface properties from an annual time series of Landsat TOA radiances during a drought episode using coupled radiative transfer models.
Bell, T.W., Allen, J.G., Cavanaugh, K.C., Siegel, D.A.	Three decades of variability in California's giant kelp forests from the Landsat satellites.
Brown, J., Tollerud, H., Barber, C., Zhou, Q., Dwyer, J., Vogelmann, J., Loveland, T., Woodcock, C., Stehman, S., Zhu, Z., Pengra, B., Smith, K., Xian, G, Horton, J., Auch, R., Sohl, T., Sayler, K., Gallant, A., Zelenak, D., Reker, R., Rover, J.	Lessons learned implementing an operational continuous United States national land change monitoring capability: the Land Change Monitoring, Assessment, and Projection (LCMAP) approach.
Bullock, E., Woodcock, C.E, Holden, C.E.	Monitoring tropical forest degradation using spectral unmixing and Landsat time series analysis.
Bullock, E., Woodcock, C.E., Olofsson, P.	Improved change monitoring using an ensemble of time series algorithms.
Cunha, J., Nóbrega, R., Rufino, I., Erasmi, S., Galvão, C., Valente, F.	Surface albedo as a proxy for land-cover clearing in seasonally dry forests: evidence from the Brazilian Caatinga.
Deng, C., Zhu, Z	Continuous subpixel monitoring of urban impervious surface using Landsat time series.
Fortin, J.A., Cardille, J.A., Perez, E.	Multi-sensor detection of forest-cover change across 45 years in Mato Grosso, Brazil.
Griffiths, P., Nendel, C., Pickert, J., Postert, P.	Towards national-scale characterization of grassland use intensity from integrated Sentinel-2 and Landsat time series.
Jaafar, H.H., Ahmad, F.	Time series trends of Landsat-based ET using automated calibration in METRIC and SEBAL: the Bekaa Valley, Lebanon.
Koltunov, A., Ramirez, C.M., Ustin, S.L., Slaton, M., Haunreiter, E.	eDaRT: the Ecosystem Disturbance and Recovery Tracker system for monitoring landscape disturbances and their cumulative effects.
Lymburner, L., Bunting, B., Lucas, R., Scarth, P., Alam, I., Phillips, C., Ticehurst, C., Held, A.A.	Mapping the multi-decadal mangrove dynamics of the Australian coastline.
Nguyen, L.H., Joshi, D.R., Clay, D.E., Henebry, G.M.	Characterizing land cover/land use from multiple years of Landsat and MODIS time series: a novel approach using land surface phenology modeling and random forest classifiers.
Pengra, B., Stehman, S., Horton, J., Dockter, D., Schroeder, T., Yang, Z., Cohen, W.B., Healey, S.P., Loveland, T.R.	Quality control and assessment of interpreter consistency of annual land cover reference data in an operational national monitoring program.
Roy, D., Yan, L.	Robust Landsat-based crop time series modelling.
Uhl, J.H., Leyk, S.	Towards a novel backdating strategy for creating built-up land time series data using contemporary spatial constraints.
Wang, X., Xiao, X., Zou, Z., Zhong, Q., Da, S., Li, B., Zhao, N., Chen, B., Li, X., Qin, Y., Dong, J., Doughty, R.B., Ma, J.	Tracking annual changes of coastal tidal flats in China during 1986–2016 through analyses of Landsat images with Google Earth Engine.
Yang, Y., Hain, C., Noormets, A., Sun, G., Sun, S., Anderson, M., Wynne, R., Thomas, V., Gao, F.	Investigating impacts of drought and disturbance on evapotranspiration over a forested landscape in North Carolina, USA using high spatiotemporal resolution remotely sensed data.
Zhu, Z., Cohen, W., Zhou, C., Yang, Z., Qiu, S., Zhang, J., Aljaddani, A.H.	Continuous monitoring of land disturbance based on Landsat time series.

over the past 10 years?" Implicitly, the mapping perspective assumes a static landscape, or at least that a representation of that landscape at any one time is useful (Singh, 1989). One might say that mapping is "characterizing what exists at a particular place at a particular time." For change detection, the underlying assumption is that something is different between two points in time, and the places where change has occurred are the primary focus. In that case, change detection is "finding the places where something has changed between two points in time." The emphasis on "two points in time" comes from the fact that, overwhelmingly in remote sensing, change has been found by comparing images of the same place from two different times (Coppin et al., 2010). One can think of this as the "endpoints" approach to change detection. The dates of the two images used become the endpoints of the time period in question. When stated this way, one question that immediately emerges is what constitutes "change".

In remote sensing, the nature of "change" tends to be defined depending on the needs and interests of any particular study. Sometime "change" means deforestation, or land cover change. In other cases, "change" means a change in the health or condition of the vegetation, such as when a pest infestation stresses trees in a forest. Looking through any particular issue of *Remote Sensing of Environment* makes it clear that many kinds of change are being detected using remote sensing. Going forward, it may be useful to develop a set of terms to characterize change in the context of remote sensing. It also helps illustrate how remote sensing is evolving in terms of how it is used to study "change".

3. Trends in time series analysis of moderate resolution data

3.1. The nature of change

In reality, all things are changing all the time; it is the nature of life and time. Some changes are more interesting and helpful to document than others. For example, if the wind moves around sand grains on a dune in the desert, one could argue that the dune is changing. However, at any moment in time, the location of the individual sand grains might not be terribly important and so knowing that they had moved slightly would not be particularly helpful. Over time, if the whole dune migrated, that would be useful information. In another example, an orchard replaces a wheat field. Does this constitute a change? From the perspective of land cover, it certainly constitutes a change as the land cover changes from a grain crop to trees. From a land use perspective it may not be an important change as both the wheat field and the orchard are agricultural land uses. However, this change could be important from many other perspectives, from phenology to hydrology to surface micrometeorology. The point is that context and perspective are important in evaluating the relevance or importance of any particular change. Other examples may prove useful. Ocean tides and even individual waves move the boundary between land and water constantly, such that images (essentially instantaneous snapshots) collected at different times are likely to have differences in the intertidal zone (Wang et al., 2019). Whether or not this constitutes useful information, or whether it is simply a noise factor in an analysis depends on context. In studies of accretion in river deltas, the differences in images resulting from tides would be a source of noise that could confuse the analysis. Many other examples are possible, particularly in the context of agriculture. For example, the degree of water stress in a field at any particular moment may be of little significance to someone interesting in mapping cultivated areas or doing crop type inventories, but it is of critical significance to a farmer.

There are a couple of different ways change can be instructively parsed (Coppin et al., 2010). There are *abrupt* changes, such as change caused by fire or a hail storm. At the other end of the spectrum are *gradual* changes, such as succession in plant communities, or erosion and depositional processes along a river meander. There are also many kinds of change that fall in between. For example, growth of an urban area does not happen abruptly, but it is also not a gradual change. It might occur as a sequence of many small abrupt changes. While the terms, “abrupt” and “gradual” may be difficult to pin down in terms of a precise definition, they are clearly helpful as relative terms. It is easy to see that remote sensing has been most useful for studying abrupt changes, but is also helping monitor more gradual changes (Vogelmann et al., 2016).

It can be instructive to differentiate *transitional* changes from *conditional* changes. Transitional changes are due to a fundamental transition in the nature of a land surface. Cutting down trees, clearing the land and erecting a building are clearly a *transitional* change. On the other hand, water stress in an agricultural field is a *conditional* change, or a change in condition at the surface.

There are many examples in the special issue that help illustrate these ways of parsing the nature of change. Examples of transitional change include: Arévalo et al. (2019) monitoring conversion of forests to pasture; Cunha et al. (2019) reporting on the clearing of Brazilian Caatinga dry forests; Fortin et al. (2019) investigating forest change in the Mato Grasso region of Brazil; Lymburner et al. (2019) monitoring the expansion of mangroves (a transition from open water to mangrove forest); Deng and Zhu (2019) and Uhl and Leyk (2019) looking at urban expansion patterns; and Bell et al. (2019) addressing changes in kelp forests off the California coast. There are also examples of conditional change. Bullock et al. (2019b) report on monitoring natural disturbance and forest degradation. In this case the areas in question remain forests, but the condition of the forest changes. A significant point is that time series analysis is allowing for monitoring more subtle kinds of changes, which are mostly conditional changes, and are increasingly used to analyze land use characteristics in croplands (Roy and Yan, 2019) and grasslands (Griffiths et al., 2019). From an operational, national-scale land monitoring perspective, Brown et al. (2019) emphasize the value of dense time series analysis to provide temporal patterns of change across large regions, provide input into a wide range of environmental studies, clarify the drivers of change, and provide more timely information for land managers.

Other studies address the analyses of surface properties rather than the detection of particular transitions or changes. Bayat et al. (2019) investigates drought-related seasonal vegetation dynamics in the California Mediterranean grasslands. Jaafar and Ahmad (2019) use thermal imagery to establish a long time series of evapotranspiration (ET) retrievals needed to understand water use and groundwater dynamics in the Bekaa Valley of Lebanon.

3.2. Monitoring intervals

One dimension of the use of remote sensing that has changed with time series analysis is the interval over which change is detected or phenomena are assessed. For change detection, the conventional “endpoints” approach, mentioned above, tended to select images at least several years apart to look for change. The result was monitoring over periods that sometimes stretched to as long as a decade. Using time series analysis, the time interval for detecting change has shrunk considerably, with most changes detected at an annual time interval or less. As the time interval between observations used in time series becomes smaller, we begin to move from away simply detecting change to more continuous monitoring (for example, see Yang et al., 2019). This movement towards monitoring has several implications and advantages. First, it will begin to allow more precise characterization of the timing of changes. Second, the improved characterization of the timing of change will advance our ability to determine the drivers of change. Perhaps more importantly, it will begin to allow for monitoring in near real-time with changes being detected very quickly after a new satellite observation becomes available. The temporal definition of “near real-time” is largely dependent on the nature of the processes being monitored and the latency in access and analysis of the time series inputs. For the purposes of the special issue and use of Landsat-like observations, near real-time generally means in most instances weeks. Some articles have goals that include operational near real-time change, but recognize the inherent challenges (Brown et al., 2019; Koltunov et al., 2019). Now that we have multiple Landsat and Sentinel 2 satellites in orbit and providing observations, it is now common to be able to acquire observations every few days for most of the world (Li and Roy, 2017). Griffiths et al. (2019), for example, show ways to combine Landsat 8 and Sentinel 2 data for mapping land use patterns in grasslands based on the analysis of intra-annual growth.

There are also benefits from longer time series; the Landsat archive being an excellent example. Having data from longer time periods allows for better characterization of trends and comparison of land dynamics now and in the past. The paper by Wang et al. (2019) is a good example as they used a 30-year time series of Landsat data to study trends in tidal flats and found important differences for the various decades they studied. Although the Landsat time series is relied on, it is important to note that most studies are limited to the use of the Landsat 4–8 record and do not incorporate the earlier Landsat 1–3 Multispectral Scanner (MSS) archive. Significant challenges remain before the full 48 year Landsat record can be fully applied to time series investigations.

Regarding extending the satellite time series record, Bell et al. (2019), stress that a time series longer than 34 years is needed to understand the connections between low frequency marine oscillations and the subsequent cooling and warming cycles that affect kelp status. Uhl and Leyk (2019) also argue that longer time series are needed to address human settlement topics.

3.3. How observations are used

The approaches used in this special issue fall into several categories. For change studies, there are those that use one good observation per year or one good observation per season, and those that attempt to use all available good observations in the time series analysis. Many of the algorithms that rely on one good observation a year use some form of image compositing to create the datasets that are then used in time series analysis (e.g., Bell et al. (2019) study kelp, Cunha et al. (2019), and Koltunov et al. (2019) forest change, and Brown et al. (2019) land cover change). There are also studies that use dense time series to investigate phenomena within a single growing season (see Bayat et al., 2019; Jaafar and Ahmad, 2019; Nguyen et al., 2019; Roy and Yan, 2019).

Other algorithms try to use many or all of the available observations that do not have clouds, shadows (or sometimes snow) directly in the time series analysis. Using all available observations has the advantage of being able to study intra-annual dynamics and faster processes that might only be visible during a limited period of time. Examples include seasonal or growing season crop dynamics, and low intensity tropical forest degradation where canopy gaps can close in a matter of a few months. The paper by Griffiths et al. (2019) highlights how the combination of harmonized Landsat 8 and Sentinel 2 data synthesized through compositing at 10-day intervals can be used to study mowing patterns in European grasslands. Sufficient valid observations are generally required and reliance on more noisy single observations rather than on “best”-pixel approaches can result in lower quality time series data.

Regardless of how observations are used, the need to select the best, or least contaminated, pixels is central to almost every study in this special issue. Cloud clearing, atmospheric correction, and gap filling, are all important for time series datasets and in cases where such analysis ready data quality cannot easily be provided from satellite data, their use for dense time series analysis remains limited.

In some ways these two divergent approaches are more similar that they might appear at first glance, as the compositing algorithms typically make use of many or all the available good observations when selecting the best observations to represent a particular time period.

3.4. Algorithms

An interesting dimension in the special issue papers is the wide variety of algorithms being used in time series analysis in remote sensing. This variety is a healthy indication of continued innovation in algorithm development, a trend we expect to continue for a long time. If one considers the fact that there are new algorithms being developed for image classification after more than 40 years of use in image classification in remote sensing, it is not hard to imagine a long period of significant innovation in time series analysis (Zhu et al., 2019). The same can be said about change detection using endpoints. There are a couple of ways to differentiate algorithms that help illuminate the variety of approaches being used in time series analysis. One distinction relates to the stage at which change is found in the analysis process. One set of approaches analyzes the individual images (or composites) to make maps of the conditions at the time of the images (typically annually), and then looks at those results for change. One example is Lymburner et al. (2019) where a map for each year of mangrove extent is made, and then change is identified by the changes between the various years of the maps.

The alternative is to use the remote sensing time series of observations directly in the identification, or monitoring of change. Arévalo et al. (2019) and Bullock et al. (2019b) showcase examples for forest and land degradation, and Deng and Zhu (2019) demonstrate this for sub-pixel urban impervious surfaces. Another is Koltunov et al. (2019) in which a two-stage process is used to detect anomalies and then characterize change. Fortin et al. (2019) use an interesting Bayesian method to compare sequences of land cover maps created from disparate sources of imagery.

There are also new approaches to time series analysis presented in the special issue. For example, Bullock et al. (2019a) combine multiple time series approaches into a “hybrid” algorithm that takes advantage of both online and offline algorithms.

An important trend is the variety of approaches used to handle the large data volumes and vast processing resources required for dense time series analysis. Cloud-based processing solutions closely linked to the satellite data archives are increasingly becoming popular for scaling from local case studies to larger area applications. Google Earth Engine has enabled rapid learning and advances in time series studies because of the unique and powerful capabilities it offers (see Bullock et al., 2019b; Fortin et al., 2019; Uhl and Leyk, 2019). The special issue contains novel local and national examples and experiences (e.g., Brown et al., 2019), but scaling such approaches for global scale analysis remains a challenge.

3.5. Sensors – and fusion of data from multiple sensors

The use of Landsat satellite time series data is most common among the papers of the special issue. It is obvious that dense time series analysis almost exclusively uses satellite sources with open data policies and easy-to-use web-based access, as well as proper calibration and preprocessing.

Multi-sensor fusion is addressed in some papers highlighting its value for increasing the density of observations and the ability to study higher-frequency land surface processes. In particular the combination of Landsat and Sentinel data seems promising for the characterization of changes and dynamics in higher detail and accuracy (Griffiths et al., 2019). On the other hand multi-sensor approaches result in higher data volumes and require algorithms to account for differences between sensors that can complicate the analysis.

3.6. Reference data and accuracy analysis

The goal of more detailed and accurate information about land dynamics using dense satellite time series requires the availability of reference data for training and validation, and procedures for assessing the accuracy of the results (Olofsson et al., 2014). The special issue examples studying land changes emphasize that visual interpretation of satellite data, sometimes augmented by selected available very high resolution images, remains the most important reference data source since other data sources (i.e., in-situ data/monitoring) are less available or suitable (Pengra et al., 2019; Wang et al., 2019). The need for consistent multi-year reference data is particularly challenging due to the variability of source imagery and image quality over long time periods. The increasing temporal detail provided by dense time series emphasizes that the accuracy of change not only relates to the question of whether it was detected correctly, but also whether it was detected correctly at the time it actually happened. There is naturally a time lag between when something changes on the ground and when it is observed and monitored with confidence from satellite data. With the time between observations becoming smaller, the importance of the temporal precision of the analysis versus the temporal detail of the time series of satellite observations and the reference data requires specific attention for accuracy analysis and building confidence in products and any associated derived estimates. Considering the quality of reference data for dense time series analysis remains an important challenge (Pengra et al., 2019).

4. Conclusions and future directions

The papers in the special issue demonstrate a paradigm shift transitioning from change detection to monitoring with remote sensing. We are moving from detecting large transitional changes to characterizing land surface dynamics and trends along a continuous data stream of time series observations. The density and rapid availability of observations helps to monitor the land surface in unprecedented detail and increasingly in near-real time. This development underpins the evolution of novel application fields beyond the traditional land cover and change questions towards land use and land management, and tracking complex spatial-temporal ecosystem dynamics and small-scale degradation processes.

While admittedly speculative, there are a number of trends we expect to emerge or continue.

1. Global Applications. We expect that investigators will find ways to productively scale time series analysis to global scales using moderate resolution imagery, and that the programs will become operational.
2. Temporal Accuracy. As the use of time series analysis matures, we expect the collection of reference data and the analysis of the temporal dimension of results to become better developed and more commonly applied.
3. Multi-sensor Fusion. While multi-sensor fusion is now being employed in some applications, we expect it to become increasingly prevalent and used effectively.
4. Near Real-time. Maybe the most exciting prospect is the use of time series analysis to provide land managers information about landscape dynamics as they unfold.
5. Operational Applications. There may be any variety of application domains, but time series analysis, and near real-time results in particular, open new doors for operational applications, even in areas like enforcement of statutes and treaties related to land use.

Author contributions

Curtis Woodcock - Conceptualization, original draft, reviewing & editing

Thomas Loveland - Conceptualization, original draft, reviewing & editing

Martin Herold - Conceptualization, original draft, reviewing & editing

Marvin Bauer - Conceptualization, original draft, reviewing & editing

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References

Arévalo, P., Woodcock, C.E., Olofsson, P., 2019. Continuous monitoring of land change activities and post-disturbance dynamics from Landsat time series: a test methodology for REDD+ reporting. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.01.013.

Bayat, B., van der Tol, C., Verhoef, W., 2019. Retrieval of land surface properties from an annual time series of Landsat TOA radiances during a drought episode using coupled radiative transfer models. Remote Sens. Environ.. https://doi.org/10.1016/j.rse.2018.09.030.

Bell, T.W., Allen, J.G., Cavanaugh, K.C., Siegel, D.A., 2019. Three decades of variability in California's giant kelp forests from the Landsat satellites. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2018.06.039.

Boschetti, M., Stroppiana, D., Brivio, P.A., Bocchi, S., 2009. Multi-year monitoring of rice crop phenology through time series analysis of MODIS images. Int. J. Remote Sens. 30 (18), 4643–4662. https://doi.org/10.1080/01431160802632249.

Brown, J., Tollerud, H., Barber, C., Zhou, Q., Dwyer, J., Vogelmann, J., Loveland, T., Woodcock, C., Stehman, S., Zhu, Z., Pengra, B., Smith, K., Xian, G., Horton, J., Auch, R., Sohl, T., Sayler, K., Gallant, A., Zelenak, D., Reker, R., Rover, J., 2019. Lessons learned implementing an operational continuous United States national land change monitoring capability: the Land Change Monitoring, Assessment, and Projection (LCMAP) approach. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.111356.

Bullock, E., Woodcock, C.E., Olofsson, P., 2019a. Improved change monitoring using an ensemble of time series algorithms. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.04.018.

Bullock, E., Woodcock, C.E., Holden, C.E., 2019b. Monitoring tropical forest degradation using spectral unmixing and Landsat time series analysis. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2018.11.011.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., Lambin, E., 2010. Digital change detection methods in ecosystem monitoring: a review. Int. J. Remote Sens. 25 (9), 1565–1596. https://doi.org/10.1080/0143116031000101675.

Cunha, J., Nóbrega, R., Rufino, I., Erasmi, S., Galvão, C., Valente, F., 2019. Surface albedo as a proxy for land-cover clearing in seasonally dry forests: evidence from the Brazilian Caatinga. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.111250.

DeFries, R., Hansen, M., 1995. Global discrimination of land cover types from metrics derived from AVHRR pathfinder data. Remote Sens. Environ. 54 (3), 209–222. https://doi.org/10.1016/0034-4257(95)00142-5.

Deng, C., Zhu, Z., 2019. Continuous subpixel monitoring of urban impervious surface using Landsat time series. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2018.10.011.

Fortin, J.A., Cardille, J.A., Perez, E., 2019. Multi-sensor detection of forest-cover change across 45 years in Mato Grosso, Brazil. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.111266.

Friedl, M.A., McIver, D.K., Hodges, J.C., Zhang, X.Y., Muchoney, D., Strahler, A.H., Woodcock, C.E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., 2002. Global land cover mapping from MODIS: algorithms and early results. Remote Sens. Environ. 83 (1–2), 287–302. https://doi.org/10.1016/S0034-4257(02)00078-0.

Griffiths, P., Nendel, C., Pickert, J., Postert, P., 2019. Towards national-scale characterization of grassland use intensity from integrated Sentinel-2 and Landsat time series. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.03.017.

Hansen, M.C., Loveland, T.R., 2012. A review of large area monitoring of land cover change using Landsat data. Remote Sens. Environ. 122, 66–74. https://doi.org/10.1016/j.rse.2011.08.024.

Hermosilla, T., Wulder, M.A., White, J.C., Coops, N.C., Hobart, G.W., 2015. Regional detection, characterization, and attribution of annual forest change from 1984 to 2012 using Landsat-derived time-series metrics. Remote Sens. Environ. 170, 121–132. https://doi.org/10.1016/j.rse.2015.09.004.

Jaafar, H.H., Ahmad, F., 2019. Time series trends of Landsat-based ET using automated calibration in METRIC and SEBAL: the Bekaa Valley, Lebanon. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2018.12.033.

Jensen, J.R., 2005. Chapter 12, Digital Change Detection. Introductory Digital Image Processing: A Remote Sensing Perspective, third. Pearson Prentice Hall, Upper Saddle River, New Jersey, pp. 467–494 ISBN:0131453610.

Justice, C.O., Townshend, J.R.G., Vermote, E.F., Masuoka, E., Wolfe, R.E., Saleous, N., Roy, D.P., Morisette, J.T., 2002. An overview of MODIS land data processing and product status. Remote Sens. Environ. 83 (1–2), 3–15. https://doi.org/10.1016/S0034-4257(02)00084-6.

Koltunov, A., Ramirez, C.M., Ustin, S.L., Slaton, M., Haunreiter, E., 2019. eDaRT: the ecosystem disturbance and recovery tracker system for monitoring landscape disturbances and their cumulative effects. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.111482.

Li, J., Roy, D., 2017. A global analysis of Sentinel-2A, Sentinel-2B and Landsat-8 data revisit intervals and implications for terrestrial monitoring. Remote Sens. 9 (9), 902. https://doi.org/10.3390/rs9090902.

Loveland, T.R., Merchant, J.W., Brown, J.F., Ohlen, D.O., Reed, B.C., Olson, P., Hutchinson, J., 1995. Seasonal land-cover regions of the United States. Ann. Assoc. Am. Geogr. 85 (2), 339–355. https://doi.org/10.1111/j.1467-8306.1995.tb01798.x.

Lymburner, L., Bunting, B., Lucas, R., Scarth, P., Alam, I., Phillips, C., Ticehurst, C., Held, A.A., 2019. Mapping the multi-decadal mangrove dynamics of the Australian coastline. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.05.004.

Nguyen, L.H., Joshi, D.R., Clay, D.E., Henebry, G.M., 2019. Characterizing land cover/land use from multiple years of Landsat and MODIS time series: a novel approach using land surface phenology modeling and random forest classifiers. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2018.12.016.

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., Wulder, M.A., 2014. Good practices for assessing accuracy and estimating area of land change. Remote Sens. Environ. 148, 42–57. https://doi.org/10.1016/j.rse.2014.02.015.

Pengra, B., Stehman, S., Horton, J., Dockter, D., Schroeder, T., Yang, Z., Cohen, W.B., Healey, S.P., Loveland, T.R., 2019. Quality control and assessment of interpreter consistency of annual land cover reference data in an operational national monitoring program. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.111261.

Roy, D., Yan, L., 2019. Robust Landsat-based crop time series modelling. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2018.06.038.

Singh, A., 1989. Review article: digital change detection techniques using remotely sensed data. Int. J. Remote Sens. 10 (6), 989–1003. https://doi.org/10.1080/01431168908903939.

Uhl, J.H., Leyk, S., 2019. Towards a novel backdating strategy for creating built-up land time series data using contemporary spatial constraints. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.05.016.

Verbesselt, J., Hyndman, R., Newnham, G., Culvenor, D., 2010. Detecting trend and seasonal changes in satellite image time series. Remote Sens. Environ. 146, 106–115. https://doi.org/10.1016/j.rse.2009.08.014.

Viovy, N., Arino, O., Belward, A.S., 1992. The Best Index Slope Extraction (BISE): a method for reducing noise in NDVI time-series. Int. J. Remote Sens. 13 (8), 1585–1590. https://doi.org/10.1080/01431169208904212.

Vogelmann, J.E., Gallant, A.L., Shi, H., Zhu, Z., 2016. Perspectives on monitoring gradual change across the continuity of Landsat sensors using time-series data. Remote Sens. Environ. 185, 258–270. https://doi.org/10.1016/j.rse.2016.02.060.

Wang, X., Xiao, X., Zou, Z., Zhong, Q., Da, S., Li, B., Zhao, N., Chen, B., Li, X., Qin, Y., Dong, J., Doughty, R.B., Ma, J., 2019. Tracking annual changes of coastal tidal flats in China during 1986–2016 through analyses of Landsat images with Google Earth Engine. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2018.11.030.

Wulder, M.A., Masek, J.G., Cohen, W.B., Loveland, T.R., Woodcock, C.E., 2012. Opening the archive: how free data has enabled the science and monitoring promise of Landsat. Remote Sens. Environ. 122, 2–10. https://doi.org/10.1016/j.rse.2012.01.010.

Yang, Y., Hain, C., Noormets, A., Sun, G., Sun, S., Anderson, M., Wynne, R., Thomas, V., Gao, F., 2019. Investigating impacts of drought and disturbance on evapotranspiration over a forested landscape in North Carolina, USA using high spatiotemporal resolution remotely sensed data. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2018.12.017.

Zhu, Z., Woodcock, C.E., 2014. Continuous change detection and classification of land cover using all available Landsat data. Remote Sens. Environ. 144, 152–171. https://doi.org/10.1016/j.rse.2014.01.011.

Zhu, Z., Cohen, W., Zhou, C., Yang, Z., Qiu, S., Zhang, J., Aljaddani, A.H., 2019. Continuous monitoring of land disturbance based on Landsat time series. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.03.009.