This paper presents a review of the current state of the art in remote sensing based monitoring of forest disturbances and forest degradation from optical Earth Observation data. Part one comprises an overview and tabular description of currently available optical remote sensing sensors, which can be used for forest disturbance and degradation mapping. A section is devoted to currently existing mapping approaches, including both operational methods and recent developments. Part two reviews the two main categories of existing mapping approaches: first, classical image-to-image change detection and second, time series analysis. With the launch of the Sentinel-2a satellite and available Landsat imagery, time series analysis has become the most promising but also most demanding category of degradation mapping approaches. Hence, an emphasis is put on methods of time series analysis, among which four different classification methods are distinguished. The methods are explained and their benefits and drawbacks are discussed. A separate chapter presents a number of recent forest degradation mapping studies for two different ecosystems: The first ecosystem comprises the temperate forests with a geographical focus on Europe.
The second ecosystem consists of the tropical forests with a geographical focus on Africa. Mapping examples from both ecosystems help to better illustrate the current state of the art.
1. Introduction

Reliable and operational methods for forest disturbance and forest degradation mapping have become increasingly important for sustainable forest management [1]. A key aspect of sustainable forest management is the monitoring of the forest status, including the assessment of forest disturbances and forest degradation. The term forest disturbance is mostly used for natural causes of crown cover or biomass loss, such as from storm damage, forest fires, drought stress, insect infestations and disease outbreaks but may also include harvesting operations with a potential negative impact. The term forest degradation mostly relates to human-induced crown cover or biomass loss, e.g. for Intergovernmental Panel on Climate Change (IPCC) carbon reporting forest degradation is described as a “direct human-induced activity that leads to a long-term reduction in forest carbon stocks” [2]. A further difference between the two terms exists with regard to the temporal impact. A disturbance is usually a single event with a short term impact and may even be regarded as part of the natural forest dynamics, while degradation has a negative long term impact that may be a consequence of one or several single disturbances [3]. Some definitions use forest degradation as an umbrella term for both natural and human-induced forest changes; e.g. the Food and Agriculture Organization of the United Nations (FAO) defines forest degradation as “changes within the forest which negatively affect the structure or function of the stand or site, and thereby lower the capacity to supply products and/or services”[4]. In this review, we follow the FAO definition and use the term forest degradation for both natural and human-induced changes but we also address methods for mapping disturbances that may not have a long term degrading effect.

Forest degradation mapping by means of remote sensing is essentially a specific application of change detection. Change detection in forest monitoring already has a long tradition starting with Landsat data in the 1980ies and 1990ies [5, 6]. Back then, the main focus was on mapping deforestation and forest regeneration. Assessing and mapping forest degradation is much more challenging than only mapping forest area change. Meanwhile yearly deforestation mapping and the derivation of deforestation rates are already operational at global [7] and also at the national level [8], but there is still only fragmented information available on the extent and magnitude of forest degradation. With Sentinel-2 image data from European Space Agency (ESA) complemented by Landsat 8 from United States Geological Survey (USGS), more high resolution optical data is now available than ever before. These data sets can be used to build a time series. Tracking areas closely over time allows detecting subtle changes (for both deforestation and forest degradation) and generates the possibility to alert in near real time, when changes are occurring.

This paper reviews and discusses available methods used for forest degradation detection from optical remote sensing with a focus on methods based on high resolution data. Methods developed for coarse resolution data e.g. from the ‘Moderate-resolution Imaging Spectroradiometer’ (MODIS) are only considered if they have the potential to be transferred to high resolution data as well. The reviewed methods can be divided into two categories: i) image to image change detection methods and ii) time series analysis. Due to the increasing availability of high frequency observation data, i.e. more than one image per month, the focus is placed on time-series analysis. Although radar data are another important information source, especially for the tropics, they are not considered for review in this article, as methods and algorithms significantly differ from those applied to optical imagery. The review is complemented by several mapping examples of the authors. Since forest types, seasonal effects as well as degradation drivers differ with geographic location, the mapping examples focus on two main ecosystems: Europe’s temperate forests and Africa’s tropical evergreen forests.
In temperate forests in Europe, damages caused by storms [9], bark beetles and fires [10] have increased throughout the twentieth century and, are likely to increase further with global warming, though decreasing fires have recently been observed in Mediterranean Europe [11]. Within the first decade of the 21st century, an increase was observed that is substantial enough to be considered a potential threat to the current and future role of European forests as carbon sinks [12]. As a result of this increase, politicians in Europe have recognized the urgent need to gather information on forest health and vitality, and to make this information available to end-users, i.e. forest administration and forest management planning entities. This need is emphasized by the Green paper [13] of the European Commission and in the new European Union (EU) Forest Strategy [1]. Information on degradation caused by storm, wind, snow and human-induced damage by forest operations can be found in the “State of Europe’s Forests 2015” report [14], which has been jointly prepared by the signatory countries of “Forest Europe”, the former “Ministerial Conference on the Protection of Forests in Europe”. However, the usability of this information is limited as it is provided as total area figures per country only and the assessment does not follow a strict nomenclature. While there is a recognized demand for information on forest degradation in Europe, the available data is not yet harmonized and only partly geo-located. Advanced remote sensing technology can provide the timely, accurate and geo-located information that is needed. Such a service is currently being developed by the European Commission (EC) funded DIABOLO project (Distributed, Integrated And Harmonised Forest Information For Bioeconomy Outlooks).

Tropical forests are under even greater pressure than temperate forests: based on a recent review [15], tropical forests once covered 3.6 billion hectares [...] almost a third have been lost as a result of deforestation. Of the remaining area, 46% is fragmented, 30% degraded, and only 24% is in a mature and relatively undisturbed state [16]. Some authors indicate even an increase in deforestation in tropical areas in the last years [17, 7]. The main drivers for tropical forest degradation are unsustainable selective logging, forest fires, mining activities and overexploitation of fuel wood [18]. Recent results indicate that tropical forest degradation has a similar or even a greater impact on carbon emissions than tropical deforestation. Depending on the source, emissions from tropical deforestation vary around 8 % [19] (7.4 % [20] and 8.5 % [21]) and from degradation between 6 % [19] and 14% [20]. Forest degradation is therefore a substantial component of overall anthropogenic carbon emissions. The large range of values given for carbon emissions from degradation reflects the difficulty in actually assessing forest degradation [22]. The EC funded project EOMonDis (Bringing Earth Observation Services for Monitoring Dynamic Forest Disturbances to the Users) aims to offer operational Earth Observation (EO) based tropical forest monitoring services to support countries and a wide range of users with accurate relevant forest information data for their management and reporting requirements.

2. Optical Earth Observation data sets

The following section presents the characteristics and timelines of different optical high resolution (HR) sensors. In this review, we define ‘high resolution’ as pixel size between 5 and 30 m. One of the important qualities when choosing the image data sources for a degradation mapping service is the spatial and temporal characteristics of the sensors. While very high spatial (VHR) resolution sensors (< 2 m multispectral pixel size) may have better degradation detection capabilities, the image generally has a much smaller footprint compared to a high or medium resolution sensor. This means that independent of
the repeat cycle and revisit frequency of the satellite, the wall to wall coverage using very high resolution sensors is generally more cost and time consuming and in case of larger areas even impossible. Medium to coarse resolution sensors (> 60 m multispectral pixel size), despite having lower cost/time requirements for wall-to-wall data coverages, are very limited in their ability to detect small area disturbances. High resolution satellite systems can be considered a good compromise, offering high enough spatial resolution and large enough footprint for cost-efficient large scale degradation monitoring. Table 1 presents the technical specifications of currently active optical HR satellites that can potentially be used for forest degradation monitoring. With regards to the repeat cycle, the values given for nadir only sensors are ignoring overlaps. The revisit frequency is calculated including possible tilting capabilities of the sensor.

Table 1 Active satellite missions overview - optical HR satellites/sensors specifications

| Satellite system | Mission start/ completion | Spectral characteristics [in µm] | Orbit height | Swath width | Resolution | Repeat Cycle | Revisit Frequency |
|------------------|---------------------------|----------------------------------|--------------|-------------|------------|--------------|------------------|
| Formosat-2 (ROCSat-2) (NSPO, Taiwan) | 2004 - * | 0.45 – 0.90 0.45 – 0.52 0.52 – 0.60 | 0.63 – 0.69 0.76 – 0.90 | 888 km | 24 km | PAN: 2m Others: 8m | 1 day 1 day |
| Landsat 7 (USGS, USA) | 1999 - * | 0.52 – 0.90 0.45 – 0.52 0.53 – 0.61 0.63 – 0.69 | 0.78 – 0.90 1.55 – 1.75 2.09 – 2.35 | 705 km | 185 km | PAN: 15m Others: 30m | 16 days 16 days |
| Landsat 8 (USGS, USA) | 2013 - * | 0.50 – 0.68 0.433 – 0.453 0.45 – 0.515 0.525 – 0.60 0.63 – 0.68 | 0.845 – 0.885 1.36 – 1.39 1.56 – 1.66 2.10 – 2.30 | 705 km | 185 km | PAN: 15m Others: 30m | 16 days 16 days |
| RapidEye (RapidEye AG, BlackBridge Germany) | 2008. * | 0.44 – 0.51 0.52 – 0.59 0.63 – 0.685 0.69 – 0.73 0.76 – 0.85 | | 630 km | 77 km | 5m | 5.5 days 1 day |
| Sentinel-2 (ESA, EU) | 2015 - * (≈ 2027) | center wavelength : band width – band : 0.443; 0.02 – 1 0.490; 0.065 – 2 0.560; 0.035 – 3 0.665; 0.03 – 4 0.705; 0.015 – 5 0.740; 0.015 – 6 0.783; 0.015 – 7 0.842; 0.015 – 8 0.865; 0.02 – 8a 0.945; 0.02 – 9 1.375; 0.03 – 10 1.610; 0.09 – 11 2.190; 0.180 – 12 | 786 km | 290 km | B2,B3,B4,B8: 10m B5,B6,B7,B8a, B11,B12: 20m B1,B9,B10: 60m | 10 days (Sentinel-2A); 5 days (Sentinel-2A & 2B) 10 days (Sentinel-2A); 5 days (Sentinel-2A & 2B) |
| Spot 6/7 (France) | 2012. - * (≈ 2025) | 0.45 – 0.745 0.45 – 0.52 0.53 – 0.59 0.625 – 0.695 0.76 – 0.89 | | 60 km | 2.2m Others: 8.8m | 26 days 1-5 days |
| UK-DMC-1/2 (SSTL, UK) | 2003. * | 0.52 – 0.62 0.63 – 0.69 0.76 – 0.90 | | 686 km | 650 km | 32m | 14 days 1 day |
| HJ-1A/1B (China) | 2008. * | 0.43 – 0.52 0.52 – 0.60 0.63 – 0.69 0.76 – 0.90 | | 650 km | 360 km | 30m | 4 days 4 days |
| CBERS-4 (Ziyuan 4-04) (China, Brazil) | 2014. * | MUXCam: 0.45-0.52 0.52-0.59 0.63-0.69 0.77-0.89 PanMUX: 0.51-0.73 (PAN) 0.52-0.59 0.63-0.69 0.77-0.89 | | 748 km | MUXCam: 120 km PanMUX : 60 km | MUXCam: 20m PanMUX: 5m (PAN), 10m (Others) | 26 days 3 – 26 days |
The table shows the list of potential candidate satellite sensors that are collecting optical EO data at high resolution and these sensors enable a new dimension of monitoring capabilities in a multi sensor approach [23], [24], [25]. A regular nadir acquisition scheme is an advantage for a regular and continuous monitoring system. Since the satellites from the Landsat series and Sentinel-2 fulfil this condition and also provide open and cost free access to archives and newly acquired images, these satellites are the workhorses for degradation mapping. The spectral capabilities of the Landsat and Sentinel-2 satellite missions complement each other (Figure 1) and, therefore, it should be possible to increase the density of the time series data by integrating the sensors.

Figure 1 Comparison of Landsat 7 and 8 bands with Sentinel-2 (source: http://landsat.gsfc.nasa.gov)

The Landsat program has been providing continuous multispectral data since 1972 and this data is available without restrictions from USGS. In addition to the Landsat Level 1 standard data products, higher level science data products (e.g. surface reflectance) can also be ordered through a number of data access sites (URLs: http://earthexplorer.usgs.gov, last accessed 29.12.2015; http://glovis.usgs.gov, last accessed 29.12.2015). The current operational satellites are Landsat 7 and Landsat 8. It should be mentioned, that Landsat 7 ETM+ has had a failure of the Scan Line Corrector (SLC) leading to missing data in all images from 2003 onwards and therefore some limitations in usability of this data. The long term continuity of data from the program is foreseen to continue well into the future, with Landsat 9 planned for launch in 2023, although there is a risk, that Landsat 8 could stop working before Landsat 9 is in orbit.
Sentinel-2 is planned as a “two satellite mission”: the first, Sentinel-2A, was launched June 23rd, 2015 (full operational readiness is planned for July 2016) and Sentinel-2B is planned for launch in 2017. The operational lifespan of the Sentinel-2 mission is 7.25 years, while the consumables can last for up to 12 years (source: ESA, https://earth.esa.int/web/guest/missions/esa-operational EO-missions/sentinel-2, accessed 22.12.2015). In order to guarantee continuity with two parallel sensors in orbit, ESA has already contracted Airbus Defense and Space for the construction of Sentinel-2C and -2D. Available Sentinel-2 images can be downloaded at the Scientific Data Hub and have been provided in the form of a “rolling archive” since December 2015.

3. Methods for forest degradation mapping

3.1. Image-to-image change detection

3.2. Time series based change detection

---

![Diagram](image.png)

Figure 2: Schematic illustration of different time series analysis methods

- a) Threshold based change detection
- b) Curve fitting
- c) Trajectory fitting
- d) Trajectory segmentation
b) Curve fitting  
c) Trajectory fitting  
d) Trajectory segmentation

4. Some Forest Degradation Mapping Examples

In the following, five mapping examples are given to illustrate the methods described above. They cover various methods explained above. In order to illustrate the examples, Figure 5 shows some resulting maps from these mapping examples.

4.1. European forest monitoring examples

4.2. Tropical forest monitoring examples in Africa

ME3: Classification vs assumed intact forest for mapping degradation in the Democratic Republic of Congo (DRC)

ME4: Trajectory fitting for degradation mapping in the Republic of Congo

5. Conclusions

The review of methods shows that there are already many methods available for bi-temporal change detection from high resolution data on the one hand and for time series analysis from coarse resolution data on the other hand. The current main challenge and research development focus is transferring these approaches to high resolution time series data which is currently becoming available from Sentinel 2 (in combination with Landsat data) and to improve the preprocessing quality of the high resolution time series. Further these methods need to be developed towards disturbance classification to enable the analysis of the different disturbance types such as e.g. fire, storm, insect caused damages, degradation by selective logging etc. along with the increasing density and length of time series. This has to be accompanied by a focus on the development of robust up- scalable methods that will enable both near real time disturbance mapping in support of operational reactive measures and as well the development of long term regional and global observation capacities for disturbances by major disturbance types.

6. Acknowledgements

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 685761 (EOMonDIS) as well as under grant agreement No 633464 (DIABOLO). The study in Congo was performed within the project GSE-Forest Monitoring REDD Extension Services, financed by ESA.
References:

[1] European Commission, “Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: A new EU Forest Strategy: for forests and the forest-based sectors.” online, last access: 11 April 2016 2013.

[2] IPCC, “Good Practice Guidance for Land Use, Land-Use Change and Forestry (GPG-LULUCF).” http://www.ipcc-nggip.iges.or.jp/public/gpglulucf/gpglulucf_contents.html, 2003. accessed 5 Oct 2016.

[3] FAO, “Forest Resources Assessment Working Paper 177: Assessing forest degradation: Towards the development of globally applicable guidelines.” http://www.fao.org/docrep/015/i2479e/i2479e00.pdf, Rome, 2011.

[4] D. Schoene, W. Killmann, H. Lüpke, and M. LoycheWilkie, “Forest and Climate Change Working Paper 5: Definitional issues related to reducing emissions from deforestation in developing countries.” ftp://ftp.fao.org/docrep/fao/009/j9345e/j9345e00.pdf, 2007. last accessed: May 25th, 2016.

[5] A. Singh, “Review article digital change detection techniques using remotely-sensed data,” International Journal of Remote Sensing, vol. 10, pp. 989–1003, jun 1989.

[6] P. R. Coppin and M. E. Bauer, “Change Detection in Forest Ecosystems with Remote Sensing Digital Imagery,” Remote Sensing Reviews, no. 13, pp. 207–234, 1996.

[7] M. C. Hansen, P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend, “High-resolution global maps of 21st-century forest cover change,” Science, vol. 342, no. 6160, pp. 850–853, 2013.

[8] P. Potapov, S. Turubanova, M. Hansen, B. Adusei, M. Broich, A. Altstatt, L. Mane, and C. Justice, “Quantifying Forest Cover Loss in Democratic Republic of Congo, 2000-2010, with Landsat ETM+ data,” Remote Sensing of Environment, vol. 122, pp. 106–116, 2012.

[9] B. Gardiner, K. Blennow, J.-M. Carnus, M. Fleischer, F. Ingemarson, G. Landmann, M. Lindner, M. Marzano, B. Nicoll, C. Orazio, J.-L. Peyron, M.-P. Reviron, M.-J. Schelhaas, A. Schuck, M. Spielmann, and T. Usbeck, “Destructive storms in European forests: past and forthcoming impacts.” http://ec.europa.eu/environment/forests/pdf/STORMS%20Final_Report.pdf, 2010. Last accessed: Oct, 5th 2016.

[10] N. Koutsias, G. Xanthopoulos, D. Founda, F. Xystrakis, F. Nioti, M. Pleniou, G. Mallinis, and M. Arianoutsou, “On the relationships between forest fires and weather conditions in Greece from long-term national observations (1894-2010),” International Journal of Wildland Fire, vol. 22, no. 4, pp. 493–507, 2013.

[11] M. Turco, J. Bedia, F. Di Liberto, P. Fiorucci, J. von Hardenberg, N. Koutsias, M.-C. Llasat, F. Xystrakis, and A. Provenzale, “Decreasing Fires in Mediterranean Europe,” PLoS ONE, vol. 11, p. e0150663, March 2016.
On the basis of an ensemble of climate change scenarios, the authors find that damage from wind, bark beetles and forest fires in Europe is likely to increase further in coming decades, and they estimate the rate of increase to be $+0.91 \times 10^6$ m$^3$ of timber per year until 2030.

European Commission, “Green Paper: On Forest Protection and Information in the EU: Preparing forests for climate change.” http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2010:0066:FIN:EN:PDF, 2010. Last accessed: Oct, 5th 2016.

“Full State of Europe’s Forests 2015.” http://www.foresteurope.org/fullsoef2015, 2015. Last accessed: Oct, 5th 2016.

International Sustainability Unit, “Tropical Forests - A Review.” http://www.pcfisu.org/wp-content/uploads/2015/04/Princes-Charities-International-Sustainability-Unit-Tropical-Forests-A-Review.pdf, 2015. Last accessed: Oct, 5th 2016.

L. L. Susan Minnemeyer, N. Sizer, C. Saint-Laurent, and P. Potapov, “A world of opportunity.” http://www.wri.org/sites/default/files/world_of_opportunity_brochure_2011-09.pdf, 2011. Last accessed: Oct, 5th 2016.

D.-H. Kim, J. O. Sexton, and J. R. Townshend, “Accelerated deforestation in the humid tropics from the 1990s to the 2000s,” Geophysical Research Letters, vol. 42, pp. 3495–3501, may 2015.

R. DeFries, F. Achard, S. Brown, M. Herold, D. Murdiyarso, B. Schlamadinger, and C. de Souza, “Earth observations for estimating greenhouse gas emissions from deforestation in developing countries,” Environmental Science & Policy, vol. 10, no. 4, pp. 385–394, 2007.

N. L. Harris, S. Brown, S. C. Hagen, S. S. Saatchi, S. Petrova, W. Salas, M. C. Hansen, P. V. Potapov, and A. Lotsch, “Baseline map of carbon emissions from deforestation in tropical regions,” Science, vol. 336, pp. 1573–1576, June 2012.

R. A. Houghton, J. I. House, J. Pongratz, G. R. van der Werf, R. S. DeFries, M. C. Hansen, C. L. Quéré, and N. Ramankutty, “Carbon emissions from land use and land-cover change,” Biogeosciences, vol. 9, pp. 5125–5142, dec 2012.

J. Grace, E. Mitchard, and E. Gloor, “Perturbations in the carbon budget of the tropics,” Global Change Biology, vol. 20, pp. 3238–3255, June 2014.

J.-P. Lanly, “Deforestation and forest degradation factors,” in Proceedings of XII World Forestry Congress, 2003.

C. Kuenzer, S. Dech, and W. Wagner, eds., Remote Sensing Time Series: Revealing Land Surface Dynamics. Springer International Publishing, 2015. Comprehensive review of different time series approaches for different data sets and applications from around the globe.
[24] M. Wulder, T. Hilker, J. White, N. Coops, J. Masek, D. Pflugmacher, and Y. Crevier, “Virtual constellations for global terrestrial monitoring,” Remote Sensing of Environment, vol. 170, pp. 62–76, 2015.

[25] P. Hostert, P. Griffiths, S. van der Linden, and D. Pflugmacher, Time Series Analyses in a New Era of Optical Satellite Data, ch. 15: Forest Cover Dynamics During Massive Ownership Changes - Annual Disturbance Mapping Using Annual Landsat Time-Series, pp. 307–322. Springer International Publishing, 2015.

[26] B. A. Margono, S. Turubanova, I. Zhuravleva, P. Potapov, A. Tyukavina, A. Baccini, S. Goetz, and M. C. Hansen, “Mapping and monitoring deforestation and forest degradation in Sumatra (Indonesia) using Landsat time series data sets from 1990 to 2010,” Environmental Research Letters, vol. 7, pp. 1–16, 2012.

[27] N. H. Ravindranath, N. Srivastava, I. K. Murthy, S. Malaviya, M. Munsi, and N. Sharma, “Deforestation and Forest Degradation in India - Implications for REDD+,” Current Science, vol. 102, pp. 1117–1125, April 2012.

[28] E. A. Matricardi, D. L. Skole, M. A. Pedlowski, W. Chomentowski, and L. C. Fernandes, “Assessment of tropical forest degradation by selective logging and fire using Landsat imagery,” Remote Sensing of Environment, vol. 114, pp. 1117–1129, 2010.

[29] C. Huang, S. Goward, J. Masek, N. Thomas, Z. Zhu, and J. Vogelmann, “An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks,” Remote Sensing of Environment, vol. 114, pp. 183–198, 2010.

[30] N. Kayastha, V. Thomas, J. Galbraith, and A. Banskota, “Monitoring wetland change using inter-annual Landsat time-series data,” Wetlands, vol. 32, pp. 1149–1162, 2012.

[31] W. Hargrove, J. Spruce, G. Gasser, L. Martin, and S. Norman, “Monitoring Regional Forest Disturbances across the US with Near Real Time MODIS NDVI Products included in the ForWarn Forest Threat Early Warning System.” Presented at the 2013 AGU Fall Meeting, 2013.

[32] J. E. Vogelmann, G. Xian, C. Homer, and B. Tolk, “Monitoring gradual ecosystem change using Landsat time series analyses: Case studies in selected forest and rangeland ecosystems,” Remote Sensing of Environment, vol. 122, pp. 92–105, 2012.

[33] E. Lehmann, J. Wallace, P. Caccetta, S. Furby, and K. Zdunic, “Forest cover trends from time series Landsat data for the Australian continent,” International Journal of Applied Earth Observation and Geoinformation, vol. 21, pp. 453–462, 2013.

[34] C. Bayr, H. Gallaun, U. Kleb, B. Kornberger, M. Steinegger, and M. Winter, “Satellite Based Forest Monitoring: Spatial and Temporal Forecast of Growing Index and Short Wave Infrared Band,” Geospatial Health, vol. 11(1), pp. 31–42, 2016.

[35] R. E. Kennedy, W. B. Cohen, and T. A. Schroeder, “Trajectory-based change detection for automated characterization of forest disturbance dynamics,” Remote Sensing of Environment, vol. 110, pp. 370 – 386, 2007.
The authors showed that time series approaches can provide good results for gradual changes such as recovery or degradation in Europe, even if only annual data is available.

R. E. Kennedy, Z. Yang, and W. B. Cohen, “Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation algorithms,” Remote Sensing of Environment, vol. 114, no. 12, pp. 2897 – 2910, 2010.

W. B. Cohen, Z. Yang, and R. Kennedy, “Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync - Tools for calibration and validation,” Remote Sensing of Environment, vol. 114, no. 12, pp. 2911–2924, 2010.

N. Koutsias, M. Pleniou, G. Mallinis, F. Nioti, and N. I. Sifakis, “A rule-based semi-automatic method to map burned areas: exploring the USGS historical Landsat archives to reconstruct recent fire history,” International Journal of Remote Sensing, vol. 34, pp. 7049–7068, oct 2013.

L. Eklundh, T. Johansson, and S. Solberg, “Mapping insect defoliation in Scots pine with MODIS time-series data,” Remote Sensing of Environment, vol. 113, pp. 1566–1573, 2009.

J. Verbesselt, R. Hyndman, G. Newnham, and D. Culvenor, “Detecting trend and seasonal changes in satellite image time series,” Remote Sensing of Environment, vol. 114, no. 1, pp. 106–115, 2010.

D. Pflugmacher, W. B. Cohen, and R. E. Kennedy, “Using landsat-derived disturbance history (1972-2010) to predict current forest structure,” Remote Sensing of Environment, vol. 122, pp. 146–165, jul 2012. This study demonstrates the unique value of the long, historic Landsat record, and suggests new potentials for mapping current forest structure with time series data.

K. Granica and M. Schardt, “User Utility Synthesis Report.” https://www.eufodos.info/sites/default/files/reports/EF-REP-JR-2012-07-26_D510_1-synth_report_v1.pdf, 2012. Last accessed: Oct. 5ht 2016.

G. P. Asner, M. Keller, R. Pereira, and J. C. Zweede, “Remote sensing of selective logging in Amazonia Assessing limitations based on detailed field observations, Landsat ETM+, and textural analysis,” Remote Sensing of Environment, vol. 80, no. 3, pp. 483–496, 2002.

G. P. Asner, D. E. Knapp, E. N. Broadbent, P. J. C. Oliveira, M. Keller, and J. N. Silva, “Selective Logging in the Brazilian Amazon,” American Association of the Advancement of Science, vol. 310, pp. 480–482, 2005.

M. Hansen, A. Krylov, A. Tyukavina, P. Potapov, S. Turubanova, B. Zutta, S. Ifo, B. Margono, F. Stolle, and R. Moore, “Humid tropical forest disturbance alerts using landsat data,” Environmental Research Letters, vol. 11, no. 3, p. 034008, 2016. This paper shows the first results of an operational forest disturbance alert system using Landsat data in three tropical countries. The results show
very high user's accuracies and moderately high producer's accuracies and are freely available on
the internet.

[47] A. Koltunov, S. Ustin, G. P. Asner, and I. Fung, “Selective logging changes forest phenology in
the Brazilian Amazon: Evidence from MODIS image time series analysis,” Remote Sensing of
Environment, vol. 113, pp. 2431–2440, 2009.

[48] M. Hirschmugl, M. Steinegger, H. Gallau, and M. Schardt, “Mapping Forest Degradation due
Selective Logging by Means of Time Series Analysis: Case Studies in Central Africa,” Remote
Sensing, vol. 6 (1), no. ISSN 2072-4292, pp. 756–775, 2014. Selective logging is a major driver of
forest degradation in Central Africa, but often goes undetected due to the fast regrowth in tropical
areas. This paper presents a method to detect the affected areas in a 10-years Landsat time series.

[49] P. Coppin, I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin, “Digital change detection
methods in ecosystem monitoring: a review,” International Journal of Remote Sensing, vol. 25, no. 9,
pp. 1565–1596, 2004.

[50] V. Walter, “Object-based classification of remote sensing data for change detection,” ISPRS
Journal of Photogrammetry and Remote Sensing, vol. 58, no. 3-4, pp. 225–238, 2004.

[51] F. Sedano, P. Kempeneers, J. S. Miguel, P. Strobl, and P. Vogt, “Towards a pan-European burnt
scar mapping methodology based on single date medium resolution optical remote sensing data,”
International Journal of Applied Earth Observation and Geoinformation, vol. 20, pp. 52–59, 2013. The
authors present a two stage approach for operational burnt scar mapping with medium resolution
remote sensing data in Mediterranean Europe with an increased capability for detection of smaller
burnt scars.

[52] S. Violini, “Deforestation: Change detection in forest cover using remote sensing,” in Seminary
Master in Emergency Early Warning and Response Space Applications, (Mario Gulich Institute, CONAE.
Argentina), pp. 1–28, 2013.

[53] A. Banskota, N. Kayasta, M. Falkowski, M. Wulder, R. Froese, and J. White, “Forest
Monitoring Using Landsat Time Series Data: A Review,” Canadian Journal of Remote Sensing, vol. 40,
no. 5, pp. 362–384, 2014. Comprehensive review of time series approaches using Landsat data
including preprocessing steps and verification methods.

[54] C. Kuenzer, S. Dech, and W. Wagner, Remote Sensing Time Series: Revealing Land Surface
Dynamics, ch. 1: Remote Sensing Time Series Revealing Land Surface Dynamics: Status Quo and the
Pathway Ahead, pp. 1–24. Springer International Publishing, 2015.

[55] L. Eklundh and P. Jönsson, Remote Sensing Time Series: Revealing Land Surface Dynamics,
ch. 7: TIMESAT: A Software Package for Time-Series Processing and Assessment of Vegetation
Dynamics, pp. 141–158. Springer International Publishing, 2015.

[56] K. Gutjahr, R. Perko, H. Raggam, and M. Schardt, “The Epipolarity Constraint in Stereo-
Radargrammetric DEM Generation,” Geoscience and Remote Sensing, IEEE Transactions on,
vol. Volume:52 , Issue: 8, pp. 5014 – 5022, Aug 2014.
[57] W. Chen, W. Chen, and J. Li, “Comparison of surface reflectance derived by relative radiometric normalization versus atmospheric correction for generating large-scale landsat mosaics,” Remote Sensing Letters, vol. 1, no. 2, pp. 103–109, 2010.

[58] D. Schlaepfer, C. C. Borel, J. Keller, and K. I. Itten, “Atmospheric precorrected differential absorption technique to retrieve columnar water vapour,” Remote Sensing of Environment, no. 65, pp. 353–366, 1998.

[59] U. Mueller-Wilm, Sentinel-2 MSI - Level-2A Prototype Processor Installation and User Manual, 2016. Last accessed 5 Oct 2016.

[60] O. Hagolle, M. Huc, D. Villa Pascual, and G. Dedieu, “A Multi-Temporal and Multi-Spectral Method to Estimate Aerosol Optical Thickness over Land, for the Atmospheric Correction of FormoSat-2, LandSat, VEnUS and Sentinel-2 Images,” Remote Sensing, vol. 7, no. 3, p. 2668, 2015.

[61] C. Chance, T. Hermosilla, N. Coops, M. Wulder, and J. White, “Effect of topographic correction on forest change detection using spectral trend analysis of Landsat pixel-based composites,” vol. 44, pp. 186–194, 2016.

[62] C. Huang, N. Thomas, S. N. Goward, J. G. Masek, Z. Zhu, J. R. G. Townshend, and J. E. Vogelmann, “Automated masking of cloud and cloud shadow for forest change analysis using Landsat images,” Int. Journal of Remote Sensing, vol. 31, pp. 5449–5464, October 2010.

[63] Z. Zhu and C. Woodcock, “Object-based cloud and cloud shadow detection in landsat imagery,” Remote Sensing of Environment, vol. 118, pp. 83–94, 2012.

[64] Z. Zhu, S. Wang, and C. E. Woodcock, “Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsats 4-7, 8, and Sentinel 2 images,” Remote Sensing of Environment, vol. 159, pp. 269 – 277, 2015.

[65] D. C. Morton, R. S. D. Y. E. Shimabukuro, L. O. Anderson, F. D. B. Espírito-Santo, M. Hansen, and M. Carroll, “Rapid Assessment of Annual Deforestation in the Brazilian Amazon Using MODIS Data,” Earth Interactions, vol. 9, no. 8, pp. 1–22, 2005.

[66] C. G. Diniz, A. A. de Almeida Souza, D. C. Santos, M. C. Dias, N. C. da Luz, D. R. V. de Moraes, J. S. Maia, A. R. Gomes, I. da Silva Narvæs, D. M. Valeriano, L. E. P. Maurano, and M. Adami, “DETER-B: The New Amazon Near Real-Time Deforestation Detection System,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, no. 7, 2015.

[67] J. Miettinen, H.-J. Stibig, F. Achard, A. Langner, and S. Carboni, “Remote Sensing of Forest Degradation in Southeast Asia - Regional Review,” Asian Journal of Geoinformation, vol. 15, pp. 23–30, 2015.

[68] P. Potapov, S. Turubanova, A. Tyukavina, A. Krylov, J. McCarty, V. Radeloff, and M. Hansen, “Eastern europe’s forest cover dynamics from 1985 to 2012 quantified from the full landsat archive,” Remote Sensing of Environment, vol. 159, pp. 28–43, 2015. The authors developed an algorithm to simultaneously process data from different Landsat platforms and sensors (TM and ETM +) to
map annual forest cover loss and decadal forest cover gain and applied it on 59,539 Landsat images across Eastern Europe and European Russia with accuracies > 75%.

[69] Z. Zhu, C. E. Woodcock, and P. Olofsson, “Continuous monitoring of forest disturbance using all available landsat imagery,” Remote Sensing of Environment, vol. 122, pp. 75–91, 2012. The Continuous Monitoring of Forest Disturbance Algorithm (CMFDA) presented in this paper flags forest disturbance by differencing the predicted and observed Landsat images with both producer’s and user’s accuracies higher than 95% in the spatial domain and temporal accuracy of approximately 94%.

[70] de Beurs, K. M. and G. M. Henebry, “A statistical framework for the analysis of long image time series,” International Journal of Remote Sensing, vol. 26, no. 8, pp. 1551–1573, 2005.

[71] M. Kuhn, “Building Predictive Models in R Using the caret Package,” Journal of Statistical Software, vol. 28, no. 5, 2008.

[72] A. Ghosh, F. E. Fassnacht, P. Joshi, and B. Koch, “A framework for mapping tree species combining hyperspectral and LiDAR data: Role of selected classifiers and sensor across three spatial scales,” International Journal of Applied Earth Observation and Geoinformation, vol. 26, pp. 49–63, Feb. 2014.