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Review

# Remote sensing of land change: A multifaceted perspective

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ABSTRACT

The discipline of land change science has been evolving rapidly in the past decades. Remote sensing played a major role in one of the essential components of land change science, which includes observation, monitoring, and characterization of land change. In this paper, we proposed a new framework of the multifaceted view of land change through the lens of remote sensing and recommended five facets of land change including change location, time, target, metric, and agent. We also evaluated the impacts of spatial, spectral, temporal, angular, and data-integration domains of the remotely sensed data on observing, monitoring, and characterization of different facets of land change, as well as discussed some of the current land change products. We recommend clarifying the specific land change facet being studied in remote sensing of land change, reporting multiple or all facets of land change in remote sensing products, shifting the focus from land cover change to specific change metric and agent, integrating social science data and multi-sensor datasets for a deeper and fuller understanding of land change, and recognizing limitations and weaknesses of remote sensing in land change studies.

## 1. Introduction

With the increasing contemporary concerns on climate change, global environmental change, and sustainability, land change science has emerged as a unique science direction for addressing these challenging issues (Gutman et al., 2004; Rindfuss et al., 2004; Turner et al., 2007). Land change science, defined as "the interdisciplinary field [that] seeks to understand the dynamics of land cover and land use as a coupled human-environment system to address theory, concepts, models, and applications relevant to environmental and societal problems, including the intersection of the two" (Turner et al., 2007), has many components, in which one of the most fundamental and critical components is the observation, monitoring, and characterization of land change.

The terrestrial surface of the Earth has been changing at an unprecedented rate. More than half of the Earth's ice-free land surface has been modified by humans (Ellis et al., 2010), and almost all land surfaces have been influenced by climate change and various kinds of land disturbances (Dale, 1997; Potter et al., 2003). Remote sensing, particularly satellite remote sensing, that can provide synoptic and repeated measurements of the global land surface at different spectral, spatial, and temporal resolutions, is of great importance for studying global land change (Justice et al., 1998; Roy et al., 2014; Sellers et al., 1995). In the past decades, big advancements have been made in large-scale mapping of land change based on remote sensing data, due to the rapidly growing amounts of earth observation satellites (Belward and Skøien, 2015; Ustin and Middleton, 2021), the free and open data policy (Woodcock et al., 2008; Wulder et al., 2012; Zhu et al., 2019), the analysis-ready data format (Dwyer et al., 2018; Frantz, 2019), the state-of-art cloud computing platform that not only provides massive parallel computing capability but also a huge amount of online datasets (Gorelick et al., 2017), and the improved capability of new algorithms for land change detection (Banskota et al., 2014; Kennedy et al., 2014; Zhu, 2017). Recently, a paradigm shift from change detection of two points in time to monitoring and tracking change continuously in time is observed in the remote sensing community, where the use of dense time-series observations gain more popularity with a capability of retrieving new land change information, such as subtle changes in ecosystem health and condition, and long-term trend of the vegetation productivity (Woodcock et al., 2020). Moreover, land change information can now be monitored in near real-time (Shang et al., 2022; Tang et al., 2020; Verbesselt et al., 2012; Xin et al., 2013; Ye et al., 2021a), which greatly improves its value to resource managers and policymakers. We have also witnessed a proliferation of land change characterization algorithms (Zhu, 2017), mostly focusing on the "from-to" information, that is, land cover and/or land use information before and after the change (Hansen

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and Loveland, 2012; Pricope et al., 2019). It should be noted that though "land cover" (the physical properties at the Earth's surface) and "land use" (the social, economic, and cultural utility of land) are quite distinct (Turner, 1997), they are often grouped together in remote sensing products, and "land cover" is usually used as a surrogate for understanding "land use", such as including cropland and developed land in the categories of land cover (Anderson et al., 1976). Considering remote sensing data provide information on land cover, rather than on land use, we will mainly focus on land cover change hereafter.

In this paper, we propose the framework of a multifaceted perspective in remote sensing of land change, in which the change in land cover is only one of the components viewed from one of the five facets of land change - the target of change or what is changing. Basically, if we detect change in satellite spectral bands, we can extract the land change information to answer five different questions, that are, when (change time), where (change location), what (change target), how (change metric), and why (change agent) the change happened. Each of the questions will occupy one facet of the change cube that contains the spectral change information derived from remotely sensed data (Fig. 1). The facet on the top of the change cube is left empty on purpose, as there may be other facets of land change that are not discussed in this paper. The two facets of "Time" and "Location" provide information on the detection and monitoring of land change, and the other three facets of "Target", "Metric", and "Agent" are related to the characterization of land change. Indeed, the topic of land change has been extensively reviewed in the remote sensing community, but most focused on change detection techniques (i.e., when and where) (Coppin et al., 2004; Hussain et al., 2013; Lu et al., 2004; Singh, 1989; Zhu, 2017). Only very few reviews mentioned other facets such as change target (Hansen and Loveland, 2012; Warner et al., 2009; Wulder et al., 2018), change metric (Gómez et al., 2016; Kennedy et al., 2009; Vogelmann et al., 2016), and change agent (Kennedy et al., 2015; Sebald et al., 2021; Shimizu et al., 2019). Pouliot and Latifovic (2016) mapped the multifaceted nature of land change, however, it was only a case study in the Athabasca oil sands region of Canada and has not reviewed the multifaceted land change in a systematic way. According to our knowledge, this paper is the first work for synopsizing the detection and characterization of land change as a five-facet task in a systematic manner, paving the way for operationalizing a holistic examination of land change as well as accomplishing efficient communication on related concepts - rather than a synthesis of sensor or methodological comparison which has been widely touched in previous works.

We will first discuss all five facets of land change as well as their relationship through the lens of remote sensing. Next, we will discuss the remote sensing issues in spectral, spatial, temporal, angular, and data-integration domains in observing, monitoring, and characterization of different facets of land change. Finally, we will discuss some of the current land change products derived from remote sensing data and conclude with a few recommendations. While most examples of this paper were illustrated using time-series datasets given by our expertise on this topic, we do appreciate the spatial and spectral merits of other data types (e.g., LiDAR, Hyperspectral, and Unmanned Aerial Vehicle (UAV)), which are equally important for characterizing land change. It has been our recognition that the integration of multiple data sources can provide a unique opportunity for the success of monitoring multifaced land change (will be discussed in Section 4.5).

## 2. The five facets of land change

If the remote sensing system is well designed for capturing the specific land change type, it is possible to extract land change information for five different facets based on the remotely sensed observations collected before, during, and/or after the land change (Fig. 2).

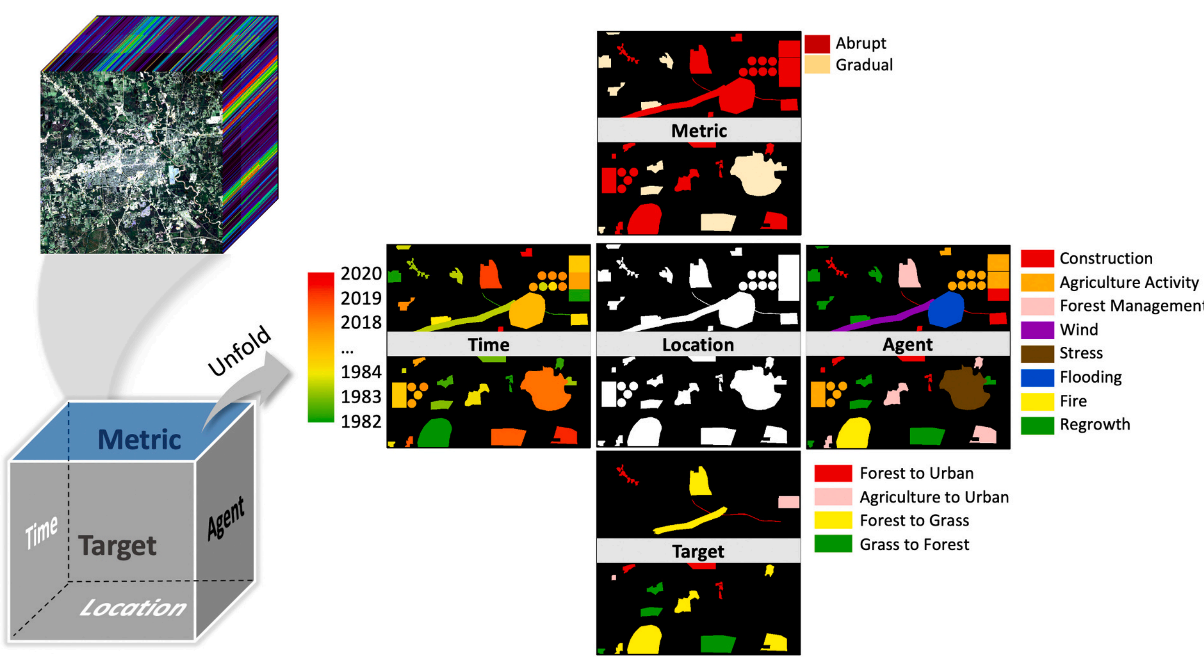


**Fig. 1.** The five facets proposed for observation, monitoring, and characterization of land change using remotely sensed data. It is worth noting that not all land change agents will lead to a change in change target or land cover in this case, and some of the change patches displayed in the other four facets are not shown (e.g., stress, flooding, and agriculture activity) or only partially shown (e.g., wind, construction, and regrowth) in the facet of change target.

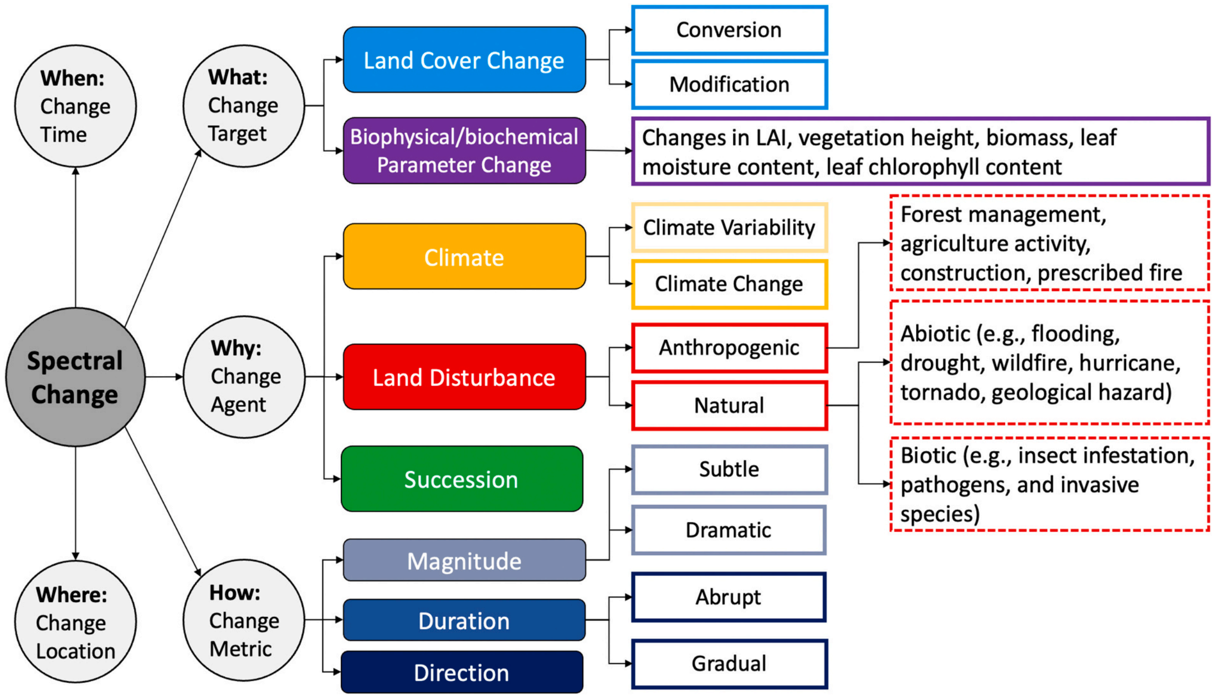


**Fig. 2.** Hierarchical classification system for the five facets of land change.

### 2.1. *Where - change location*

The first facet of land change is to answer the question of where the change has occurred or determine the change location. Theoretically, by differencing two georeferenced remotely sensed images collected at a different time from the same spectral band and same location, any kind of land surface change that occurred between the two dates would have larger difference values than places that have not changed. By using a simple threshold, the location of change could be identified. The land change detected in this way is sometimes called "spectral change" (Brown et al., 2020; Healey et al., 2018; Xian et al., 2022), as clearly there is a spectral value change between the two dates of the remotely sensed images, but this does not always correspond to the changes on the land surface. Other factors, such as image registration, atmospheric condition, natural soil wetness fluctuation, vegetation phenology, sensor-solar-geometry, and topography illumination, may also contribute to the spectral change (Kennedy et al., 2014; Zhu, 2017). Therefore, one of the most foundational steps before the remotely sensed images are used for detecting land change is removing or at least reducing changes in spectral values that are not caused by land surface change. Advanced algorithms have been developed to provide more accurate image registration results (Gao et al., 2009; Yan et al., 2016), perform atmospheric correction and cloud/cloud shadow detection (Masek et al., 2006; Qiu et al., 2019b; Zhu and Woodcock, 2012), include precipitation information (Tollerud et al., 2020), model and exclude seasonality (Verbesselt et al., 2010; Zhu et al., 2020; Zhu and Woodcock, 2014), apply Bidirectional Reflectance Distribution Function (BRDF) to correct sensor-solar-geometry (Roy et al., 2016; Schaaf et al., 2002), remove bandpass difference (Claverie et al., 2018; Shang and Zhu, 2019), and perform topographic correction (Buchner et al., 2020; Tan et al., 2013). It is worth noting that though these algorithms have the potential to reduce spectral changes that are not related to changes on land surfaces, they may also introduce artifacts, and it is not always necessary to apply all these algorithms before conducting change detection (Qiu et al., 2019a; Song et al., 2001).

### 2.2. *When - change time*

The second facet of land change is to answer the question of when the change occurred or determine the change time. Basically, the closer the two images are selected for detecting change, the more accurate the change time can be determined. Compared to detecting change based on real images, there are also new change detection methods that difference the model predicted values with actual remote sensing observations to identify land change (Verbesselt et al., 2012; Zhu and Woodcock, 2014) and the detected change time is determined based on how soon the new clear observations are collected for each pixel location. These time-series-based approaches do not need to wait for two clear remote sensing images and can provide more rapid change detection results. The remote sensing community has shifted from using images collected decades apart (Homer et al., 2007; Masek et al., 2008), to annual (Huang et al., 2010; Kennedy et al., 2010), and is currently shifting all the way to near-real-time change detection (Shang et al., 2022; Tang et al., 2019; Verbesselt et al., 2012; Woodcock et al., 2020; Ye et al., 2021a). This is particularly true with the successful launch of Sentinel-2 A/B (Drusch et al., 2012), Landsat 9 (Masek et al., 2020), and the hundreds of orbiting CubeSats (Huang and Roy, 2021), that could provide subweekly or even daily land surface observations at medium to high spatial resolutions (Li and Roy, 2017; Roy et al., 2021).

### 2.3. *What - change target*

The third and probably the most studied facet of land change is to answer the question of what is changing or determining the change target. The change target is sometimes defined as changes in categorical classes such as land cover type (e.g., *forest, urban, water, grass, shrub, snow/ice, agriculture*, etc.), or defined as changes in continuous variables of biophysical/biochemical parameters, such as Impervious Surface Area (ISA), land surface temperature, Leaf Area Index (LAI), vegetation height, biomass, leaf moisture content, leaf chlorophyll content, etc. Remotely sensed data contain rich information on the characteristics of the land surface. A feature space of more than a few dozens to even hundreds of dimensions could be created from the electromagnetic radiation (EMR) that is recorded at different wavelengths, the texture of the spectral bands, and the intra-annual/inter-annual temporal trajectory from the time series observations, which could be further used to determine the land cover based on image classification (Gómez et al., 2016; Pouliot and Latifovic, 2016) or to estimate the biophysical/biochemical parameters based on machine learning or regression from empirical models (Garbulsky et al., 2011; Lin et al., 2020; Verrelst et al., 2015). Recently, the deep-learning-based approaches, particularly Convolutional Neural Network (CNN), have shown better performance in land cover classification compared to the traditional machine-learning-based methods (Kussul et al., 2017; Liu et al., 2021b; Pouliot et al., 2021), and are capable of incorporating the spatial domain of the remote sensing data by automatically extracting a suitable representation of the remote sensing data through a hierarchy of spatial filters at different sizes, which avoids the feature creation and selection processes that most traditional machine learning methods require in advance for preparation of the classification predictors (Molinier et al., 2021).

Theoretically, if we can create land cover or biophysical/biochemical parameter maps accurately at different time points, we can compare their maps to identify changes in different land cover or a specific biophysical/biochemical parameter. However, as land changes are usually very small in size (e.g., 1–5% of the land surface) (Hansen et al., 2013; Song et al., 2018), and all image classification and biophysical/biochemical parameter retrieval algorithms contain errors, comparing maps of land cover or biophysical/biochemical parameters at different time points to detect land change may lead to compounded errors in the final change map at a magnitude way larger than the total change area (Olofsson et al., 2013). Therefore, land change is usually better detected based on the magnitude of spectral change and if a spectral change is detected, we can then estimate land cover or biophysical/biochemical parameters before and after the spectral change (Deng and Zhu, 2020; Jin et al., 2019; Latifovic and Pouliot, 2005; Xian et al., 2009; Zhu and Woodcock, 2014). It is worth noting that even if there is a spectral change detected, the classified categorical land cover type may still be the same (Hermosilla et al., 2018), as the land change that occurred on this land cover may not be dramatic enough to change the land cover type, and we usually call this land cover modification or land cover condition change (Comber and Wulder, 2019; Rogan et al., 2008). For example, if forest cover is defined as trees covering >10% of the pixel following the U.S. Forest Service definition (Riemann et al., 2010), and if selective logging is reducing forest cover from 90% to 30%, we are very likely to detect a spectral change, but based on the definition, the land cover is still forest before and after the spectral change. However, if the forest harvest is reducing forest cover from 90% to 5%, then the land cover will be likely changed from forest to barren or grass, and we usually call this land cover conversion, which is corresponding to more substantial land changes that cause land cover transitions from one to another. In the remote sensing community, huge efforts have been given to land cover conversions (Chowdhury et al., 2021; Colditz et al., 2014; Homer et al., 2015, 2020; Pouliot et al., 2021, Pouliot et al., 2014), but fewer studies were targeted on the land cover modification, which often occur at a spatial scale similar to or even larger than land cover conversion (Asner et al., 2005; Qin et al., 2021; Rigge et al., 2019). Detecting land cover modification is inherently difficult in remote sensing, as the subtle spectral change signal may be at a change magnitude similar to other background noise. Subpixel analyzing methods, such as spectral mixture analysis (Asner et al., 2009), continuous fields (Hansen and DeFries, 2004), fuzzy (or soft) classification (Foody and Doan, 2007), and the continuous subpixel monitoring approach (Deng and Zhu, 2020), have shown their capability in the detection of land cover modification at subpixel scales.

### 2.4. How - change metric

The fourth facet of land change is to answer the question of how it is changing by a number of change metrics, such as change magnitude, change duration, and change direction (Gómez et al., 2016; Kennedy et al., 2014; Petit et al., 2001). As remotely sensed data measure land surface reflected or emitted EMR, any state transition can be reflected as surface reflectance changes from the spectral bands, making remote sensing data particularly useful for tracking the change trajectories and characterizing the specific change process based on different change metrics (Comber and Wulder, 2019; Kennedy et al., 2014). The most important remote sensing observations for calculating different change metrics are the ones that are collected during the land change events.

According to the change duration metric (how long the change event last), land change can be divided into abrupt change and gradual change. Most remote sensing change detection algorithms were developed to detect abrupt changes that occur within a short time in response to a punctuated event, as these changes can be detected directly by comparing two remotely sensed images collected at different time points before and after the change event (Coppin and Bauer, 1996; Woodcock et al., 2020). On the other hand, gradual changes usually last for a much longer time as a result of a variety of causes such as damage to vegetation from disease and insects, ecological succession, and climate change (Lawrence, 2005; Vogelmann et al., 2012, 2016). There are also remote sensing methods developed to quantify gradual changes based on long-term time series observations (e.g., > 10 years) with the capability of separating co-existing gradual and abrupt changes (De Jong et al., 2012; Vogelmann et al., 2016; Zhu et al., 2016a), enabling more accurate estimation of gradual changes.

Based on the change magnitude metric (spectral distance between the changed and unchanged observations), land change can be divided into subtle change and dramatic change. Subtle change modifies the land cover, and the impact could be either short-lived, which is sometimes called ephemeral change (e.g., gypsy moth infestation and flooding), or persistent at a much longer time (e.g., > 1 year), which is also called gradual change. Dramatic change is mainly caused by severe disturbance events, which may lead to land cover conversion. Dramatic change is relatively easy to identify as large differences will be observed in remotely sensed imagery, but subtle change detection is much more difficult and requires change agent- or land cover-specific algorithms with a careful model parameter calibration (Ye et al., 2021b). The change direction, measured by the angularity of the spectral change vector, indicates the nature of the change process (Lambin and Strahler, 1994) and has the potential of providing more accurate detection of land change when used simultaneously with change magnitude (Zhu et al., 2020). It is worth noting that other change metrics could also provide valuable information for characterizing how the land surface is changing, such as time since last change, spectral stability period, and occurrence change intensity (Brown et al., 2020; Pekel et al., 2016).

### 2.5. Why - change agent

The fifth facet of land change is to answer the question of why it is changing or determine the change agent. Climate, land disturbance, and succession are the three major change agents that occur at quite different timescales (Fig. 3). Though the three change agents are quite different conceptually, they interplay with various kinds of positive and negative feedbacks (Dale et al., 2001; Guo et al., 2018; Johnson and Miyanishi, 2021; Laflower et al., 2016; Seidl et al., 2017).

Land disturbance has been defined in various ways (Clements, 1916; Grime, 1977; Sousa, 1984; Turner, 2010; White and Pickett, 1985), and one of the most commonly used definitions by ecologists is "any relatively discrete event in time that disrupts ecosystems, community or population structure and changes resources, substrate availability, or the physical environment" (White and Pickett, 1985). Most of the time, land disturbance occurs in a very short time ranging from hours to years and can be anthropogenic or natural. Anthropogenic disturbance, sometimes called mechanical change or land use change, refers to human activity-related land change, such as *forest management*, *agriculture activity*, *construction*, and *prescribed fire*. Natural disturbance can be further divided into abiotic disturbance, such as *wildfire*, *flooding*,

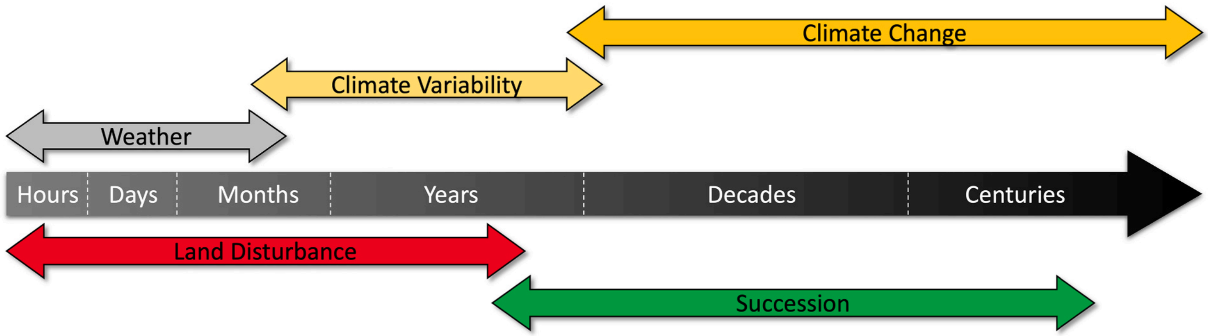


**Fig. 3.** Timescales applicable to weather, climate variability, climate change, land disturbance, and succession.

*tornado, hurricane*, *drought, geological hazard*, and biotic disturbance, such as *insect infestation*, *pathogens*, and *invasive species*. It is worth noting that there is a long debate on whether drought should be included as one type of land disturbance, and it has only started to be considered as a disturbance type over the past decade (Peters et al., 2011). Fire can be both natural (*wildfire*) and anthropogenic (*prescribed fire*) (Bowman et al., 2011), and remote sensing can detect both burning fires and fire burned areas (Justice et al., 2002; Lentile et al., 2006). Most remote sensing algorithms developed for detecting disturbance are only limited to a single change target, such as forest disturbance (Healey et al., 2018; Huang et al., 2010; Jin and Sader, 2005; Kennedy et al., 2007; Zhu et al., 2012a), and only a few algorithms can provide more general disturbance results, such as the MODIS Global Disturbance Index (MGDI) algorithm (Mildrexler et al., 2009), the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) algorithm (Kennedy et al., 2015), and the COntinuous monitoring of Land Disturbance (COLD) algorithm (Zhu et al., 2020). As disturbance will create a spectral change signal that deviates from the normal data fluctuation, it can be better captured after the normal data fluctuation is well defined and modeled. However, for certain disturbance types, such as *selective logging* and *insect infestation*, they may only change a small fraction of the pixel or slightly change the health condition of the ecosystem, which makes these kinds of disturbance agents extremely difficult to detect and distinguish in remote sensing data (Asner et al., 2005; Senf et al., 2017; Ye et al., 2021b).

Unlike weather that describes "snapshot-like" atmospheric condition (e.g., rainstorms and tropical cyclones) that changes every hour, day, and maybe months, the term "climate" depicts the mean and variability of temperature, precipitation, or wind for a much longer time, ranging from months to centuries. Climate variability refers to the short-term (e.g., months, seasons, or years) variation in climate patterns such as El-Niño Southern Oscillation, and climate change refers to the long-term changes (e.g., decades or centuries) in climates such as global warming and sea-level rise. Climate variability can be detected using remotely sensed vegetation indices by comparing a certain year with a baseline computed from a longer satellite time series (Saleska et al., 2007; Samanta et al., 2010), and climate change can be also evaluated based on the long-term trend of remotely sensed vegetation indices (Myneni et al., 1997; Zhu et al., 2016b). As both climate variability and disturbance will cause remote sensing observations to deviate abruptly from their past trajectories with a change magnitude larger than a pre-defined threshold, climate variability is sometimes identified as one kind of disturbance type in remote sensing (Huete, 2016), and will be particularly noticeable in semiarid areas where the amount of precipitation will have a large impact on the local ecosystems.

Climate change and land disturbance initiate succession (e.g., primary succession and secondary succession), which is defined as the process that the structure of a biological community changes over time (Huston and Smith, 1987). The process of succession is often accompanied with a sequence of biotic community replacement, such as the well-known four-stage Oliver and Larson Model (Oliver and Larson, 1996). Primary succession is the process that plants and animals colonize a barren habitat for the first time, which could take hundreds of years, while secondary succession begins after a major disturbance that transformed the original landscape. As remote sensing has a relatively short history, and the longest earth observation satellite, such as Landsat, only has a half-century record (Wulder et al., 2022), it is not ideal to quantify primary succession, and there are only limited studies on this topic (e.g., Knoflach et al., 2021; Lawrence, 2005). However, remote sensing data have been frequently used for quantifying secondary succession after disturbance with regards to its recovery rate or succession stages. The post-disturbance recovery rate was often estimated via spectral recovery rate as the proxy from the temporal trend analysis of satellite time series (Bartels et al., 2016; Kennedy et al., 2010; Pérez-Cabello et al., 2021; Senf et al., 2015; White et al., 2022; Zhao et al., 2018). Combined with ground measurements (Huang et al., 2019; White et al., 2019) and laser scanning data (Chirici et al., 2020; White et al., 2018), the use of dense satellite time series has enabled a better evaluation for re-establishment of forests over large areas (Chu et al., 2016; White et al., 2017), offering new insights on forests resilience (Forzieri et al., 2022; Senf and Seidl, 2022), recovery characterization (Bartels et al., 2016), and climate effects (Sulla-Menashe et al., 2018). Differently, the succession stages were often characterized through a single-date species mapping based on optical or LiDAR datasets (Osińska-Skotak et al., 2019; Raitsos et al., 2013; Rittenhouse et al., 2022), and sometimes required to be linked to field observations (e.g., Hall et al., 1991).

Observing and monitoring places where disturbance, climate, and succession occurred is important, but what is more critical is to identify the specific change agent, and this effort is sometimes called change agent characterization (or attribution) in remote sensing. Among the variety of possible land change agents, we can divide them into direct or proximate causes (e.g., agriculture activity, construction, fire, forest management, etc.) and distal or underlying driving forces (e.g., human population dynamics, human attitudes and behavior, economic transformation, climate change, etc.) (Geist and Lambin, 2002; Lambin et al., 2001). A majority of the remote sensing studies are only focusing on creating change agent maps of the proximate causes, in which some of them are more focused on anthropogenic agents (Kennedy et al., 2015; Shimizu et al., 2019) and others are more of a natural agent focus (Oeser et al., 2017; Schroeder et al., 2017). Most of the remotely sensed change agent types are quite broad, and some of the typical categories include *agriculture activity*, *forest management*, *construction*, *insect*, *windstorm*, *fire*, *flooding*, and *vegetation stress*. Satellite time series observation collected before, during, and/or after the disturbance events and supervised machine learning classifiers are usually used together for change agent classification (Shimizu et al., 2019), and the inclusion of spatial domain of remote sensing data is frequently found helpful in improving separation of different change agents (Kennedy et al., 2015; Sebald et al., 2021; Shimizu et al., 2019). It should be noted that remote sensing of change agent is never an easy task. Changes of different agents can happen simultaneously or in close proximity to each other, which makes untangling these agents extremely hard sometimes (e.g., harvest following by a pest infestation in forests). Moreover, different disturbance agents may result in the same or similar change consequences (for example, windstorms, wildfire, insect infestation, and drought will all lead to defoliation), which makes the spectral change signature very similar among the different agents. Additionally, it is extremely challenging to collect high-quality change agent training data consistently across a large geographic region at a national or global scale. Synthesizing all the land change agent related open data, such as the Land Change Monitoring, Assessment, and Projection (LCMAP) reference sample (Pengra et al., 2020), LANDFIRE reference data (Rollins, 2009), USGS Land Cover Trends data (Loveland et al., 2002), USFA National Insect and Disease Survey database (Johnson and Wittwer, 2008), NASA Cooperative Open Online Landslide Repository (COOLR) Landslide data (Kirschbaum et al., 2010), NOAA Severe Weather Data Inventory (SWDI) (NOAA, 2022), and Monitoring Trends in Burn Severity (MTBS) data (Eidenshink et al., 2007), and refining training data based on prior knowledge of change agent characteristics could be a potential solution. Remote sensing can also help better understand the underlying driving forces behind global land change based on qualifying and quantifying human-environment interaction at a multitude of spatial and temporal scales (Pricope et al., 2019). By integrating social science data and statistical methods such as fixed-effects models (Firebaugh et al., 2013), it is possible to provide deeper understanding of the complex land change transitions and teleconnection/telecoupling (Friis et al., 2016; Lambin et al., 2001; NRC, 1998, 1999; Pricope et al., 2019; Seto et al., 2012).

## 3. Relationship of various kinds of change terminologies

A variety of change terminologies have been introduced and used for remote sensing of land change. Though they are all related to land change, their relationship is rather complicated and confusing. Fig. 4 illustrates the relationship of some widely used land change terminologies, including spectral change, land surface change, land cover change, land cover modification, land cover conversion, land disturbance, climate variability, climate change, succession, and biophysical/biochemical parameter change. Spectral change (the grey rectangle in Fig. 4), defined as the temporal change in remote sensing spectral value, has been widely used in many remote sensing change detection studies (Cohen and Goward, 2004; Coppin and Bauer, 1996; Verstraete and Pinty, 1996). Spectral change is the broadest of all land change terminologies that could include all kinds of land changes (e.g., changes

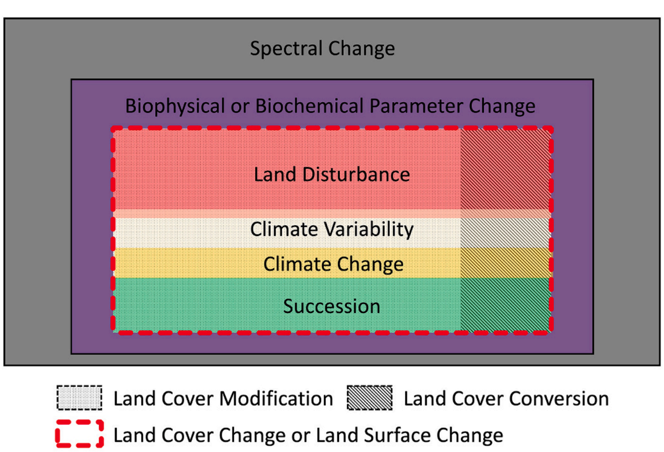


**Fig. 4.** Relationship of some widely used land change terminologies, including spectral change, land surface change, land cover change, land cover conversion, land cover modification, land disturbance, climate variability, climate change, succession, and biophysical/biochemical parameter change.

caused by vegetation phenology and abrupt/gradual land surface changes), as well as the spectral changes that have nothing to do with land change on the ground, such as atmospheric influences and data noise. On the other hand, land surface change (the region within red dashed line in Fig. 4), which shared the same area as land cover change, has also gained a lot of visibility in remote sensing studies of land change (Brown et al., 2020; de Beurs et al., 2015; Sohl et al., 2004; Woodcock et al., 2020; Zhu and Woodcock, 2014). Land surface change or land cover change includes all land change (e.g., all kinds of land cover conversions and modifications) that occurs on the Earth's surface, except for cyclic changes that are often caused by vegetation phenology and snow/ice seasonality. Biophysical/biochemical parameter change (the purple rectangle in Fig. 4) includes land surface change (or land cover change), that will inevitably lead to changes in certain biophysical/biochemical parameters, as well as cyclic changes that cause changes in LAI and leaf chlorophyll contents. Land disturbances (the light red rectangle in Fig. 4) are discrete events that disrupts ecosystems, and if they are severe enough, they can lead to land cover conversion, and are sometimes overlapped with climate variability (e.g., drought). Climate variability (the light yellow rectangle in Fig. 4) and climate change (the dark yellow rectangle in Fig. 4) are driven by the mean and variability of temperature, precipitation, or wind, and climate variability refers to the short-term variations in climate patterns (e.g., months, seasons, or years) while climate change refers to the long-term changes (e.g., decades or centuries). Both can lead to land cover conversion when it is persistent or have a significant impact on the land surface. Succession (the green rectangle in Fig. 4), defined as the process of the structure of a biological community changing over time can also change the land cover categories (e.g., transitioned from grass to shrub, and all the way to forest) with enough time and adequate recovery speed (Brown et al., 2020). Note that land disturbance, climate variability, climate change, and succession may all lead to categorical land cover change - land cover conversion (the rectangles filled with stripes in Fig. 4), but most of the time they will only lead to within-state modifications or condition change - land cover modifications (the rectangles filled with dots in Fig. 4), such as changes in the value of a certain biophysical/biochemical parameter.

## 4. The current issues for monitoring multifaceted land change

It would be ideal that the remote sensor was designed to detect all land changes with the right spectral, spatial, temporal resolutions, and viewing angles. However, the practical issues from spectral, spatial, temporal, angular, and data-integration domains have hindered the remote sensing platform's capability of detecting and characterizing land change.

### 4.1. The spectral issues

Visible, Near Infrared (NIR), Shortwave Infrared (SWIR), thermal, and microwave electromagnetic radiation is absorbed, reflected, and transmitted in different ways by terrestrial materials. Land changes, in essence, are partial or complete changes of the terrestrial materials, and hence a certain type of land changes can manifest distinct detection performance at different wavelengths. In practice, if the spectral ranges capable of separating the two different types of land surfaces are not included in the remote sensing bands, it is almost impossible to detect change location and time, not to mention accurate identification of change target, metric, and agent. For example, when forests are burned, the land-change signals are barely discernable from the visible Landsat bands, such as blue, green, and red, and certain microwave bands (e.g., C-Band). In contrast, much larger spectral differences could be observed between before- and after-change images as decreasing NIR and increasing SWIR1, SWIR2, and thermal bands (Fig. 5) due to post-fire char, reduced vegetation and water content, so these bands are critical to fire damage assessment. Some studies also reported that narrow

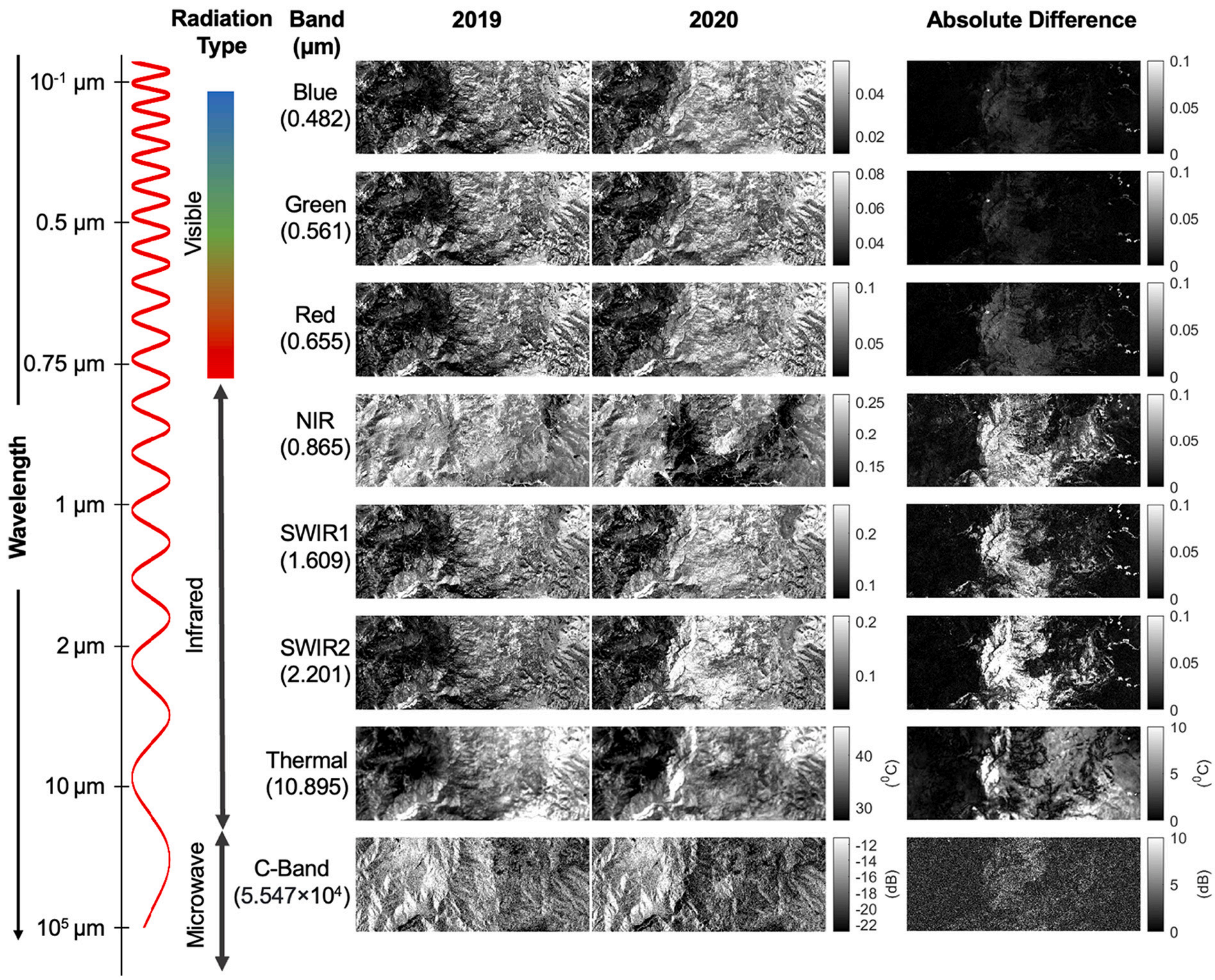


**Fig. 5.** Spectral change at different band wavelengths induced by a fire disturbance. The spectral differences are subtle in visible bands and the microwave band but are substantial in NIR, SWIR, and thermal bands. Blue, green, red, NIR, SWIR1, SWIR2, and thermal bands were derived from Landsat 8 surface reflectance and brightness temperature data, and microwave C-Band was selected from Sentinel-1C-Band synthetic aperture radar data with dual-band cross-polarization (Vertical transmit/Horizontal receive) at descending orbit. All the remotely sensed images were acquired at central latitude/longitude (40.100 /−120.607) in June 2019 and 2020 and clipped to the same geographic extent (1001 pixels by 401 pixels) at 30 m spatial resolution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

spectral bands, such as red edge bands (680–730 nm), are particularly useful for discriminating subtle/gradual vegetation changes which are often unrecognizable from broadband remote sensing (Ortiz et al., 2013; Xie et al., 2018). Generally, the selection of involved bands/indices is of enormous importance to the effectiveness of such change detection tasks, which necessitates more studies on target-based approaches for determining optimal spectral inputs (Yang et al., 2022; Ye et al., 2021b).

Besides change detection, the spectral selection is also critical to characterizing change target, agent, and metric. The band selection is known as the prerequisite for the success of a cover classification task to identify change targets such as before-change and after-change cover types (Guo et al., 2006). While given cover types may have similar and indistinguishable spectral responses at specific points in time, in most cases, the spectral behavior of different cover types varies over time, and the combined ability to look both multi-spectrally and multi-temporally may provide new insights for discriminating cover types (Fang et al., 2020; Key et al., 2001; Pasquarella et al., 2018; Zhu et al., 2012b). The multispectral change, also known as spectral change vector, often presents diagnostic attributes such as change direction (Lambin and Strahler, 1994) and has been employed as the key variable for categorizing change agents (Zhang et al., 2022). The change metrics, such as "subtle vs dramatic" in the change magnitude, are also spectrum dependent. Furthermore, change magnitudes based on different remote sensing bands/indices can help identify biological change phases: for example, Red-Green Index (RGI) was often used to indicate the red stage (i.e., the needles turn red) for a beetle-infestation process (Coops et al., 2006), while a substantial drop of Normalized Difference Vegetation Index (NDVI) could be treated as a sign of the grey stage (i.e., all foliage drop) (Hart and Veblen, 2015). A successful change characterization requires careful investigation of the most relevant spectral inputs; more important might be recognizing change characterization as a multi-spectral problem for a thorough examination of a change process.

### *4.2. The spatial issues*

The spatial resolution, defined as the dimension in meters of the ground-projected Instantaneous-Field-of-View (IFOV), determines the minimum mapping unit on the ground (e.g., a Landsat 8 pixel covers a 30 m × 30 m land area). Remotely sensed images from various kinds of platforms can provide a wide range of spatial resolutions from sub-meters to tens of kilometers (Belward and Skøien, 2015). The choice of spatial resolution also has important implications for the downstream satellite-based product (Mascorro et al., 2015). Remote sensing data with a higher spatial resolution are generally preferred as the input for change detection, as the higher the spatial resolution, the better the capability in detecting small-scale land changes. However, when the spatial resolution is too high (e.g., < 1 m), the image quality may be severely impacted by the shadow of land surface features (Bruzzone and Bovolo, 2012). On the other hand, if the spatial resolution is too coarse, small-sized land surface changes may not exhibit obvious spectral signals (see the MODIS images in Fig. 6), and the large difference in point-spread-function and BRDF impacts will lead to new data noise and make change signals even more diluted (Xin et al., 2013). Therefore, medium resolution satellites with resolution between 10 and 100 m, such as SPOT, Sentinel-2, and Landsat, are often more preferable than the coarse resolution sensors for mapping cover type change (Martin and Howarth, 1989; Szostak et al., 2018; Zhu, 2017), and the coarse resolution data, such as MODIS and AVHRR, are mostly used to extract gradual change based on long time series data (Myneni et al., 1997; Pouliot et al., 2009; Zhu et al., 2016b). It is worth noting that the impacts of spatial resolution of the remotely sensed imagery may differ based on the specific image analyzing unit, such as pixel-based versus object-based approaches (Baker et al., 2013).

When change units of interest are smaller than the resolution cells, land change may only occur on a small fraction of a pixel (the fraction is a continuous variable), which is also known as the L-resolution situation (Strahler et al., 1986). To facilitate response design for reference sample pixels, a thresholding strategy is often needed to determine whether a pixel is considered as a "change pixel" from a ground view. For example, in Hansen et al. (2013), forest change is defined as a pixel with >50% change in forest cover within a pixel. On the other hand, the definition of land cover also directly determines the scope of the change (mainly land cover conversion) under investigation. For example, if a forest class is defined as >10% of tree cover, and grassland is defined as a >10% of grass cover, the pixel will be considered to have undergone land cover conversion from the forest class to grass class only if >90% of the trees are removed from a fully forested pixel and replaced by grassland (Fig. 6). This is because the land cover definition is usually resource-driven, and when classes meet the definition of more than one category, classes with a higher priority are given preference in assigning labels (e.g., urban > forest > grass). Similarly, if some proportion of forest is converted to built-up lands, it will be labeled as urban even if the urban proportion of the pixel is small (but at least >10%) (Pengra et al., 2020). For example, if >10% of trees were removed from a forest pixel, and replaced by a new house, the pixel would still be considered to have undergone land cover conversion (from forest to urban), even though the remaining forest cover is just slightly <90% (Fig. 6).

### 4.3. The temporal issues

The temporal resolution of a remote sensing system refers to the revisiting period of a satellite sensor (e.g., Landsat 8 revisits the same location every 16 days). A variety of remote sensing systems collect observations every minute, hour, daily, weekly, monthly, or for a few years (Jensen, 2009). Essentially, more accurate detection of change time could be achieved based on observations of higher temporal

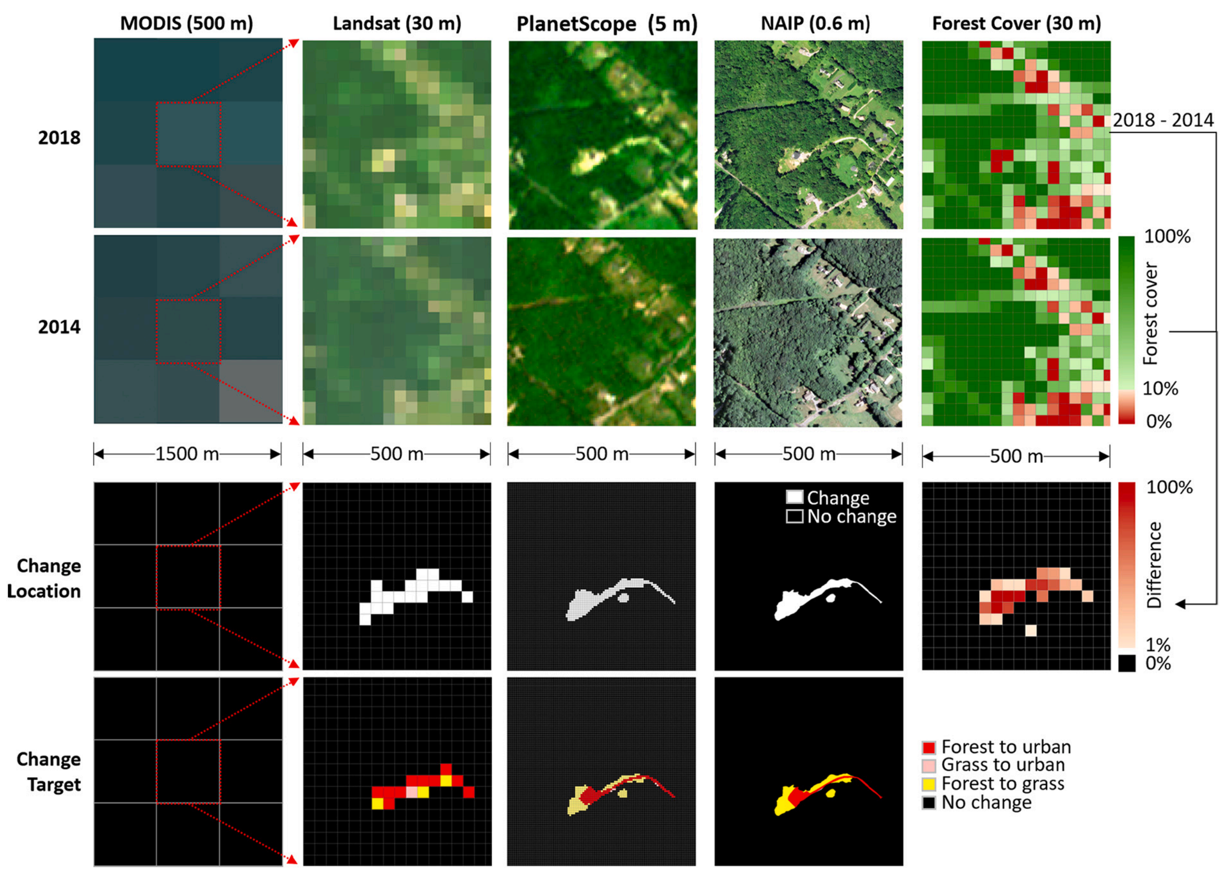


**Fig. 6.** The impacts of spatial resolution on mapping change location and change target between 2014 and 2018. All the remotely sensed images were acquired at central latitude/longitude (41.781/−72.234) in the summer of 2014 and 2018 and reprojected into the WGS84 UTM Zone 19 N. The MODIS, Landsat, and PlanetScope images were collected at a coarse resolution (500 m), medium resolution (30 m), and high resolution (5 m), respectively. Two National Agriculture Imagery Program (NAIP) aerial images (0.6 m) were classified into forest, urban, and grass which were used as the reference maps. To generate change location and change target maps for each image type, we aggregated the reference maps at each resolution and labeled cover types and change pixels by investigating sub-pixel fraction: forest is defined as pixels with >10% coverage of trees, and urban is defined as pixels with >10% coverage of built areas; changes were labeled when cover types for >10% of the pixel changed. No change signals were present from MODIS images (500 m) under the definition but became detectable in the other remote sensing images at 0.6–30 m spatial resolutions.

resolutions, as change time can be contained within a narrower time interval, and this has been echoed by the fact that remote sensing change detection algorithms are using denser time series (Zhu, 2017). The choice of temporal resolution is particularly important when the short-lived phenomena need to be monitored or persistent clouds limit a clear view. For example, with two sensors working simultaneously, the Landsat time series can provide 8 days of revisit observations for the same location if we do not consider observations contaminated by cloud, cloud shadow, and snow/ice. For ephemeral change such as floods that only last a few days, it is less likely to be observed based on Landsat time series alone (Fig. 7a). In Fig. 7a, we serendipitously collected one clear Landsat image located during the flooding, but if it was blocked by clouds, it would be impossible for detecting this kind of ephemeral change as the system had recovered to the pre-change state before acquisition of the next available observation unless other active sensors such as radar were used. For grassland change (i.e., abrupt greenness change) caused by climatic variability and forest change caused by beetle infestation, they can last for a year or multiple years, respectively, and are usually detectable if annual Landsat observations are used (Fig. 7b-c). Another extreme is that land changes relating to urban expansion (Fig. 7d) that is often non-reversible and could be successfully captured even by two Landsat images collected at an interval of 5 to 10 years. Therefore, the minimum temporal resolution required for different land change applications is usually quite different. Generally, the denser the time series observations used, the more accurate the detection of the time and location of change.

Even if all clear observations have remained for analysis, the time series may have different temporal resolutions at different places and at different times due to the overlap of adjacent swaths, the presence of cloud or snow/ice, and the data acquisition strategies (Brown et al., 2020; Zhu et al., 2018). For example, Gypsy Moth infestation usually only lasts for one or two months, and if all available Landsat data are used, we can have around four clear observations (without using observations from the neighboring path) in two months for most places (assume cloud cover is 50%). In certain places where two Landsat paths overlap with each other (the overlap areas), we could have around eight

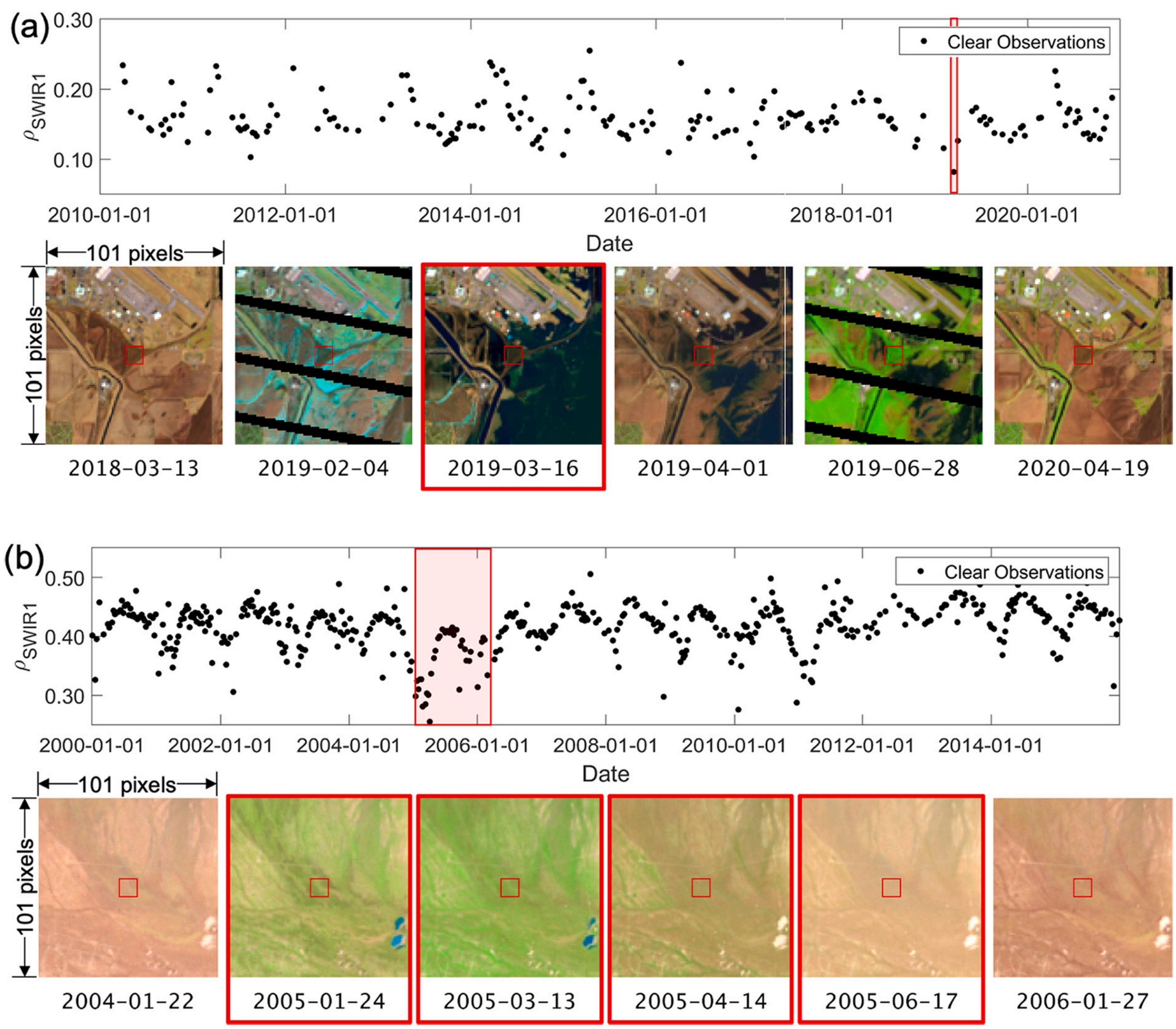


**Fig. 7.** The impact of temporal resolution on land change detection. (a) A flood event that lasted for a few days at central latitude/longitude (41.103/−95.906). Of all the available Landsat observations, only a single observation was observed during this ephemeral event. (b) Climatic variability over grassland that lasted almost a year at central latitude/longitude (34.838/−117.460). (c) Beetle infestation related land change that lasted for several years at central latitude/longitude (40.226/−106.064). (d) Urbanization over forested areas located at latitude/longitude (41.70/−71.57). In each figure, the time series plot in the upper panel was derived from all available Landsat observations at the center of the smaller red square of the false color composite images at the lower panel. The change period was highlighted by the red rectangles in the upper panel and the larger red rectangle surrounding the false color composite images in the lower panel. The false color composite images were shown in Landsat SWIR1, NIR, and red bands at the same color stretch setting. Some of the images have black stripes due to the Landsat 7 Scan Line Corrector-off issue. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

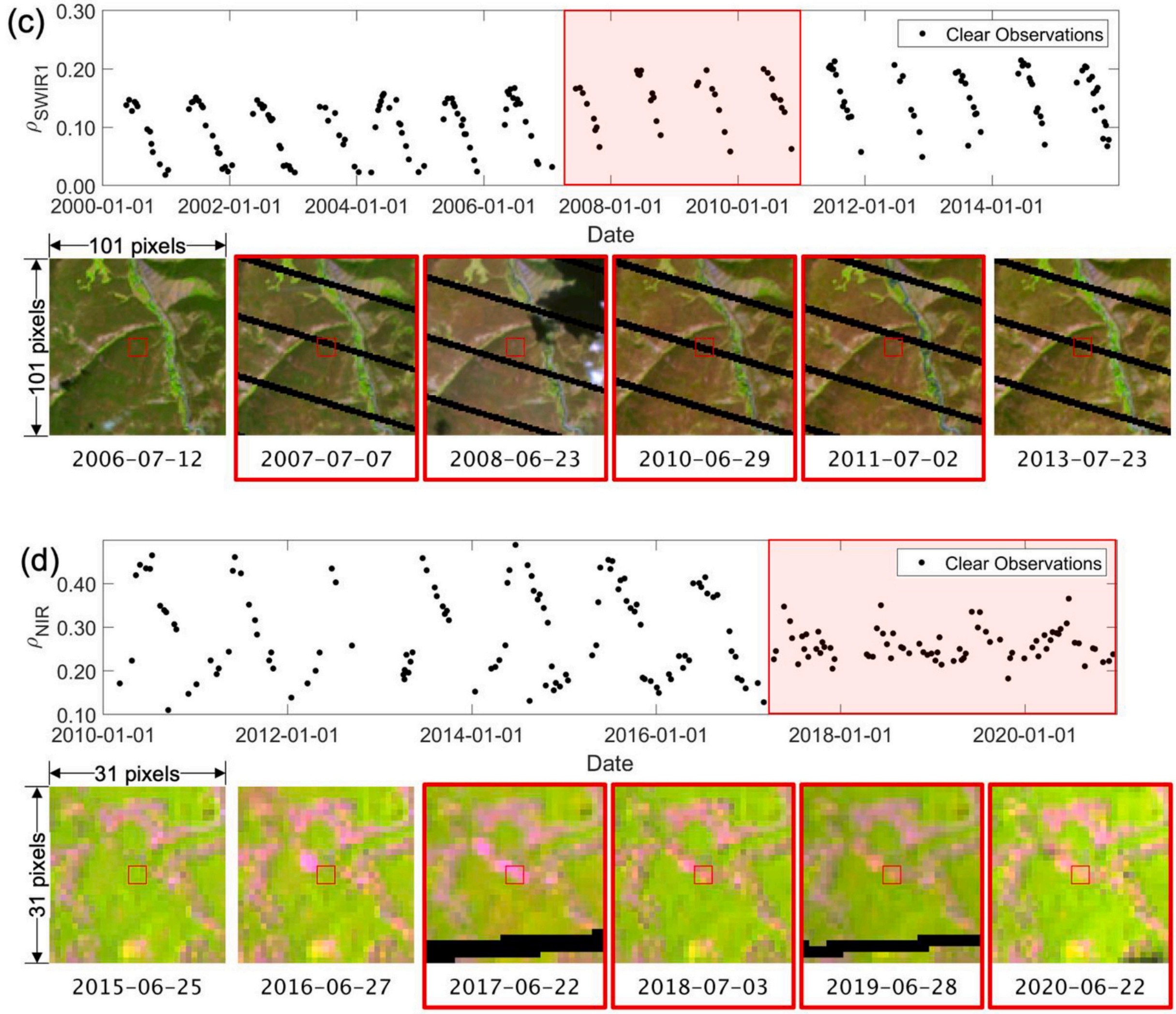


**Fig. 7.** (*continued*).

clear observations which increased the likelihood of detecting these short-lived changes if a fixed number of consecutive observations is used to analyze change anomaly (Fig. 8). The use of overlap-path observations brings new science capability for Landsat data, but also result in inconsistency to the final land change maps (between the overlap and non-overlap areas). This is particularly problematic for large-scale remote sensing change products, as large differences in land change patterns will show up both spatially and temporally. Methods that select data from the same path or adjust the number of observations to confirm change based on data density could be possible solutions to alleviate this issue, but it is at the sacrifice of losing the temporal density for certain places, which may lead to omission errors (Fig. 8).

Temporal resolution is of critical relevance to detecting day-sensitive changes such as vegetation phenology. The coarse resolution data, such as MODIS and VIIRS, are capable of providing daily repeated observations and has been widely used for land surface phenology products (Ganguly et al., 2010; Zhang et al., 2018, 2020). Practically, owing to cloud and snow/ice contamination, multi-day compositing was often employed to produce clear observations at a temporal resolution lower than the daily frequency. A longer compositing interval will reduce computational and data storage demand and also ensure the observation inputs are of sufficient quality to be useful for model fitting, yet its low temporal resolution comes at the cost of hampering accuracies for characterizing phenometrics. Fig. 9 depicts an example of phenological transition date detection from daily (only clear observations remained), eight-day, and 32-day MODIS-based (500 m) composite time series on a cropland pixel (Indiana, USA). The daily and the eight-day composite time series have similar predictions on green-up and dormancy dates (the difference $\leq$ 2 days), while a significant discrepancy for the dormancy date (12 days later than that of the daily time series) was observed on the 32-day composite time series. This can be explained by that lower data density often results in a poorer model fit, especially for the phenological window where spectral reflectance often changes rapidly. A wide body of the literature supports that a moderately high temporal resolution (three- to 16-day interval) is often necessitated to accurately inform phenological dates (Cui et al., 2020; Henson et al., 2018; Zhang et al., 2009).

Additionally, the use of dense time series can create new information or more accurate change detection/characterization that the traditional two-date image difference method cannot provide. For example, we can get to know how the change is occurring based on the change magnitude, the change direction, and the duration of the change. The information embedded in the time series data provides important spectral-temporal information about the pixel and we can extract this information based on estimated time series model coefficients and statistical metrics to provide a more accurate classification of the change target (Zhu, 2017). These derived spectral-temporal metrics could even revolutionize the current land cover classification system and bring in new land cover categories that are continuous in time and embedded with changing conditions, such as *greening urban*, *young forest*, *mature forest*,

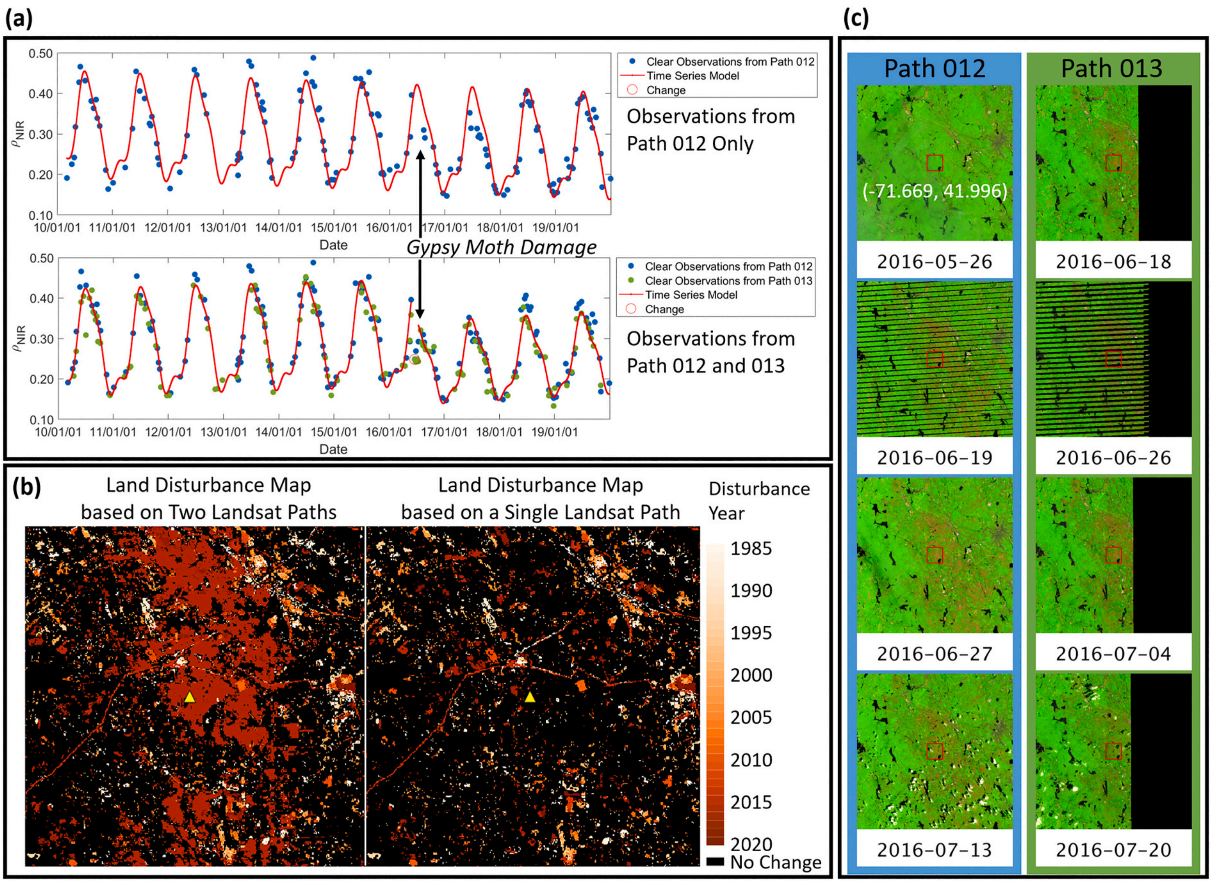


**Fig. 8.** A comparison of change detection results caused by Gypsy Moth damage using two Landsat paths (or swaths) data and a single path data. (a) Landsat NIR surface reflectance observations at the center of the red square of the false color composite images on the right (c) at central latitude/longitude (41.996/−71.669). The blue dots are from Landsat path #12 and the green dots are from path #13. The red line is the estimated time series model, and the red circle is the land surface change captured by the COLD algorithm with six consecutive observations to confirm a change (Zhu et al., 2020). (b) A land disturbance map was created based on the COLD algorithm using Landsat observations from two paths and a single path (#12). The darker the color, the more recent the land disturbance was detected. (c) The false color composite Landsat images from path #12 (in blue outlines) and path #13 (in green outlines) were shown in SWIR1, NIR, and red bands, and they are directly comparable because of the same stretch display. This figure demonstrated that for places with two Landsat path coverage, Gypsy Moth damage is possible to detect by the COLD algorithm, but not possible for places with only a single Landsat path coverage. COLD: COntinuous monitoring of Land Disturbance.

and *declining forest* (Zhu and Woodcock, 2014). Finally, the time series before, during, and after land change all contain rich spectral-temporal information on the change agent and could be used as major inputs for change agent classification.

In addition to the repeat frequency, the time of day the remote sensing observations are collected is also helpful for better understanding different facets of land change. For example, most of the time series we discussed are remotely sensed data collected during the daytime (e.g., around 10 am), which relies on the reflected electromagnetic radiation from the sun. There is also another type of satellite dataset for imaging land surface at nighttime, which provide versatile data sources for studying human activities, as most of the nighttime lights are artificial lights (Levin et al., 2020; Li et al., 2017; Zhao et al., 2019). Time-series nighttime light data have been widely used to monitor anthropogenic-related land change and usually at a large scale. However, as there are also other sources of light at night, such as moonlight, aurora, and lighting, the use of dense time series of nighttime light data is still very rare (Wang et al., 2021), and the densest time series data ever used is still the average monthly or yearly nighttime light observations (Elvidge et al., 2021; Levin, 2017). Recently, NASA has created a Black Marble product that has corrected most of these nonhuman-activity-related light sources and has provided the potential of using daily nighttime light observations for land change studies (Román et al., 2018).

### 4.4. *The angular issues*

The energy acquired by the remote sensing systems contains very specific angular characteristics, which is a function of illumination source (e.g., Sun for a passive system or the sensor itself for active systems) angles and the sensor viewing angles, known as the Bidirectional Reflectance Distribution Function (BRDF) (Schaaf et al., 2002). This bidirectional nature of remote sensing systems will cause inconsistency among the radiance by the same sensor, as well as impact current surface reflectance retrieval models, thereby limiting our capability for detecting real change signals (Xin et al., 2013). Even for some of the sensors that only collect near nadir observations, such as Landsat, the changes in the solar angles and view zenith angles (mostly for observations collected in overlap swaths) will still cause large reflectance differences (Qiu et al., 2019a; Zhang et al., 2018), and potentially lead to omission or commission errors in change detection (Fig. 10a). Fortunately, with enough remote sensing observations collected at the different view and solar angles within a short time, this BRDF function can be modeled, and local-noon nadir observation can be estimated for some coarse resolution satellites, such as MODIS and VIIRS (Liu et al., 2017; Schaaf et al., 2002), and these BRDF parameters can help reduce BRDF effect in medium resolution satellites, such as Landsat and Sentinel-2 (Claverie et al., 2018; Roy et al., 2016). Other solutions such as selecting observations within the same swath and creating time series models that estimate the solar angle difference along with vegetation phenology

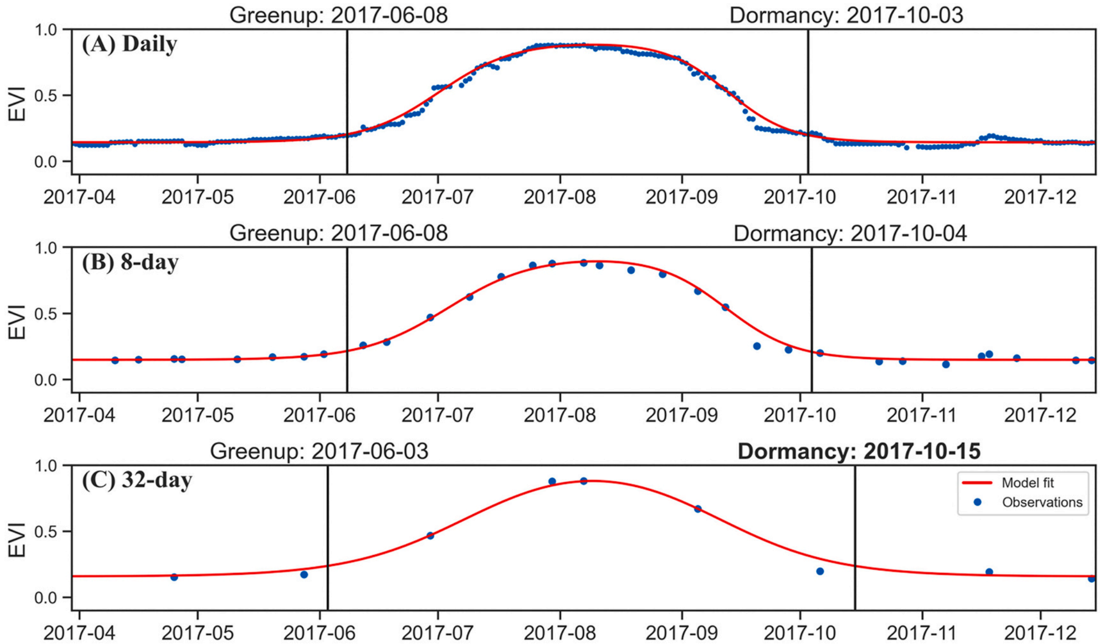


**Fig. 9.** Cropland-based phenometrics predicted by different temporal resolutions at latitude/longitude (40.681/−86.912). The daily MODIS Enhanced Vegetation Index (EVI) were generated from Nadir BRDF-Adjusted Reflectance (NBAR) daily dataset (MCD43A4) at 500-m resolution. The composite time series was further produced using the maximum index. The phenological curve was modeled using Beck's double logistic regression (Beck et al., 2006), and green-up and dormancy dates were determined by using the rate of change in curvature (Zhang et al., 2003). The dormancy date for the 32-day composite time series (in the bold text) was unrealistically 12 days later than the other two due to its poor model fit brought by inadequate observations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

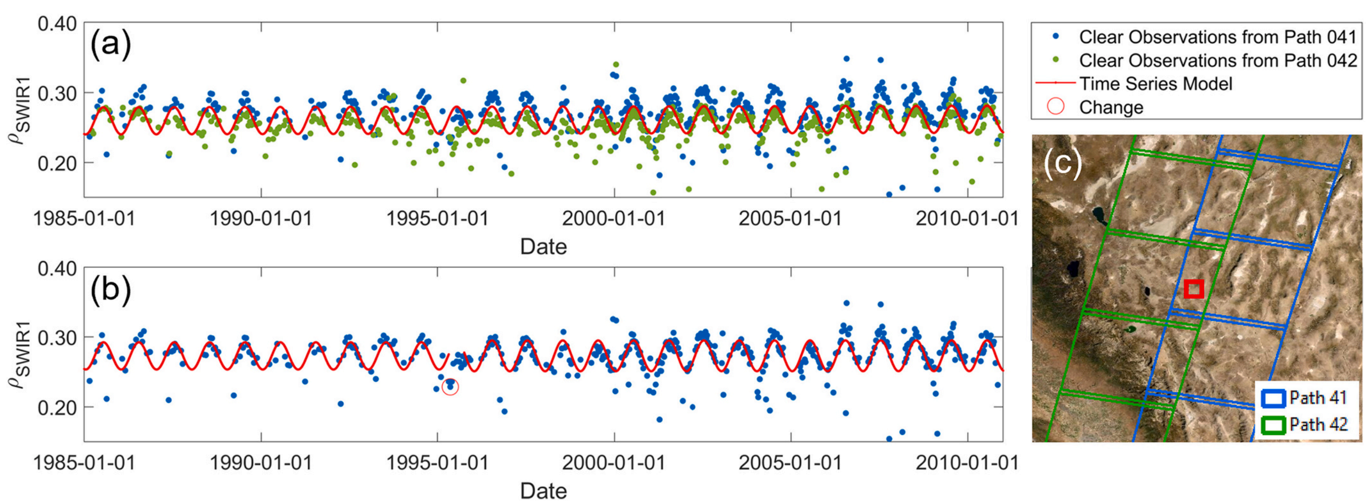


**Fig. 10.** The impact of BRDF on land change detection. (a) Change detection using all observations collected in overlap paths. The BRDF effect, dominated by the different sensor view angles from two adjacent paths, results in an omission error. (b) Change detection using all observations in a single path with minimum view zenith angle. The land change can be successfully detected when the BRDF effect is reduced in time series observations collected from a single swath. (c) Landsat Path/Row tiles. The blue and green polygons indicate Landsat paths #41 and #42, respectively. The center of the red square indicates the location of the time series plots (a) and (b) at latitude/longitude (38.737/−117.880). This change detection example was generated from all available Landsat time series and a time-series-based change detection method called COLD (Zhu et al., 2020). COLD: COntinuous monitoring of Land Disturbance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

changes can also remove or at least reduce the BRDF differences embedded in the satellite data, and in this way, the change pixel can be correctly identified (Fig. 10b) using a time-series based change detection algorithm (Zhu et al., 2020). It is worth noting that the angular information can be useful for identifying the target and location of land change, such as improving land cover classification (Jiao et al., 2011), detecting moving objects such as clouds (Frantz et al., 2018), aircraft (Liu et al., 2020b), and detection of newly built houses (Huang et al., 2020), due to the inclusion of 3D information.

### *4.5. Data-integration issues*

With the increased availability of Earth observation satellites, the integration of multi-sensor datasets could offer complementary views on spatial, temporal, and spectral dimensions, providing a unique opportunity for approaching a multifaceted land change problem (Dong et al., 2009). Methods for integrating multi-sensor datasets for multifaceted land change studies can be generally categorized into observation fusion, decision fusion, and information fusion. Observation fusion refers to the strategy of combining multiple data sources into a consistent blending observation set to create a finer temporal, spatial or spectral resolution dataset as the algorithm's inputs (Emelyanova et al., 2013; Gao et al., 2006; Shang et al., 2022). Decision fusion, also named "competitive integration" (Schmitt and Zhu, 2016), combines similar change facet information from different sensor-specific pipelines, aiming at producing more reliable results for one single change facet (Cardille et al., 2022; Reiche et al., 2018). Information fusion, such as the "complementary integration" (Schmitt and Zhu, 2016), is the fusion of multi-sensor pipeline results targeted at different change facets, with a goal of providing complementary change information. While a comprehensive review of these integration techniques is beyond the scope of this article, it is important to recognize their conceptual difference in the context of multifaceted change analysis. Observation and decision fusion have been widely applied to single-facet tasks such as change detection or land cover classification to answer "when", "where", and "what", but much fewer were on change metrics or agents (Fernandez-Manso et al., 2019; Meng et al., 2018);comparatively, a paucity of information fusion studies on monitoring land change was reported, partly due to a lack of recognizing change as a multifaceted problem. Another challenge for information fusion is that different data sources may have different geographic coverage, for example, LiDAR and hyperspectral images are often unable to provide wall-to-wall land change information similar to medium or coarse-resolution images, which implies that data interpolation is often required.

Beyond remote sensing observations, an increasing array of social science data have shown their great promise for unveiling social/economic processes that are not manifested on the landscape, pinpointing the question of "why" the land change happened. Social science datasets, such as population density, capital investment, poverty gap index, were often manipulated as explanatory variables for establishing empirical models and used to infer causes or drivers of land changes observed from remote sensing images (NRC, 2013; Seto and Kaufmann, 2003; Wyman and Stein, 2010). While such applications for integrating the remotely sensed (pixels) data with social science (people) data have been a major focus in land change science (Lambin, 2004), their fundamental differences in data format create lots of challenges. The national Academy of Science volume "People and Pixels" (NRC, 1998) and Rindfuss et al. (2012) have exemplified several data integration issues, such as different data presentations (e.g., "discrete" vs "continuous"), inconsistent temporal depth and data complexities, and traversing the languages and terminology from different disciplines. Conventionally, the social science data were collected based on field observations, interviews with local people, and surveys, which is time consuming, labor intensive, and usually out-of-date. The Volunteered Geographic Information (VGI) has been a paradigm shift that offers an alternative mechanism for collecting and compiling the georeferenced social science data (Goodchild, 2007). Through content retrieval, categorization and meta-data analysis (Daume et al., 2014), and georeferenced VGI data (such as from media reports or geotagged social media posts) can be integrated at decision or information levels, which improves insights not just on the disturbance agents from a "local view", but also uniquely uncovers the socioeconomic drivers underlying land surface change, such as narcotrafficking (Sesnie et al., 2017; Tellman et al., 2020) and population increase (Minale, 2013). Another notable advantage of the VGI data is that their availability is usually more timely (e.g., social media data), and by combining with other near real-time satellite data sources, the social media datasets have showcased their capacity for advancing those time-sensitive change detection tasks such as rapid disaster mapping (Fohringer et al., 2015; Rosser et al., 2017; Schnebele et al., 2014). Despite its great potential, several factors preclude populating the VGI dataset of the present day for a wall-to-wall land change mapping. First and foremost, the data quality of VGI is questionable due to their geolocation inaccuracy, participants' bias, or context ambiguity; trickier might be that data uncertainty accompanying VGI data, unlike remote sensing datasets, are mostly unmeasurable and unmanageable (Goodchild and Li, 2012). The coverage of the VGI dataset is also limited and cannot be extended to the same level as remotely sensed images, causing a grave technical challenge for enabling a geographically consistent mapping. Lastly, VGI data may not uncover some change agents such as gradual stress-related changes. Generally, the blending of VGI and remote sensing datasets is in infancy, and its relevance to land change studies is still inconclusive. More foundational research on data processing protocols and well-verified, localized study cases are both anticipated for the future, allowing for a broader examination for incorporation of VGI datasets into the current production workflow.

## 5. Current land change products

Lots of remote sensing-based land change products have been created, and some of them have been widely used in a variety of fields, such as environmental sustainability, land management, biodiversity conservation, and ecosystem health assessment. However, most of these land change products only focus on three facets of land change – the location, time, and target of change (mostly land cover), and very few products are trying to provide some of the other facets of land change, such as change agent or change metric (Table 1).

Most of the current large-scale land change products are only focusing on a single change target, such as changes in *forest*, *urban*, or *water* (Table 1). For instance, Hansen et al. (2013) created the 2000–2019 global 30-m forest cover and forest cover change (i.e., forest loss and forest grain) products based on time series spectral metrics of Landsat data and a supervised classification approach. The North American Forest Dynamics (NAFD) project implemented the Vegetation Change Tracker (VCT) algorithm (Huang et al., 2010) to produce annual forest disturbance maps for the conterminous United States (CONUS) from 1986 to 2010 based on annual Landsat time series data (Zhao et al., 2018). Liu et al. (2020a) created 30-m Global Annual Urban Dynamics (GAUD) dataset for providing information on urban expansion and green recovery from 1985 to 2015 based on existing global urban extent maps and Landsat time series data. European Space Agency (ESA) produced the Global Human Settlement Layer (GHSL) for multiple years, which can provide new global spatial information, evidence-based analytics, and knowledge describing the human presence such as built-up area and population distribution on the Earth (Pesaresi et al., 2016). The ESA Global Surface Water (GSW) dataset provides different facets of the spatial and temporal distribution of surface water over long time periods at a 30-m resolution based on 30+ years of Landsat data, such as water occurrence for presenting overall water dynamics, water recurrence for describing how frequently water returned from one year to another, and water seasonality for capturing the intra-annual dynamics of water surfaces (Pekel et al., 2016). This dataset also includes water occurrence change intensity maps between two epochs (1984 to 1999, and 2000 to 2020), which can provide information on where surface water occurrence increased, decreased, or remained the same. In addition, products of single change agent are available as well, particularly for fire. For example, Giglio et al. (2018) applied dynamic thresholds of a burn-sensitive vegetation index composite data (derived from daily 500 m MODIS time series) to generate a global burned area product, in which the date of the burned area will be provided within each MODIS tile with 10 degrees by 10 degrees.

Only a few products can provide information on land change on different kinds of land surfaces. The National Land Cover Database (NLCD) provides multi-temporal land cover and land cover change products for CONUS, Hawaii, Alaska, and Puerto Rico between 2001 and 2019 for every 2–3 year interval, based on decadal Landsat data as well as other ancillary datasets (Jin et al., 2019). Using daily seamless data cubes generated from multi-source remote sensing data, Liu et al.

**Table 1**
A select list of current global and North America land change products. Only the most recent literature is listed here.

| Product Name | Coverage | Change Location | Change Time (Period) | Change Target | Change Metric | Change Agent | Satellite Data | Citation |
|---|---|---|---|---|---|---|---|---|
| Hansen forest change map | Global | 30-m | Annual (2000–2019) | Forest gain Forest loss | N/A | N/A | Landsat | (Hansen et al., 2013) |
| Global Surface Water | Global | 30-m | Intra-annual Annual (1984–2020) | Water seasonality Water transitions Annual water recurrence | Water occurrence Change intensity | N/A | Landsat | (Pekel et al., 2016) |
| MODIS burned area | Global | 500-m | Day of Year (2000-Present) | Burned area | N/A | Fire | MODIS | (Giglio et al., 2018) |
| NAFD-NEX | CONUS | 30-m | Annual (1986–2010) | Forest disturbance | N/A | N/A | Landsat | (Zhao et al., 2018) |
| GHSL | Global | 30-, 250-, and 1000-m | Multiple years (1975, 1990, 2000, and 2014) | Built-up area | N/A | N/A | Landsat | (Pesaresi et al., 2016) |
| NLCD | United States | 30-m | 2–3 years (2001–2019) | Land cover change Forest disturbance | N/A | N/A | Landsat | (Jin et al., 2019) |
| LANDFIRE | United States | 30-m | Annual Day of Year (1999–2020) | Vegetation transition | Disturbance severity Time since disturbance | Fire, Mechanical, Insect, Windthrow | Landsat | (Rollins, 2009) |
| GAUD | Global | 30-m | Annual (1985–2015) | Urban expansion Green recovery | N/A | N/A | Landsat | (Liu et al., 2020a) |
| LCMAP | CONUS | 30-m | Annual Day of Year (1985–2019) | Land cover change Land spectral change | Change magnitude Spectral stability period Time since last change | N/A | Landsat | (Brown et al., 2020) |
| iMap | Global | 30-m | Annual Seasonal (1985–2010) | Land cover change | N/A | N/A | Landsat, MODIS, and AVHRR | (Liu et al., 2021a) |
| NALCMS | North America | 30- and 250-m | 5 years (2001–2015) | Land cover change | N/A | N/A | Landsat and MODIS | (Latifovic et al., 2016) |
| NTEMS | Canada | 30-m | Annual (1984–2019 for land cover; 1985–2017 for recovery; 1985–2015 for disturbance agent) | Land cover change | Post-disturbance recovery rate | Fire, Harvest, Road, Non-stand replacing disturbance | Landsat and LiDAR | (Hermosilla et al., 2022; White et al., 2017, 2022) |
| GLanCE | Global | 30-m | Annual (2001−2020) | Land cover change | N/A | N/A | Landsat | (Friedl et al., 2022) |
| GLCLUC2020 | Global | 30-m | Annual (2000−2020) | Land cover change | N/A | N/A | Landsat | (Potapov et al., 2022) |

Notes: CONUS: COnterminous United States; NLCD: National Land Cover Database; LCMAP: Land Change Monitoring, Assessment, and Projection; GHSL: Global Human Settlement Layer; GAUD: Global Annual Urban Dynamics; NAFD-NEX: North American Forest Dynamics - NASA Earth Exchange; NALCMS: North American Land Cover Change Monitoring System; NTEMS: National Terrestrial Ecosystem Monitoring System; GLanCE: Global Land Cover Estimation; GLCLUC: Global Land Cover and Land Use Change.

(2021a) generated 30 m resolution global land cover map data for 36 years by combining strategies of sample migration, machine learning, and spatio-temporal adjustment, which can be used to study global land change. Recently, Friedl et al. (2022) and Potapov et al. (2022) have also created annual global land cover change maps between 2000 and 2020 based on the Landsat time series. Among all these products, Land Change Monitoring, Assessment, and Projection (LCMAP) (Brown et al., 2020), LANDFIRE (Rollins, 2009), and National Terrestrial Ecosystem Monitoring System (NTEMS) (Hermosilla et al., 2022; White et al., 2017, 2022) are some of the few land change products that not only can provide change location and time, change target, but also land change metrics, or even land change agent information.

## 6. Conclusion and recommendations

Land change science has made big advancements with the development of remote sensing technology, and questions of where, when, what, why, and how this change takes place can be fully evaluated and mapped. We proposed a new concept of the multifaceted view of land change through the lens of remote sensing and recommended five facets including change location, time, target, metric, and agent. We also discussed the relationship of various kinds of land change terminologies including spectral change, land surface change, biophysical/biochemical parameter change, land disturbance, climate change, climate variability, succession, land cover change, land cover conversion, and land cover modifications, in which large differences were identified among these terminologies. The impacts of spatial, spectral, temporal, and angular domains of the remotely sensed data on observation, monitoring, and characterization of land change were also evaluated. We emphasized the importance of selecting the "right" spectral bands and spatial resolution of remote sensing data for the specific land change problem. We discussed the benefits and challenges when dense time-series and multi-angle satellite observations are used for observing and characterizing land change. We also reviewed some of the current land change products and observed the lack of products that provide multiple, or all land change facets, particularly for the facets of land change agent and metric.

Therefore, we have a few recommendations on remote sensing of land change as follows. First, it is important to recognize the multifaceted nature of land change, and when remote sensing data are used to study land change, specifying which land change facet is being studied, is usually the first step. Second, remote sensing-derived land change products reported with all five facets are highly recommended, as land change can only be fully understood if they are viewed from all different angles. Third, we think a major shift in the focus from change target to change metric and change agent is expected in future remote sensing studies, as these two facets are far less studied in the remote sensing community, and why and how global land is changing are some of the most difficult and important science questions. Fourth, land change science has transitioned into more complex systems such as land system science (Turner et al., 2021), which requires deeper and more comprehensive land change information. For example, most of the current remote sensing change agent products are not detailed enough for social sciences to answer the question of "why", and the combined use of social science data and multiple remote sensing data sources could provide new and deeper insights. Finally, we need to recognize that every remote sensing system has limitations and weaknesses in land change studies, and a thorough evaluation of all spectral, spatial, temporal, and angular issues is highly recommended.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The remote sensing data used in this review were downloaded from USGS, NASA, Copernicus, and Planet Labs.

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## References

Anderson, J.R., Hardy, E.E., Roach, J.T., Witmer, R.E., 1976. A land use and land cover classification system for use with remote sensor data, Washington, DC: government printing office (US geological survey. Professional Paper 964. https://doi.org/10.3133/pp964.

Asner, G.P., Knapp, D.E., Balaji, A., Páez-Acosta, G., 2009. Automated mapping of tropical deforestation and forest degradation: CLASlite. J. Appl. Remote. Sens. 3, 33543. https://doi.org/10.1117/1.3223675.

Asner, G.P., Knapp, D.E., Broadbent, E.N., Oliveira, P.J.C., Keller, M., Silva, J.N., 2005. Selective logging in the brazilian Amazon. Science 310, 480–482. https://doi.org/10.1126/science.1118051.

Baker, B.A., Warner, T.A., Conley, J.F., McNeil, B.E., 2013. Does spatial resolution matter? A multi-scale comparison of object-based and pixel-based methods for detecting change associated with gas well drilling operations. Int. J. Remote Sens. 34, 1633–1651.

Banskota, A., Kayastha, N., Falkowski, M.J., Wulder, M.A., Froese, R.E., White, J.C., 2014. Forest monitoring using landsat time series data: a review. Can. J. Remote. Sens. 40, 362–384. https://doi.org/10.1080/07038992.2014.987376.

Bartels, S.F., Chen, H.Y.H., Wulder, M.A., White, J.C., 2016. Trends in post-disturbance recovery rates of Canada's forests following wildfire and harvest. For. Ecol. Manag. 361, 194–207. https://doi.org/10.1016/j.foreco.2015.11.015.

Beck, P.S.A., Atzberger, C., Høgda, K.A., Johansen, B., Skidmore, A.K., 2006. Improved monitoring of vegetation dynamics at very high latitudes: a new method using MODIS NDVI. Remote Sens. Environ. 100, 321–334.

Belward, A.S., Skøien, J.O., 2015. Who launched what, when and why; trends in global land-cover observation capacity from civilian earth observation satellites. ISPRS J. Photogramm. Remote Sens. 103, 115–128. https://doi.org/10.1016/j.isprsjprs.2014.03.009.

Bowman, D.M.J.S., Balch, J., Artaxo, P., Bond, W.J., Cochrane, M.A., D'antonio, C.M., DeFries, R., Johnston, F.H., Keeley, J.E., Krawchuk, M.A., 2011. The human dimension of fire regimes on earth. J. Biogeogr. 38, 2223–2236. https://doi.org/10.1111/j.1365-2699.2011.02595.x.

Brown, J.F., Tollerud, H.J., Barber, C.P., Zhou, Q., Dwyer, J.L., Vogelmann, J.E., Loveland, T.R., Woodcock, C.E., Stehman, S.V., Zhu, Z., Pengra, B.W., 2020. Lessons learned implementing an operational continuous United States national land change monitoring capability: the land change monitoring, assessment, and project (LCMAP) approach. Remote Sens. Environ. 238, 111356 https://doi.org/10.1016/j.rse.2019.111356.

Bruzzone, L., Bovolo, F., 2012. A novel framework for the design of change-detection systems for very-high-resolution remote sensing images. Proceedings of the IEEE 101 (3), 609–630. https://doi.org/10.1109/JPROC.2012.2197169.

Buchner, J., Yin, H., Frantz, D., Kuemmerle, T., Askerov, E., Bakuradze, T., Bleyhl, B., Elizbarashvili, N., Komarova, A., Lewińska, K.E., 2020. Land-cover change in the Caucasus Mountains since 1987 based on the topographic correction of multi-temporal landsat composites. Remote Sens. Environ. 248, 111967 https://doi.org/10.1016/j.rse.2020.111967.

Cardille, J.A., Perez, E., Crowley, M.A., Wulder, M.A., White, J.C., Hermosilla, T., 2022. Multi-sensor change detection for within-year capture and labelling of forest disturbance. Remote Sens. Environ. 268, 112741.

Chirici, G., Giannetti, F., Mazza, E., Francini, S., Travaglini, D., Pegna, R., White, J.C., 2020. Monitoring clearcutting and subsequent rapid recovery in Mediterranean coppice forests with landsat time series. Ann. For. Sci. 77, 1–14.

Chowdhury, S., Peddle, D.R., Wulder, M.A., Heckbert, S., Shipman, T.C., Chao, D.K., 2021. Estimation of land-use/land-cover changes associated with energy footprints and other disturbance agents in the upper peace region of Alberta Canada from 1985 to 2015 using landsat data. Int. J. Appl. Earth Obs. Geoinf. 94, 102224.

Chu, T., Guo, X., Takeda, K., 2016. Remote sensing approach to detect post-fire vegetation regrowth in siberian boreal larch forest. Ecol. Indic. 62, 32–46.

Claverie, M., Ju, J., Masek, J.G., Dungan, J.L., Vermote, E.F., Roger, J.C., Skakun, S.V., Justice, C., 2018. The harmonized landsat and Sentinel-2 surface reflectance data set. Remote Sens. Environ. 219, 145–161. https://doi.org/10.1016/j.rse.2018.09.002.

Clements, F.E., 1916. Plant succession: an analysis of the development of vegetation. Carnegie Institution of Washington.

Cohen, W.B., Goward, S.N., 2004. Landsat's role in ecological applications of remote sensing. Bioscience 54, 535–545. https://doi.org/10.1641/0006-3568(2004)054[0535:LRIEAO]2.0.CO;2.

Colditz, R.R., Pouliot, D., Llamas, R.M., Homer, C., Latifovic, R., Ressl, R.A., Tovar, C.M., Hernández, A.V., Richardson, K., 2014. Detection of North American land cover change between 2005 and 2010 with 250m MODIS data. PE&RS. Photogramm. Eng. Remote Sens. 80, 918–924.

Comber, A., Wulder, M., 2019. Considering spatiotemporal processes in big data analysis: Insights from remote sensing of land cover and land use. Trans. GIS 23, 879–891.

Coops, N.C., Johnson, M., Wulder, M.A., White, J.C., 2006. Assessment of QuickBird high spatial resolution imagery to detect red attack damage due to mountain pine beetle infestation. Remote Sens. Environ. 103, 67–80.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., Lambin, E., 2004. Digital change detection methods in ecosystem monitoring: a review. Int. J. Remote Sens. 25, 1565–1596.

Coppin, P.R., Bauer, M.E., 1996. Digital change detection in forest ecosystems with remote sensing imagery. Remote Sens. Rev. 13, 207–234. https://doi.org/10.1080/02757259609532305.

Cui, T., Martz, L., Zhao, L., Guo, X., 2020. Investigating the impact of the temporal resolution of MODIS data on measured phenology in the prairie grasslands. GIScience Remote Sens. 57, 395–410.

Dale, V.H., 1997. The relationship between land-use change and climate change. Ecol. Appl. 7, 753–769. https://doi.org/10.1890/1051-0761(1997)007[0753:TRBLUC]2.0.CO;2.

Dale, V.H., Joyce, L.A., McNulty, S., Neilson, R.P., Ayres, M.P., Flannigan, M.D., Hanson, P.J., Irland, L.C., Lugo, A.E., Peterson, C.J., 2001. Climate change and forest disturbances: climate change can affect forests by altering the frequency, intensity, duration, and timing of fire, drought, introduced species, insect and pathogen outbreaks, hurricanes, windstorms, ice storms, or landslides. Bioscience 51, 723–734. https://doi.org/10.1641/0006-3568(2001)051[0723:CCAFD]2.0.CO;2.

Daume, S., Albert, M., von Gadow, K., 2014. Forest monitoring and social media–Complementary data sources for ecosystem surveillance? For. Ecol. Manag. 316, 9–20.

de Beurs, K.M., Henebry, G.M., Owsley, B.C., Sokolik, I., 2015. Using multiple remote sensing perspectives to identify and attribute land surface dynamics in Central Asia 2001–2013. Remote Sens. Environ. 170, 48–61. https://doi.org/10.1016/j.rse.2015.08.018.

De Jong, R., Verbesselt, J., Schaepman, M.E., De Bruin, S., 2012. Trend changes in global greening and browning: Contribution of short-term trends to longer-term change.

Glob. Chang. Biol. 18, 642–655. https://doi.org/10.1111/j.1365-2486.2011.02578.x.
Deng, C., Zhu, Z., 2020. Continuous subpixel monitoring of urban impervious surface using Landsat time series. Remote Sens. Environ. 238, 110929 https://doi.org/10.1016/j.rse.2018.10.011.
Dong, J., Zhuang, D., Huang, Y., Fu, J., 2009. Advances in multi-sensor data fusion: Algorithms and applications. Sensors 9, 7771–7784.
Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., Bargellini, P., 2012. Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. Remote Sens. Environ. 120, 25–36. https://doi.org/10.1016/j.rse.2011.11.026.
Dwyer, J., Roy, D., Sauer, B., Jenkerson, C., Zhang, H., Lymburner, L., 2018. Analysis Ready Data: Enabling Analysis of the Landsat Archive. Remote Sens. 10, 1363. https://doi.org/10.3390/rs10091363.
Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z., Quayle, B., Howard, S., Falls, S., Falls, S., 2007. A Project for Monitoring Trends in Burn Severity. Fire Ecol. 3, 3–21. https://doi.org/10.4996/fireecology.0301003.
Ellis, E.C., Klein Goldewijk, K., Siebert, S., Lightman, D., Ramankutty, N., 2010. Anthropogenic transformation of the biomes, 1700 to 2000. Glob. Ecol. Biogeogr. 19, 589–606. https://doi.org/10.1111/j.1466-8238.2010.00540.x.
Elvidge, C.D., Zhizhin, M., Ghosh, T., Hsu, F.-C., Taneja, J., 2021. Annual time series of global VIIRS nighttime lights derived from monthly averages: 2012 to 2019. Remote Sens. 13, 922. https://doi.org/10.3390/rs13050922.
Emelyanova, I.V., McVicar, T.R., Van Niel, T.G., Li, L.T., Van Dijk, A.I.J.M., 2013. Assessing the accuracy of blending Landsat–MODIS surface reflectances in two landscapes with contrasting spatial and temporal dynamics: A framework for algorithm selection. Remote Sens. Environ. 133, 193–209.
Fang, F., McNeil, B.E., Warner, T.A., Maxwell, A.E., Dahle, G.A., Eutsler, E., Li, J., 2020. Discriminating tree species at different taxonomic levels using multi-temporal WorldView-3 imagery in Washington DC, USA. Remote Sens. Environ. 246, 111811.
Fernandez-Manso, A., Quintano, C., Roberts, D.A., 2019. Burn severity analysis in Mediterranean forests using maximum entropy model trained with EO-1 Hyperion and LiDAR data. ISPRS J. Photogramm. Remote Sens. 155, 102–118.
Firebaugh, G., Warner, C., Massoglia, M., 2013. Fixed effects, random effects, and hybrid models for causal analysis. In: Handbook of Causal Analysis for Social Research. Springer, pp. 113–132.
Fohringer, J., Dransch, D., Kreibich, H., Schröter, K., 2015. Social media as an information source for rapid flood inundation mapping. Nat. Hazards Earth Syst. Sci. 15, 2725–2738.
Foody, G.M., Doan, H.T.X., 2007. Variability in soft classification prediction and its implications for sub-pixel scale change detection and super resolution mapping. Photogramm. Eng. Remote Sens. 73, 923–933. https://doi.org/10.14358/PERS.73.8.923.
Forzieri, G., Dakos, V., McDowell, N.G., Ramdane, A., Cescatti, A., 2022. Emerging signals of declining forest resilience under climate change. Nature 608, 534–539. https://doi.org/10.1038/s41586-022-04959-9.
Frantz, D., 2019. FORCE—Landsat+ Sentinel-2 analysis ready data and beyond. Remote Sens. 11, 1124. https://doi.org/10.3390/rs11091124.
Frantz, D., Haß, E., Uhl, A., Stoffels, J., Hill, J., 2018. Improvement of the Fmask algorithm for Sentinel-2 images: Separating clouds from bright surfaces based on parallax effects. Remote Sens. Environ. 215, 471–481. https://doi.org/10.1016/j.rse.2018.04.046.
Friedl, M.A., Woodcock, C.E., Olofsson, P., Zhu, Z., Loveland, T., Stanimirova, R., Arevalo, P., Bullock, E., Hu, K.-T., Zhang, Y., Turlej, K., Tarrio, K., McAvoy, K., Gorelick, N., Wang, J.A., Barber, C.P., Souza, C., 2022. Medium Spatial Resolution Mapping of Global Land Cover and Land Cover Change Across Multiple Decades From Landsat. Front. Remote Sens. 3 https://doi.org/10.3389/frsen.2022.894571.
Friis, C., Nielsen, J.Ø., Otero, I., Haberl, H., Niewöhner, J., Hostert, P., 2016. From teleconnection to telecoupling: Taking stock of an emerging framework in land system science. J. Land Use Sci. 11, 131–153. https://doi.org/10.1080/1747423X.2015.1096423.
Ganguly, S., Friedl, M.A., Tan, B., Zhang, X., Verma, M., 2010. Land surface phenology from MODIS: Characterization of the Collection 5 global land cover dynamics product. Remote Sens. Environ. 114, 1805–1816.
Gao, F., Masek, J., Schwaller, M., Hall, F., 2006. On the blending of the Landsat and MODIS surface reflectance: Predicting daily Landsat surface reflectance. IEEE Trans. Geosci. Remote Sens. 44, 2207–2218.
Gao, F., Masek, J.G., Wolfe, R.E., 2009. Automated registration and orthorectification package for Landsat and Landsat-like data processing. J. Appl. Remote. Sens. 3, 033515 https://doi.org/10.1117/1.3104620.
Garbulsky, M.F., Peñuelas, J., Gamon, J., Inoue, Y., Filella, I., 2011. The photochemical reflectance index (PRI) and the remote sensing of leaf, canopy and ecosystem radiation use efficiencies: A review and meta-analysis. Remote Sens. Environ. 115, 281–297. https://doi.org/10.1016/j.rse.2010.08.023.
Geist, H.J., Lambin, E.F., 2002. Proximate Causes and Underlying Driving Forces of Tropical DeforestationTropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. Bioscience 52, 143–150. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2.
Giglio, L., Boschetti, L., Roy, D.P., Humber, M.L., Justice, C.O., 2018. The Collection 6 MODIS burned area mapping algorithm and product. Remote Sens. Environ. 217, 72–85. https://doi.org/10.1016/j.rse.2018.08.005.
Gómez, C., White, J.C., Wulder, M.A., 2016. Optical remotely sensed time series data for land cover classification: A review. ISPRS J. Photogramm. Remote Sens. 116, 55–72. https://doi.org/10.1016/j.isprsjprs.2016.03.008.
Goodchild, M.F., 2007. Citizens as sensors: the world of volunteered geography. GeoJournal 69, 211–221. https://doi.org/10.1007/s10708-007-9111-y.
Goodchild, M.F., Li, L., 2012. Assuring the quality of volunteered geographic information. Spat Stat 1, 110–120. https://doi.org/10.1016/j.spasta.2012.03.002.
Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031.
Grime, J.P., 1977. Evidence for the existence of three primary strategies in plants and its relevance to ecological and evolutionary theory. Am. Nat. 111, 1169–1194.
Guo, B., Gunn, S.R., Damper, R.I., Nelson, J.D.B., 2006. Band selection for hyperspectral image classification using mutual information. IEEE Geosci. Remote Sens. Lett. 3, 522–526.
Guo, X., Feng, J., Shi, Z., Zhou, X., Yuan, M., Tao, X., Hale, L., Yuan, T., Wang, J., Qin, Y., 2018. Climate warming leads to divergent succession of grassland microbial communities. Nat. Clim. Chang. 8, 813–818. https://doi.org/10.1038/s41558-018-0254-2.
Gutman, G., Janetos, A.C., Justice, C.O., Moran, E.F., Mustard, J.F., Rindfuss, R.R., Skole, D., Turner II, B.L., Cochrane, M.A., 2004. Land change science: observing, monitoring and understanding trajectories of change on the earth's surface. Springer Science & Business Media.
Hall, F.G., Botkin, D.B., Strebel, D.E., Woods, K.D., Goetz, S.J., 1991. Large-scale patterns of forest succession as determined by remote sensing. Ecology 72, 628–640.
Hansen, M.C., DeFries, R.S., 2004. Detecting long-term global forest change using continuous fields of tree-cover maps from 8-km advanced very high resolution radiometer (AVHRR) data for the years 1982–99. Ecosystems 7, 695–716, 10.1007%2Fs10021-004-0243.
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.
Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853. https://doi.org/10.1126/science.1244693.
Hart, S.J., Veblen, T.T., 2015. Detection of spruce beetle-induced tree mortality using high- and medium-resolution remotely sensed imagery. Remote Sens. Environ. 168, 134–145. https://doi.org/10.1016/j.rse.2015.06.015.
Healey, S.P., Cohen, W.B., Yang, Z., Kenneth Brewer, C., Brooks, E.B., Gorelick, N., Hernandez, A.J., Huang, C., Joseph Hughes, M., Kennedy, R.E., Loveland, T.R., Moisen, G.G., Schroeder, T.A., Stehman, S.V., Vogelmann, J.E., Woodcock, C.E., Yang, L., Zhu, Z., 2018. Mapping forest change using stacked generalization: An ensemble approach. Remote Sens. Environ. 204, 717–728. https://doi.org/10.1016/j.rse.2017.09.029.
Henson, S.A., Cole, H.S., Hopkins, J., Martin, A.P., Yool, A., 2018. Detection of climate change-driven trends in phytoplankton phenology. Glob. Chang. Biol. 24, e101–e111.
Hermosilla, T., Wulder, M.A., White, J.C., Coops, N.C., 2022. Land cover classification in an era of big and open data: Optimizing localized implementation and training data selection to improve mapping outcomes. Remote Sens. Environ. 268, 112780.
Hermosilla, T., Wulder, M.A., White, J.C., Coops, N.C., Hobart, G.W., 2018. Disturbance-Informed Annual Land Cover Classification Maps of Canada's Forested Ecosystems for a 29-Year Landsat Time Series. Can. J. Remote. Sens. 44, 67–87. https://doi.org/10.1080/07038992.2018.1437719.
Homer, C., Dewitz, J., Fry, J., Coan, M., Hossain, N., Larson, C., Herold, N., McKerrow, A., VanDriel, J.N., Wickham, J., 2007. Completion of the 2001 national land cover database for the counterminous United States. Photogramm. Eng. Remote Sens. 337–341.
Homer, C., Dewitz, J., Jin, S., Xian, G., Costello, C., Danielson, P., Gass, L., Funk, M., Wickham, J., Stehman, S., 2020. Conterminous United States land cover change patterns 2001–2016 from the 2016 national land cover database. ISPRS J. Photogramm. Remote Sens. 162, 184–199.
Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N., Wickham, J., Megown, K., 2015. Completion of the 2011 National Land Cover Database for the conterminous United States–representing a decade of land cover change information. Photogramm. Eng. Remote Sens. 81, 345–354.
Huang, C., Goward, S.N., Masek, J.G., Thomas, N., Zhu, Z., Vogelmann, J.E., 2010. An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks. Remote Sens. Environ. 114, 183–198. https://doi.org/10.1016/j.rse.2009.08.017.
Huang, H., Roy, D.P., 2021. Characterization of Planetscope-0 Planetscope-1 surface reflectance and normalized difference vegetation index continuity. Sci. Remote Sens. 3, 100014 https://doi.org/10.1016/j.srs.2021.100014.
Huang, S., Ramirez, C., McElhaney, M., Clark, C., Yao, Z., 2019. Quantifying spatiotemporal post-disturbance recovery using field inventory, tree growth, and remote sensing. Earth Sp. Sci. 6, 489–504.
Huang, X., Cao, Y., Li, J., 2020. An automatic change detection method for monitoring newly constructed building areas using time-series multi-view high-resolution optical satellite images. Remote Sens. Environ. 244, 111802 https://doi.org/10.1016/j.rse.2020.111802.
Huete, A., 2016. Vegetation's responses to climate variability. Nature 531, 181–182. https://doi.org/10.1038/nature17301.
Hussain, M., Chen, D., Cheng, A., Wei, H., Stanley, D., 2013. Change detection from remotely sensed images: From pixel-based to object-based approaches. ISPRS J. Photogramm. Remote Sens. https://doi.org/10.1016/j.isprsjprs.2013.03.006.
Huston, M., Smith, T., 1987. Plant succession: life history and competition. Am. Nat. 130, 168–198. https://doi.org/10.1016/j.ecoleng.2021.106331.

Jensen, J.R., 2009. Remote Sensing of the Environment: An Earth Resource Perspective 2/e. Pearson Education India.
Jiao, Z., Woodcock, C., Schaaf, C.B., Tan, B., Liu, J., Gao, F., Strahler, A., Li, X., Wang, J., 2011. Improving MODIS land cover classification by combining MODIS spectral and angular signatures in a Canadian boreal forest. Can. J. Remote. Sens. 37, 184–203. https://doi.org/10.5589/m11-030.
Jin, S., Homer, C., Yang, L., Danielson, P., Dewitz, J., Li, C., Zhu, Z., Xian, G., Howard, D., 2019. Overall methodology design for the United States national land cover database 2016 products. Remote Sens. 11 https://doi.org/10.3390/rs11242971.
Jin, S., Sader, S.A., 2005. MODIS time-series imagery for forest disturbance detection and quantification of patch size effects. Remote Sens. Environ. 99, 462–470. https://doi.org/10.1016/j.rse.2005.09.017.
Johnson, E.A., Miyanishi, K., 2021. Disturbance and succession. In: Johnson, E.A., Miyanishi, K.B.T.-P.D.E. (Eds.), Plant Disturbance Ecology, Second edition. Academic Press, San Diego, pp. 1–15. https://doi.org/10.1016/B978-0-12-818813-2.00001-0.
Johnson, E.W., Wittwer, D., 2008. Aerial detection surveys in the United States. Aust. For. 71, 212–215. https://doi.org/10.1080/00049158.2008.10675037.
Justice, C.O., Giglio, L., Korontzi, S., Owens, J., Morisette, J.T., Roy, D., Descloitres, J., Alleaume, S., Petitcolin, F., Kaufman, Y., 2002. The MODIS fire products. Remote Sens. Environ. 83, 244–262. https://doi.org/10.1016/S0034-4257(02)00076-7.
Justice, C.O., Vermote, E., Townshend, J.R.G., Defries, R., Roy, D.P., Hall, D.K., Salomonson, V.V., Privette, J.L., Riggs, G., Strahler, A., 1998. The Moderate Resolution Imaging Spectroradiometer (MODIS): land remote sensing for global change research. IEEE Trans. Geosci. Remote Sens. 36, 1228–1249.
Kennedy, R.E., Andréfouët, S., Cohen, W.B., Gómez, C., Griffiths, P., Hais, M., Healey, S. P., Helmer, E.H., Hostert, P., Lyons, M.B., 2014. Bringing an ecological view of change to Landsat-based remote sensing. Front. Ecol. Environ. 12, 339–346. https://doi.org/10.1890/130066.
Kennedy, R.E., Cohen, W.B., Schroeder, T.A., 2007. Trajectory-based change detection for automated characterization of forest disturbance dynamics. Remote Sens. Environ. 110, 370–386. https://doi.org/10.1016/j.rse.2007.03.010.
Kennedy, R.E., Townsend, P.A., Gross, J.E., Cohen, W.B., Bolstad, P., Wang, Y.Q., Adams, P., 2009. Remote sensing change detection tools for natural resource managers: Understanding concepts and tradeoffs in the design of landscape monitoring projects. Remote Sens. Environ. 113, 1382–1396. https://doi.org/10.1016/j.rse.2008.07.018.
Kennedy, R.E., Yang, Z., Braaten, J., Copass, C., Antonova, N., Jordan, C., Nelson, P., 2015. Attribution of disturbance change agent from Landsat time-series in support of habitat monitoring in the Puget Sound region, USA. Remote Sens. Environ. 166, 271–285. https://doi.org/10.1016/j.rse.2015.05.005.
Kennedy, R.E., Yang, Z., Cohen, W.B., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr—Temporal segmentation algorithms. Remote Sens. Environ. 114, 2897–2910. https://doi.org/10.1016/j.rse.2010.07.008.
Key, T., Warner, T.A., McGraw, J.B., Fajvan, M.A., 2001. A comparison of multispectral and multitemporal information in high spatial resolution imagery for classification of individual tree species in a temperate hardwood forest. Remote Sens. Environ. 75, 100–112.
Kirschbaum, D.B., Adler, R., Hong, Y., Hill, S., Lerner-Lam, A., 2010. A global landslide catalog for hazard applications: method, results, and limitations. Nat. Hazards 52, 561–575. https://doi.org/10.1007/s11069-009-9401-4.
Knoflach, B., Ramskogler, K., Talluto, M., Hofmeister, F., Haas, F., Heckmann, T., Pfeiffer, M., Piermattei, L., Ressl, C., Wimmer, M.H., 2021. Modelling of vegetation dynamics from satellite time series to determine proglacial primary succession in the course of global warming—a case study in the Upper Martell Valley (Eastern Italian Alps). Remote Sens. 13, 4450.
Kussul, N., Lavreniuk, M., Skakun, S., Shelestov, A., 2017. Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data. IEEE Geosci. Remote Sens. Lett. 14, 778–782. https://doi.org/10.1109/LGRS.2017.2681128.
Laflower, D.M., Hurteau, M.D., Koch, G.W., North, M.P., Hungate, B.A., 2016. Climate-driven changes in forest succession and the influence of management on forest carbon dynamics in the Puget Lowlands of Washington StateUSA. For. Ecol. Manage. 362, 194–204. https://doi.org/10.1016/j.foreco.2015.12.015.
Lambin, E.F., 2004. Linking socioeconomic and remote sensing data at the community or at the household level. In: People and the Environment. Springer, pp. 223–240.
Lambin, E.F., Strahler, A.H., 1994. Change-vector analysis in multitemporal space: A tool to detect and categorize land-cover change processes using high temporal-resolution satellite data. Remote Sens. Environ. 48, 231–244. https://doi.org/10.1016/0034-4257(94)90144-9.
Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., Folke, C., 2001. The causes of land-use and land-cover change: Moving beyond the myths. Glob. Environ. Chang. 11, 261–269. https://doi.org/10.1016/S0959-3780(01)00007-3.
Latifovic, R., Homer, C., Ressl, R., Pouliot, D., Hossain, S.N., Colditz, R.R., Olthof, I., Giri, C.P., Victoria, A., 2016. North American land-change monitoring system. Remote Sens. 303. L. use L. Cover.
Latifovic, R., Pouliot, D., 2005. Multitemporal land cover mapping for Canada: methodology and products. Can. J. Remote. Sens. 31, 347–363.
Lawrence, R., 2005. Remote sensing of vegetation responses during the first 20 years following the 1980 eruption of Mount St. Helens: a spatially and temporally stratified analysis. In: Ecological Responses to the 1980 Eruption of Mount St. Helens. Springer, New York, NY, pp. 111–123. https://doi.org/10.1007/0-387-28150-9_8.
Lentile, L.B., Holden, Z.A., Smith, A.M.S., Falkowski, M.J., Hudak, A.T., Morgan, P., Lewis, S.A., Gessler, P.E., Benson, N.C., 2006. Remote sensing techniques to assess active fire characteristics and post-fire effects. Int. J. Wildl. Fire 15, 319–345. https://doi.org/10.1071/WF05097.
Levin, N., Kyba, C.C.M., Zhang, Q., de Miguel, A.S., Román, M.O., Li, X., Portnov, B.A., Molthan, A.L., Jechow, A., Miller, S.D., 2020. Remote sensing of night lights: A review and an outlook for the future. Remote Sens. Environ. 237, 111443.
Levin, Noam, 2017. The impact of seasonal changes on observed nighttime brightness from 2014 to 2015 monthly VIIRS DNB composites. Remote Sens. Environ. 193, 150–164. https://doi.org/10.1016/j.rse.2017.03.003.
Li, J., Roy, D.P., 2017. A global analysis of Sentinel-2A, Sentinel-2B and Landsat-8 data revisit intervals and implications for terrestrial monitoring. Remote Sens. 9, 902. https://doi.org/10.3390/rs9090902.
Li, X., Elvidge, C., Zhou, Y., Cao, C., Warner, T., 2017. Remote sensing of night-time light. Int. J. Remote Sens. 38, 5855–5859.
Lin, Y., Zhu, Z., Guo, W., Sun, Y., Yang, X., Kovalskyy, V., 2020. Continuous monitoring of cotton stem water potential using Sentinel-2 imagery. Remote Sens. 12, 1176. https://doi.org/10.3390/rs12071176.
Liu, H., Gong, P., Wang, J., Wang, X., Ning, G., Xu, B., 2021a. Production of global daily seamless data cubes and quantification of global land cover change from 1985 to 2020 - iMap World 1.0. Remote Sens. Environ. 258, 112364. https://doi.org/10.1016/j.rse.2021.112364.
Liu, X., Huang, Y., Xu, X., Li, Xuecao, Li, Xia, Ciais, P., Lin, P., Gong, K., Ziegler, A.D., Chen, A., Gong, P., Chen, J., Hu, G., Chen, Y., Wang, S., Wu, Q., Huang, K., Estes, L., Zeng, Z., 2020a. High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015. Nat. Sustain. 3, 564–570. https://doi.org/10.1038/s41893-020-0521-x.
Liu, Y., Wang, Z., Sun, Q., Erb, A.M., Li, Z., Schaaf, C.B., Zhang, X., Román, M.O., Scott, R.L., Zhang, Q., Novick, K.A., Syndonia Bret-Harte, M., Petroy, S., SanClements, M., 2017. Evaluation of the VIIRS BRDF, Albedo and NBAR products suite and an assessment of continuity with the long term MODIS record. Remote Sens. Environ. 201, 256–274. https://doi.org/10.1016/j.rse.2017.09.020.
Liu, Y., Xu, B., Zhi, W., Hu, C., Dong, Y., Jin, S., Lu, Y., Chen, T., Xu, W., Liu, Yongchao, Zhao, B., Lu, W., 2020b. Space eye on flying aircraft: From Sentinel-2 MSI parallax to hybrid computing. Remote Sens. Environ. 246, 111867 https://doi.org/10.1016/j.rse.2020.111867.
Liu, J., Yang, Z., Liu, Y., Mu, C., 2021b. Hyperspectral remote sensing images deep feature extraction based on mixed feature and convolutional neural networks. Remote Sens. 13 https://doi.org/10.3390/rs13132599.
Loveland, T.R., Sohl, T.L., Stehman, S.V., Gallant, A.L., Sayler, K.L., Napton, D.E., 2002. A strategy for estimating the rates of recent United States land-cover changes. Photogramm. Eng. Remote Sens. 68, 1091–1099.
Lu, D., Mausel, P., Brondizio, E., Moran, E., 2004. Change detection techniques. Int. J. Remote Sens. 25, 2365–2401.
Martin, L., Howarth, P.J., 1989. Change-detection accuracy assessment using SPOT multispectral imagery of the rural-urban fringe. Remote Sens. Environ. 30, 55–66. https://doi.org/10.1016/0034-4257(89)90047-3.
Mascorro, V.S., Coops, N.C., Kurz, W.A., Olguín, M., 2015. Choice of satellite imagery and attribution of changes to disturbance type strongly affects forest carbon balance estimates. Carbon Balance Manag. 10, 1–15.
Masek, J.G., Huang, C., Wolfe, R., Cohen, W., Hall, F., Kutler, J., Nelson, P., 2008. North American forest disturbance mapped from a decadal Landsat record. Remote Sens. Environ. 112, 2914–2926. https://doi.org/10.1016/j.rse.2008.02.010.
Masek, J.G., Vermote, E.F., Saleous, N.E., Wolfe, R., Hall, F.G., Huemmrich, K.F., Gao, F., Kutler, J., Lim, T.-K., 2006. A Landsat surface reflectance dataset for North America, 1990–2000. IEEE Geosci. Remote Sens. Lett. 3, 68–72. https://doi.org/10.1109/LGRS.2005.857030.
Masek, J.G., Wulder, M.A., Markham, B., McCorkel, J., Crawford, C.J., Storey, J., Jenstrom, D.T., 2020. Landsat 9: Empowering open science and applications through continuity. Remote Sens. Environ. 248, 111968 https://doi.org/10.1016/j.rse.2020.111968.
Meng, R., Dennison, P.E., Zhao, F., Shendryk, I., Rickert, A., Hanavan, R.P., Cook, B.D., Serbin, S.P., 2018. Mapping canopy defoliation by herbivorous insects at the individual tree level using bi-temporal airborne imaging spectroscopy and LiDAR measurements. Remote Sens. Environ. 215, 170–183.
Mildrexler, D.J., Zhao, M., Running, S.W., 2009. Testing a MODIS global disturbance index across North America. Remote Sens. Environ. 113, 2103–2117. https://doi.org/10.1016/j.rse.2009.05.016.
Minale, A.S., 2013. Retrospective analysis of land cover and use dynamics in Gilgel Abbay Watershed by using GIS and remote sensing techniquesNorthwestern Ethiopia. Int. J. Geosci. 4, 1003.
Molinier, M., Miettinen, J., Ienco, D., Qiu, S., Zhu, Z., 2021. Optical satellite image time series analysis for environment applications: from classical methods to deep learning and beyond. In: Change Detection and Image Time Series Analysis 2: Supervised Methods. Wiley Online Library, pp. 109–154.
Myneni, R.B., Keeling, C.D., Tucker, C.J., Asrar, G., Nemani, R.R., 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. Nature 386, 698–702. https://doi.org/10.1038/386698a0.
Noaa, 2022. Severe Weather Data Inventory [WWW Document]. NOAA (accessed 1.4.22). https://www.ncei.noaa.gov/products/severe-weather-data-inventory.
Nrc, 2013. Advancing Land Change Modeling: Opportunities and Research Requirements. National Academies Press.
Nrc, 1999. Human Dimensions of Global Environmental Change: Research Pathways for the Next Decade. National Academies Press.
Nrc, 1998. <book-title>People and Pixels: Linking Remote Sensing and Social </book-title>Science. National Academies Press.

Oeser, J., Pflugmacher, D., Senf, C., Heurich, M., Hostert, P., 2017. Using intra-annual Landsat time series for attributing forest disturbance agents in Central Europe. Forests 8, 251. https://doi.org/10.3390/f8070251.

Oliver, C.D., Larson, B.C., 1996. Forest Stand Dynamics, Updated edition. John Wiley and sons.

Olofsson, P., Foody, G.M., Stehman, S.V., Woodcock, C.E., 2013. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. Remote Sens. Environ. 129, 122–131. https://doi.org/10.1016/j.rse.2012.10.031.

Ortiz, S.M., Breidenbach, J., Kändler, G., 2013. Early detection of bark beetle green attack using TerraSAR-X and RapidEye data. Remote Sens. 5, 1912–1931.

Osińska-Skotak, K., Radecka, A., Piórkowski, H., Michalska-Hejduk, D., Kopeć, D., Tokarska-Guzik, B., Ostrowski, W., Kania, A., Niedzielko, J., 2019. Mapping succession in non-forest habitats by means of remote sensing: Is the data acquisition time critical for species discrimination? Remote Sens. 11, 2629.

Pasquarella, V.J., Holden, C.E., Woodcock, C.E., 2018. Improved mapping of forest type using spectral-temporal Landsat features. Remote Sens. Environ. 210, 193–207. https://doi.org/10.1016/j.rse.2018.02.064.

Pekel, J.-F., Cottam, A., Gorelick, N., Belward, A.S., 2016. High-resolution mapping of global surface water and its long-term changes. Nature 540, 418–422. https://doi.org/10.1038/nature20584.

Pengra, B.W., Stehman, S.V., Horton, J.A., Dockter, D.J., Schroeder, T.A., Yang, Z., Cohen, W.B., Healey, S.P., Loveland, T.R., 2020. Quality control and assessment of interpreter consistency of annual land cover reference data in an operational national monitoring program. Remote Sens. Environ. 238, 111261 https://doi.org/10.1016/j.rse.2019.111261.

Pérez-Cabello, F., Montorio, R., Alves, D.B., 2021. Remote sensing techniques to assess post-fire vegetation recovery. Curr. Opin. Environ. Sci. Heal. 21, 100251.

Pesaresi, M., Ehrlich, D., Ferri, S., Florczyk, A., Freire, S., Halkia, M., Julea, A., Kemper, T., Soille, P., Syrris, V., 2016. Operating Procedure for the Production of the Global Human Settlement Layer from Landsat Data of the Epochs 1975, 1990, 2000, and 2014. Publications Office of the European Union, Luxembourg (Luxembourg). https://doi.org/10.2788/656115.

Peters, D.P.C., Lugo, A.E., Chapin III, F.S., Pickett, S.T.A., Duniway, M., Rocha, A.V., Swanson, F.J., Laney, C., Jones, J., 2011. Cross-system comparisons elucidate disturbance complexities and generalities. Ecosphere 2, 1–26. https://doi.org/10.1890/ES11-00115.1.

Petit, C., Scudder, T., Lambin, E., 2001. Quantifying processes of land-cover change by remote sensing: resettlement and rapid land-cover changes in south-eastern Zambia. Int. J. Remote Sens. 22, 3435–3456. https://doi.org/10.1080/01431160010006881.

Potapov, P., Hansen, M.C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X.-P., Baggett, A., Kommareddy, I., Kommareddy, A., 2022. The Global 2000–2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results. Front. Remote Sens. 3 https://doi.org/10.3389/frsen.2022.856903.

Potter, C., Tan, P., Steinbach, M., Klooster, S., Kumar, V., Myneni, R., Genovese, V., 2003. Major disturbance events in terrestrial ecosystems detected using global satellite data sets. Glob. Chang. Biol. 9, 1005–1021. https://doi.org/10.1046/j.1365-2486.2003.00648.x.

Pouliot, D., Alavi, N., Wilson, S., Duffe, J., Pasher, J., Davidson, A., Daneshfar, B., Lindsay, E., 2021. Assessment of Landsat Based Deep-Learning Membership Analysis for Development of from–to Change Time Series in the Prairie Region of Canada from 1984 to 2018. Remote Sens. 13, 634.

Pouliot, D., Latifovic, R., 2016. Land change attribution based on Landsat time series and integration of ancillary disturbance data in the Athabasca oil sands region of Canada. GIScience Remote Sens. 53, 382–401.

Pouliot, D., Latifovic, R., Olthof, I., 2009. Trends in vegetation NDVI from 1 km AVHRR data over Canada for the period 1985–2006. Int. J. Remote Sens. 30, 149–168.

Pouliot, D., Latifovic, R., Zabcic, N., Guindon, L., Olthof, I., 2014. Development and assessment of a 250 m spatial resolution MODIS annual land cover time series (2000–2011) for the forest region of Canada derived from change-based updating. Remote Sens. Environ. 140, 731–743.

Pricope, N.G., Mapes, K.L., Woodward, K.D., 2019. Remote sensing of human–environment interactions in global change research: a review of advances, challenges and future directions. Remote Sens. https://doi.org/10.3390/rs11232783.

Qin, Y., Xiao, X., Wigneron, J.-P., Ciais, P., Brandt, M., Fan, L., Li, X., Crowell, S., Wu, X., Doughty, R., 2021. Carbon loss from forest degradation exceeds that from deforestation in the Brazilian Amazon. Nat. Clim. Chang. 11, 442–448. https://doi.org/10.1038/s41558-021-01026-5.

Qiu, S., Lin, Y., Shang, R., Zhang, J., Ma, L., Zhu, Z., Qiu, S., Lin, Y., Shang, R., Zhang, J., Ma, L., Zhu, Z., 2019a. Making landsat time series consistent: evaluating and improving landsat analysis ready data. Remote Sens. 11 https://doi.org/10.3390/RS11010051.

Qiu, S., Zhu, Z., He, B., 2019b. Fmask 4.0: Improved cloud and cloud shadow detection in Landsats 4–8 and Sentinel-2 imagery. Remote Sens. Environ. 231, 111205 https://doi.org/10.1016/j.rse.2019.05.024.

Raitsos, D.E., Pradhan, Y., Brewin, R.J.W., Stenchikov, G., Hoteit, I., 2013. Remote sensing the phytoplankton seasonal succession of the Red Sea. PLoS One 8, e64909.

Reiche, J., Hamunyela, E., Verbesselt, J., Hoekman, D., Herold, M., 2018. Improving near-real time deforestation monitoring in tropical dry forests by combining dense Sentinel-1 time series with Landsat and ALOS-2 PALSAR-2. Remote Sens. Environ. 204, 147–161. https://doi.org/10.1016/j.rse.2017.10.034.

Riemann, R., Wilson, B.T., Lister, A., Parks, S., 2010. An effective assessment protocol for continuous geospatial datasets of forest characteristics using USFS Forest Inventory and Analysis (FIA) data. Remote Sens. Environ. 114, 2337–2352. https://doi.org/10.1016/j.rse.2010.05.010.

Rigge, M., Shi, H., Homer, C., Danielson, P., Granneman, B., 2019. Long-term trajectories of fractional component change in the Northern Great Basin, USA. Ecosphere 10, e02762.

Rindfuss, R.R., Walsh, S.J., Turner, B.L., Fox, J., Mishra, V., 2004. Developing a science of land change: challenges and methodological issues. Proc. Natl. Acad. Sci. 101, 13976–13981. https://doi.org/10.1073/pnas.0401545101.

Rindfuss, R.R., Walsh, S.J., Turner, B.L., Moran, E.F., Entwisle, B., 2012. Linking Pixels and People. In: Gutman, G., Janetos, A.C., Justice, C.O., Moran, E.F., Mustard, J.F., Rindfuss, R.R., Skole, D., Turner, Billy Lee, Cochrane, M.A. (Eds.), Land Change Science: Observing. Monitoring and Understanding Trajectories of Change on the Earth's Surface. Springer, Netherlands, Dordrecht, pp. 379–394. https://doi.org/10.1007/978-1-4020-2562-4_22.

Rittenhouse, C.D., Berlin, E.H., Mikle, N., Qiu, S., Riordan, D., Zhu, Z., 2022. An Object-Based Approach to Map Young Forest and Shrubland Vegetation Based on Multi-Source Remote Sensing Data. Remote Sens. 14, 1091.

Rogan, J., Franklin, J., Stow, D., Miller, J., Woodcock, C., Roberts, D., 2008. Mapping land-cover modifications over large areas: A comparison of machine learning algorithms. Remote Sens. Environ. 112, 2272–2283.

Rollins, M.G., 2009. LANDFIRE: A nationally consistent vegetation, wildland fire, and fuel assessment. Int. J. Wildl. Fire 18, 235–249. https://doi.org/10.1071/WF08088.

Román, M.O., Wang, Z., Sun, Q., Kalb, V., Miller, S.D., Molthan, A., Schultz, L., Bell, J., Stokes, E.C., Pandey, B., 2018. NASA's Black Marble nighttime lights product suite. Remote Sens. Environ. 210, 113–143. https://doi.org/10.1016/j.rse.2018.03.017.

Rosser, J.F., Leibovici, D.G., Jackson, M.J., 2017. Rapid flood inundation mapping using social media, remote sensing and topographic data. Nat. Hazards 87, 103–120.

Roy, D.P., Huang, H., Houborg, R., Martins, V.S., 2021. A global analysis of the temporal availability of PlanetScope high spatial resolution multi-spectral imagery. Remote Sens. Environ. 264, 112586 https://doi.org/10.1016/j.rse.2021.112586.

Roy, D.P., Wulder, M.A., Loveland, T.R., Ce, W., Allen, R.G., Anderson, M.C., Helder, D., Irons, J.R., Johnson, D.M., Kennedy, R., Scambos, T.A., Schaaf, C.B., Schott, J.R., Sheng, Y., Vermote, E.F., Belward, A.S., Bindschadler, R., Cohen, W.B., Gao, F., Hipple, J.D., Hostert, P., Huntington, J., Justice, C.O., Kilic, A., Kovalskyy, V., Lee, Z. P., Lymburner, L., Masek, J.G., McCorkel, J., Shuai, Y., Trezza, R., Vogelmann, J., Wynne, R.H., Zhu, Z., 2014. Landsat-8: Science and product vision for terrestrial global change research. Remote Sens. Environ. 145, 154–172. https://doi.org/10.1016/j.rse.2014.02.001.

Roy, D.P., Zhang, H.K., Ju, J., Gomez-Dans, J.L., Lewis, P.E., Schaaf, C.B., Sun, Q., Li, J., Huang, H., Kovalskyy, V., 2016. A general method to normalize Landsat reflectance data to nadir BRDF adjusted reflectance. Remote Sens. Environ. 176, 255–271. https://doi.org/10.1016/j.rse.2016.01.023.

Saleska, S.R., Didan, K., Huete, A.R., Da Rocha, H.R., 2007. Amazon forests green-up during 2005 drought. Science 318, 612. https://doi.org/10.1126/science.1146663.

Samanta, A., Ganguly, S., Hashimoto, H., Devadiga, S., Vermote, E., Knyazikhin, Y., Nemani, R.R., Myneni, R.B., 2010. Amazon forests did not green-up during the 2005 drought. Geophys. Res. Lett. 37 https://doi.org/10.1029/2009GL042154.

Schaaf, C.B., Gao, F., Strahler, A.H., Lucht, W., Li, X., Tsang, T., Strugnell, N.C., Zhang, X., Jin, Y., Muller, J.-P.P., Lewis, P., Barnsley, M., Hobson, P., Disney, M., Roberts, G., Dunderdale, M., Doll, C., D'Entremont, R.P., Hu, B., Liang, S., Privette, J.L., Roy, D., 2002. First operational BRDF, albedo nadir reflectance products from MODIS. Remote Sens. Environ. 83, 135–148. https://doi.org/10.1016/S0034-4257(02)00091-3.

Schmitt, M., Zhu, X.X., 2016. Data fusion and remote sensing: An ever-growing relationship. IEEE Geosci. Remote Sens. Mag. 4, 6–23.

Schnebele, E., Cervone, G., Kumar, S., Waters, N., 2014. Real time estimation of the Calgary floods using limited remote sensing data. Water 6, 381–398.

Schroeder, T.A., Schleeweis, K.G., Moisen, G.G., Toney, C., Cohen, W.B., Freeman, E.A., Yang, Z., Huang, C., 2017. Testing a Landsat-based approach for mapping disturbance causality in US forests. Remote Sens. Environ. 195, 230–243. https://doi.org/10.1016/j.rse.2017.03.033.

Sebald, J., Senf, C., Seidl, R., 2021. Human or natural? Landscape context improves the attribution of forest disturbances mapped from Landsat in Central Europe. Remote Sens. Environ. 262, 112502 https://doi.org/10.1016/j.rse.2021.112502.

Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., Wild, J., Ascoli, D., Petr, M., Honkaniemi, J., 2017. Forest disturbances under climate change. Nat. Clim. Chang. 7, 395–402. https://doi.org/10.1038/nclimate3303.

Sellers, P.J., Meeson, B.W., Hall, F.G., Asrar, G., Murphy, R.E., Schiffer, R.A., Bretherton, F.P., Dickinson, R.E., Ellingson, R.G., Field, C.B., 1995. Remote sensing of the land surface for studies of global change: Models—algorithms—experiments. Remote Sens. Environ. 51, 3–26. https://doi.org/10.1016/0034-4257(94)00061-Q.

Senf, C., Pflugmacher, D., Wulder, M.A., Hostert, P., 2015. Characterizing spectral–temporal patterns of defoliator and bark beetle disturbances using Landsat time series. Remote Sens. Environ. 170, 166–177.

Senf, C., Seidl, R., 2022. Post-disturbance canopy recovery and the resilience of Europe's forests. Glob. Ecol. Biogeogr. 31, 25–36.

Senf, C., Seidl, R., Hostert, P., 2017. Remote sensing of forest insect disturbances: Current state and future directions. Int. J. Appl. Earth Obs. Geoinf. 60, 49–60. https://doi.org/10.1016/j.jag.2017.04.004.

Sesnie, S.E., Tellman, B., Wrathall, D., McSweeney, K., Nielsen, E., Benessaiah, K., Wang, O., Rey, L., 2017. A spatio-temporal analysis of forest loss related to cocaine trafficking in Central America. Environ. Res. Lett. 12, 54015.

Seto, K.C., Kaufmann, R.K., 2003. Modeling the drivers of urban land use change in the Pearl River Delta, China: Integrating remote sensing with socioeconomic data. Land Econ. 79, 106–121.

Seto, K.C., Reenberg, A., Boone, C.G., Fragkias, M., Haase, D., Langanke, T., Marcotullio, P., Munroe, D.K., Olah, B., Simon, D., 2012. Urban land teleconnections and sustainability. Proc. Natl. Acad. Sci. 109, 7687–7692. https://doi.org/10.1073/pnas.1117622109.

Shang, R., Zhu, Z., 2019. Harmonizing Landsat 8 and Sentinel-2: A time-series-based reflectance adjustment approach. Remote Sens. Environ. 235, 111439 https://doi.org/10.1016/j.rse.2019.111439.

Shang, R., Zhu, Z., Zhang, J., Qiu, S., Yang, Z., Li, T., Yang, X., 2022. Near-real-time monitoring of land disturbance with harmonized Landsats 7–8 and Sentinel-2 data. Remote Sens. Environ. 278, 113073 https://doi.org/10.1016/j.rse.2022.113073.

Shimizu, K., Ota, T., Mizoue, N., Yoshida, S., 2019. A comprehensive evaluation of disturbance agent classification approaches: Strengths of ensemble classification, multiple indices, spatio-temporal variables, and direct prediction. ISPRS J. Photogramm. Remote Sens. 158, 99–112. https://doi.org/10.1016/j.isprsjprs.2019.10.004.

Singh, A., 1989. Digital change detection techniques using remotely-sensed data. Int. J. Remote Sens. 10, 989–1003. https://doi.org/10.1080/01431168908903939.

Sohl, T.L., Gallant, A.L., Loveland, T.R., 2004. The characteristics and interpretability of land surface change and implications for project design. Photogramm. Eng. Remote Sensing 70, 439–448. https://doi.org/10.14358/PERS.70.4.439.

Song, C., Woodcock, C.E., Seto, K.C., Lenney, M.P., Macomber, S.A., 2001. Classification and change detection using Landsat TM data: when and how to correct atmospheric effects? Remote SensEnvironment 75, 230–244. https://doi.org/10.1016/S0034-4257(00)00169-3.

Song, X.P., Hansen, M.C., Stehman, S.V., Potapov, P.V., Tyukavina, A., Vermote, E.F., Townshend, J.R., 2018. Global land change from 1982 to 2016. Nature 560, 639–643. https://doi.org/10.1038/s41586-018-0411-9.

Sousa, W.P., 1984. The role of disturbance in natural communities. Annu. Rev. Ecol. Syst. 15, 353–391.

Strahler, A.H., Woodcock, C.E., Smith, J.A., 1986. On the nature of models in remote sensing. Remote Sens. Environ. 20, 121–139.

Sulla-Menashe, D., Woodcock, C.E., Friedl, M.A., 2018. Canadian boreal forest greening and browning trends: an analysis of biogeographic patterns and the relative roles of disturbance versus climate drivers. Environ. Res. Lett. 13, 14007.

Szostak, M., Hawryło, P., Piela, D., 2018. Using of Sentinel-2 images for automation of the forest succession detection. Eur. J. Remote Sens. 51, 142–149. https://doi.org/10.1080/22797254.2017.1412272.

Tan, B., Masek, J.G., Wolfe, R., Gao, F., Huang, C., Vermote, E.F., Sexton, J.O., Ederer, G., 2013. Improved forest change detection with terrain illumination corrected Landsat images. Remote Sens. Environ. 136, 469–483. https://doi.org/10.1016/j.rse.2013.05.013.

Tang, X., Bullock, E.L., Olofsson, P., Estel, S., Woodcock, C.E., 2019. Near real-time monitoring of tropical forest disturbance: New algorithms and assessment framework. Remote Sens. Environ. 224, 202–218. https://doi.org/10.1016/j.rse.2019.02.003.

Tang, X., Bullock, E.L., Olofsson, P., Woodcock, C.E., 2020. Can VIIRS continue the legacy of MODIS for near real-time monitoring of tropical forest disturbance? Remote Sens. Environ. 249, 112024.

Tellman, B., Sesnie, S.E., Magliocca, N.R., Nielsen, E.A., Devine, J.A., McSweeney, K., Jain, M., Wrathall, D.J., Dávila, A., Benessaiah, K., 2020. Illicit drivers of land use change: Narcotrafficking and forest loss in Central America. Glob. Environ. Chang. 63, 102092.

Tollerud, H.J., Brown, J.F., Loveland, T.R., 2020. Investigating the effects of land use and land cover on the relationship between moisture and reflectance using Landsat time series. Remote Sens. 12, 1919. https://doi.org/10.3390/rs12121919.

Turner, B.L., 1997. The sustainability principle in global agendas: implications for understanding land-use/cover change. Geogr. J. 163, 133–140.

Turner, B.L., Lambin, E.F., Verburg, P.H., 2021. From land-use/land-cover to land system science. Ambio 50, 1291–1294. https://doi.org/10.1007/s13280-021-01510-4.

Turner, B.L., Lambin, E.F., Reenberg, A., 2007. The emergence of land change science for global environmental change and sustainability. Proc. Natl. Acad. Sci. 104, 20666–20671. https://doi.org/10.1073/pnas.0704119104.

Turner, M.G., 2010. Disturbance and landscape dynamics in a changing world. Ecology 91, 2833–2849. https://doi.org/10.1890/10-0097.1.

Ustin, S.L., Middleton, E.M., 2021. Current and near-term advances in Earth observation for ecological applications. Ecol. Process. 10, 1–57. https://doi.org/10.1186/s13717-020-00255-4.

Verbesselt, J., Hyndman, R., Newnham, G., Culvenor, D., 2010. Detecting trend and seasonal changes in satellite image time series. Remote Sens. Environ. 114, 106–115. https://doi.org/10.1016/j.rse.2009.08.014.

Verbesselt, J., Zeileis, A., Herold, M., 2012. Near real-time disturbance detection using satellite image time series. Remote Sens. Environ. 123, 98–108. https://doi.org/10.1016/j.rse.2012.02.022.

Verrelst, J., Camps-Valls, G., Muñoz-Marí, J., Rivera, J.P., Veroustraete, F., Clevers, J.G. P.W., Moreno, J., 2015. Optical remote sensing and the retrieval of terrestrial vegetation bio-geophysical properties–A review. ISPRS J. Photogramm. Remote Sens. 108, 273–290. https://doi.org/10.1016/j.isprsjprs.2015.05.005.

Verstraete, M.M., Pinty, B., 1996. Designing optimal spectral indexes for remote sensing applications. IEEE Trans. Geosci. Remote Sens. 34, 1254–1265.

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.

Vogelmann, J.E., Xian, G., Homer, C., Tolk, B., 2012. Monitoring gradual ecosystem change using Landsat time series analyses: Case studies in selected forest and rangeland ecosystems. Remote Sens. Environ. 122, 92–105. https://doi.org/10.1016/j.rse.2011.06.027.

Wang, Z., Román, M.O., Kalb, V.L., Miller, S.D., Zhang, J., Shrestha, R.M., 2021. Quantifying uncertainties in nighttime light retrievals from Suomi-NPP and NOAA-20 VIIRS Day/Night Band data. Remote Sens. Environ. 263, 112557 https://doi.org/10.1016/j.rse.2021.112557.

Warner, T., Almutairi, A., Lee, J.Y., 2009. Remote Sensing of Land Cover Change. SAGE, London, UK.

White, J.C., Hermosilla, T., Wulder, M.A., Coops, N.C., 2022. Mapping, validating, and interpreting spatio-temporal trends in post-disturbance forest recovery. Remote Sens. Environ. 271, 112904.

White, J.C., Saarinen, N., Kankare, V., Wulder, M.A., Hermosilla, T., Coops, N.C., Pickell, P.D., Holopainen, M., Hyyppä, J., Vastaranta, M., 2018. Confirmation of post-harvest spectral recovery from Landsat time series using measures of forest cover and height derived from airborne laser scanning data. Remote Sens. Environ. 216, 262–275.

White, J.C., Saarinen, N., Wulder, M.A., Kankare, V., Hermosilla, T., Coops, N.C., Holopainen, M., Hyyppä, J., Vastaranta, M., 2019. Assessing spectral measures of post-harvest forest recovery with field plot data. Int. J. Appl. Earth Obs. Geoinf. 80, 102–114.

White, J.C., Wulder, M.A., Hermosilla, T., Coops, N.C., Hobart, G.W., 2017. A nationwide annual characterization of 25 years of forest disturbance and recovery for Canada using Landsat time series. Remote Sens. Environ. 194, 303–321.

White, P.S., Pickett, S.T.A., 1985. Natural disturbance and patch dynamics: an introduction. In: Pickett, S.T.A., White, P.S. (Eds.), The Ecology of Natural Disturbance and Patch Dynamics. Academic Press, San Diego, pp. 3–13.

Woodcock, C.E., Allen, R., Anderson, M., Belward, A., Bindschadler, R., Cohen, W., Gao, F., Goward, S.N., Helder, D., Helmer, E., Nemani, R., Oreopoulos, L., Schott, J., Thenkabail, P.S., Vermote, E.F., Vogelmann, J., Wulder, M.A., Wynne, R., 2008. Free access to Landsat imagery. Science 320, 1011. https://doi.org/10.1126/science.320.5879.1011a.

Woodcock, C.E., Loveland, T.R., Herold, M., Bauer, M.E., 2020. Transitioning from change detection to monitoring with remote sensing: A paradigm shift. Remote Sens. Environ. 238, 111558 https://doi.org/10.1016/j.rse.2019.111558.

Wulder, M.A., Coops, N.C., Roy, D.P., White, J.C., Hermosilla, T., 2018. Land cover 2.0. Int. J. Remote Sens. 39, 4254–4284. https://doi.org/10.1080/01431161.2018.1452075.

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.

Wulder, M.A., Roy, D.P., Radeloff, V.C., Loveland, T.R., Anderson, M.C., Johnson, D.M., Healey, S., Zhu, Z., Scambos, T.A., Pahlevan, N., Hansen, M., 2022. Fifty years of Landsat science and impacts. Remote Sens. Environ. 280, 113195 https://doi.org/10.1016/j.rse.2022.113195.

Wyman, M.S., Stein, T.V., 2010. Modeling social and land-use/land-cover change data to assess drivers of smallholder deforestation in Belize. Appl. Geogr. 30, 329–342.

Xian, G., Homer, C., Fry, J., 2009. Updating the 2001 National Land Cover Database land cover classification to 2006 by using Landsat imagery change detection methods. Remote Sens. Environ. 113, 1133–1147.

Xian, G.Z., Smith, K., Wellington, D., Horton, J., Zhou, Q., Li, C., Auch, R., Brown, J.F., Zhu, Z., Reker, R.R., 2022. Implementation of the CCDC algorithm to produce the LCMAP Collection 1.0 annual land surface change product. Earth Syst. Sci. Data 14, 143–162.

Xie, Q., Dash, J., Huang, W., Peng, D., Qin, Q., Mortimer, H., Casa, R., Pignatti, S., Laneve, G., Pascucci, S., 2018. Vegetation indices combining the red and red-edge spectral information for leaf area index retrieval. IEEE J. Sel. Top. Appl. earth Obs. Remote Sens. 11, 1482–1493.

Xin, Q.C., Olofsson, P., Zhu, Z., Tan, B., Woodcock, C.E., 2013. Toward near real-time monitoring of forest disturbance by fusion of MODIS and Landsat data. Remote Sens. Environ. 135, 234–247. https://doi.org/10.1016/J.Rse.2013.04.002.

Yan, L., Roy, D.P., Zhang, H., Li, J., Huang, H., 2016. An automated approach for sub-pixel registration of Landsat-8 Operational Land Imager (OLI) and Sentinel-2 Multi Spectral Instrument (MSI) imagery. Remote Sens. 8, 520. https://doi.org/10.3390/rs8060520.

Yang, X., Zhu, Zhe, Qiu, S., Kroeger, K.D., Zhu, Zhiliang, Covington, S., 2022. Detection and characterization of coastal tidal wetland change in the northeastern US using Landsat time series. Remote Sens. Environ. 276, 113047 https://doi.org/10.1016/j.rse.2022.113047.

Ye, S., Rogan, J., Zhu, Z., Eastman, J.R., 2021a. A near-real-time approach for monitoring forest disturbance using Landsat time series: Stochastic continuous change detection. Remote Sens. Environ. 252, 112167 https://doi.org/10.1016/j.rse.2020.112167.

Ye, S., Rogan, J., Zhu, Z., Hawbaker, T.J., Hart, S.J., Andrus, R.A., Meddens, A.J.H., Hicke, J.A., Eastman, J.R., Kulakowski, D., 2021b. Detecting subtle change from dense Landsat time series: Case studies of mountain pine beetle and spruce beetle disturbance. Remote Sens. Environ. 263, 112560 https://doi.org/10.1016/j.rse.2021.112560.

Zhang, X., Friedl, M.A., Schaaf, C.B., 2009. Sensitivity of vegetation phenology detection to the temporal resolution of satellite data. Int. J. Remote Sens. 30, 2061–2074.

Zhang, X., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C.F., Gao, F., Reed, B.C., Huete, A., 2003. Monitoring vegetation phenology using MODIS. Remote Sens. Environ. 84, 471–475.

Zhang, X., Liu, L., Liu, Y., Jayavelu, S., Wang, J., Moon, M., Henebry, G.M., Friedl, M.A., Schaaf, C.B., 2018. Generation and evaluation of the VIIRS land surface phenology product. Remote Sens. Environ. 216, 212–229.

Zhang, X., Wang, J., Henebry, G.M., Gao, F., 2020. Development and evaluation of a new algorithm for detecting 30 m land surface phenology from VIIRS and HLS time series. ISPRS J. Photogramm. Remote Sens. 161, 37–51.

Zhang, Y., Woodcock, C.E., Chen, S., Wang, J.A., Sulla-Menashe, D., Zuo, Z., Olofsson, P., Wang, Y., Friedl, M.A., 2022. Mapping causal agents of disturbance in boreal and arctic ecosystems of North America using time series of Landsat data. Remote Sens. Environ. 272, 112935 https://doi.org/10.1016/j.rse.2022.112935.

Zhao, F., Huang, C., Goward, S.N., Schleeweis, K., Rishmawi, K., Lindsey, M.A., Denning, E., Keddell, L., Cohen, W.B., Yang, Z., Dungan, J.L., Michaelis, A., 2018. Development of Landsat-based annual US forest disturbance history maps (1986–2010) in support of the North American Carbon Program (NACP). Remote Sens. Environ. 209, 312–326. https://doi.org/10.1016/j.rse.2018.02.035.

Zhao, M., Zhou, Y., Li, Xuecao, Cao, W., He, C., Yu, B., Li, Xi, Elvidge, C.D., Cheng, W., Zhou, C., 2019. Applications of satellite remote sensing of nighttime light observations: Advances, challenges, and perspectives. Remote Sens. 11, 1971.

Zhu, Z., 2017. Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications. ISPRS J. Photogramm. Remote Sens. 130, 370–384. https://doi.org/10.1016/j.isprsjprs.2017.06.013.

Zhu, Z., Fu, Y., Woodcock, C.E., Olofsson, P., Vogelmann, J.E., Holden, C., Wang, M., Dai, S., Yu, Y., 2016a. Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014). Remote Sens. Environ. 185, 243–257. https://doi.org/10.1016/j.rse.2016.03.036.

Zhu, Z., Piao, S., Myneni, R.B., Huang, M., Zeng, Z., Canadell, J.G., Ciais, P., Sitch, S., Friedlingstein, P., Arneth, A., Cao, C., Cheng, L., Kato, E., Koven, C., Li, Y., Lian, X., Liu, Y., Liu, R., Mao, J., Pan, Y., Peng, S., Peuelas, J., Poulter, B., Pugh, T.A.M., Stocker, B.D., Viovy, N., Wang, X., Wang, Y., Xiao, Z., Yang, H., Zaehle, S., Zeng, N., 2016b. Greening of the Earth and its drivers. Nat. Clim. Chang. 6, 791–795. https://doi.org/10.1038/nclimate3004.

Zhu, Z., Qiu, S., He, B., Deng, C., 2018. Cloud and cloud shadow detection for Landsat images : the fundamental basis for analyzing Landsat time series. Remote Sens. Time Ser. Image Process. 3–24 https://doi.org/10.1201/9781315166636-10.

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., Woodcock, C.E., 2012. Object-based cloud and cloud shadow detection in Landsat imagery. Remote Sens. Environ. 118, 83–94. https://doi.org/10.1016/j.rse.2011.10.028.

Zhu, Z., Woodcock, C.E., Olofsson, P., 2012a. Continuous monitoring of forest disturbance using all available Landsat imagery. Remote Sens. Environ. 122, 75–91. https://doi.org/10.1016/j.rse.2011.10.030.

Zhu, Z., Woodcock, C.E., Rogan, J., Kellndorfer, J., 2012b. Assessment of spectral, polarimetric, temporal, and spatial dimensions for urban and peri-urban land cover classification using Landsat and SAR data. Remote Sens. Environ. 117, 72–82. https://doi.org/10.1016/j.rse.2011.07.020.

Zhu, Z., Wulder, M.A., Roy, D.P., Woodcock, C.E., Hansen, M.C., Radeloff, V.C., Healey, S.P., Schaaf, C., Hostert, P., Strobl, P., Pekel, J.F., Lymburner, L., Pahlevan, N., Scambos, T.A., 2019. Benefits of the free and open Landsat data policy. Remote Sens. Environ. 224, 382–385. https://doi.org/10.1016/j.rse.2019.02.016.

Zhu, Z., Zhang, J., Yang, Z., Aljaddani, A.H., Cohen, W.B., Qiu, S., Zhou, C., 2020. Continuous monitoring of land disturbance based on Landsat time series. Remote Sens. Environ. 238, 111116 https://doi.org/10.1016/j.rse.2019.03.009.