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 most critical 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, process, and agent. We also evaluated the impact of spatial, spectral, temporal, and angular dimensions 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 all remote sensing of land change efforts, reporting multiple or full facets of land change in remote sensing products, shifting the focus from land cover change to identify the specific change process and agent, integrating socioeconomic data as well as new social-environment framework for a deeper and fuller understanding of land change, and recognizing the limitations and weaknesses of remote sensing platforms in land change studies.

1 Introduction

With the increasing contemporary concerns on climate change, global environmental change, and sustainability, land change science emerged as a unique science direction for addressing these knotty issues (Gutman et al., 2004; Rindfuss et al., 2004; Turner et al., 2007). Land change science, defined as "the interdisciplinary field 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 modified or transformed by humans at an unprecedented rate. More than half of the Earth's ice-free land surface has been affected 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 are 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; Zhu, 2019), the increasing computing capabilities (Gorelick et al., 2017; Ma et al., 2015), and the availability of new algorithms for 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 remote sensing community, where the use of dense time-series observations is more common and new land change information, such as subtle changes in ecosystem health and condition and long-term trend of the vegetation productivity, is more reachable (Woodcock et al., 2020). Moreover, land change information can now be monitored in near real-time (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), with majority of them focusing on the "from-to" information, that is, land cover and/or land use information before and after the change (Hansen 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 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 here.

In this paper, we propose the framework of 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 (Fig. 1). Basically, if we detect change in satellite spectral bands, we can extract land change information to answer five different questions, that are, when (change time), where (change location), what (change target), how (change process), 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. The facet on the top of the change cube is left empty on purpose (Fig. 1), as there may be other facets of land change that are not discussed here. The two facets on "Time" and "Location" provide information on observation and monitoring of land change, and the other three facets on "Target", "Process", and "Agent" are related to the characterization of land change. In this paper, 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, and angular 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 future recommendations.

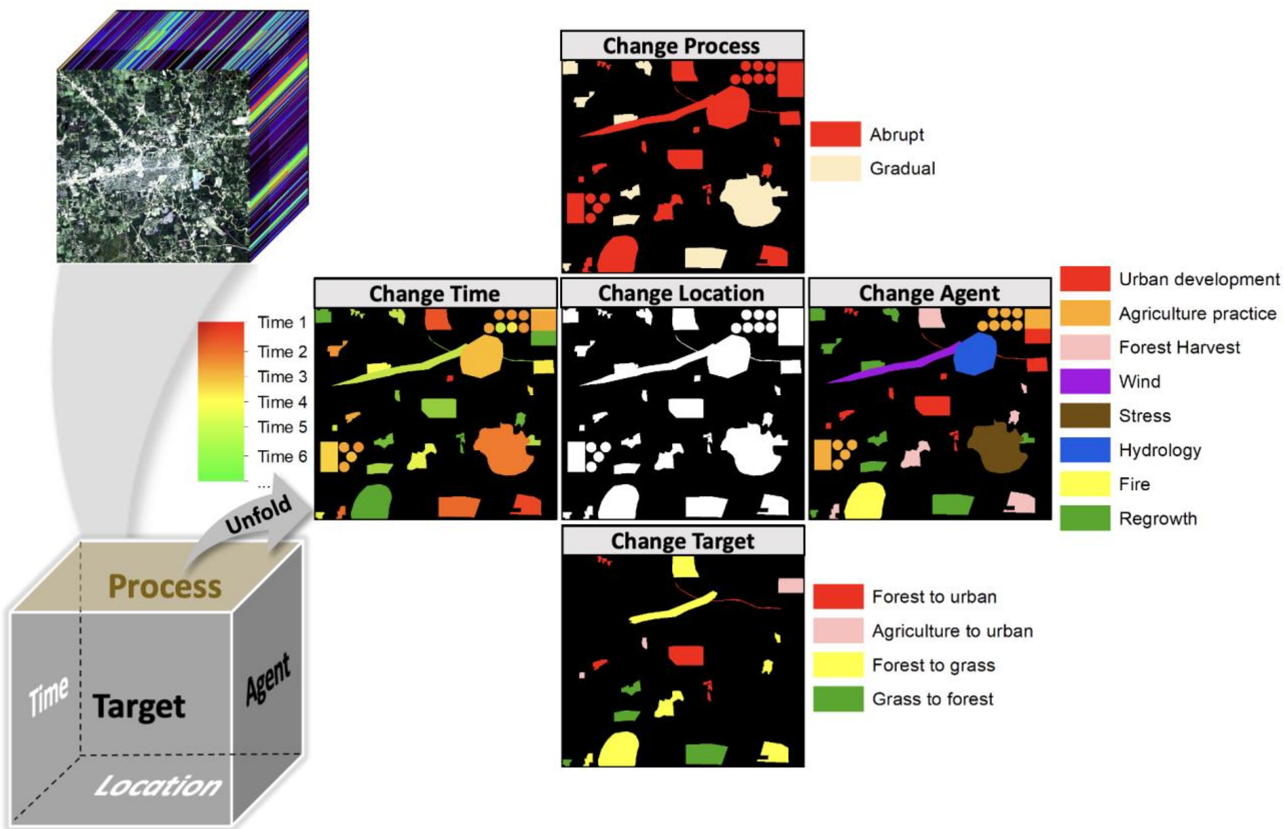


Fig. 1. The five facets proposed for observation, monitoring, and characterization of land change using remotely sensed data. It is worth noting that not all land change agent will lead to a change in change target or land cover in this case, and some of the change patches shown in the other four facets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

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).

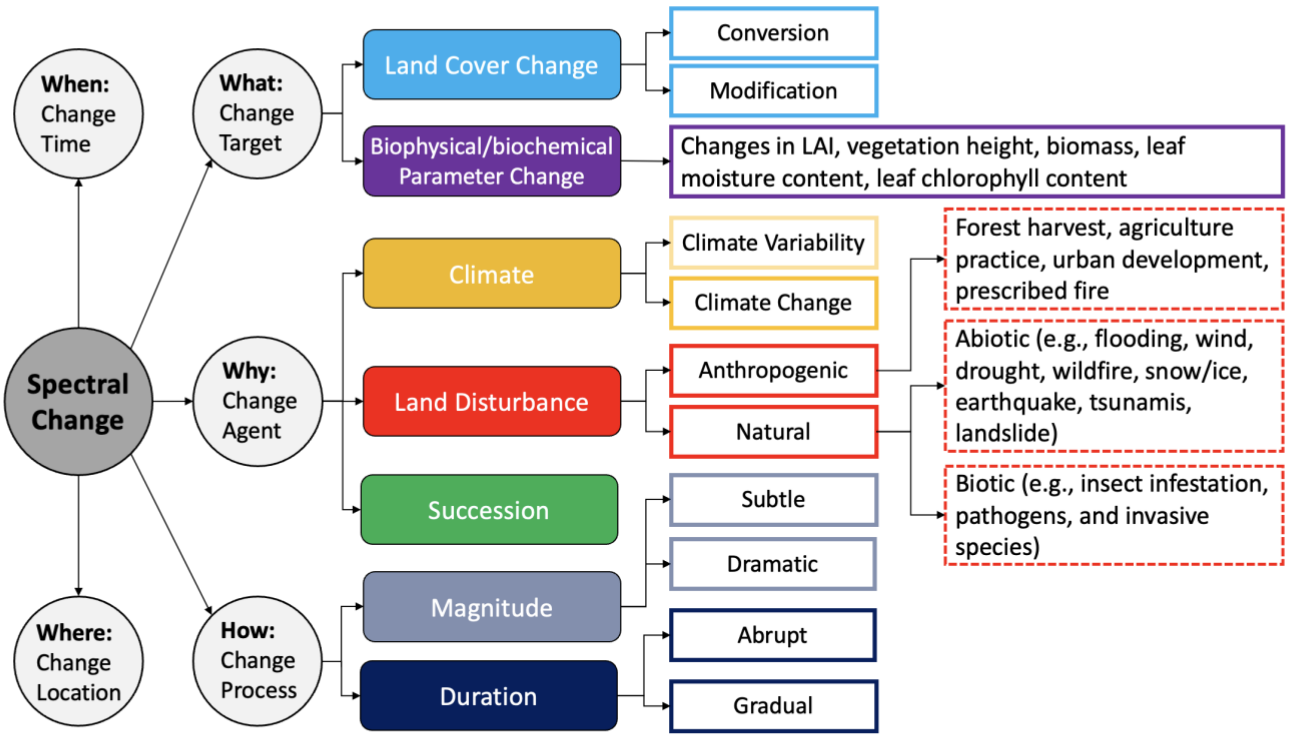


Fig. 2. Hierarchical classification system for the five facets of land change.

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 easily. The land change detected in this way is sometimes called “spectral change”, 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, topography illumination, will all contribute to the spectral change (Kennedy et al., 2014; Zhu, 2017). Therefore, one of the most critical 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 (mostly driven by phenology) (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 corrections (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 surface, 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 from decades apart, to annual, and is currently shifting all the way to near-real-time change detection (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 determine 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 contains rich information on the characteristics of the land surface. 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, to determine the land cover based on image classification (Gómez et al., 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).

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 will lead to compounded errors in the final change map at a magnitude way larger than the total change area (Olofsson et al., 2013). For example, if we assume the classification error is randomly distributed and the overall accuracy is 90%, the compounded error of change map by differencing the two land cover maps is $100\% - 90\% \times 90\% = 19\%$ of the image, which is approximately four times of the land change area (if it is 5% of the total area). Therefore, land change is usually 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; 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, as the land change that occurred on this land cover may not be dramatic enough to change the land cover types, and we usually call this land cover modification or land cover condition change. For example, if forest cover is defined as trees covering more than 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 are 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, but fewer studies have addressed the land cover modification issues, which may be at a scale similar to or even larger than land cover conversion (Asner et al., 2005; Qin et al., 2021). 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 detection of land cover modification at subpixel scales.

2.4 How - Change Process

The fourth facet of land change is to answer the question of how it is changing or determine the change process (Kennedy et al., 2014; Petit et al., 2001). As remotely sensed data measure land surface reflected or emitted EMR, changes occurred on the land surface will also likely cause changes in the spectral band at the corresponding time, making remote sensing data particularly useful for tracking the land surface change trajectories and studying the specific change process (Kennedy et al., 2014). The most important remote sensing observations for studying change process are the ones that are collected during the land change events, and we can describe the change process based on the duration and magnitude of land change.

According to the change duration, change process can be divided into abrupt change and gradual change. Most of the remote sensing change detection algorithms are 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 hand other, gradual changes usually last for a much longer time as a result from a variety of causes such as damage to vegetation from disease and insects, ecological succession, and climate change (Vogelmann et al., 2016, 2012). There are also remote sensing methods developed to quantify gradual changes based on long-term time series observations (e.g., > 10 years), and algorithms that could address gradual and abrupt changes simultaneously are appearing and could provide more accurate estimation of gradual changes (De Jong et al., 2012; Vogelmann et al., 2016; Zhe Zhu et al., 2016).

Based on the change magnitude, change process can be divided into subtle change and dramatic change. Subtle change modifies the land cover and the impact could be either ephemeral in time, 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 usually 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 that are carefully calibrated against the kind of subtle change to be identified (Ye et al., 2021b). It is worth noting that other variables could also provide information on the temporal trajectories of land change for studying change process, 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 actually 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).

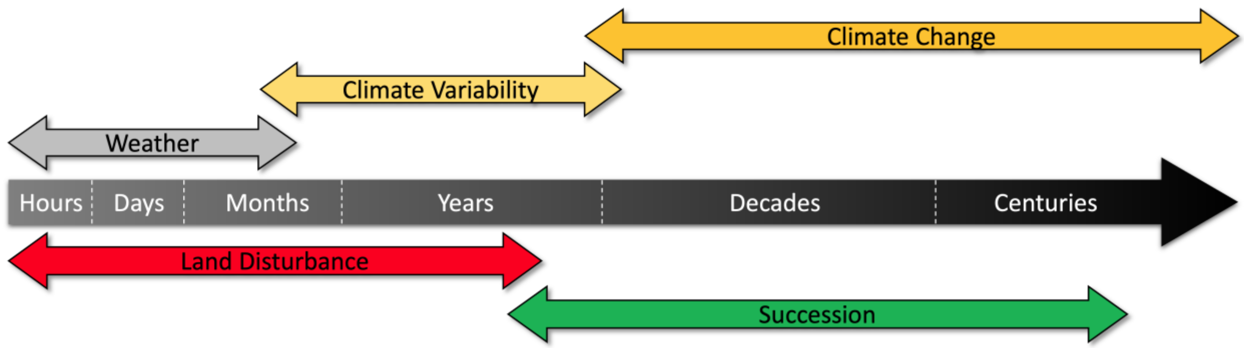


Fig. 3. Timescales applicable to weather, climate variability, climate change, land disturbance, and succession.

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**).** Zhu et al. (2020) modified and simplified this definition for detecting land disturbance based on satellite time series, in which land disturbance is defined as "any discrete event that occurs outside the range of natural variability of land surface". 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 harvest*, *agriculture practice*, *urban development*, and *prescribed fire*. Natural disturbance can be further divided into abiotic disturbance, such as *wildfire*, *flooding*, *wind*, *drought*, *snow/ice*, *earthquake*, *tsunamis*, *landslide*, 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 over the past decade (Peters et al., 2011). Fire can be both natural (wildfires) and anthropogenic (prescribed fires) (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., 2012), 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 LandTrendr Landsat time-series-based algorithms (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 is outside the range of natural variability of land surface, it can be captured after the range of natural variability is well defined. 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 hard to detect and distinguish in remote sensing data (Asner et al., 2005; Senf et al., 2017; Ye et al., 2021b).

Unlike weather that describes current atmospheric condition (e.g., rainstorms and tropical cyclones) that changes every hour, day, and maybe months, climate measures the mean and variability of temperature, precipitation, or wind for a much longer time, ranging from months to centuries, in which 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; Zaichun Zhu et al., 2016). As both climate variability and disturbance will cause remote sensing observations to deviate abruptly from past trajectories with a spectral change magnitude larger than the natural variability, 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 the structure of a biological community changes over time (Huston and Smith, 1987). Primary succession is the process that plants and animals colonize a barren habitat for the first time, which could take hundreds of years. On the other hand, secondary succession begins after a major disturbance that transformed the original landscape, and if this land is undisturbed for some time, the evolving biological community will reach a stable ecological structure again. As remote sensing has a relatively short history, and the longest earth observation satellite, such as Landsat, only has a half-century record, it is not ideal to quantify primary succession, and there are only limited studies on this topic (e.g., Knoflach et al., 2021 and Lawrence, 2005). However, remote sensing data have been frequently used for quantifying secondary succession after disturbance, which is usually called post-disturbance recovery or vegetation regrowth (Bartels et al., 2016; Zhao et al., 2016). Basically, we can quantify the rate of recovery using the slope of the vegetation index calculated based on remotely sensed time-series observations, and the larger the positive slope in a vegetation index the quicker the recovery.

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 practice, urban development, fire, harvest, 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). Majority of the remote sensing studies are only focusing on creating change agents 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 practice*, *forest harvest*, *urban development*, *inset*, *wind*, *fire*, *hydrology*, 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 are 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., understory fire following by a pest infestation in forests). Moreover, different disturbance agents may result in the same or similar mechanism (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, high-quality change agent training data is extremely hard to collect consistently at large-scales. Unlike land cover training data that can be interpreted from any high-resolution remote sensing image, it is much hard to find training data of land change, and it is even more difficult to interpret the causality of the change based on the remotely sensed data alone (Pengra et al., 2020). 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 understanding the underlying driving forces behind global land change based on qualifying and quantifying human-environment interaction at multitude of spatial and temporal scales (Pricope et al., 2019). By integrating socioeconomic data with remotely sensed data and incorporating models (e.g., fixed-effects statistical) that are widely used by social scientists, 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, 1999, 1998; Pricope et al., 2019; Seto et al., 2012)

3 Relationship of various kinds of change terminologies

A variety of change terminologies have been introduced 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, and succession, and biophysical/biochemical parameter change. Spectral change (the grey rectangle in Fig. 4), defined as the temporal changes 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 caused by vegetation phenology and abrupt/gradual land surface changes), as well as spectral changes that have nothing to do with land change on the ground, such as atmospheric influences and data noises. On the other hand, land surface change (the region within red dashed line rectangle in Fig 4 that is also shared with 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), which usually 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 caused by vegetation phenology. As cyclic changes from vegetation phenology can also lead to biophysical/biochemical parameter changes, 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 seasonal changes that cause changes in LAI and leaf chlorophyll contents. Land disturbance (the light red rectangle in Fig. 4), defined as any discrete event that occurs outside the range of natural variability of the land surface, if severe enough, can lead to land cover conversion, and is 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) and 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.

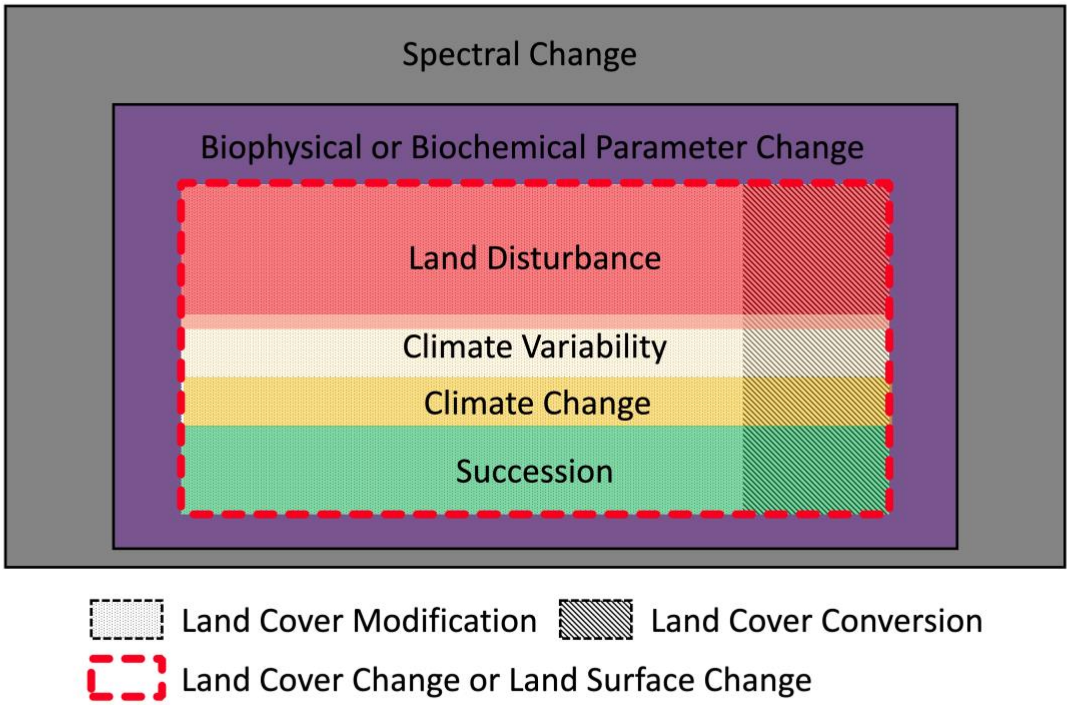


Fig. 4. Relationship of some widely used land change terminologies, including spectral change, land surface change, land cover change, land cover conversion, land cover modification, land disturbance, climate variability, climate change, succession, and biophysical/biochemical parameter change.

4 The spectral, spatial, temporal, and angular issues in detecting land change

If the remote sensor is designed perfectly at the right spectral, spatial, temporal resolutions and viewing angles, all land changes should show up with large magnitudes of spectral change. However, this is never the case in reality, and issues from spectral, spatial, temporal, and angular domains will all greatly impact the remote sensing platform's capability of detecting land change.

4.1 The spectral issues

The spectral values record the amount of electromagnetic energy in specific wavelengths, such as visible, Near Infrared (NIR), Short-Wave Infrared (SWIR), thermal, and microwave bands. Remote sensing of land change assumes that different land surfaces will have different spectral values, and if we difference the spectral values collected at different time points, we can identify the change. In practice, the different land surfaces may share the same or similar spectral values for certain spectral bands, and if the spectral bands that can separate the two different kinds of land surface do not exist in the remote sensing bands, there will be no way to detect changes occurred between the two land surface types. For example, when forests are burned, the changes in visible bands, such as Blue, Green, and Red, and certain microwave bands (e.g., C-Band) are usually very subtle (Fig. 5) and if those bands are used for detecting burned areas, it would be extremely hard for any kind of change detection algorithms. However, large differences will usually show in NIR, SWIR1, SWIR2 bands (reduced vegetation and water content), and thermal band (higher temperature) after forest fire (Fig. 5), and the burned areas can be easily detected if spectral bands within these four spectral ranges exist. Note that there are remote sensors that can provide many narrow spectral bands, and some of the bands, such as red edge bands (in the NIR band range), can provide new change information (e.g., forest structure and health change) that the broadband cannot provide (Cho et al., 2012; Eitel et al., 2011).

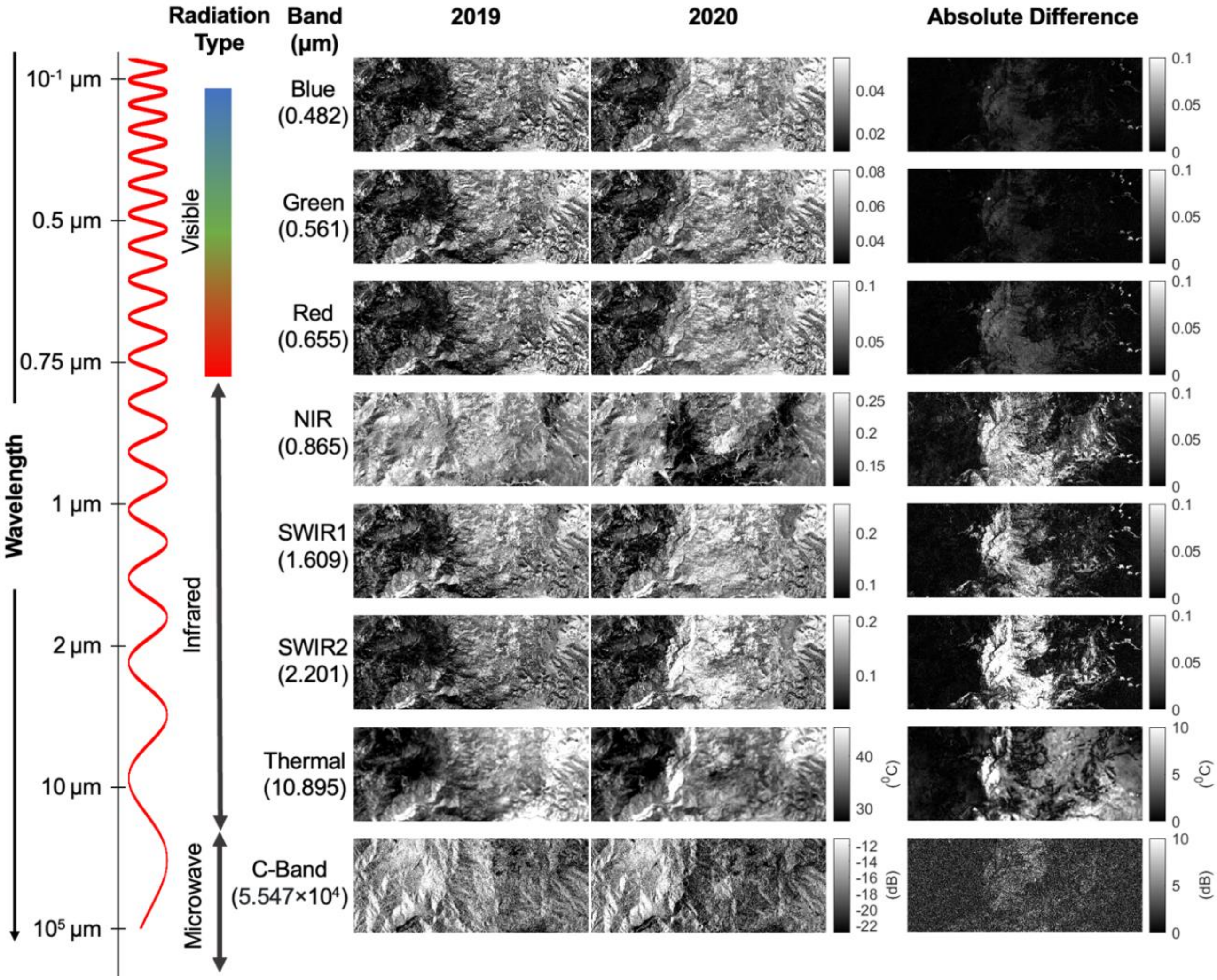


Fig. 5. Spectral change before and after the land change caused by fire. The changes in visible bands and microwave band are very subtle, but substantial in NIR, SWIR, and thermal bands. Blue, Green, Red, NIR, SWIR1, SWIR2, and thermal bands are derived from Landsat 8 surface reflectance and brightness temperature data, and microwave C-Band is from Sentinel-1 C-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 same extent of 1001 pixels by 401 pixels at 30 m spatial resolution.

Additionally, the selection of the right spectral bands is particularly critical to identify the change agent, change target, as well as determine the specific change process. The spectral change values in different bands, sometimes called spectral change vector, are the key variables for separate different change agents, as both the change vector angle and change vector magnitude contain rich information on the kind of change that is occurring (Lambin and Strahlers, 1994). On the other hand, the spectral values before and after the change are the most important input variables for characterizing the change target. 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 should introduce evidence that can be used to discriminate different cover types. For land change process characterization, as the change vector magnitude is used directly to separate dramatic and subtle changes, the selection of the right spectral bands with the best capability to quantify the severity of change is extremely important.

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 30x30 m^2 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). Remote sensing data with the 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 (Coppin et al., 2004). However, when the spatial resolution is too high (e.g., < 1 meter), the shadow from the land surface objects will start to show up (Bruzzone and Vovolo, 2012), and the trade-off between spatial and temporal resolutions will make it extremely hard to find another revisit image unless it is pointed to the same location after changing its view angle, which will cause artifact again due to the large view angle difference in the image. On the other hand, if the spatial resolution is too coarse, not only small-scale changes will not be able to show up in satellite signals (see the MODIS images in Fig. 6), but also the large difference in point-spread-function and BRDF impact will make change signals easily buried in the data noise (Xin et al., 2013). Therefore, most of the remotely sensed data used for land change studies are based on medium resolution satellites with resolution between 10–100 meters, such as SPOT, Sentinel-2, and Landsat (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; Zhu et al., 2016).

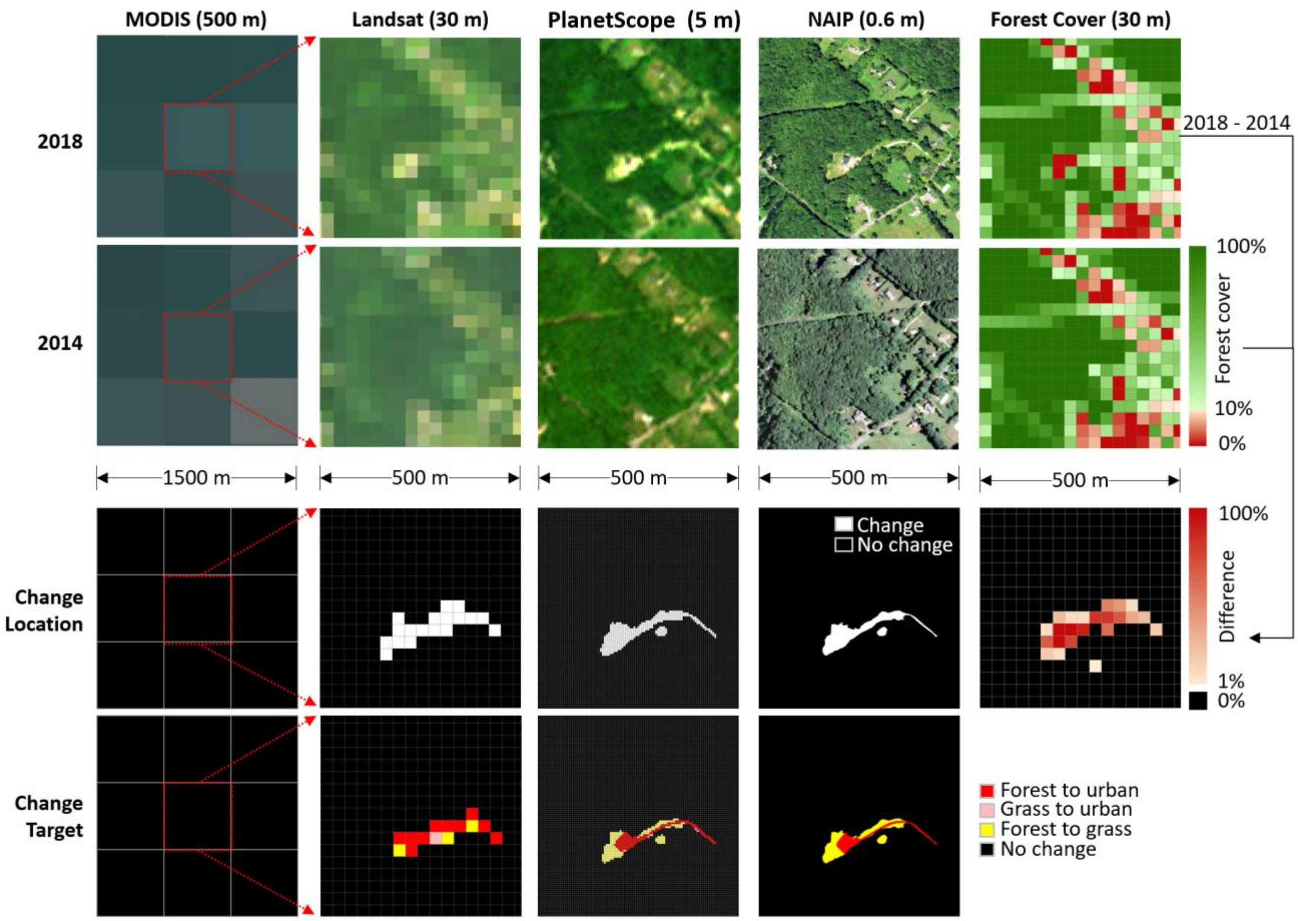


Fig. 6. The impact of spatial resolution on maps of change location and change target between 2014 and 2018. All the remotely sensed images were acquired at central latitude/longitude (41.781/-72.234) in summer 2014 and 2018 and reprojected into the WGS84 UTM Zone 19N. The MODIS, Landsat, and PlanetScope satellites provide remote sensing images at coarse resolution (500 m), medium resolution (30 m), and high resolution (5 m), respectively. The National Agriculture Imagery Program (NAIP) data are aerial photos, that can be considered as a reference of the land changes at 0.6 m resolution. The change location and change target maps are derived from MODIS, Landsat, PlanetScope, and NAIP images, respectively. Changes are detectable when >10% of the pixel changed. Forest is defined as pixels with >10% coverage of trees, and urban is defined as pixels with >10% coverage of built areas. None of the changes are detectable from MODIS images (500 m), but detectable at the other remote sensing images at 0.6-30 m spatial resolutions. Note that due to the

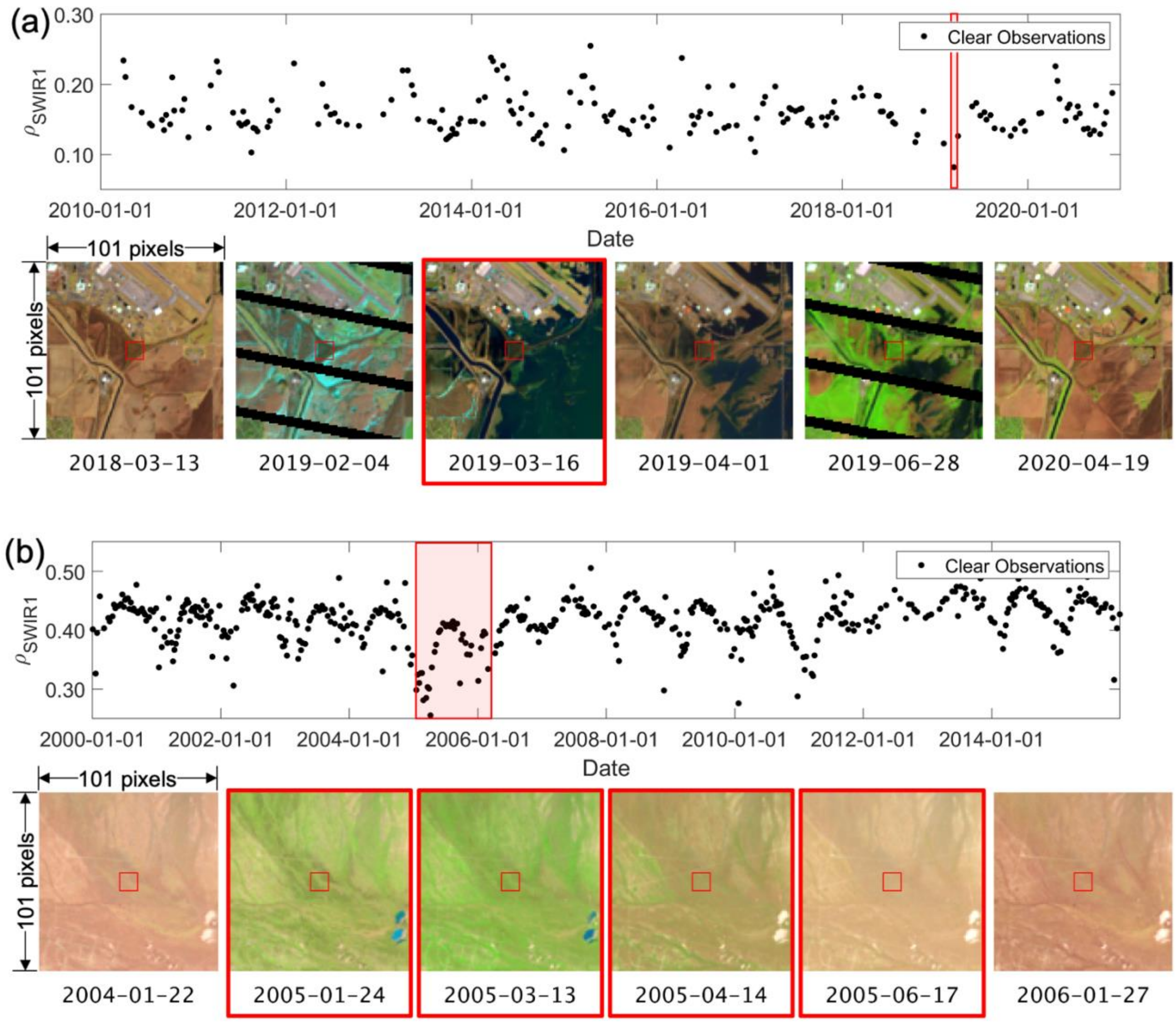
difference in spatial resolution, the change location and change target maps are all different, particularly when the pixel size is larger than 30 m.

Land changes are usually occurring at small scales. When the pixel size is relatively large, pixels mixed with multiple land cover types happen frequently, and changed areas smaller than the pixel size are also seen very often. Therefore, a lot of time, land change may only occur on a small fraction of a pixel (the fraction is a continuous variable), which may not match well with categorical change maps, such as change/stable (change location) and land cover change (change target) maps (Fig. 6). Usually, a threshold is introduced to determine whether a pixel has changed or not. For example, in Hansen et al. (2013), forest change is defined as a pixel with more than 50% change in forest cover within a pixel. On the other hand, the definition of land cover also plays a major role in determining whether there is a land cover conversion or not after the change event. For example, if a forest pixel is defined as a pixel with more than 10% of tree cover, and grass land is defined as a pixel with more than 10% of grass cover, land cover conversion from forest to grass will happen only if more than 90% of the trees are removed for a fully forested pixel (Fig. 6). The situation could be different if some proportion of forest is converted to built-up lands. This is because land cover definition is usually resources driven, and certain classes will have a higher priority than the other classes in the classification system (e.g., urban > forest > grass), and when there are multiple cover types present in the same pixel, it will be labeled as urban or developed even if it covers a small proportion of the pixel (e.g., > 10%) (Pengra et al., 2020). In this case, if within a fully forested pixel, more than 10% of trees have been removed, and a new house is established to cover that area, even with the remaining forest cover slightly less than 90%, this pixel is still considered to have gone land cover conversion (from forest to urban) (Fig. 6).

4.3 The temporal issues

The temporal resolution of a remote sensing system refers to how often the remote sensor records imagery of a particular area (e.g., Landsat 8 visits the same location every 16 days), and there are remote sensing systems that can collect observations every minute, hours, daily, weekly, monthly, and a few years (Jensen, 2009). The temporal resolution of the remote sensing data plays a major role in determining the change time, improving detection of change location, and at the same time providing rich information in detection of change process, agent, and target.

Essentially, more accurate detection of change time could be achieved based on observations of higher temporal 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 revisit time of remote sensing data should be shorter than the lasting time of the change event to be able to detect the change we are interested in, otherwise, these change events may already be fully recovered before the next visit of remote sensors. For example, with two sensors working simultaneously, Landsat time series can provide 8 days revisit observations for the same location if we do not consider observations blocked 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 are lucky enough to have one clear Landsat image located during the flooding, but if it is blocked by clouds, there is no way to detect this kind of ephemeral changes, even if we used all available Landsat time series. 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 for urban development related changes (Fig. 7d), they are usually more permanent, and Landsat data that are 5 or 10 years apart are still able to capture them. Therefore, the minimum temporal resolution required for different land change applications is usually quite different, and the denser the time series observations used, the more accurate in detection of the time and location of change.



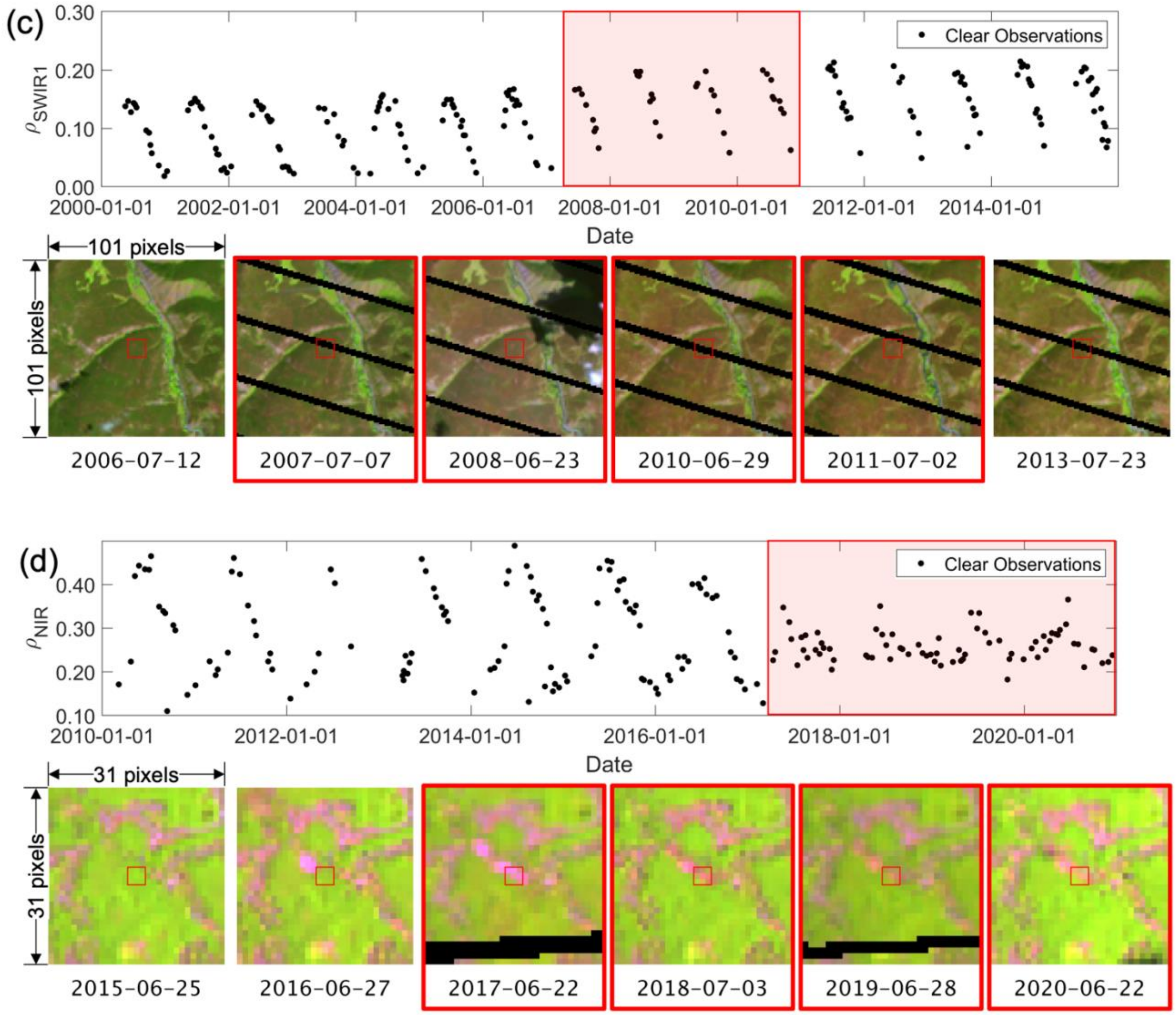


Fig. 7. The impact of temporal resolution on land change detection. (a) A flood event that lasted for a few days at central latitude/longitude (41.103/-95.906). Of all the available Landsat observations, only a single observation can observe this ephemeral event. (b) Climatic variability over grassland 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 is derived from all available Landsat observations at the center of the smaller red square of the false color composited images at the lower panel. The change period is highlighted by the red rectangles in the upper panel and the larger red rectangle surrounding the false color composited images in the lower panel. The false color composited images are shown in Landsat SWIR1, NIR, and Red bands, and they are directly comparable because of the same stretch display. Some of the images have black stripes which are due to the Landsat 7 Scan Line Corrector-off issue.

The use of dense time-series observations could also introduce issues in change detection, as for ephemeral changes that last for a short time, only observations with temporal resolutions higher than the time interval of ephemeral changes can capture this kind of land change. Therefore, changes detected based on the dense time series will be different when remote sensing data of different temporal resolutions are used, and usually, the denser the time series, the more changes will be detected. Even if a single remote sensing system is used (e.g., Landsat), 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 is 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 clear observations, and if we use more than four consecutive observations to confirm a change, this land change can only be detected in the overlap areas (Fig. 8a). The use of overlap path observations brings new science capability for Landsat data, but also brings 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. 8b). Moreover, the time-series observations collected at different temporal density and irregularity can also impact the accuracies of change detection algorithms that reply on dense time-series observations, making detection accuracy differ for different locations and dates (Zhang et al., 2021).

Additionally, the use of dense time series can create new information or more accurate change information that the traditional two-date image difference method cannot provide. For example, we can get to know how this change is occurring or the change process based on the trend of the time series, the change magnitude, and the duration of the change. The information embedded in the time series data provides important spectral-temporal information of 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 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*, *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 input for change agent classification.

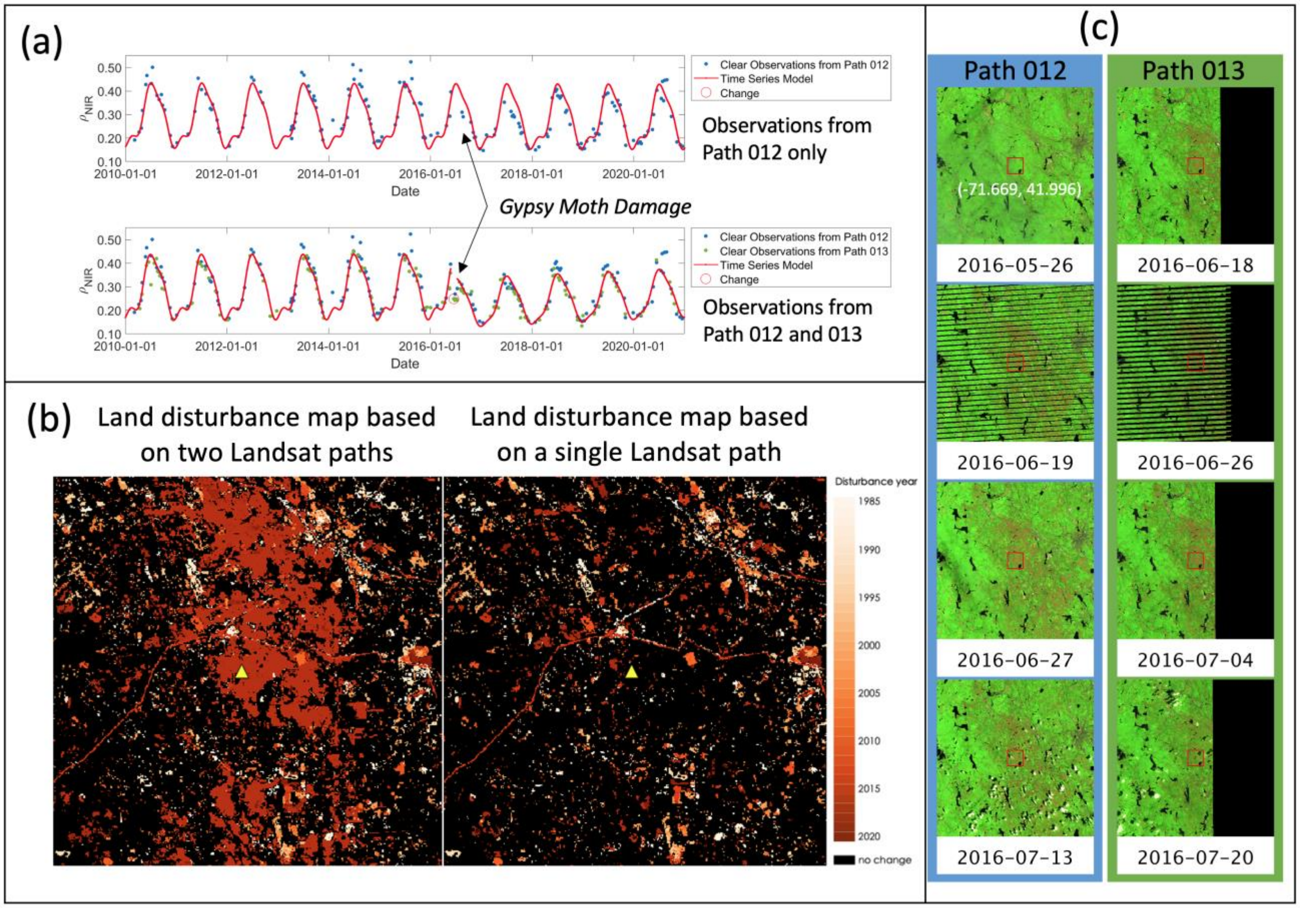


Fig. 8. A comparison of change detection results caused by Gypsy Moth damage using two Landsat paths (or swaths) data and a single path data. (a) Landsat NIR surface reflectance observations at the center of the red square of the false color composited images on the right (c) at central latitude/longitude (41.996/-71.669). The blue dots are from the Landsat path #12 and green dots are from the 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) Land disturbance map 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 detection. (c) The false color composited Landsat images from the path #12 (in blue outlines) and the 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 paths coverage, Gypsy Moth damage is possible with the COLD algorithm, but not possible for places with only a single Landsat path coverage. COLD: COntinuous monitoring of Land Disturbance.

In addition to the repeating 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 satellite data with a high signal-to-noise ratio that can take images at nighttime, which can provide unique information on human activities, as most of the nighttime lights are from artificial lights. 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, lighting, the use of dense time series of nighttime light data are 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 and Noam, 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 recorded 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 bi-directional nature of remote sensing systems will cause differences in the sensor collected radiance, as well as influence the calculation of surface reflectance, which are some of the major “noise” sources in detecting change locations (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. 9a). 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 changes can also remove or reduce the BRDF differences embedded in the satellite data, and in this way, the change pixel can be correctly identified (Fig. 9b) 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 cloud (Frantz et al., 2018), aircraft (Liu et al., 2020), and detection of newly built houses (Huang et al., 2020), due to the inclusion of 3D information.

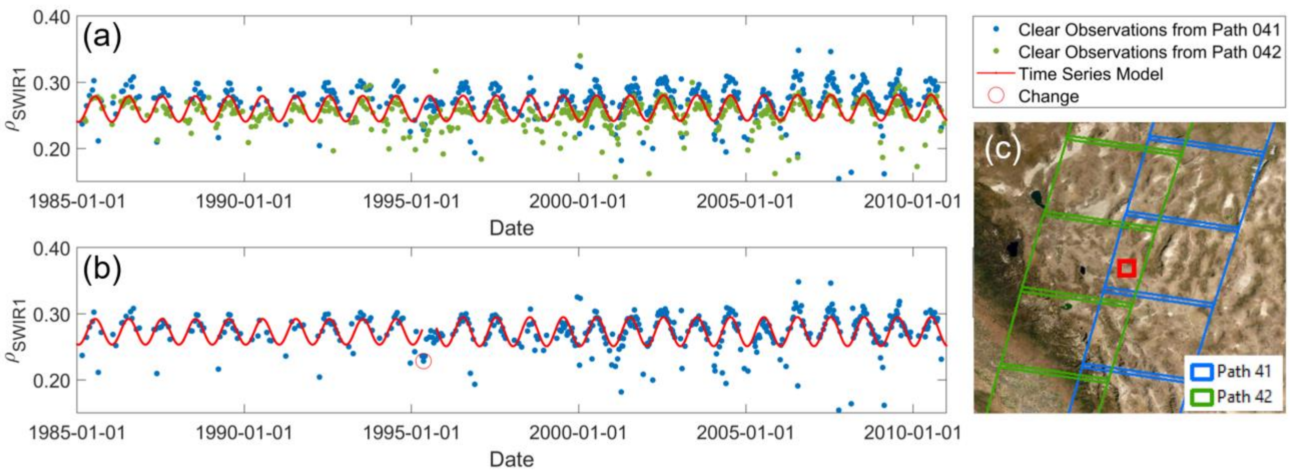


Fig. 9. The impact of BRDF on land change detection. (a) Change detection using all observations collected in overlap paths. The BRDF effect, dominated by the different sensor view angles from two adjacent paths, results in an omission error. (b) Change detection using all observations in a single path with minimum view zenith angle. The change caused by climate variability 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 the Landsat path #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 is 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.

5 Current land change products

Lots of remote sensing-based land change products have been created, and some of them have been widely used for a variety of fields, such as environmental sustainability, land management, biodiversity conservation, and ecosystem health assessment. However, most of these land change products are only focusing 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 process (Table 1). Most of these products are replying on medium resolution images (<30 m) and dense time-series observations (e.g., yearly, or monthly, or even weekly observations).

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 2000-2012 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. (2020) 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-meter resolution based on 30+year 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 global burned area product, in which the date of burn area will be provided within each individual 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. (2021) 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. Among all these products, the newly released Land Change Monitoring, Assessment, and Projection (LCMAP) product is one of the few land change products that not only can provide change location and time (e.g., Time of Spectral Change product), change target (e.g., Annual Land Cover Change product), but also has products on land change process information (e.g., Change Magnitude, Time Since Last Change, and Spectral Stability Period products), through a suite of ten LCMAP science products (Fig. 10) (Brown et al., 2020). The list of products also demonstrated the difficulty of providing information on change agent at large-scales.

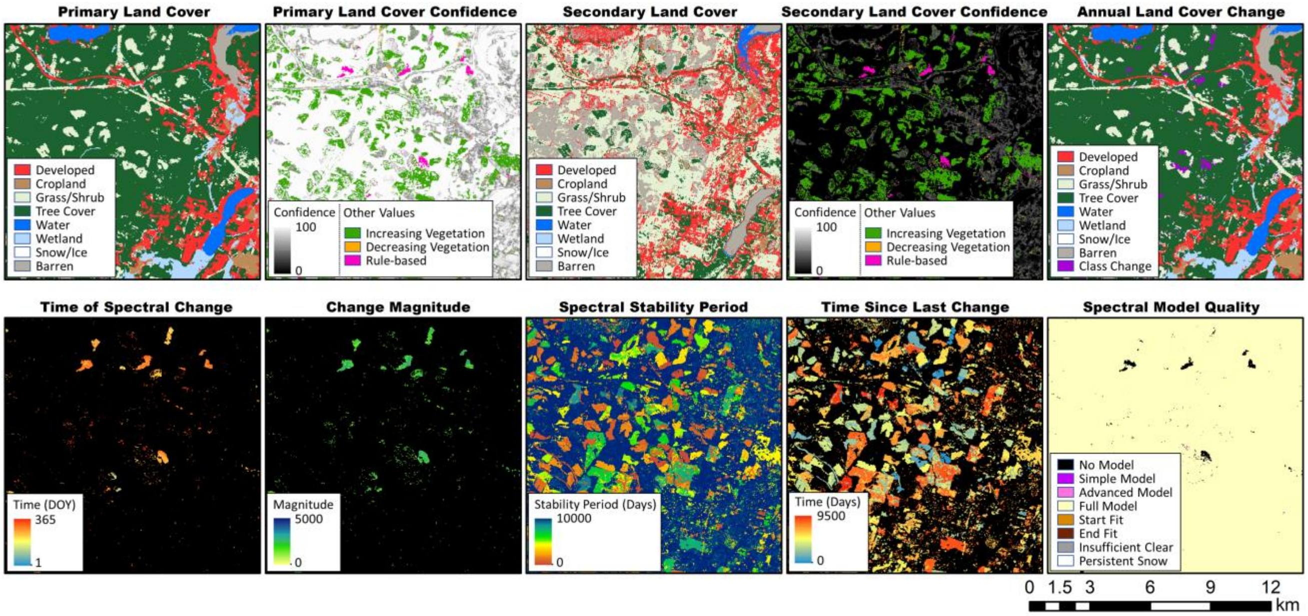


Fig 10. LCMAP Ten Individual Products. This example is derived from LCMAP product version 1.2 in 2010 at Washington state, U.S. LCMAP: Land Change Monitoring, Assessment, and Projection.

Table 1. A list of current large-scale land change products. Only the most recent literatures are listed here.

Product Name	Coverage	Change Location	Change Time (Period)	Change Target	Change Process	Change Agent	Satellite Data	Citation
Hansen forest change map	Global	30-meter	Annual (2000- 2019)	Forest gain Forest loss	N/A	N/A	Landsat	(Hansen et al., 2013)
Global Surface Water	Global	30-meter	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-meter	Day of Year (2000-Present)	Burned area	N/A	Fire	MODIS	(Giglio et al., 2018)
NAFD-NEX	CONUS	30-meter	Annual (1986-2010)	Forest disturbance	N/A	N/A	Landsat	(Zhao et al., 2018)
GHSL	Global	30-, 250-, and 1000-meter	Multiple years (1975, 1990, 2000, and 2014)	Built-up area	N/A	N/A	Landsat	(Pesaresi et al., 2016)
NLCD	United States	30-meter	2-3 years (2001-2019)	Land cover change Forest disturbance	N/A	N/A	Landsat	(Jin et al., 2019)
GAUD	Global	30-meter	Annual (1985-2015)	Urban expansion Green recovery	N/A	N/A	Landsat	(Liu et al., 2020)
LCMAP	CONUS	30-meter	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-meter	Annual Seasonal (1985-2010)	Land cover change	N/A	N/A	Landsat, MODIS, and AVHRR	(Liu et al., 2021)

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.

6 Conclusion and future 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, process, 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 impact of spatial, spectral, temporal, and angular domains of the remotely sensed data on observation, monitoring, and characterization of land change was 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 full land change facets, particularly for the facets of land change agent and process.

Therefore, we have a few future 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 on the focus from land target change to land process and agent change detection are expected in future remote sensing studies, as these two facets are far less studied in 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 socioeconomic data and more integrated social-environment theory could provide new and deeper insights (Tellman et al., 2020). 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.

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Reference

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/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

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/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. Manage. 361, 194–207. https://doi.org/https://doi.org/10.1016/j.foreco.2015.11.015

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/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/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

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/https://doi.org/10.1016/j.rse.2020.111967

Cho, M.A., Debba, P., Mutanga, O., Dudeni-Tlhone, N., Magadla, T., Khuluse, S.A., 2012. Potential utility of the spectral red-edge region of SumbandilaSat imagery for assessing indigenous forest structure and health. Int. J. Appl. Earth Obs. Geoinf. 16, 85–93. https://doi.org/https://doi.org/10.1016/j.jag.2011.12.005

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/https://doi.org/10.1641/0006-3568(2004)054[0535:LRIEAO]2.0.CO;2

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. https://doi.org/10.1080/0143116031000101675

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/https://doi.org/10.1080/02757259609532305

Dale, V.H., 1997. The relationship between land-use change and climate change. Ecol. Appl. 7, 753–769. https://doi.org/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/https://doi.org/10.1641/0006-3568(2001)051[0723:CCAFD]2.0.CO;2

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/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/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

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

Eitel, J., Vierling, L.A., Litvak, M.E., Long, D.S., Schulthess, U., Ager, A., Dan, J.K., Stoscheck, L., 2011. Broadband, red-edge information from satellites improves early stress detection in a New Mexico conifer woodland. Remote Sens. Environ. 115, 3640–3646.

https://doi.org/https://doi.org/10.1016/j.rse.2011.09.002

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/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. https://doi.org/10.3390/rs13050922

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/https://doi.org/10.14358/PERS.73.8.923

Frantz, D., 2019. FORCE—Landsat+ Sentinel-2 analysis ready data and beyond. Remote Sens. 11, 1124. https://doi.org/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

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/https://doi.org/10.1080/1747423X.2015.1096423

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/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/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/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

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/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, 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/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.

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. https://doi.org/http://dx.doi.org/10.1007%2Fs10021-004-0243-3

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

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

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/https://doi.org/10.1016/j.srs.2021.100014

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/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/https://doi.org/10.1038/nature17301

Huston, M., Smith, T., 1987. Plant succession: life history and competition. Am. Nat. 130, 168–198. https://doi.org/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. (Second E. (Eds.), Plant Disturbance Ecology. Academic Press, San Diego, pp. 1–15. https://doi.org/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/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/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/https://doi.org/10.1016/j.rse.2007.03.010

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

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.

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 State, USA. For. Ecol. Manage. 362, 194–204. https://doi.org/https://doi.org/10.1016/j.foreco.2015.12.015

Lambin, E.F., Strahlers, 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/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/https://doi.org/10.1016/S0959-3780(01)00007-3

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/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/https://doi.org/10.1071/WF05097

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/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

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/https://doi.org/10.3390/rs12071176

Liu, H., Gong, P., Wang, J., Wang, X., Ning, G., Xu, B., 2021. 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., 2020. 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/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., 2020. Space eye on flying aircraft: From Sentinel-2 MSI parallax to hybrid computing. Remote Sens. Environ. 246, 111867. https://doi.org/https://doi.org/10.1016/j.rse.2020.111867

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 Sensing 68, 1091–1099.

Ma, Y., Wu, H., Wang, L., Huang, B., Ranjan, R., Zomaya, A., Jie, W., 2015. Remote sensing big data computing: Challenges and opportunities. Futur. Gener. Comput. Syst. 51, 47–60. https://doi.org/10.1016/j.future.2014.10.029

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

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

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/https://doi.org/10.1016/j.rse.2009.05.016

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. URL https://www.ncei.noaa.gov/products/severe-weather-data-inventory (accessed 1.4.22).

NRC, 1999. Human dimensions of global environmental change: Research pathways for the next decade. National Academies Press.

NRC, 1998. People and pixels: Linking remote sensing and social 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/https://doi.org/10.3390/f8070251

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/https://doi.org/10.1016/j.rse.2012.10.031

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

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, Luxembourg (Luxembourg): Publications Office of the European Union. 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/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/https://doi.org/10.1080/01431160010006881

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

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/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

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/https://doi.org/10.1016/j.rse.2010.05.010

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/https://doi.org/10.1073/pnas.0401545101

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/https://doi.org/10.1016/j.rse.2018.03.017

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/https://doi.org/10.1016/j.rse.2021.112586

Roy, D.P., Wulder, M.A., Loveland, T.R., C.E., 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/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

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 U.S. 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/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/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/https://doi.org/10.1016/0034-4257(94)00061-Q

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/https://doi.org/10.1016/j.jag.2017.04.004

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/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

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/https://doi.org/10.1016/j.isprsjprs.2019.10.004

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 Sens. Environ. 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.

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/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/https://doi.org/10.1016/j.rse.2019.02.003

Tellman, B., Magliocca, N.R., Turner, B.L., Verburg, P.H., 2020. Understanding the role of illicit transactions in land-change dynamics. Nat. Sustain. 3, 175–181. https://doi.org/10.1038/s41893-019-0457-1

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/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., 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/https://doi.org/10.1073/pnas.0704119104

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, M.G., 2010. Disturbance and landscape dynamics in a changing world. Ecology 91, 2833–

2849. https://doi.org/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/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/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/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. https://doi.org/10.1016/j.rse.2016.02.060

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/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/https://doi.org/10.1016/j.rse.2021.112557

White, P.S., Pickett, S.T.A., 1985. Natural disturbance and patch dynamics: an introduction, in: PICKETT, S.T.A., WHITE, P.S.B.T.-T.E. of N.D. and P.D. (Eds.), The Ecology of Natural Disturbance and Patch Dynamics. Academic Press, San Diego, pp. 3–13. https://doi.org/https://doi.org/10.1016/B978-0-08-050495-7.50006-5

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, 1011–1011. 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/https://doi.org/10.1016/j.rse.2019.111558

Woodcock, C.E., Strahler, A.H., 1987. The factor of scale in remote sensing. Remote Sens. Environ. 21, 311–332. https://doi.org/https://doi.org/10.1016/0034-4257(87)90015-0

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

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/https://doi.org/10.3390/rs8060520

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/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/https://doi.org/10.1016/j.rse.2021.112560

Zhang, J., Shang, R., Rittenhouse, C., Witharana, C., Zhu, Z., 2021. Evaluating the impacts of models, data density and irregularity on reconstructing and forecasting dense Landsat time series. Sci. Remote Sens. 100023. https://doi.org/https://doi.org/10.1016/j.srs.2021.100023

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/https://doi.org/10.1016/j.rse.2018.02.035

Zhao, F.R., Meng, R., Huang, C., Zhao, M., Zhao, F.A., Gong, P., Yu, L., Zhu, Z., 2016. Long-term post-disturbance forest recovery in the greater Yellowstone ecosystem analyzed using Landsat time series stack. Remote Sens. 8, 898. https://doi.org/https://doi.org/10.3390/rs8110898

Zhu, Z., 2019. Science of Landsat analysis ready data. Remote Sens. 11, 2166. https://doi.org/https://doi.org/10.3390/rs11182166

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, Zhe, Fu, Y., Woodcock, C.E., Olofsson, P., Vogelmann, J.E., Holden, C., Wang, M., Dai, S., Yu, Y., 2016. 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, Zaichun, 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., 2016. 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., 2012. 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., 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

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