Bringing an ecological view of change to Landsat-based remote sensing

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When characterizing the processes that shape ecosystems, ecologists increasingly use the unique perspective offered by repeat observations of remotely sensed imagery. However, the concept of change embodied in much of the traditional remote-sensing literature was primarily limited to capturing large or extreme changes occurring in natural systems, omitting many more subtle processes of interest to ecologists. Recent technical advances have led to a fundamental shift toward an ecological view of change. Although this conceptual shift began with coarser-scale global imagery, it has now reached users of Landsat imagery, since these datasets have temporal and spatial characteristics appropriate to many ecological questions. We argue that this ecologically relevant perspective of change allows the novel characterization of important dynamic processes, including disturbances, long-term trends, cyclical functions, and feedbacks, and that these improvements are already facilitating our understanding of critical driving forces, such as climate change, ecological interactions, and economic pressures.

Front Ecol Environ 2014; doi:10.1890/130066

Ecologists increasingly include remotely sensed measurements in their efforts to describe ecosystem states and dynamics, and the number and capacity of tools available is continually expanding. For example, ecologists can turn to a growing suite of very high spatial resolution (VHSR) products to describe plot-level conditions in two and three dimensions (Wulder *et al.* 2004; Vierling *et al.* 2011), and to imagers at the global scale to examine the ecological status of the entire biosphere (Justice *et al.* 2011). Although availability, cost, and spatial scale are critical factors when determining appropriate remote-sensing tools, ecologists attempting to move beyond descriptions of state and toward an understanding of dynamics must consider another critical issue: does a given remote-sensing tool describe change over time in a manner consistent with the ecological process of interest?

In a nutshell:

- Natural and anthropogenic processes affecting ecosystems can be conceptualized using a range of mathematical response functions, but traditional remote-sensing analysis has been largely unable to fully capture such dynamics
- Recent technical advances and improvements in data policy have moved remote-sensing analysis closer to an ecological view of landscape dynamics, a shift that is increasingly being applied to Landsat data, the longest-running archive of imagery available
- Through examples drawn from recent literature, we argue that Landsat data can effectively quantify when and where important natural and human-caused changes are occurring, allowing improved understanding of forces that shape ecosystems

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Historically, the concepts of change among the remote-sensing community have been incongruous with those in the ecological disciplines. To an ecologist, landscapes change continuously, influenced by interacting natural and anthropogenic processes that feed back on one another at multiple spatial and temporal scales. But much of the traditional remote-sensing literature viewed ecosystems as mostly static entities, with occasional disruptions causing dramatic contrasts in images taken before and after the change (Coppin *et al.* 2004). The temporal dimension – critical to understanding processes – has generally been sparse at the spatial scales needed by ecologists. Thus, ecologists using remotely sensed data often draw inference from incomplete temporal characterizations of landscape dynamics, and limit their assessment to broad-scale, dramatic events. Beginning with coarse-scale imaging systems in the 2000s, changes in image data availability have combined with improvements in image analysis, hardware, and software to produce a paradigm shift in remote sensing of landscape change. That conceptual shift has arrived at the scale of the Landsat family of sensors (Wulder *et al.* 2012). As the oldest continuously running imaging system designed to monitor the Earth's ecosystems, Landsat sensors offer unparalleled temporal consistency at a spatial resolution relevant to ecological disciplines. In this review, we show how Landsat-based concepts of change are rapidly moving closer to those found in ecology and related

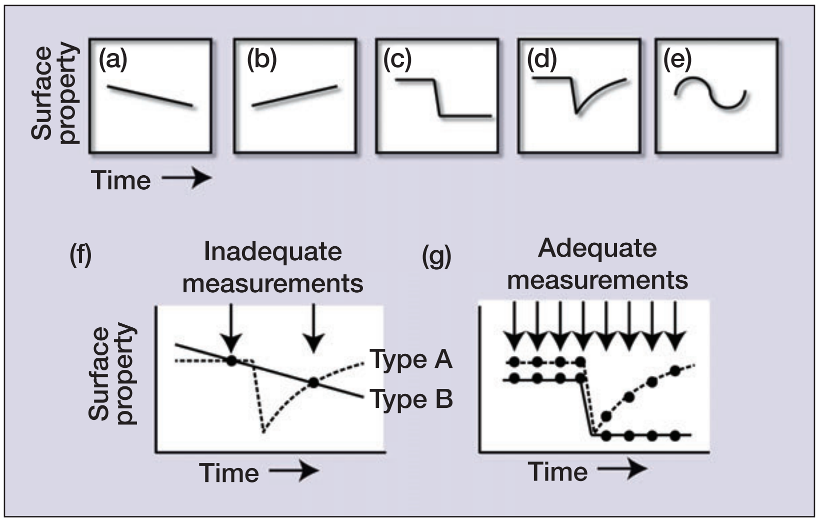

Figure 1. *An ecological view of changing landscapes. Over time, landscapes are affected by processes that alter measurable biophysical or ecological quantities over time. The trajectory of the quantity can be conceptualized as a mathematical response function, the shape of which provides insight into the process causing the change. Shown are idealized functions of biomass, for example, being affected by processes such as (a) stress or chronic loss, (b) growth or increase, (c) state change, (d) change and resilience, and (e) cyclical change. If measurements are sparse, the ability to match observations with functional forms is hampered, and it becomes difficult to determine which process might be acting on the ecosystem (f). To fully characterize or distinguish among processes, measurements should be frequent relative to the form of the function of interest (g).*

disciplines, and how important ecological findings are already emerging from this new paradigm.

An ecological view of change

A dominant theme in ecology is understanding how driving forces, such as climate or economics, affect ecosystems. Driving forces catalyze or constrain endogenous or exogenous processes (eg competition, photosynthesis, disturbance, etc), which then alter ecosystem properties (eg biodiversity, biomass) over time (Oliver and Larson 1996), with potential feedbacks among both natural and anthropogenic effects (Gunderson and Holling 2002; Cumming *et al.* 2006). Conceptually, the evolution of ecosystem properties over time provides insight into the process affecting the system. The evolution of ecosystem processes can be described using simple response functions (Oliver and Larson 1996), and the better these functions can be described mathematically, the greater insight ecologists can draw about ecosystem dynamics.

Response functions can take on many forms. For a deciduous shrubland, for example, drought stress might cause a steady decrease in biomass (Figure 1a); secondary succession a steady increase (Figure 1b); urbanization or fire an abrupt decline followed by stasis (Figure 1c) or recovery (Figure 1d), respectively; and seasonal variation in insolation and temperature a sinusoidal increase and decrease (Figure 1e). In practice, ecological systems have many such natural and anthropogenic effects acting simultaneously and feeding back on one another at different temporal and spatial scales, often resulting in complex or non-linear combinations of simpler response functions.

Although inference of process from spatial pattern is a goal in ecology (McIntire and Fajardo 2009), characterization of ecological response functions is achieved most directly through carefully timed, repeated measurements. For instance, field-based observations of shrubland biomass made before and soon after a fire event would allow quantification of the fire's impact. But timing is critical: if the second measurement were made many years after the fire, the effects of the disturbance would become mixed with the effects of subsequent vegetative recovery. Discerning the impact of fire from that of other processes such as a slow, drought-related decline in biomass would be difficult (Figure 1f). Thus, to accurately understand ecological dynamics, researchers must rely on measurements that are frequent relative to the shape of the response function (Figure 1g). The challenge, however, is to know in advance where on a landscape to invest in measurements, particularly with stochastic processes. For this reason, remotely sensed images – which measure broad areas and may allow opportunistic retrospective analysis – are attractive.

A remote-sensing view of change

In the traditional remote-sensing literature, landscape change is understood as a measurable difference between two or more digital images (Coppin *et al.* 2004). Efforts have focused more on representing that difference and less on the processes causing it. The challenge to faithful representation of change is that a remotely sensed digital image is a model of the real landscape: atmospheric effects, clouds, sensor degradation, illumination angle, and geometric misalignments all introduce measurement error in the model (Figure 2a). Ideally, image pixels should be well calibrated and converted to physically meaningful units, such as reflectance, or radiance. Even with these efforts, issues of spatial scale and measurement sensitivity affect the relationship between the observed signal and the surface qualities at the time of observation. Finally, these estimates of surface condition must be translated into quantities or descriptors that have ecological meaning. The better each image models the real landscape, the more likely that image differences correspond to real and ecologically relevant landscape change (Figure 2b).

When defined as the difference between two images, change either occurs or does not, implying a unidirectional, abrupt change of state: a step-function. In much high- to moderate-resolution imagery attractive to ecological studies, this implied step-function concept of change emerged largely as a practical matter of image cost. Images were expensive, and the time, expertise, and computing power needed to handle them were costly. These costs placed an upper limit on the number of images used for analysis. Thus, most studies of change were based on observing change in pairs of cloud-free images that were separated by relatively coarse temporal intervals (Coppin *et al.* 2004; Hansen and Loveland 2012).

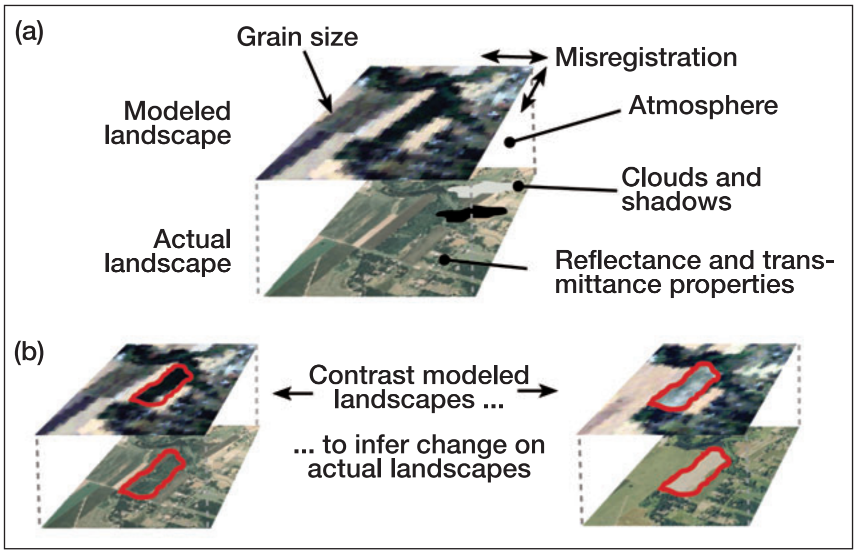

Figure 2. *A Landsat remote-sensing view of changing landscapes. (a) A satellite digital image is a grid-based model of an actual landscape, and it is important to maximize the information content of that model by removing "noise" (variations) caused by the measurement system errors and impacts of non-target effects, such as atmospheric contamination. (b) Landscape change (outlined in red) is inferred by contrasting the modeled landscapes. Ineffective removal of noise factors will reduce the clarity of contrast, making it more challenging to determine where change has occurred.*

A new era in remote sensing

A shift in viewpoint occurred with the advent of data from the National Aeronautics and Space Administration's space-borne MODIS (Moderate Resolution Imaging Spectroradiometer) sensor in 2000. A critical conceptual advance with MODIS was to provide cost-free data in a format usable by non-specialists, designed with user-community needs in mind. With reduced obstacles to utilizing multiple images, researchers could begin to consider the entire archive as a cohesive temporal record, rather than as a series of individual images. This advance led to a range of innovative algorithms and applications that began to examine not just the state of systems but their dynamics as well (Justice *et al.* 2011). Despite these new developments, the large pixel size of MODIS (and AVHRR – the Advanced Very High Resolution Radiometer, another satellite-based sensor pre-dating MODIS) prevented observation of many finer-grained processes of interest to the ecological community (Figure 3).

Thus, in 2008, when the US Geological Survey (USGS) began providing Landsat images in a cost-free, consistent, and easy-to-use format, it catalyzed several advances that moved the conceptual advances of MODIS to a finer spatial resolution that is useful to ecologists (Wulder *et al.* 2012). First, effective temporal resolution of Landsat imagery improved dramatically (Figure 3a). With no cost limitation on the number of images and with all images well-aligned, cloud-free composites could be created by merging clear zones of various partly cloudy images (Helmer *et al.* 2010; Roy *et al.* 2010), rendering any clear pixel useful. This pixel-based view of the Landsat archive represents a fundamental conceptual shift. Second, dense, long time-series could be constructed for each pixel (as far back as 1972), providing the temporal signal-to-noise ratios needed to detect subtle, long-term trends, episodic events, and sinusoidal fingerprints of seasonal phenology (Zhu *et al.* 2012). Third, regional- to continental-scale applications became more feasible. Consequently, a suite of methods and applications is now emerging (Wulder *et al.* 2012) that increasingly allows direct observation of dominant change processes over large spatial extents of interest to ecologists.

Emerging methods and findings

The literature is rapidly maturing, with increasing numbers of techniques, results, and applications to characterize the ecosystem response functions idealized in Figure 1 at spatial and temporal scales relevant to ecology.

Step-functions

Step-functions (Figure 1, c and d) typically correspond to abrupt (ie short-term) disturbance events, such as fires, land clearance for development, or resource extraction. Mapping of such abrupt transformations, often easy to detect with only two images, has long been a dominant theme in remote sensing (Coppin *et al.* 2004). However, when only one image was used before and one after a change, accuracy was compromised. Clouds could obscure the change, and if the second image was delayed too long after the change, recovery processes could mask the disturbance event. The relatively coarse temporal scales afforded by use of infrequently captured imagery did not match the temporal scale of the processes driving the changes.

By using the best available pixels at any time in the archive, wall-to-wall disturbance mapping – where no pixels on a landscape are obscured by clouds – is possible

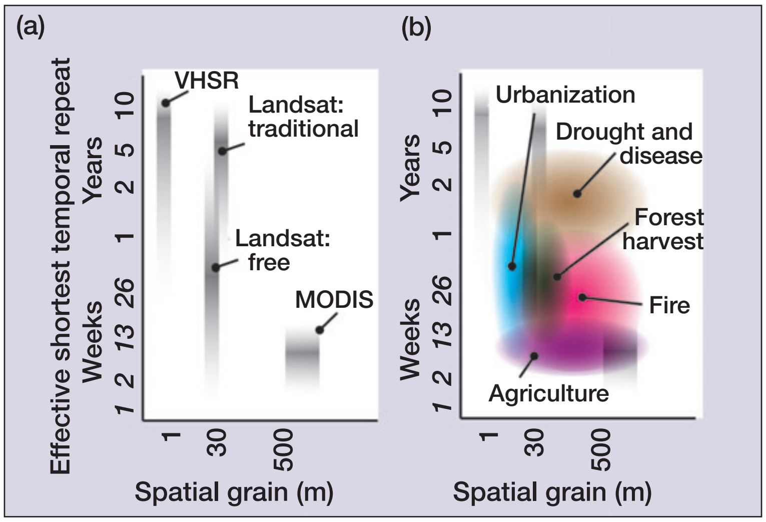

Figure 3. *Spatial and temporal characteristics of common satellite sensors (VHSR: very high spatial resolution sensors and photography; MODIS: Moderate Resolution Imaging Spectroradiometer) and the landscape dynamics. (a) Engineering constraints lead to trade-offs between spatial and temporal resolution of the original measurements, but costs of processing further limited the effective repeat cycle of Landsat data. With free Landsat data now available, the usable repeat cycle of Landsat data for individual pixels has vastly improved. (b) This allows Landsat data to capture the effects of many more landscape processes than before, including those not captured by other remote-sensing methods. Colors in (b) are used for visual distinction only.*

now in areas where clouds and sparse data coverage previously hindered any mapping (Hansen and Loveland 2012). Even in areas where prior mapping efforts existed, methods have improved temporal resolution of maps (Huang *et al.* 2010).

Enhanced temporal resolution over longer periods has facilitated more meaningful use of abrupt disturbance information. Unprecedented regional- to continental-scale mapping is providing insight into spatial distributions of forest disturbances, allowing hypothesis testing with regard to drivers of change, including weather variation (Lutz *et al.* 2011), macroeconomic changes (Masek *et al.* 2013), and regional-scale policy changes (Danaher *et al.* 2010; Kennedy *et al.* 2012). Long-term monitoring of disturbance patterns provides insight into potential impacts on habitat specialists such as grizzly bears (*Ursus arctos horribilis*; White *et al.* 2011) and various bird species (Helmer *et al.* 2010). Enhanced temporal resolution also allows direct linkage of forest disturbance with mechanistic biogeochemical models (Turner *et al.* 2011). Better characterization of disturbance timing and intensity leads to improved estimation of forest height and biomass in recovering forests (Helmer *et al.* 2009; Li *et al.* 2011). The ability to exploit seasonal and multi-year imagery helps to resolve confusion in areas where individual picture elements contain mixtures of cover types, enabling routine monitoring of land-cover change and urbanization in heterogeneous environments (Lyons *et al.* 2012; Schneider 2012), and revealing how policy alters urbanization rates (Powell *et al.* 2008). In nearshore marine ecosystems, annual or sub-annual Landsat monitoring is revealing long-term trends and short-term shifts in the amount and distribution of seagrass cover (Lyons *et al.* 2012), with implications for the science and management of faunal assemblages and the role of seagrasses as indicators of coastal water quality.

Trend functions

Competition, succession, regeneration, chronic stress, and other slow changes to ecosystems are central to ecological studies, but traditionally have been difficult to map at broad scales. Many hypothesized regional- to continental-scale impacts of climate change involve slow shifts in location or frequency of these processes (IPCC 2007), but at spatial scales too small for coarse-resolution imagers.

Landsat-based analyses of slow trends rely on the pixel-based conceptual view of the image archive, and many share a simple statistical strategy of fitting linear functions to time-series observations that was proposed in studies that predate the era of free imagery (Hostert *et al.* 2003). Method development continues with extensions to different ecosystem types (Sonnenschein *et al.* 2011) and to more complex statistical functions (Goodwin *et al.* 2010).

Insights into ecological dynamics are emerging from these efforts. In forests, recent studies suggest that insect outbreaks have variable temporal signatures ranging from abrupt to multi-decadal (Goodwin *et al.* 2010; Meigs *et al.* 2011), with implications for habitat, hydrology, and carbon cycling. Management impacts of grazing are evident in long-term trends observed in herbaceous systems (Hostert *et al.* 2003), and the spatial detail of the Landsat record allows testing of nuanced relationships between grazing accessibility and negative or positive long-term impacts (Röder *et al.* 2008). Local-scale woody vegetation encroachment can now be quantified with Landsat data, suggesting the potential to test hypotheses regarding management and competitive effects at spatial scales meaningful to ecologists and land managers (Vogelmann *et al.* 2012). Recent studies in tundra ecosystems suggest that infilling of shrubs in favorable niches is more robust than encroachment into previously inhospitable areas (Fraser *et al.* 2011; McManus *et al.* 2012). This highlights the importance of multiple constraints on establishment and growth, allowing more nuanced tests of climate-change hypotheses.

Furthermore, Landsat data have shown promise in capturing long-term records of coral reef and coastal change. The technical challenges of using satellite imagery in marine environments are considerable (Andréfouët *et al.* 2001), and although aerial photographs are more accurate in mapping reef habitat at a specific time, long-term monitoring through the use of Landsat is feasible when detection targets are suitably generic (Lyons *et al.* 2012). This suggests that a mixed approach – merging VHSR data with Landsat temporal data (Palandro *et al.* 2008) – could provide a means of scaling up reef change information to broader areas.

Cyclic functions

Cycles of vegetation phenology are often critical markers of ecosystem function and health, and have long been of interest to ecologists and naturalists. Characterization of phenology with coarse-resolution sensors such as MODIS is an active area of research (de Beurs and Henebry 2010), particularly as changes in phenology relate to climate change (Myneni *et al.* 1997). But because finer temporal-grained observations are needed for more detailed use of phenological information, algorithms that blend Landsat and MODIS data are being developed (Gao *et al.* 2006) and applied to phenology research (Coops *et al.* 2012). Moreover, improved density of Landsat imagery alone is allowing characterization of natural vegetative cycles at spatial resolutions fine enough to link directly to field data and measurements (Fisher *et al.* 2006; Melaas *et al.* 2013). This concept is taken to its limit with algorithms that use all available clear Landsat pixels and model seasonal cycles to enhance and accelerate detection of land-cover change (Schneider 2012; Zhu *et al.* 2012). Characterization of cyclic dynamics also improves separation of subtle contrasts in vegetative vigor, allowing the development of management strategies for herbaceous systems affected by grazing (Danaher *et al.* 2010).

Interactions and feedbacks

Although strict separation of process functional types described thus far is heuristically helpful, it oversimplifies the dynamics of many ecosystems. Ecological processes give rise to and feed back on one another (Gunderson and Holling 2002), and when combined with social mechanisms may even generate novel dynamics at a variety of scales (Cumming *et al.* 2006). With a uniquely long historical archive, Landsat data offer direct observation of sequential dynamics, leading to better characterization of response to and facilitation among change processes. Perhaps more importantly, by examining large areas, Landsat data may uncover contrasting responses to similar events, allowing tests of hypotheses of resistance, resilience, and steady-state conditions.

To date, efforts have focused primarily on characterizing the responses to disturbance. By disrupting ecosystem inertia (ie resistance to change), disturbances set the stage for recovery processes that may send the system into a different state. In a classic study, Lawrence and Ripple (1999) used dense time-series Landsat imagery to illustrate the richness of growth dynamics after a volcanic eruption. For less dramatic but more widespread effects, several Landsat-based studies have shown that both climate and management affect post-disturbance regrowth dynamics (Viedma *et al.* 1997; Schroeder *et al.* 2007; Hais *et al.* 2009; Griffiths *et al.* 2012; Sen *et al.* 2012), which in turn affect carbon dynamics of the system (Kuemmerle *et al.* 2009; Gómez *et al.* 2012). This improved understanding of ecosystem function can also lead to a better estimation of the state of the system (Helmer *et al.* 2010; Li *et al.* 2011). Again, ecological information can be gained by integrating the temporal data provided by Landsat with spatial information provided by higher-resolution imaging systems, including light detection and ranging (LiDAR; Pflugmacher *et al.* 2012).

Using the Landsat archive, scientists have the potential to move beyond describing event/response dynamics and toward revealing how those combined processes facilitate subsequent events. Research in this area is nascent, regardless of the type of remotely sensed dataset, but examples are emerging using both Landsat and coarser-scale imagery to link impacts of one anthropogenic (forest clearing) or natural (El Niño–Southern Oscillation) process to a secondary natural or anthropogenic process (fire) (Siegert *et al.* 2001; Alencar *et al.* 2006). At the Landsat level, comprehensive studies of interactions have yet to be made, but initial investigations have been promising. In tropical forests, hurricane-affected areas may be more susceptible to later burning (Helmer *et al.* 2010), and in dry temperate forests, the ability to estimate levels of insect-related tree mortality from the Landsat archive (Meigs *et al.* 2011) suggests that it is possible to explicitly test hypotheses linking insect outbreaks and wildfire. The potential to document the spatial and temporal patterns of successive landscape processes is perhaps the greatest long-term attraction of the Landsat archive in terms of validating ecological theory.

■ Continued evolution, challenges, and opportunities

Concepts of change developed in MODIS studies pushed the emergence of related concepts in the Landsat domain, and a similar progression can be anticipated in the domain of VHSR and hyperspectral imagery. The archive of VHSR imagery is increasing in temporal depth, suggesting that it will be possible to capture ecological change at the scale of individual study plots, and unmanned aerial vehicles may offer novel ways of monitoring study sites (Anderson and Gaston 2013). Yet the characteristics that make these imagers attractive also create challenges: high resolution exacerbates the problems caused by viewing angle, illumination effects, and geometrical variability, making it difficult to extract consistent information from a single point in space across time, unless the fine-resolution data are aggregated to coarser mapping units (Wulder *et al.* 2008). Nevertheless, as other medium- and high-resolution satellite image sources accumulate within the temporal record of Landsat, the examples discussed here and new applications may be adapted to VHSR sources. Similar advances

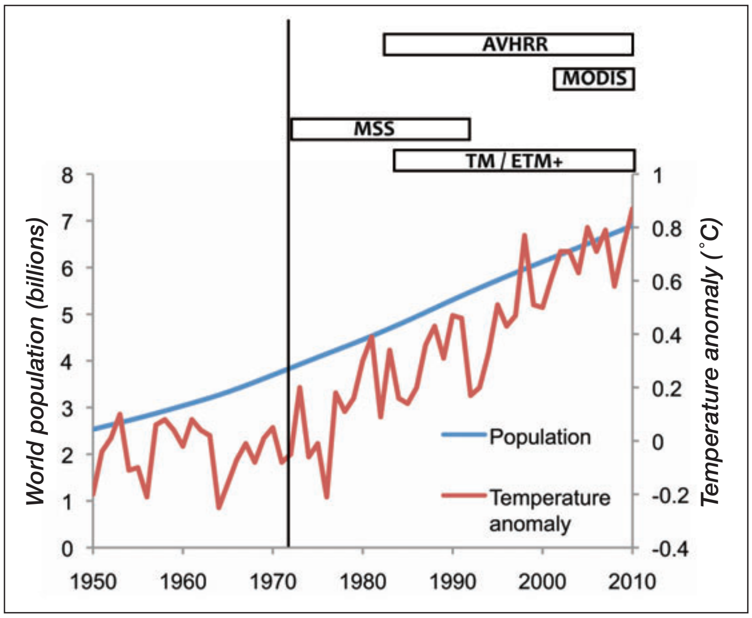

Figure 4. *Measurement periods for commonly-used satellite sensors in relation to global human population and atmospheric temperature trends. Sources: United Nations (Population); NASA GISS (Temperature).*

can be anticipated in the realm of hyperspectral imagery, where rapid expansion of sensors and an increasing historical archive will lead to markedly improved discriminatory power among vegetation types and direct sensing of chemical and biophysical properties (Chambers *et al.* 2007), both of which are challenging to accomplish using coarse spectral data such as Landsat.

Another area with potential for improved understanding of ecological dynamics is the linkage between the Landsat multi-decadal record and other long-term datasets. Field data from ecological observing networks, such as the Long Term Ecological Research Network in the US (www.lternet.edu) or the Terrestrial Ecosystem Research Network in Australia (www.tern.org.au), and from regular surveys of field plots, such as the US Forest Service's Forest Inventory and Analysis program (www.fia.fs.fed.us) or the US Department of Agriculture's Agricultural Resource Management Survey (www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices.aspx) offer the potential for understanding changes and feedbacks observed in the satellite signal. By relying on spatially consistent Landsat data, researchers can extrapolate "lessons learned" at data-rich locations to the larger landscape. Other surveys, such as those estimating populations of humans or other species, may be used to examine potential drivers or impacts of change observed in the Landsat record.

Although the Landsat archive offers substantial promise for gaining new ecological insights, several technical and conceptual challenges remain before this potential can be fully realized. Complete exploitation of the Landsat archive back to 1972 requires that Multispectral Scanner (MSS) imagery be brought into automated analysis workflows, and although progress is being made (Helmer *et al.* 2009; Pflugmacher *et al.* 2012), seamless automation has not yet been achieved. Greater use of time-series thermal data from Landsat may also provide important new insights into ecological systems, but to date these data have been underutilized. Global extension of many of the methodological advances will require use of Landsat images that currently exist only at international ground stations, and data storage media deterioration may be causing the loss of historical images. Central collection and archiving of international archives is a high priority for the USGS. Finally, and perhaps most importantly, there is the issue of data continuity into the future: the successful deployment of Landsat 8 and the planned European Sentinel-2 mission promise near-term data collection, but continuity beyond those sensors' life spans is unknown.

Conceptual challenges remain as well. Ecological dynamics rarely conform to single Landsat pixels, making it vital to continue extension of sub-pixel methods and pixel-to-patch aggregation methods into the complex temporal realm afforded by Landsat data (Sen *et al.* 2012; Wulder *et al.* 2012). To fully record the Earth's recent history, we argue that fusion of data from different sensor types must continue to expand and generalize, while maintaining the measurement consistency needed to track individual pixels seamlessly through time. As complex temporal dynamics are increasingly well understood, field observations and other reference data to interpret those dynamics must expand and improve. Better integration into mechanistic models must continue, and Landsat-based data that record change must be translated into user-relevant products whose analysis can lead to policy implementation by better informed decision makers. Both these efforts require much better integration with scientific and user community needs. Fortunately, as the tools available to utilize Landsat imagery become more accessible (WebPanel 1; WebTable 1), Landsat data become less the domain of specialists, diminishing the obstacles that have made such integration and broader use difficult.

■ Conclusions

When studying the processes that shape ecological systems, ecologists increasingly recognize value in the unique perspective offered by remote-sensing technologies. Although their broad scale of measurement has long been appreciated, it is the ability of remote-sensing systems to consistently observe ecosystems over time that is proving critical for improved understanding of ecological dynamics. Fortunately, the concepts of ecosystem change in the remote-sensing community are becoming more aligned with those in ecological disciplines, allowing deeper understanding of the profound pressures exerted on the Earth system during the satellite era (Figure 4). As we have argued here, the application of these concepts to the Landsat image archive is already yielding insight in a way that no other currently available tools can. We anticipate major scientific advances as this innovative view of ecological processes becomes better integrated into modeling, field studies, and theory.

Acknowledgements

With so many authors contributing to this paper, we wish to extend an overarching acknowledgement to our respective institutions and governments for the many ecological Landsat-related projects that are included herein. We wish to single out the US Geological Survey for its leadership in the data policy that facilitated the advances in ecological science we describe here, and for its co-leadership (along with NASA) of the Landsat Science Team, under whose support the primary author and several coauthors developed this paper. Additionally, we wish to thank our anonymous reviewers whose comments greatly helped focus this paper for the needs of the ecological community.

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WebPanel 1.

Steps in the processing of Landsat imagery have become increasingly automated in recent years, greatly improving the accessibility and usability of Landsat data for analysis. Non-specialists can now find sources of cost-free images that have been corrected for effects of geometry, atmosphere, and clouds, as well as sources of seamless geographic mosaics of imagery. Even those who seek more control over image analysis have many more resources available than before. Additionally, the range of US Government sources of maps showing both land cover and change continues to increase.

WebTable 1. Resources for increased use of Landsat imagery

Use	*Description*	*Source*	*Name*
Seamless mosaics	Browse and download weekly, monthly, seasonal, and yearly mosaics	http://weld.cr.usgs.gov	Web-enabled Landsat Data
	Visually browse the entire Landsat archive at USGS	http://landsatlook.usgs.gov	USGS Landsat Look Utility
	Global Landsat image mosaics for 1970s, 1980s, 1990s, and 2000s	http://glcf.umd.edu/data/gls/	Global Land Survey
	Web-based visual change detection	http://changematters.esri.com/compare	ESRI's ChangeMatters change mapping tool
	Global seamless time series	http://earthengine.google.org	Google's EarthEngine
Processing tools	Official site to identify and download all Landsat imagery	http://earthexplorer.usgs.gov/	Earth Explorer
	Site to download "climate data record" versions of Landsat imagery	http://landsat.usgs.gov	Landsat Climate Data Records
	Software to identify clouds automatically	http://code.google.com/p/fmask/downloads/list	Fmask
	Instructions for filling gaps in imagery	http://landsat.usgs.gov/ERDAS_Approach.php	Instructions only
	Fully automated atmospheric correction to surface reflectance	http://code.google.com/p/ledaps/	Ledaps
	Tools to fuse Landsat and MODIS imagery and to precision-match images to the ground surface	http://ledaps.nascom.nasa.gov/tools/tools.html	STARFM; AROP
Analysis tools	Automated algorithm for forest disturbance mapping	Huang *et al.* (2010)	VCT
	Temporal segmentation algorithms for landscape change monitoring	http://landtrendr.bu.edu/	LandTrendr
	Free image-processing software	https://engineering.purdue.edu/~biehl/MultiSpec/; http://opticks.org/confluence/display/opticks/Welcome+To+Opticks	Multispec; Optiks
Maps	Land-cover maps at regular intervals	www.mrlc.gov/nlcd.php	National Land Cover Database maps for 1992, 2001, 2006, and 2011
		www.csc.noaa.gov/ccapatlas	Land-cover change analysis for areas in US within 100 km of shorelines
	Detailed vegetation maps	www.landfire.gov	US-wide maps of vegetation types

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