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Remote sensing change detection tools for natural resource managers: Understanding concepts and tradeoffs in the design of landscape monitoring projects

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ABSTRACT

Remote sensing provides a broad view of landscapes and can be consistent through time, making it an important tool for monitoring and managing protected areas. An impediment to broader use of remote sensing science for monitoring has been the need for resource managers to understand the specialized capabilities of an ever-expanding array of image sources and analysis techniques. Here, we provide guidelines that will enable land managers to more effectively collaborate with remote sensing scientists to develop and apply remote sensing science to achieve monitoring objectives. We first describe fundamental characteristics of remotely sensed data and change detection analysis that affect the types and range of phenomena that can be tracked. Using that background, we describe four general steps in natural resource remote sensing projects: image and reference data acquisition, pre-processing, analysis, and evaluation. We emphasize the practical considerations that arise in each of these steps. We articulate a four-phase process that guides natural resource and remote sensing specialists through a collaborative process to articulate goals, evaluate data and options for image processing, refine or eliminate unrealistic paths, and assess the cost and utility of different options.

1. Introduction

Remote sensing science has become a critical and universal tool for natural resource managers and researchers in government agencies, conservation organizations, and industry (Gross et al., 2006; Philipson & Lindell, 2003; Stow et al., 2004). The range of applications addressed in the papers of this special issue of Remote Sensing of Environment is testament to the growing use of remote sensing in natural resource management. For the resource manager, a particular attraction of satellite remote sensing technology is the ability to provide consistent measurements of landscape condition, allowing detection of both abrupt changes and slow trends over time. Detection and characterization of change in key resource attributes allows resource managers to monitor landscape dynamics over large areas, including those areas where access is difficult or hazardous, and facilitates extrapolation of expensive ground measurements or strategic deployment of more expensive resources for monitoring or management (Li et al., 2003; Schuck et al., 2003). In addition, long-term change detection results can provide insight into the stressors and drivers of change, potentially allowing for management strategies targeted toward cause rather than simply the symptoms of the cause.

Despite their increased exposure to and appreciation of remote sensing, managers often must rely heavily on remote sensing specialists to design and implement monitoring programs based on change detection of remotely sensed data (Woodward et al., 2002). The authors' collective experience in monitoring projects has shown that success is the responsibility of both parties: the remote sensing scientists must understand the needs and the scientific underpinnings of the managers' goals, and the managers must have or develop an understanding of the fundamental remote sensing issues that arise in remote sensing change detection and monitoring projects. The primary targets of this paper are natural resource managers or researchers who are considering remote sensing for monitoring resource attributes over time, and a fundamental goal is to provide them with enough information about the full arc of a remote sensing project to actively collaborate in designing successful monitoring projects. By doing so, we also hope to aid this audience in evaluating the case studies found in the other papers in this special issue. Despite our focus on educating natural resource managers, we emphasize that the dialog between managers and remote sensing specialists is bi-directional and iterative.

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To discuss the full arc of a remote sensing study, we require the reader to have a basic understanding of a few key concepts in remote sensing change detection. The natural resource manager may consult the many excellent review papers (Cihlar, 2000; Coppin et al., 2004; Lu et al., 2004; Mas, 1999; Mouat et al., 1993; Yuan et al., 1998) and texts (Campbell, 1996; Lillesand & Kiefer, 2000; Lunetta & Elvidge, 1998; Richards, 1993; Sabins, 1997; Schott, 1997; Schowengerdt, 1997; Wulder & Franklin, 2007) written on remote sensing in general and on change detection in particular. Despite the utility of these references, we find that the existing literature leaves two gaps. First, the natural resource manager will struggle to find references written for the non-specialist that also distill the key technical concepts needed to effectively make practical decisions about planned remote sensing projects. While we do not intend to be a simple review paper on basic remote sensing, our experience suggests that it is critical to highlight a few central concepts in remote sensing to lay the groundwork for later discussion. Second, most reviews focus on evaluating image types and analytical methods for change detection, but few review these issues in the context of long-term monitoring, particularly how decisions and constraints at all stages of a project can influence the types of monitoring goals that can be reached. To wisely distribute time and funds, a natural resource manager must be able to evaluate trade-offs among all of the components of the study before final plans are made. This paper represents our attempt to fill these two gaps.

For simplicity of terminology, we refer in this paper to the "natural resource manager," but in practice we consider our audience to be the broader group of scientists, managers, and agency officials who must bring remote sensing data into the realm of natural resource management. Because it is impossible in this paper to address each unique situation faced by natural resource managers and scientists, we have developed a set of broad resource attributes or indicators that encompass many specific issues faced by managers, scientists, and agency personnel (Table 1). All subsequent tables will be structured around these attributes. Rather than being considered an exhaustive list, however, the attributes should be considered for their heuristic value in capturing the continuum of effects of different processes on landscapes.

Table 1
Common natural resource attributes or indicators that are the focus of monitoring programs, grouped into broad categories according to the process or threat influencing that attribute.

Resource attributes/Indicators	Process of interest/Threat
Change in size or shape of patches of related cover types	Vegetative expansion, infilling, or encroachment,[a] erosion[b]
Change in width or character of narrow, linear features	Visitor use of paths or roads, flooding effects on stream vegetation[c]; dynamics of terrestrial and submerged near-shore aquatic vegetation[d]
Slow changes in cover type or species composition	Succession,[e] competition, eutrophication, exotic species invasion[f]
Abrupt changes in state of cover	Disturbance, human-mediated development,[g,h] land management[i]
Slow changes in condition of a single cover type	Climate-related changes in vegetative productivity,[j] slowly-spreading forest mortality caused by insect or diseases,[k] changes in moisture regime
Changes in timing or extent of seasonal processes	Snow cover dynamics, vegetation phenology[l]

[a] Hudak and Wessman, 1998, Harris et al., 2003.
[b] Allard, 2003.
[c] Nagler et al., 2009-this issue.
[d] Wang et al., 2007.
[e] Hostert et al., 2003.
[f] Asner and Vitousek, 2005.
[g] Goetz et al., 2009-this issue.
[h] Townsend et al., 2009-this issue.
[i] Huang et al., 2009-this issue.
[j] Skakun et al., 2003, Wulder et al., 2005.
[k] Nemani et al., 2009-this issue.
[l] Reed et al., 2009-this issue.

The paper has three sections. The first describes underlying concepts in remote sensing and change detection that must be understood to effectively communicate with remote sensing specialists. The second section describes the steps involved in a typical remote sensing study designed for monitoring of natural resources, showing how the key concepts described in the first section are applied in practice. The third section provides a general framework of evaluation phases that should be considered before a remote sensing monitoring program begins. Throughout this paper, we use studies described in companion papers of this special issue to illustrate key concepts.

2. Key concepts

To appreciate the decisions that must be made in a remote sensing monitoring project, the natural resource manager must understand how sensors make measurements, how information is ascribed to those measurements, and how change is inferred from them.

The fundamental process in remote sensing is the measurement of electromagnetic energy to obtain useful information (Schott, 1997). That energy can originate from the sun or from a source associated with the sensor, such as a laser or radio emitter, or can be emitted directly from the material because of its temperature. Like human eyes, electronic sensors are designed to measure reflected energy in discrete regions of the electromagnetic spectrum called "spectral bands." Because the physical and chemical properties of a given material cause it to absorb, reflect, and emit electromagnetic energy differentially in different parts of the electromagnetic spectrum, the relative amounts of energy measured in different spectral bands can be used to infer something about the character of the object being observed (Schott, 1997; Verbyla, 1995). For optical imagery, measurements made in each spectral band are arranged in regular grids of picture elements (pixels), and grids combined from different spectral bands create familiar color digital images. LIDAR data are provided as postings, at either regular or irregular intervals, but can be, and usually are aggregated to regular grid cells for interpretation, analysis and change detection. Depending on the type of lidar (discrete return or waveform), data may be provided as elevations of one or several returns from each posting or as a continuous record or return intensity with height. Likewise, synthetic aperture radar (SAR) images are generally processed to regular grids, but originate as side-looking images recording the differences in travel times and return intensity of transmitted microwave signals.

Extracting information from a digital image begins with "spectral space" (which for our purposes includes SAR intensity or comparable LIDAR measurements). Spectral space is the data space that can be visualized by plotting measured intensity of reflected radiance in different spectral bands against each other (Lillesand & Kiefer, 2000; Richards, 1993). Fig. 1 illustrates this concept for a picture of a flower and green leaves. All objects that appear to be the same color in the digital image have pixels whose reflectance values group together in the same region of spectral space. Thus, green leaves and reddish flower bases occupy different regions of the spectral space defined by plotting the reflectance values in the red versus the green bands. Once regions of spectral space are labeled "flower" or "leaf," all pixels that fall in that region of spectral space can be ascribed those labels. Note, however, that the observed spectral space depends not only on the object itself, but on the illumination source, and that consistency in illumination is needed to apply labels in spectral space. Similarly, the spectral space of an image of a landscape can be labeled with regions corresponding to labels such as forest, water, etc.

Labeling the regions of spectral space requires external information. In the case of the flower in Fig. 1, the external information is the observer's prior knowledge of the spatial and spectral properties of a

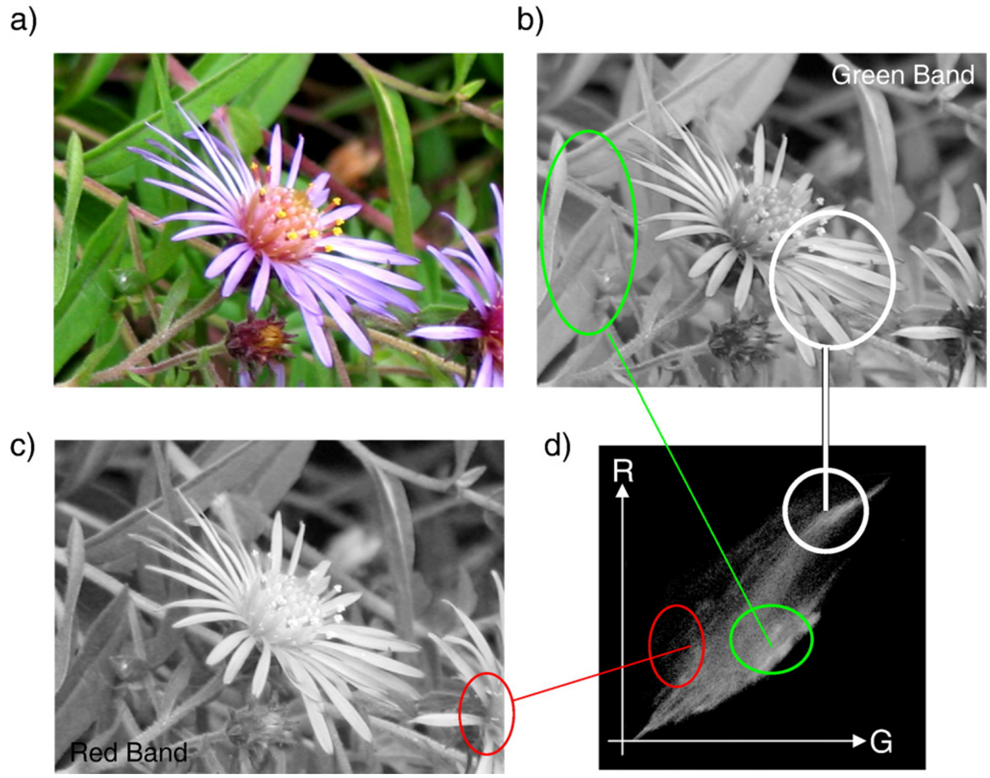

Fig. 1. An illustration of spectral space. a) A standard digital photo of a flower and green leaves taken with a handheld digital camera. b) The reflectance of green energy for that photo (e.g. the "green band" of the image). c) The red band of the image. d) A plot of the intensity of red versus green band reflected energy for the images in b and c. The nearly-white parts of the flower petals are high in both red and green reflectance, placing them in a different part of spectral space from the reddish pixels from the base of the flower. Those pixels are fairly low in red reflectance (i.e. not near the top of the red axis), but even lower in green reflectance, making them appear dark red.

flower in a picture. In the case of an image of a landscape acquired by a satellite, external information is most commonly obtained from the observer's prior knowledge of the landscape, from actual descriptive measurements made at sample locations on the landscape, or from other imagery more detailed than that for which the spectral space labels are needed. Examples of such data would include airphoto-interpreted land cover type, field-measured species composition within 1-ha plots, or field-measured estimates of forest basal area or cover-type areal proportions. More advanced approaches to obtain external data include the use of (sometimes complex) models of systems and/or system components (Peddle et al., 2007). Some model-based approaches can provide structural information that cannot be derived solely from spectral characteristics. Regardless of the source, without such reference data the measurements from a satellite image may be of limited utility to a natural resource manager. Thus, the acquisition of appropriate reference data is critical in any remote sensing study.

With appropriate reference data, several methods of labeling regions in spectral space are possible (Fassnacht et al., 2006; Fraser et al., 2009-this issue). A common approach is discrete classification, where hard boundaries are drawn between discrete regions, resulting in a categorical map with discrete labels of land cover (Lillesand & Kiefer, 2000). Another approach is to allow overlap between regions in spectral space, resulting in "fuzzy" labels that retain some of the information about mixtures of components within a pixel (Foody, 1996; Wang, 1990). Alternatively, gradients within spectral space can be related to variables that vary continuously, such as the percent vegetative cover within a pixel or to proportions of spectrally pure cover types (Cohen et al., 2003).

The heart of change detection and monitoring is comparing the position of a pixel in spectral space at different points in time. Images are acquired of a landscape in different years or different seasons, and the spectral space of those images compared. If a pixel's spectral values place it in a spectral region associated with one land cover type in one date and in another land cover type in another date, we could infer that a change has occurred on the ground for the area measured by that pixel. However, a variety of other effects could cause change in spectral values for pixels over time, and separating informative changes from non-informative types remains a central challenge in remote sensing change detection. Much like the case of a single spectral space, changes in spectral space can be described using categorical, fuzzy, and gradient-based techniques, with properties discussed in Section 3.3 below.

In summary, the foundational process in most remote sensing change detection is quantifying and labeling changes in the spectral space represented by a given sensor. The types of change that can be detected, the ability to meaningfully label them, and the confidence in those labels all depend on the specific choices made during several sequential steps in a change detection project.

3. Steps in a remote sensing change detection study

Remote sensing change detection studies involve a series of sequential steps that are detailed extensively elsewhere (e.g. Cihlar, 2000; Coops et al., 2007; Lunetta, 1998; Schott, 1997). For the natural resource manager, our goal here is to simplify these steps into four broad stages: data acquisition, preprocessing and/or enhancement, analysis, and evaluation. The better a manager understands how decisions in each stage affect the outcome of the study or project, the better he or she can guide those decisions.

3.1. Data acquisition

The data acquired in this step are both image data and the reference data that will ultimately be used to label information in the image and to evaluate the efficacy of products.

Table 2
Resource attributes and specific image characteristics that need to be considered when acquiring imagery to monitor the attributes.

Resource attribute(s)	Image type	Opportunities and challenges in tracking over time			
		Spatial	Spectral	Temporal	Image quality
Change in size or shape of patches of related cover types Change in width or character of narrow, linear features	Fine grain (IKONOS, Quickbird, Airphoto)	Fine grain allows delineation of shape; but detection of change in shape requires strong geometric integrity over time.[a,b]	Change information is mostly tied to spatial, not spectral, properties.[a]	Tasked-acquisition may allow better control over image timing, but historical archive unpredictable.	The orbit orientation and narrow swath width of fine grain imaging satellites may require multiple days to acquire image data for an entire study area, which may affect the effectiveness of investigating time-sensitive subjects on the ground.[c]
Slow changes in cover type or species composition	Fine grain (IKONOS, Quickbird, Airphoto)	Useful when spatial texture distinguishes cover types or species, but limited spatial extent may increase costs.	Broad physiognomic distinctions between cover types possible, but finer distinction of species and cover types compromised by poor spectral depth.[d]	See above.	Differences in view-angle and shadowing introduce distortions that affect interpretation of cover and changes in cover over time.[e]
	Moderate grain, multispectral (Landsat, SPOT, ASTER)	For many ecosystem types, slow changes in cover occur over areas larger than the grain of these sensors, making them useful for delineating bounds of affected areas	Additional spectral depth of short-wave infrared and thermal bands can improve separation among types, but change in species composition often impossible to track.	Historical archive of this type of imagery among the longest available and can be leveraged to extract slow change information.[f] Repeat interval is often appropriate for changes that occur over months or across years, but relatively infrequent overpasses can make matching with seasonal or climatic phenomena challenging.[g]	Consistent view angles aid in change detection, but unaccounted-for atmospheric variations can introduce error; cloudiness often a key constraint.
	Moderate grain, hyperspectral (AVIRIS)	Often used for tracking changes in proportions of sub-pixel sized components[h]; spatial extent often smaller than multispectral sensors.	The best chance for distinction of species-composition, although atmospheric correction critical for detection of subtle changes over time.	Tasked-acquisition may allow better control over image timing, but in practice can be difficult to control.	Image quality typically high, but geometric correction of airborne platforms can be challenging, and may introduce more error than from analogous satellite platforms.
Abrupt changes in state of cover	Fine grain (IKONOS, Quickbird, Airphoto)	Inference of land-use and land-use change often possible through direct image interpretation, but automation algorithms still in research phase; small spatial extent may require multiple images for large study areas. Thus, costs may be high.	Poor spectral depth rarely a hindrance because fine spatial resolution often allows detection of disturbance or development events.	Temporal depth of airphoto archive (often many decades) allows for detection of long-term trends, but typically at a fairly coarse temporal grain.	Image quality of historical photos can sometimes reduce confidence in some land cover labeling projects.
	Moderate grain, multispectral and hyperspectral (Landsat, SPOT, Aster, AVIRIS)	Grain size a good compromise that allows detection of many disturbance type events across large landscapes, although unusable for some subtle types of development or very small disturbance events.[i]	Spectral depth allows detection of many disturbance events from spectral properties alone.[j]	Repeat interval generally appropriate for most disturbance types, although tracking of subtle effects can be hampered by time-of-season and cloud issues. Long archive provides a useful baseline for long-term monitoring.[f,k,l]	For most common disturbance types, image quality sufficient. Clouds can obscure some ephemeral disturbance events.[m]
	Coarse grain (MODIS, SPOT VEGETATION)	Grain size appropriate for large disturbances; subpixel disturbances may be detectable as proportional change.[n,o]	Spectral depth, particularly thermal bands, can allow rapid detection of fires.	Dense temporal record useful for detecting lasting changes in land cover at the sub-pixel scale.[n]	Cloud-screening and geometric qualities of mosaicked images can sometimes require temporal smoothing to detect trends.[n,q]
Slow changes in condition of a single cover type	Fine grain (IKONOS, Quickbird, Airphoto)	Can be useful if process causes noticeable changes in condition (loss of vegetation, mortality) in individual plants.[d]	Poor spectral resolution can sometimes make detection of subtle changes difficult[d]; spectral distinction from background likely difficult to automate, forcing manual interpretation or development of new methods for automation.[r]	High cost of acquisitions may make repeat imagery untenable for capture of trends.	For long-term trends (many decades), airphotos are the only option, but shadowing and view angle effects can make even manual interpretation of subtle change difficult.[e]
	Moderate grain, multispectral and hyperspectral (Landsat, SPOT, ASTER, AVIRIS)	Many processes of interest operate at spatial grain larger than grain size of pixels, making these sensors especially useful.	Relative to fine-grain sensors, spectral depth of these sensors improves spectrally-based detection of changes in condition, but subtle effects may be difficult to discern spectrally without hyperspectral imagery.[s] Background noise can be especially problematic because signal of change is weak relative to noise.	Long archive of some data (Landsat) allows detection of subtle effects over time.[f] If effects are only manifested in a narrow time of year (e.g. peak biomass), however, lack of control over timing of image acquisition may introduce noise.	Cloud effects are an issue, but may be reduced if images over many years are used to track slow changes.[j]
	Coarse grain (MODIS, SPOT VEGETATION)	Large grain and extent make these sensors especially useful for detection of change in vegetation condition over very large areas.[t] Coarse grain may make it difficult to ascribe cause to changes within pixels.	Spectral depth of coarse grained sensors generally more than sufficient to capture slow changes in vegetative cover.[x]	Temporal archive of AVHRR data long enough to capture trends,[u] but MODIS and SPOT vegetation have records that are currently too short to capture long-term changes.	Ability to develop composite cloud-free images allows for capture of conditions at a consistent point in the season across years.

(continued on next page)

Table 2 (*continued*)

Resource attribute(s)	Image type	Opportunities and challenges in tracking over time			
		Spatial	Spectral	Temporal	Image quality
Changes in timing or extent of seasonal processes	Coarse grain (MODIS, SPOT VEGETATION)	Broad extent allows detection of regional trends in cyclic processes; coarse grain size and mosaicking make pixel-level tracking of phenology difficult.[v]	Spectral depth sufficient for tracking phenology and snow cover.[w]	Most products are composited to near-weekly or bi-weekly temporal grain,[x] which can diminish precision of estimates.	Most natural resource managers will likely be interested in using automatically-produced maps whose quality depends on specific algorithms[y]. However, case-specific maps can be created from high-quality raw data by remote sensing specialists.[z]

[a] Zhang and Fraser, 2007.
[b] Wang and Ellis, 2005a,b.
[c] Wang et al., 2007.
[d] Leckie et al., 2004.
[e] Fensham et al., 2007, Fensham and Fairfax, 2007.
[f] Kennedy et al., 2007b.
[g] Olthof et al., 2004.
[h] Asner et al., 2005.
[i] Cohen and Goward, 2004.
[j] Huang et al., 2009-this issue.
[k] Kennedy et al., 2007a.
[l] Wang et al., 2009-this issue.
[m] Olthof et al., 2004.
[n] Potter et al., 2005.
[o] Zhan et al., 2002.
[q] Reed et al., 2009-this issue.
[r] Pacifici et al., 2007.
[s] Asner and Heidebrecht, 2002.
[t] Wessels et al., 2004.
[u] Myneni et al., 1998, Potter et al., 2005.
[v] White et al., 2005.
[w] Reed et al., 2009-this issue, Hall et al., 2002.
[x] Nemani et al., 2009-this issue.
[y] Cohen et al., 2006.
[z] Vikhamar and Solberg, 2003.

3.1.1. Image data acquisition

Rather than recreate lists found elsewhere of image sources or the broad categories of sensors (Kramer, 1996; Lefsky & Cohen, 2003; Sabins, 1997), our goal is to describe the underlying considerations in image acquisition as they will specifically relate to the phases of decision-making in designing a remote sensing project (Section 4 of this paper). The four primary considerations are type, timing, quality, and cost of imagery. Table 2 lists the issues and challenges associated with using different image sources for each of the broad monitoring goals listed in Table 1.

Radar and LIDAR imagery are not included in Table 2, as they have not been used as widely for landscape change studies as have optical data, largely due to the comparable lack of availability of suitable data for land cover change detection until recently. However, SAR images have been used for a wide array of studies that are highly applicable to tracking changes in flooding (Smith, 1997; Townsend, 2001), wetlands monitoring (Hess et al., 2003; Lang & Kasischke, 2008; Wdowinski et al., 2008), for interferometric studies of geologic phenomena (Gens & VanGenderen, 1996; Massonnet & Feigl, 1998; Kaab et al., 2005), and to a lesser extent for landscape change studies (but see Quegan et al., 2000; Rignot & Vanzyl, 1993). SAR imagery has been found to be especially useful for detection of change in urban areas (Dierking & Skriver, 2002; Gamba et al., 2006; Henderson & Xia, 1997; Ridd & Liu, 1998; Seto & Liu, 2003). With increasing availability of airborne LIDAR data, more studies will likely use LIDAR to detect changes, especially in vegetation structure (Wulder et al., 2007a,b; Yu et al., 2006, 2008) and topographic change (Woolard & Colby, 2002; White & Wang, 2003; Rosso et al., 2006).

Type of imagery refers to its spatial, temporal and spectral qualities, and reflects the tradeoffs among these qualities in the design of sensors (Verbyla, 1995). The spatial grain of a sensor is the area on the ground captured by a single sensor element, effectively the pixel size (although see Schott (1997) for a more detailed discussion), while the extent is the geographic scope of an image. The temporal grain is the frequency at which images of a given point on the Earth are acquired, and the temporal extent is the historical depth of that imagery. The spectral grain of a sensor relates to the width of the spectral bands in which it makes measurements, and the spectral extent to the breadth of the electromagnetic spectrum captured by all of the sensors. Generally, grain and extent in each domain are related: Finer-grain elements result in smaller extents. Tradeoffs across domains arise from engineering constraints. Spatial and spectral grain are opposed because the energy coming from a surface is finite, and as that energy is divided into increasingly smaller pixels or narrower spectral bands, the signal strength falls (Schowengerdt, 1997). To maintain a signal above a critical threshold, one domain must be sacrificed to facilitate finer division of the other. In orbiting satellite systems, tradeoffs between spatial grain and temporal grain come about because larger pixels capture more of the Earth's surface at a time, allowing for more frequent overlap between images acquired on successive orbits and shorter repeat cycles for sensors with large pixels (Sabins, 1987). The practical implication of these tradeoffs is that the natural resource manager may need to prioritize which domain is most relevant for a given monitoring goal of interest. A key consideration driving many analytical and practical considerations in remote sensing studies is the relationship between the grain of the entities being mapped and the grain of the sensor (Woodcock & Strahler, 1987).

Image timing and image quality must be chosen to minimize the influence of unwanted effects on spectral space, since such effects can obscure real change or produce the false appearance of change. Key issues to consider are phenological state of the landscape, sun angle, atmospheric condition, and geometric and radiometric quality of the imagery. These issues are described in greater depth in these key references (Coops et al., 2007; Yuan et al., 1998). Cost of imagery is an important consideration for most natural resource agencies, and is amply discussed in other references (Gross et al., 2006; Turner et al., 2003). Note that the greatest cost in many remote sensing studies is not the acquisition of imagery, but in the labor needed to process the imagery, derive information, and evaluate the results (Lunetta, 1998).

3.1.2. Reference data acquisition

Reference data are independent sources of information that allow a remote sensing specialist to relate patterns in spectral space to real quantities or phenomena on the earth surface, or to validate or evaluate the products that come from such a process (Campbell, 1996). For example, field crews may make areal measurements on the ground of percent cover of different land cover types, and these land cover type proportions can be linked to the spectral space to build generalized rules that relate regions in spectral space to those land cover labels. If some data are withheld from the rule-making process, their measured land cover type proportions may also be used to evaluate how well the rules apply outside of the plots used to make them, providing a measure of the utility of the rules. Because the reference data affect the rules used to make maps as well as the ability to quantify their robustness, the quality and availability of reference data may drive the questions that can actually be addressed with remote sensing. This, in turn, makes assessment of reference data a critical step in the planning process. Table 3 lists the challenges and opportunities associated with using various reference data in support of the monitoring resource attributes listed in Table 1.

Although not universal, reference data collected in a probabilistic statistical framework are commonly used to both train the classifier and to assess classification accuracy. The statistical framework provides rigor and credibility, and may be used to minimize bias and estimate variance, key to assessing data quality (Stehman, 2000, 2001). The statistically-based accuracy assessment consists of three primary components, a) a response design that describes how the “true” value for the ground

Table 3
Resource attributes and the issues involved in collecting reference data to monitor these attributes.

Resource attribute(s)	Reference data source	Opportunities and challenges in tracking over time
Change in size or shape of patches of related cover types Change in width or character of narrow, linear features	Airphotos	Direct observation of patches or features often possible, but subtle changes in shape or size may be difficult when comparing images from two different acquisitions because of differences in sun or view angle,[a] or in phenological state.[b]
	Ground measurements	Low ambiguity about species or feature type, but relatively low precision of measurement of patch or linear feature metrics may diminish sensitivity to subtle change over time.[c] Historical reference data may be difficult to co-locate.[d]
Slow changes in cover type or species composition	Airphotos	Subtle distinction of species type may be difficult. Quantification of composition may not be sufficient for subtle change.[e]
	Ground measurements	Direct observation of land cover type or species usually reliable on the ground, but co-location of plots and imagery often difficult,[f] and semantics of land cover or species groupings may vary among observers or projects over time. Subtle distinctions in cover or species type require many samples to resolve statistically, which is often challenging with ground-based measurements.[g]
Abrupt changes in state of cover	Indirect measurements (census data, development data)	Useful for validation of remotely-sensed measurements of development at broad spatial extents (county, state level).
	Airphotos	Often the best approach for quick and effective interpretation of abrupt disturbance events[h,i]; historical data allow for statistically valid observation of low-frequency disturbance events.
	Ground measurements	Field validation often must occur shortly after the event for field observers to discern disturbance type; before- and after-field observations of disturbance events often sparse.[j]
	Repeat fixed-wing or helicopter overflights	Reliable and sometimes used for resource inventories (such as the USDA Forest Service's Forest Health Monitoring program[k]), but expensive to implement. Attention need be paid to geographic precision.[f]
	Moderate grain sensors	Landsat-type sensors can provide a measure of state or of changes in broadly-defined land cover types for validation of coarse-grained sensors.[l]
Slow changes in condition of a single cover type	Airphotos	May be possible for changes that result in mortality, but often challenging for more subtle measurements of vigor or health.[n]
	Ground measurements	Single date-direct measurements may allow discrimination of subtle changes in condition,[m] but repeat measurements of plots are ideally needed to validate changes.
Changes in timing or extent of seasonal processes	Repeat fixed-wing or helicopter overflights	See comments on same type above.
	Indirect measurements (stream flow data, etc.)	May allow comparison of aggregated effects at watershed or basin scale, but connection with remotely-sensed data may require mechanistic modeling.
	Airphotos	Capture of processes difficult, but may be useful to model or to test estimates of cover or phenological state at one point in time
	Ground measurements	Often the only means of capturing seasonal processes, but small spatial grain of ground measurements and low number of samples make direct comparison with remotely-sensed data challenging. Also timing of field data collection is critical because of speed of change in processes, making field costs high.

[a] Wang et al., 2007.
[b] Goetz et al., 2003.
[c] Johansen et al., 2007.
[d] Kennedy et al., 2007a.
[e] Wulder et al., 2007a,b.
[f] Sánchez-Azofeifa et al., 2003.
[g] Congalton and Biging, 1992.
[h] Cohen et al., 1998
[i] Jantz et al., 2005.
[j] Boutet and Weishampel, 2003.
[k] http://fhm.fs.fed.us/.
[l] DeFries et al., 2000.
[m] Leckie et al., 2004.

condition will be assigned and interpreted (what is "true on the ground"), b) a sampling design that describes how we will pick our specific field sampling locations, and c) analysis protocols that specify formulas and methods applied to the sampled reference data in estimating the value and accuracy of change (Strahler et al., 2006).

Ideal reference data are those that match imagery spatially and temporally, that measure a property that is thought to be detectable with the imagery, and that are designed to allow construction of the models required to label spectral space and to evaluate the robustness of final maps (Congalton & Green, 1999). For the most part, such data rarely exist unless they were collected specifically for the purposes of remote sensing. Typical ecological measurements often do not capture the average conditions of an entire pixel, are not collected at the correct time, and are difficult to geographically link with the imagery (Kennedy et al., 2007a). The heterogeneity of the conditions within each reference plot is also critical for building and evaluating models with reference data (Fassnacht et al., 2006), as high classification accuracies are harder to achieve in more heterogeneous environments (Smith et al., 2002), and the appropriate sampling for reference data is also affected by spatial autocorrelation and heterogeneity (Congalton & Green, 1999; Friedl et al., 2000; Strahler et al., 2006). In addition to these challenges encountered with any remote sensing mapping project, challenges arise that are specific to the mapping of change. First, reference data ideally should be available for conditions before and after a change, which in practice can lead to validation using different data sources at different times (e.g. Huang et al., 2007). Second, even with similar data sources before and after a change, it is often difficult to completely replicate a given reference datum on the ground because of geolocational imprecision, and in high-resolution airphotos or imagery because of shadowing and view angle variations across years (Paine, 1981; Wang et al., 2007).

In remote sensing, it is often preferable to collect many field plots of slightly lower quality or richness rather than collecting few plots that are rich in information. Strategies for sampling are well-covered elsewhere for both the general case (Cochran, 1977; Congalton & Green, 1999; Thompson, 2002) and the special case of remote sensing change detection (Biging et al., 1998; Stehman, 1999). Regardless of the particular method chosen, the geographic location of reference data should be determined before setting foot in the field or obtaining aerial photos, etc., using a process that eliminates human bias in choosing plots. A common strategy is to use a higher-resolution remote sensing product to validate a coarser product (Cohen et al., 2001; Congalton & Green, 1999; Lambin & Ehrlick, 1997; White et al., 1996). Several papers in this special issue illustrate a range of approaches for reference data collection, from intensive field measurements of habitat condition at a relatively small number of plots, to simpler measurements of cover type at a larger number of plots (Nagler et al., 2009-this issue), to relatively quick GPS-linked field photos at an extremely large number of plots (Wang et al., 2009-this issue).

3.2. Image pre-processing

The goal of pre-processing is to ensure that each pixel faithfully records the same type of measurement at the same geographic location over time (Lunetta, 1998). Preprocessing is especially critical in change studies because the detection of change assumes that the spectral properties of non-changed areas are stable, and inadequate pre-processing can increase error by causing false change in spectral space. (Coops et al., 2007; Lu et al., 2004; Lunetta, 1998; Peddle et al., 2003; Schowengerdt, 1997) Increasingly, pre-processing steps are becoming automated and resulting in free datasets of relatively high quality (Fraser et al., 2009-this issue; Masek et al., 2006). Note, however, that each step in pre-processing alters the position or spectral properties of pixels in the imagery, and thus each step has the potential to introduce error.

A final step often labeled pre-processing is image enhancement, which is the mathematical rotation, compression, or distortion of spectral space to accentuate desired features and suppress noise (Lillesand & Kiefer, 2000). Many natural resource managers may be familiar with one type of enhancement known as vegetation indices, such as the normalized difference vegetation index (NDVI; Tucker, 1979), but a wide range of enhancements are possible. Several papers in this special issue utilize derived indices as a key step in their process (Crabtree et al., 2009-this issue; Nagler et al., 2009-this issue; Nemani et al., 2009-this issue; Townsend et al., 2009-this issue). Note that image enhancement techniques do not create new information, but rather they highlight information present in the original spectral data.

In theory, if pre-processing has been perfectly successful, all changes in spectral value in a given pixel between two images can be ascribed to actual changes in the conditions of the surface represented by that pixel. In practice, no pre-processing steps account for all effects perfectly. Thus, some portion of the spectral change observed in a pixel over time is uninformative, and the analytical techniques in the next phase of the project must take this into account.

3.3. Extracting information

Once two or more images have been pre-processed and/or enhanced, many mathematical approaches are available to detect and label pixels that have or have not changed (Yuan et al., 1998). Despite the variety of methods, most change detection approaches contain a modeling (or functional algorithm) phase and a subtraction phase. The modeling phase refers to the development or implementation of algorithms to infer meaning from spectral data, while subtraction refers to the process of comparing dates via image algebra or other methods. Key considerations are how the functional step treats spectral information, and whether the subtraction phase precedes or follows the modeling phase (Gong & Xu, 2003; Yuan et al., 1998). Table 4 lists how various analytical techniques relate to the broad monitoring goals listed in Table 1.

The algorithm phase can involve discrete, fuzzy or continuous methods. Discrete methods are attractive because changes are typically defined in terms of land cover classes that are familiar to natural resource managers (Wang et al., 2009-this issue) and that can be used directly in subsequent habitat fragmentation or similar analyses (Townsend et al., 2009-this issue). The primary drawbacks are that subtle changes of condition within a land cover class are missed, and that pixels near the spectral boundaries of classes are more likely to be incorrectly labeled as having changed, simply due to imperfect pre-processing, unless the change analysis is constrained by available high resolution vector GIS data. Fuzzy methods acknowledge the potential confusion among classes in spectral space, and can be designed to capture subtle change within classes (Foody & Boyd, 1999; Kennedy et al., 2007a). The fuzzy nature of these classes may be non-intuitive, however, and labeling change among a matrix of many overlapping classes may be untenable or non-informative in practice. Continuous-variable approaches allow for capture of subtle distinctions between two dates, but effort must be made to develop robust methods to define what level of change is actually meaningful (Yuan et al., 1998). In addition, continuous-variable methods that simultaneously track several variables often must be collapsed into categorical variables to simply make sense of the change (Chen et al., 2003), potentially diminishing the advantage over strictly discrete methods.

If the models are first applied separately to the spectral space of each image to create two maps, then change is detected and labeled by comparing (differencing) those maps (Fig. 2a; also Haertel et al., 2004). From the practical perspective of the land manager, taking this approach places a high premium on appropriate reference data tied temporally to each image, and less on costs associated with

Table 4
Resource attributes and the considerations involved in analytical change detection techniques to detect meaningful changes in them.

Resource attribute(s)	Analytical techniques	Opportunities and challenges in applying to change detection
Change in size or shape of patches of related cover types	Segmentation or classification and patch analysis applied to two images, followed by subtraction	Direct measurement of changes in patch shape closely meets monitoring goal,[a,b] but patch edge delineation may be difficult to reproduce over time. Also, patch by patch observation over time is not a common technique, and summary metrics of patch shapes, sizes,[c] etc. may obscure local-level issues.
Change in width or character of narrow, linear features	Subtraction of images, identification of changes, followed by segmentation or classification and patch analysis	Focus on change may diminish false negatives relative to prior approach, but requires that the change event be spectrally separable in the image data. Labeling of the change may be difficult to automate if the shape characteristic patches of change are ambiguous.
Abrupt changes in state of cover	Time-series analysis of many years of continuous-variable image data Discrete classification of two images, followed by comparison of classified maps	See comments in above cell. Loss of baseline conditions caused by differencing can make labeling the land cover change difficult.[d] Allows detection of phenomena more subtle than classified approaches, and use of time-series can reduce problems of variable image backgrounds and phenology.[e,f,g] Preprocessing steps are highly important, however, and reference data to match each image are often impossible to find.[f] Labeling of change is straightforward and radiometric pre-processing is of minor importance,[h,i] but errors in two single-date images are compounded. Subtle effects are often difficult to detect. Reference data needed for both images, often forcing use of image-based reference.[j]
Slow changes in cover type or species composition		Slow changes in land cover type can only be detected using discrete classification if the interval between images is large.[h] Generally, continuous-variable methods are more appropriate.[k]
Slow changes in condition of a single cover type	Two or more images subtracted, followed by continuous-variable modeling of change (regression, change vector analysis) Continuous-variable models of sub-pixel proportions (regression, spectral unmixing, fuzzy-classification) applied to two or more images, followed by subtraction. Time-series analysis of many years of continuous-variable image data or derived (vegetation index) data	Focus on change may limit geographic scope needed to understand processes,[l] but reference data that match beginning and end points are critical. Labeling of change can be difficult because of loss of baseline.[d] Proportional representation allows for detection of subtle effects,[m] but is also more sensitive to variation in background reflectance caused by year-to-year variation in conditions during image acquisition. A high premium is placed on accurate pre-processing,[n] and reference data must be robust and widespread to allow building of statistical models. Detection of subtle trends more feasible than with any two-date approach, but image pre-processing steps critical, including cloud and cloud-shadow screening, and subtle change in sun angle or phenology may cause false positives.[f]
Changes in timing or extent of seasonal processes		Allows detection of broad geographic and temporal patterns generally undetectable with two-date approaches.[e] Preprocessing steps (including cloud screening, image mosaicking, and trend smoothing) are critical to success of method and often challenging.

[a] Weisberg et al., 2007.
[b] Ellis et al., 2006.
[c] Li et al., 2003.
[d] Cohen and Fiorella, 1998.
[e] Potter et al., 2005.
[f] Kennedy et al., 2007b.
[g] Huang et al., 2009-this issue.
[h] Wang et al., 2009-this issue.
[i] ViÒa et al., 2007.
[j] Cohen et al., 1998, Kennedy et al., 2007a.
[k] Dougherty et al., 2004.
[l] Lambin and Strahler, 1994.
[m] Roberts et al., 1998.
[n] Yuan et al., 1998.

normalizing the spectral space of the two images (Yuan et al., 1998). A key challenge, however, is that errors in the maps from each image are compounded in the change detection map, limiting the maximum accuracy that can be achieved (Cohen & Fiorella, 1998). If spectral space is first differenced (often through simple subtraction) and then an algorithm is applied to the spectral difference image, change is inferred from the spectral character of the spectral difference space (Fig. 2b; also Lambin & Strahler, 1994). The expected spectral difference for no-change is zero in all spectral bands, and change is detected as deviation from zero (although usually with a non-zero threshold to compensate for imperfect pre-processing). This approach is attractive in its explicit focus on the change, and avoids compounding errors in maps. It also allows for detection of change in any spectral direction (Lambin & Strahler, 1994; Malila, 1980), for detection of subtle effects like insect defoliation (Muchoney & Haack, 1994; Townsend et al., 2004), and for development of general models that can be applied across images from many years (Cohen et al., 2006). The challenge in using this approach is that radiometric normalization (e.g., for atmospheric, phenological or BRDF differences [bidirectional reflectance distribution function, Schaepman-Strub et al., 2006]) must be very robust, and that reference data that specifically measure change (rather than just state) must be available. Moreover, the results can be confusing because the differencing step removes information about the origin or terminus of the pixel in spectral space (Cohen & Fiorella, 1998).

Some important approaches combine or omit the differencing phase. One strategy begins with an existing land cover classification map, and then uses image algebra to detect locations of change on the map. New classification models are then applied only to label the changes, while the classification labels from non-changed areas are simply carried forward (Fig. 3; also Fraser et al., this issue; Parmenter et al., 2003). For natural resource monitoring, this is attractive in allowing use of existing or familiar land cover maps while focusing on the change component of the spectral signal. However, it cannot be extended indefinitely: cover classes in the original map are constantly degraded by change, reducing their spectral fidelity over time and requiring eventual creation of a new land cover map. Another approach that does not include the differencing stage involves application of a model to the combined (stacked) spectral space from all of the component images (different years or dates) to infer information about change. Such an approach diminishes the need for robust normalization among images, but results can be

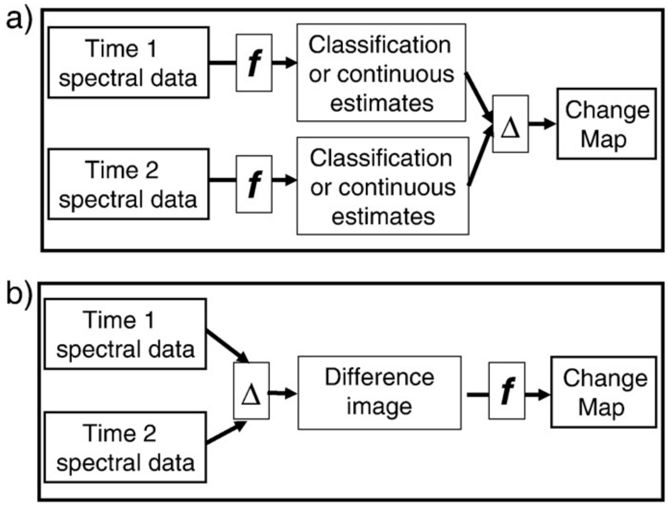

Fig. 2. Two means of conducting remote sensing based change detection. a) From two separate spectral images, a mapping or classification function is applied, resulting in two separate maps. These maps are then compared through differencing or analogous process to derive change. b) The spectral values of the two images are differenced directly, and a mapping or classification algorithm is applied to that different space.

difficult to interpret and are generally applicable solely to the combined data space under study (Coppin et al., 2004; Fung & Siu, 2000). A second family of approaches using more than two dates of imagery seeks to identify temporal patterns or trajectories in the sequence of imagery (Garcia-Haro et al., 2001; Hostert et al., 2003; Huang et al., 2009-this issue; Kennedy et al., 2007b; Lawrence & Ripple, 1999; Lu et al., 2003; Potter et al., 2005). These approaches are attractive because they capture overall temporal trends, but generally require robust radiometric normalization and may involve complex statistical analysis to infer change. As image processing and data storage capabilities improve, however, these approaches hold great promise in removing year-to-year variation from classifications of single date images, in detecting longer term processes than those typically captured, and in detecting more subtle processes than can be achieved through two-date change detection alone.

3.4. Evaluation and reporting

Monitoring may stimulate costly management responses. Erroneous information may lead to inappropriate action, for example, remediation when it is unnecessary, or lack of action when intervention is needed (Ronnback et al., 2003). Therefore, information quality must be evaluated. In addition, the procedures used to create this information must be reported such that external parties can assess their results.

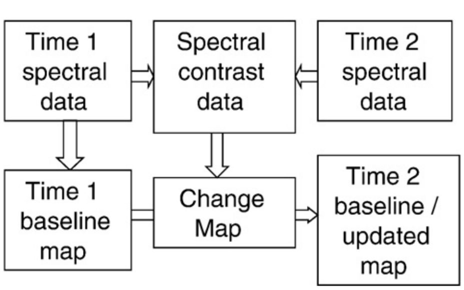

Fig. 3. An amalgam approach to change detection, where differencing is used to identify only pixels that have changed, and single date mapping rules are applied only to those changed pixels.

3.4.1. Evaluation

Scientists have developed standard techniques for assessing map accuracy (Congalton & Green, 1999; Gopal & Woodcock, 1994). Error is typically quantified statistically by comparing the map to independent reference data at a sample of locations in a landscape. When the map is categorical, the errors are reported as proportions accurately described within each class, often summarized across all classes in a table known as a contingency matrix and sometimes summarized on a per class basis (Wang et al., 2009-this issue; Fig. 4). When the map is a continuous variable, the errors are reported as real numbers such as mean error, root mean square error, or other summary statistic. The actual agreement between the reference data and the map is a function of both the spatial accuracy of the two data sources, and the agreement in the labels assigned, but in practice the contribution of spatial error to the final agreement is difficult to disentangle. In all cases, large sample sizes improve estimation, but sometimes statistical approaches can be used to leverage small sample sizes (such as bootstrap or jackknifing procedures), allowing evaluation of accuracy when expensive field samples are sparse (Cohen et al., 2003).

To conduct a proper accuracy assessment, the independent data must be considered "truth," in that they were collected without error (Congalton & Green, 1999). In practice, reference data have errors in both location and in label, just as the map data do, and measurements not designed for remote sensing typically do not capture the average conditions of an entire pixel (Wulder et al., 2007a,b). Acknowledging that some error exists in reference data, values are often deemed true when they are known at substantially higher accuracy than the mapped values. When reference data are known to an accuracy level only moderately better than the map itself, the analysis is more appropriately considered an evaluation of agreement rather than a true accuracy assessment.

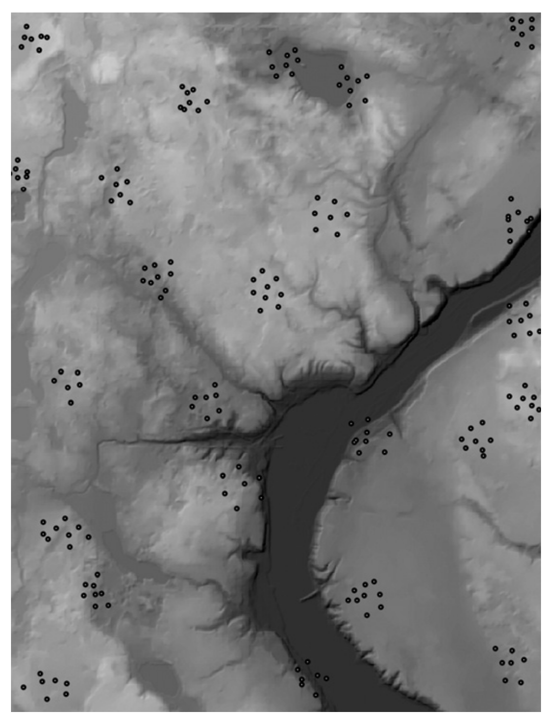

Fig. 4. Sample locations are often selected based on a randomized cluster method. Cluster samples are selected across the landscape using some random process. A number of points are then sampled in some distance-constrained manner near the cluster center, either in random process (shown), or some systematic process (not shown). Clustering reduces travel time among samples, thereby increasing the sample size on a fixed budget. Cluster sampling is often an optimum tradeoff between the need to seek independent samples, and increase the statistical power through higher sample numbers.

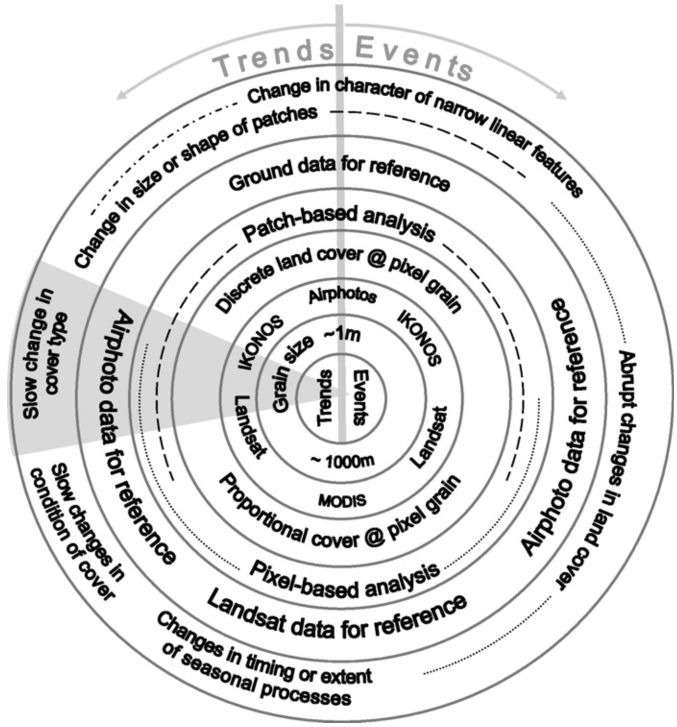

Fig. 5. A heuristic tool to illustrate the connections among image type, analytical techniques, analysis form, and the various monitoring goals outlined in Table 1. To use the figure, begin at the edge with one of the monitoring goals. The area defined by that goal or the dashed/dotted lines indicates the domain of that goal in most common change detection studies. By following that domain in towards the center of the circle along the perpendicular, the other components most commonly associated with that goal are encountered. The shaded pie shape illustrates this for just one goal.

The balance between quality of reference data and number of samples must be considered carefully. Because larger sample sizes improve the precision of the estimate, it may be advisable to sacrifice some precision of measurement at any single reference plot in the interest of acquiring many more plots. This is particularly true in change detection studies, because areas that have changed typically occupy only a small portion of the landscape, and because there may be many different categories of possible change. Stratified, cluster, and double-sampling methods may be particularly attractive approaches to distributing samples (Fig. 5, also see Czaplewski & Patterson, 2003; Kalkhan et al., 1998). These sampling strategies can increase the number of sample plots that can be collected for a given time or budget constraint, which is particularly important for monitoring projects where repeat visits across many years are planned. Stratification and focus on those areas that have changed has been advocated to increase precision in the change estimate (Biging et al., 1998), as this often gives a more precise estimate, but requires useful strata be available. Changed areas are often 25% of the landscape or less, and without stratification, these small regions may be under-sampled. While stratification and clustering may substantially improve accuracy estimates and/or save time and money (Lohr, 1999), many of these sampling strategies cannot be implemented without some knowledge of the spatial autocorrelation in the sampled variable, as most statistical accuracy estimates depend on an assumption of sample independence, and the estimates must be adjusted if samples are autocorrelated (Congalton, 1998).

3.4.2. Reporting

Long-term monitoring will eventually rely on different sensors, training datasets, and analytical techniques. Accurate reporting of all phases of a project is thus critical to ensuring the long-term value of the data and the ability to evaluate prior results and infer change.

Data acquisition reporting should follow reporting requirements for non-imagery spatial and non-spatial data (Michener et al., 1997, FGDC: http://www.fgdc.gov/standards/standards.html). Sources and disposition of data, including agreements on access and distribution, should be included in documentation. It may be important to include a discussion of the criteria used to choose imagery so that parallel criteria can be applied in the future. Part of this process is to document whether the spatial, spectral, or temporal characteristics of the imagery imposed constraints for the particular monitoring goals of the study. When ancillary spatial data are included as part of the project, they should be described from the perspective of how their spatial and temporal properties could affect the final products. Documentation of reference data should be sufficient to allow future users to either recreate the data or re-visit a site.

Reporting on image pre-processing steps is critical because of the many image analysis steps involved in a typical remote sensing study. Documentation must be comprehensive enough to permit duplication of all steps, including the use of the same algorithms or models and parameters as well as discussions of why the methods were chosen. Errors associated with each model should be reported, noting that errors were caused by algorithm assumptions, by inaccurate reference data, and/or by spatial and temporal variation in imagery and datasets.

Analytical techniques for mapping and change detection also require detailed reporting. For projects that involve land cover class maps, particularly those specific to a given site, documentation of steps used to build the classification must be provided to allow crosswalking between current and future land cover schemes. Legend design and cross walk procedures should follow an established approach (e.g., Strahler et al., 2006). Error assessments conducted in the evaluation phase should include all raw data as well as the summary data used to evaluate overall performance. For all such data, the spatial and temporal grain of the analysis should be documented, especially if the analysis is conducted on the multi-pixel basis (for example, as average conditions across larger polygons). Also, it is important to evaluate whether the errors are equally distributed across the spatial extent of the study area, or whether different areas have different error properties (Fassnacht et al., 2006).

A part of reporting is archiving enough data to allow future investigators to re-evaluate or re-process the data. All raw imagery must be archived, using formats that are as transparent and generic as possible, as well as all models and reference data. Archiving of all intermediate products is not necessary, provided all information and algorithms needed to recreate those data are archived. If interpretation of imagery (including photos) was conducted, then libraries of voucher specimens (type photos) should be included.

4. Summary

The four phases of a remote sensing project described here are generally carried out in sequential order, but planning for such a study must consider all phases simultaneously. Each phase depends on prior phases, and decisions made early on can constrain options or inference later. Thus the entire arc of the study needs to be considered when managers are evaluating whether and how to include remote sensing in the monitoring of natural areas (Lunetta, 1998). This is the subject of the next section.

5. Phases in the design of remote-sensing based monitoring projects

This paper focuses on the remote sensing aspects of monitoring projects. Before initiating a project, the project manager must first ensure two conditions exist. First, there must be an explicit process, with sufficient time, for collaborative development between natural resource and remote sensing specialists. Second, there must be a sufficiently clear and precise articulation of the monitoring (change detection) objectives. Fancy et al. (2008) emphasize the importance of clear monitoring objectives. The monitoring objectives may be slightly revised during the collaborative development process, but inadequate specification of objectives commonly leads to failure.

Ultimately, the appropriate strategy for extracting information on change will depend on the type of change being sought, the availability of appropriate imagery to detect that change, as well as the availability of reference observations to interpret and label the changes that are detected. Although in theory any combination of imagery, analytical technique, and reference data could be used in a natural resource monitoring study, in practice some combinations work more effectively and are found together more often in the literature. Fig. 5 shows how this reality can simplify the decisions that must be made during planning to monitor resource attributes listed in Table 1 and replicated in the outside ring of Fig. 5. By traversing the concentric rings inward from any monitoring goal, the typical data types, reference data sources (e.g. "Airphoto data for reference"), and analytical techniques used to meet that type of goal are encountered. As an example, the pie-shaped shaded area in Fig. 5 shows that monitoring slow change in cover type typically requires airphoto data to develop reference information, could be analyzed at either the patch or the pixel level, could use either proportional or discrete descriptors of cover type, and likely would need moderate to high resolution imagery to carry out. Note that this figure is intended to be suggestive rather than exhaustive; Turner et al. (2003), Kerr and Ostrovsky (2003) note ecological applications of similar sensors not identified in Fig. 5.

5.1. Phase 1: Identify imagery appropriate to detect changes in resource attributes

5.1.1. Step 1. Identify management or conservation attribute or indicator

In the initial phase of planning, the natural resource manager must identify the focal resource (*sensu* Fancy et al., 2008), key processes that act on the resource, and the resource attributes that are the focus of the monitoring. These are analogous to the Values/Threats/Indicators paradigm of resource management (Hockings et al., 2006), but applied more broadly. The focal resource may range from a specific organism to an entire landscape or region, and may be biotic or abiotic. The processes that act on the focal resource may be external (e.g. hurricanes, fire, climate change, land cover conversion) or internal (e.g. succession of vegetation communities, eutrophication of water bodies). Such processes correspond to column 2 in Table 1.

Key questions to address: What is the focal resource? What is (are) the process(es) of interest that act on that resource? What are the manifestations of that process on the resource attributes of primary interest? Is it critical that changes in the focal resource be detected everywhere they occur, or is a summary of an average effect useful? What are the management/conservation decisions influenced by detecting changes in the resource attributes? How quickly must changes be detected to implement appropriate management responses?

5.1.2. Step 2. Identify potential imagery of appropriate grain and extent

In consultation with remote sensing specialists, use spatial, temporal, and spectral properties of the resource attributes to identify potential image sources. In all aspects of this phase, consider both the cover type (i.e. focal resource) of interest and the process that acts on it. Phinn et al. (2003) provided one framework for determining appropriate imagery.

Key spatial questions: What is the spatial grain needed to resolve the focal resource? What is the spatial grain of key process that acts on that resource? Is it necessary to capture the fate of individual organisms to capture changes in resource attributes, or can the behavior of many neighboring organisms at a larger grain size capture the necessary information? Over how large an area must change be tracked? Can a sample of images be used?

Key temporal questions: How fast do detectable changes in the focal resource occur? Do changes occur quickly in one place and then not recur for a long time (e.g. fire, flood, etc.) or are changes a 'trend' that occurs slowly in the same place over time (e.g. successional changes, slow melting of glaciers, etc.)? Does the focal resource return to its prior state (in spectral terms) rapidly following the change, or do the spectral effects of the change persist? To capture resource changes with snapshots, what frequency of observations is required (considering the pace of the process and the management activities that need to respond to it)? Are there certain windows of time when observations should or should not be obtained? Over what period must measurements occur to detect or track relevant changes in resource attributes?

Key spectral questions: Does the focal resource have a spectral quality that distinguishes it from its background? If not, is it related to some other resource or surface characteristic that is distinguishable? When the process acts on that resource, what changes in spectral quality are expected? Do those changes differ from ambient changes in spectral qualities of other areas unaffected by the process? Is there a sensor whose spectral measurements (grain and extent of spectral measurements) facilitate measurement of those spectral differences? If not, are there other related focal resources or associated resource attributes that have spectral properties that better match those of a given sensor?

5.1.3. Step 3: Evaluate availability of potential imagery

Note cost and availability of both historic and future imagery, relative to spatial and temporal extent. If the imagery must be purchased, consider the costs needed to match its properties to the properties of existing data to which it will be compared. Resolve potential tradeoffs in spatial and temporal properties and availability, and explore whether modifications to monitoring objectives or a reframing of questions could add alternative imagery types to the list.

5.2. Phase 2: Estimate costs of pre-processing and analysis

With the assistance of remote sensing specialists, evaluate the preprocessing steps and analytical techniques that are required to detect meaningful changes in the resource attributes from conditions of no-change and of uninteresting change.

Key questions: What level of geometric processing is needed to align images to capture the spatial grain of the process or resource attribute of interest? Do the spectral changes associated with the resource attributes require normalization between images, and if so, what level of root-mean-square error is acceptable? Given the availability of imagery, are uninteresting changes (in the background, in the ambient vegetation, etc.) likely to be confused with spectral changes in resource attributes of interest? Do the changes of interest result in changes in cover type, or are they more closely associated with changes in the condition of the cover type? Should change information be detected and labeled with categorical variables, or is it necessary to capture change as a continuous variable? Do maps resulting from the change detection require additional processing (e.g. patch or pattern analysis, etc.) to provide useful information? How much labor/processing time and cost is likely associated with all of these steps? How much of the process can be automated? What level of expertise would be needed to carry it out?

At the end of this phase, each candidate set of imagery should have an associated set of potential processing and analytical steps associated with it, and a set of estimated costs for each step.

5.3. Phase 3: Evaluate the availability and cost of appropriate reference data

Consider the full range of possible independent sources of information, including: field measurements, finer-grained image data, ancillary geospatial information (vector or raster data), and expert knowledge.

Key questions: Do the reference data agree in spatial and temporal scope with the image source? If not, what potential error may be introduced when these data are used to train or evaluate change detection results? Do these data record quantities that can be related to the metrics resulting from the change detection techniques defined in Phase 2? Can the precision and accuracy of the reference measurements be quantified? What is the cost of acquiring these data?

At the end of this phase, the full suite of image, analysis, and reference data should be available to address the monitoring objective. This process may need to be repeated for other monitoring objectives that are to be addressed in a coordinated, parallel effort.

5.4. Phase 4: Characterize performance of different options in terms of cost, confidence in resulting maps, and the ultimate utility of those maps

Each combination of image, pre-processing steps, analytical techniques, and reference data will likely produce a map or analytical result with different information content and different expected sources and magnitudes of error. The information content and errors may also vary for different focal resources. The goal in this final phase of planning is to evaluate the costs and benefits of the different options and select the approach that provides the best all-around benefit. Most monitoring programs will want to simultaneously track as many resources and attributes as possible, and decisions on imagery sources and processing methods will necessarily require compromise that balances cost, imagery availability, and ability to detect changes in resource attributes of most interest. Practically speaking, a solution that meets 80% of monitoring goals at a small cost will be selected over a very expensive solution that attempts to meet all goals.

This final decision is a type of cost–benefit analysis, but it is important to recognize that resultant change detection maps will have essentially two levels of benefit. The first level relates to how much the map itself can be trusted in the information it provides, which can be quantified in a standard error analysis based on the reference data. This provides an important sense of how "good" the map is, and is often the criterion on which remote sensing specialists focus. However, the ultimate utility to a natural resource manager also depends on whether the information in the map is actually relevant and useful for management. A map that is 90% accurate for a given attribute is still useless if that attribute has no management relevance, and conversely, a map that is 60% accurate for a different attribute may be extremely useful for a manager, because the starting point on that attribute may be essentially zero (Czaplewski & Patterson, 2003).

It is also important to recognize that remote sensing data may not be appropriate for many monitoring goals. This is particularly true when monitoring seeks to detect processes that result in little or no spectral change, for changes that require frequent, high-spatial resolution monitoring, or for subtle changes that occur within a background matrix of extreme variability. It may be more cost-effective to design a field-based sampling design, perhaps stratified in accordance with information from remotely sensed data.

6. Conclusions

Natural resource managers will increase the likelihood of meeting their monitoring goals with remote sensing by actively participating in the design and planning of a project. Remote sensing science can aid natural resource managers in understanding landscape dynamics over time, and the ultimate utility of derived maps can be strongly enhanced by matching the manager's expectations and needs with the available tools and techniques. In this paper, we developed a general framework that we have successfully used to collaboratively develop operational natural resource monitoring based on remotely sensed data. An understanding of the concepts and process articulated in this paper will help natural resource managers, and remote sensing scientists, productively engage in developing monitoring protocols.

We rely heavily on the concept of extracting change information from spectral space, but we emphasize that spectral space represents the more generic multivariate spaces derived from new sensor technologies and from other spatial data that describe landscapes. Other technologies will have different specific benefits, but ultimately the information source being tapped for information is variability in a data space. Increasingly, these data spaces involve a larger suite of environmental variables used to describe landscapes (Goetz et al., 2009-this issue; Ohmann & Gregory, 2002). Because many of these ancillary data (elevation, average climate, etc.) are historically static, image data are often the most dynamic variables in the multivariate space used to track changes over time. Nevertheless, remote sensing change analyses are increasingly being incorporated into a *data assimilation* framework, i.e. the merger of available weather/climate, ocean, stream/lake, and ecosystems data with imagery and models to facilitate coordinated and operational analyses of environmental change (see http://www.jcsda.noaa.gov/).

Although the change detection framework described in this paper is likely relevant to the remote sensing portion of many monitoring projects, the resultant maps of change may be just the first step in a larger modeling or pattern analysis effort (Crabtree et al., 2009-this issue; Townsend et al., 2009-this issue; Goetz et al., 2009-this issue). A detailed consideration of pattern analysis or ecosystem modeling is beyond the scope of this paper, but the requirements for those (or similar) efforts may need to be part of the evaluation of overall utility of different remote sensing projects. Measurement information content (discrete vs. continuous variables) and the spatial and temporal grain will likely need to align with subsequent analyses.

In summary, remote sensing data are an increasingly important component of natural resource monitoring programs (Coppin et al., 2004; Gross et al., 2006; Wiens et al., 2009-this issue). The utility of remotely sensed data for monitoring is maximized by understanding the constraints and capabilities of the imagery and change detection techniques, relative to the monitoring objectives. This understanding is best achieved through a collaborative process that leverages the expertise of both natural resource specialists and remote sensing specialists throughout the entire planning and implementation process. A careful consideration of the spatial, temporal, and spectral properties of focal resources and their alignment with imagery data will help determine the suitability of using remotely sensed imagery to effectively achieve monitoring objectives.

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