PERSPECTIVES ON MONITORING GRADUAL CHANGE ACROSS THE CONTINUITY OF LANDSAT SENSORS USING TIME-SERIES DATA

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Abstract

There are many types of changes occurring over the Earth's landscapes that can be detected and monitored using Landsat data. Here we focus on monitoring "within-state," gradual changes in vegetation in contrast with traditional monitoring of "abrupt" land-cover conversions. Gradual changes result from a variety of processes, such as vegetation growth and succession, damage from insects and disease, responses to shifts in climate, and other factors. Despite the prevalence of gradual changes across the landscape, they are largely ignored by the remote sensing community. Gradual changes are best characterized and monitored using time-series analysis, and with the successful launch of Landsat 8 we now have appreciable data continuity that extends the Landsat legacy across the previous 43 years. In this study, we conducted three related analyses: (1) comparison of spectral values acquired by Landsats 7 and 8, separated by eight days, to ensure compatibility for time-series evaluation; (2) tracking of multitemporal signatures for different change processes across Landsat 5, 7, and 8 sensors using anniversary-date imagery; and (3) tracking the same type of processes using all available acquisitions. In

this investigation, we found that data representing natural vegetation from Landsats 5, 7, and 8 were comparable and did not indicate a need for major modification prior to use for long-term monitoring. Analyses using anniversary-date imagery can be very effective for assessing long term patterns and trends occurring across the landscape, and are especially good for providing insights regarding trends related to long-term and continuous trends of growth or decline. We found that use of all available data provided a much more comprehensive level of understanding of the trends occurring, providing information about rate, duration, and intra- and inter-annual variability that could not be readily gleaned from the anniversary date analyses. We observed that using all available clear Landsat 5–8 observations with the new Continuous Change Detection and Classification (CCDC) algorithm was very effective for illuminating vegetation trends. There are a number of potential challenges for assessing gradual changes, including atmospheric impacts, algorithm development and visualization of the changes. One of the biggest challenges for studying gradual change will be the lack of appropriate data for validating results and products.

Keywords:

Landsat data continuity; Gradual change; TM; ETM+; OLI; Continuous change detection; Time series

1. Introduction

The Landsat series of satellites has enabled the characterization of the Earth's surface since 1972. The more than 33 years of data provided by Landsats 4 through 8 have proven especially well-suited for land characterization activities, owing in large part to the spatial, spectral, and radiometric qualities of the data (Wulder et al., 2008). One common theme that has emerged through the many Landsat data

analyses that have been conducted is that the Earth's surface is constantly changing and that the types, magnitudes, rates, and aerial extents of the changes vary markedly from location to location and epoch to epoch. These changes, and the many agents that cause them, are of interest to a large community of scientists and managers who use the information for an array of applications, including assessing effects of global change on biodiversity, carbon cycling, fire fuels, crop types and yields, and hydrology, among others. Another common theme emerging from these analyses is that there is a constant need for current information on land cover and condition for assessing the impacts of the wide array of changes taking place across the Earth's landscapes.

The changes that scientists and natural resource managers are interested in monitoring can be summarized as abrupt change, seasonal change, ephemeral change, and gradual change (Verbesselt et al., 2010). Abrupt changes are often associated with major alterations in land cover, such as forest harvest, urban development, and wildfire, and most land-change assessments conducted over large areas using medium spatial resolution data have focused on abrupt changes (Hansen and Loveland, 2012). Seasonal changes are related to the phenological cycles of vegetation green-up and senescence and to other temporal responses associated with annual cycles of day length, solar angle, and related climatic characteristics. Although seasonal changes are more noticeable in particular regions or biomes, such as areas of deciduous forests and grasslands, these cycles are characteristic of most vegetated areas of the Earth to some degree. Ephemeral changes represent temporary interruptions in the usual energy responses from the landscape, such as from flooding, short term defoliators, or short-term drought (e.g., duration of one or two years). Gradual changes relate to "within-state" (i.e., within land-cover type) shifts in energy response, often with regard to vegetation communities, that are not related to normal phenological cycles (although persistent shifts in phenological responses can constitute gradual change). Gradual changes result from a variety of processes, such as damage to vegetation from

insects and disease, vegetation growth and succession, vegetative decline from prolonged drought or air pollution, shrinking of glaciers and polar ice caps, long-term drying of lake beds, sea level rise along shorelines, and many others.

The landscape is constantly changing and many of the changes are gradual. Indeed, it may be the exception when a landscape remains static. Despite the pervasiveness and impacts of gradual change across our landscapes, systematic monitoring and assessment of gradual forms of change have been rarely pursued with mid-resolution or fine-scaled satellite sensors. The four-decade depth of the Landsat data archive offers a wealth of information for characterizing gradual change, but until recently it has been challenging to assemble appropriate time-series data to support the needed analyses. Our main objective in this paper is to draw attention to gradual change. We describe the role of remote sensing for assessing gradual change. We discuss types of change that are important to characterize, how such changes could be characterized, potential difficulties in characterizing gradual change, and future considerations. We include examples of locations undergoing different types of gradual change to facilitate discussion in the science community.

2. Types and Characteristics of Gradual Change

For the most part, we consider gradual changes to be those that are occurring over a period of several years or more, usually involving gradual spectral transitions over that time period. Conceptually, some of the most straightforward cases of gradual change relate to landscapes undergoing a systematic shift through time, such as increasing biomass associated with plant succession and growth, decreasing biomass associated with some particular stress agents, or gradual shifts in species composition related to a number of potential factors. There are many other types of gradual changes and users of such

information (Table 1). Depending on the cause, such changes can occur over several years to several decades or longer (Table 1). Unlike abrupt changes, which can often be readily detected using two images (a “before” and “after” image pair), gradual changes are often overlooked or ignored, in part because they are not observable as distinct patterns with well-defined boundaries in the imagery and require analyses of a series of images to have confidence that a change actually has occurred. It is worth noting that most of the examples of gradual change listed in Table 1 are observable at the pixel level. However, the effects of mountain pine beetle infestation and shifting patterns of agriculture may be fundamentally different in that the gradual change occurs at a broader scale (forest stand and agricultural region, respectively). Cumulative effects from ephemeral phenomena could perhaps be included in the list, and similarly may best be assessed using analyses at the landscape level. Regardless, all of these types of gradual changes generally tend to be best characterized through the analysis of time-series data.

It is worthwhile to provide examples of what we do not consider to be a gradual change. Most major and readily discernable land-cover changes, such as forest harvest and urbanization, are not considered to be gradual change. We also do not include annual green-up and senescence cycles (i.e., those associated with plant phenology). However, if the phenological cycle is shifting through time (e.g., lengthening of the growing season), then that would be gradual change. Events that occur over very short duration, such as associated with fires, storms, floods, tornadoes, or other disasters, are certainly not gradual changes, although they may represent intra-state changes. This is because these changes occur in response to a punctuated event that results in an “abrupt change.” However, the long-term recovery from these events could be considered as gradual change. It is also worthwhile to make a distinction between “gradual change” and “subtle change.” Subtle changes are very difficult to detect,

often because the spectral responses are very minor. Subtle changes may be gradual (e.g. very slow successional changes) or they may be abrupt (e.g., low impact selective logging).

Similar drivers can lead to different types of change. For instance, the mountain pine beetle can impact forests very quickly (often over a single year), as opposed to the western spruce budworm, which impacts forests more slowly, across multiple years (Gray, 2008). Thus, pest infestation as a change agent can sometimes result in abrupt changes, such as can occur with the pine beetle, or in gradual change, such as can occur with the spruce budworm. Both are examples of intra-state changes (healthy trees are replaced with dead or dying trees) that will bring about gradual change during subsequent vegetation re-growth. Conversely, a gypsy moth infestation defoliates trees over a season or two, from which most trees recover the following year (refoliation). This represents an ephemeral change, although it is possible the forest community might change over a period of years in response to the gypsy moth infestation, which could constitute a gradual change.

3. The Requirement for Gradual Change Assessment

Remote sensing provides broad overviews of the Earth's changing landscapes. Few would dispute the importance of developing a comprehensive understanding of the rates, causes, patterns, and trends of land-cover changes. Such understanding is key to a number of important programs and missions throughout the world. As an example, the US National Science Foundation requested clear understanding of land-use and land-cover change through the Grand Challenges in Environmental Sciences (NRC, 2001) and indicated that comprehensive knowledge of changes in land use and land cover is critical to understanding biogeochemical cycling, ecosystem functioning and services, and human welfare. Characterizing and understanding land-cover change is also of critical concern to various European groups and agencies, including the European Copernicus program, which is a European Union

flagship program with goals of providing land-change information in support of policymakers and business. This is being done in association with the European Commission and the European Space Agency (ESA, 2014).

An assessment completed by the US Geological Survey (USGS Trends, 2015) estimated that the amount of land-cover change that occurred across the US during five periods from 1973 to 2000 ranged from a low of 0.5% for the Chihuahuan Desert ecoregion to a high of 28.7% for the Puget Lowlands ecoregion (Sleeter et al., 2012). These estimates reflected only abrupt changes, as the project focused on land cover conversion events. The MultiResolution Land Characteristics Consortium's National Land Cover Database (NLCD; <http://www.mrlc.gov>) has also mapped land cover and change across the US for several time periods (Xian et al., 2009; Jin et al., 2013), but like the Land Cover Trends project, the NLCD product so far has focused on capturing abrupt change, although it currently is expanding to incorporate changes in continuous land-cover variables, such as changes in canopy cover, shrub cover, and percent imperviousness. Information provided by the Land Cover Trends and NLCD products can be used to assess effects of land-cover change on various ecosystem services, such as carbon storage and fluxes (Zhu and Reed, 2012, 2014). Statistics from the Land Cover Trends and NLCD projects suggest that most regions have not undergone major land-cover change, implying a high degree of stasis. However, this may only be part of the story, and several questions remain. For instance, what were the within-state responses in landscapes that exhibited little abrupt change? Would information on gradual change have significantly influenced estimates from carbon models? Would impacts from these changes have had much influence on a per-hectare basis, or only when summed at the regional scale? Various growth models and simulators (e.g., Dixon, 2002; Weiskittel et al., 2011) can help us understand the impacts of gradual change across the landscape, but direct measurements through comprehensive analysis with time-series data are needed to document the timing, rates, and patterns of gradual change.

4. Approaches and Challenges to Detecting Gradual Change

Much of the research using remotely sensed data to detect gradual change has been based on data from sensors that can provide information daily, such as the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectrometer (MODIS). The daily repeat cycle of these sensors supports the dense time-series needed for assessing gradual and phenological changes (e.g., Myeni et al., 2007; Reed et al., 1994; Stow et al., 2004; Zhang et al., 2003). Most investigators have used weekly, biweekly, or monthly composited data from these sensors to provide time steps that are suitable for detecting gradual changes without the burden of an enormous cumulative volume of daily data. The temporal compositing also enables cloud avoidance by offering multiple opportunities for clear observations within the composite period.

A common approach for monitoring and characterizing trends in land-cover responses from high temporal resolution time-series data is to use vegetation index-transformed data, such as the Normalized Difference Vegetation Index (NDVI) (Tucker et al., 2005; Goward et al., 1991). Data noise from atmospheric haze, smoke, intermittent snow cover, and other types of interference, as well as from the compositing process (dependent on the quality and timing of the observations used), can persist in these time-series products, so the data sometimes are further smoothed temporally to reduce effects of noise to maximize the detection of response trends (Brown et al., 2008; Swets et al., 1999; Wylie et al., 2014). There are many applications for which data of high temporal resolution are informative, but the coarse spatial resolution (ranging from 250 m to many km) limits the relative dynamic ranges of response that can be detected (the larger the pixel, the greater the mix of land cover

types and/or vegetation species being represented) and can add imprecision in detecting change. The spatial resolution of the Landsat sensors is much finer, allowing a larger proportion of pixels to represent pure cover types, which boosts the dynamic range of response and sensitivity to the timing of change for given cover types.

Despite the long and continuous Landsat data record acquired from 1972 to present, generating dense time-series to study gradual change has been challenging. Landsat's less frequent overpass schedule and lack of on-board recorders for platforms prior to Landsat 7 make the assembly of time-series data vulnerable to cloud contamination and global coverage issues, resulting in large temporal gaps in the data record for certain regions and/or periods in time. This has been underscored during intervals when only a single Landsat satellite sensor was operating. Another challenge has been the lack of an efficient method for users to acquire and compile Landsat time-series data. Download of data has been scene-based for one overpass at a time, a tremendous time- and space-consuming requirement, given the multiple hundreds of repeat overpasses that have accumulated in the archive for many parts of the globe. Once data have been downloaded, users must perform radiometric and cross-sensor calibrations to ensure data comparability across time and sensors. After these steps have successfully been completed, users are faced with limitations from image processing packages, which have not yet evolved to support analysis of dense time-series data stacks. Recent advances in technology and methodological approaches and tools (e.g., Roy et al., 2010; and see <http://bfast.r-forge.r-project.org> and http://landsat.usgs.gov/documents/espa_odi_userguide.pdf) are converging to help users overcome these challenges so that assembling and analyzing Landsat data time-series is becoming easier (e.g., Hansen et al., 2011).

Another factor limiting the straightforward use of Landsat data time-series is that spectral and spatial resolution properties of the multispectral scanner (MSS) sensors on Landsats 1–3 are very different from the sensors on Landsats 4–5 (Thematic Mapper [TM]), Landsat 7 (Enhanced Thematic Mapper Plus [ETM+]), and Landsat 8 (Operational Land Imager [OLI]), and require much effort and calibration to crosswalk land-cover responses across sensor types. Relatively recent advances in calibration engineering and science facilitate comparisons across data from Landsats 4–7 (Chander et al., 2009). Landsat 8’s OLI represents many enhancements, including improved radiometric quality and new spectral bands. Bandwidths on OLI have been somewhat narrowed from those on Landsats 4–7, but most are reasonably similar to the previous sensors (Table 2). The near-infrared band of Landsat 8, however, is much narrower than those of the earlier Thematic Mapper series, and this can affect some time-series comparisons across sensors, which we will discuss in the next section.

The literature is replete with examples and approaches for two-date change detection using Landsat data, as summarized in excellent reviews by Singh (1989), Coppin et al. (2004), and Lu et al. (2004). Methods for conducting time-series analysis with Landsat data are relatively more recent, facilitated by the ready access to free Landsat data and the opening of the archive in 2008 (Wulder et al., 2012). Efforts have transitioned from using a few dates of imagery scattered across years to detect change (e.g., Jensen et al., 1995; Yang and Lo, 2002) to using annual or nearly annual dates in the Landsat time-series stack (e.g., Kennedy et al., 2010; Huang et al., 2010; Vogelmann et al., 2012). Of these latter approaches, the Vegetation Change Tracker algorithm (Huang et al., 2010) targets pixels that have undergone an abrupt disturbance event and provides information on the disturbance year and magnitude of the change. The Landtrendr algorithm (Kennedy et al., 2010) characterizes temporal trajectories of spectral data extracted from Landsat time-series data sets. Both regression-based and point-to-point fitting of spectral indices as a function of time are used, which allows the capture of both

slowly evolving processes, as well as more abrupt events. The approach employed by Vogelmann et al. (2012) uses linear regression of trends over specific time periods, with the goal of characterizing gradual changes, including detection of the locations, directions, magnitudes, and statistical uncertainty of the changes. These three change-detection approaches yield the best results when there is one good growing-season observation for each pixel for each year and when the data sets used are from approximately the same time of year to represent comparable phenological stage across years. However, cloud contamination of scenes and interannual differences in weather characteristics can make it difficult to assemble imagery for approximate anniversary dates in every year, and temporal trajectories are subject to data gaps that may adversely impact change-detection results.

A new paradigm for compiling Landsat time-series data for change detection has been developed by Zhu et al. (2012) based on assembling all clear observations at the pixel level, rather than relying on largely cloud-free scenes. This approach uses the Continuous Change Detection and Classification (CCDC) algorithm, which assembles dense time-series of observations for each pixel. These observations can be used to better characterize temporal trajectories for every pixel through time (Zhu et al., 2012; Zhu and Woodcock, 2014) and flag abrupt change events as well as periods of gradual change (Zhu et al., submitted). The dense trajectories at the pixel level illuminate the annual phenological responses with Landsat data, making it easier to recognize departures from each pixel's past response history. By using all available good observations for a given place, the CCDC algorithm is capable of modeling both the intra-annual change (phenological change) and the inter-annual change, including trends of the time-series. The intra-annual change is developed based on harmonic (Fourier) models (Davis, 1986; Rayner, 1971), and the trend of the time-series is estimated based on a slope component (Zhu and Woodcock, 2014; Zhu et al., 2015). Alternatively, the CCDC algorithm also identifies abrupt surface change based on the difference between the model predicted observation and the actual observed observation (Zhu and

Woodcock, 2014). If the difference between the observed and predicted values exceeds a threshold for several consecutive (usually 5–6) overpasses, the departure is identified as a break (abrupt change). A new time-series model comprised of a slope component and harmonic models will then be generated following the abrupt change using the post-change observations. By doing this for every pixel in the Landsat image, the CCDC algorithm identifies the three kinds of change (abrupt, phenological, and gradual) discussed above.

5. Cross-Sensor Calibration Considerations

To assess gradual trends in land-cover responses with several sensors that span a substantial period of time the data must be comparable. This is not a trivial undertaking, and our understanding of how best to accomplish this is constantly evolving. Historically, researchers have used a variety of approaches to help normalize time-series data sets, such as radiometric rectification (Schott et al., 1988; Hall, 1991) and dark pixel subtractions (Chavez, 1988). Many of these normalization approaches have evolved and have been replaced with calibration of images to reflectance (as opposed to relative units). From an applications standpoint, many of the earlier radiometric calibration efforts focused on development of at-sensor radiance or reflectance products (Homer et al., 2007; Xian et al., 2009), whereas more recent activities have focused on operational development of atmospherically corrected data sets (Zhu et al., 2012; Zhu and Woodcock, 2014).

The Landsat series of satellites, most notably Landsats 4–8, have had a remarkable history of calibration activities associated with them, and the calibration of their sensors is extremely well understood. It was recognized during the early phases of the Landsat history that coefficients to enable transformation of image data into well-calibrated data sets were not always available or appropriate for applications. In

response to this, there was much initial focus on developing an accurate understanding of Landsat 5 TM calibration, with attention centered on understanding the lifetime radiometric calibration responses (e.g., Chander et al, 2009). One of the findings during this phase was that the Landsat 5 radiometric calibration evolved through time and that the uncertainty was somewhat greater in the early years than during the later years, when the sensor was more stable (Helder et al., 2008).

Similar to Landsat 5, Landsat 7 radiometry has been very well characterized (Thome et al., 2004; Chander et al., 2010; Markham et al., 2004). In addition to the calibration of Landsat 7, early in its mission, Landsat 7 was temporarily placed in an orbit very close to that of Landsat 5, enabling acquisition of data sets at nearly the same time. This was done to facilitate cross-sensor calibration between the TM and ETM+ instruments. Similarly, Landsat 8 was temporarily placed in an orbit close to that of Landsat 7 to facilitate cross-calibration between the ETM+ and OLI instruments. Regarding the TM versus ETM+ comparisons, it was found that the TM and ETM+ responsivities were very consistent with each other to within 2% or better (Teillet et al., 2001), although the calibration of Landsat 7 was more precise (and better) than Landsat 5. Investigators analyzing time-series data need to be aware that there are improvements in calibration through time and that there will be some differences among Landsat sensors. Nonetheless, these differences are generally smaller than other types of errors in remotely sensed data, such as from atmospheric variables, wind, and bidirectional reflectance.

In an analysis of Landsat 8 versus Landsat 7 radiometric properties, we compared homologous bands graphed pixel by pixel using atmospherically corrected reflectance data for three consecutive Landsat images (acquired eight days apart) over four path/rows (45/30 in Oregon; 31/27 in North Dakota; 35/32 in Colorado, and 36/38 in Arizona). For two of the path/rows, the sequence was Landsat 7 imagery

302 acquired first, Landsat 8 imagery acquired second, and Landsat 7 imagery acquired third. For the other
303 two path/rows, the sequence was reversed (i.e. Landsat 8 followed by Landsat 7 followed by Landsat 8).
304 For each path/row, clouds, shadows, Landsat 7 data gaps, water, agriculture, urban areas and edge
305 areas (i.e. zones where large spectral differences existed between different land cover types) were
306 masked out. The water, agriculture and urban areas were identified using data from the National Land
307 Cover Database (NLCD; Homer et al., 2015), and edges were identified using a 3x3 moving window that
308 calculated standard deviation within the moving window. A single mask representing all of these
309 features was developed for each path/row, and after applying it to the images, the remaining pixels
310 represented spatially contiguous tracts of non-agricultural, non-urban vegetation. For each path/row,
311 two Landsat 7 versus Landsat 8 comparisons were made, as well as one comparison for either Landsat 7
312 versus Landsat 7, or Landsat 8 versus Landsat 8 (two of each of the latter were generated). Linear
313 regression equations were developed for each comparison (three for each path row; twelve
314 comparisons total). Landsat 7 versus Landsat 8 equations were averaged for each band (eight
315 comparisons representing four path/rows were used for each band), and plotted +/- one standard
316 deviation. Results from one of the Landsat 7 versus 8 comparisons is shown for the six homologous
317 bands in Figure 1. For this comparison, data were acquired on July 20, 2013 (Landsat 7), and July 28,
318 2013 (Landsat 8). Turquoise shades in Figure 1 indicate the highest frequency of observations. For this
319 type of comparison, data on the one-to-one line (indicated in Figure 1 by the red line) are perfectly
320 correlated. In reality, a number of factors, including imperfect registrations and likely changes occurring
321 over the eight-day time interval between data acquisitions, contributed to a moderate level of scatter
322 between the two dates of imagery. Nonetheless, there is very high agreement between most of the
323 homologous band pairs. The green, red, and two shortwave-infrared bands showed especially high
324 agreement between the two sensors. The band pair with the most disagreement for this particular
325 comparison was the blue band.

326

327 Comparisons showing the mean of Landsat 7 versus 8 linear regression results, plus and minus one
328 standard deviation (Figure 2), indicate a high degree of similarity between homologous Landsat 7 and 8
329 bands. The mean linear regression lines are not appreciably different from “one-to-one lines” (not
330 shown because they would mostly overlap with the mean lines), with the minor exception of slight
331 offsets observable where surface reflectance is very low (i.e., near 0%) for the blue and green bands. It
332 is noteworthy that the variability among comparisons is highest for the blue band, followed by the green
333 band and then the red band. Because the wavelengths of the visible bands for Landsats 7 and 8 are
334 nearly identical (Table 2), the likely explanations for the differences relate to atmospheric corrections
335 and differences in atmospheric properties during data acquisitions. These differences generally have
336 greater impact on visible than near-infrared and shortwave-infrared bands. Variability for the near-
337 infrared and the two shortwave-infrared bands is very low, which implies that the radiometry for these
338 bands is quite similar between Landsat 7 and 8 for natural vegetation. At the outset of this comparison,
339 we were concerned that the wavelength differences for the near-infrared band between Landsats 7 and
340 8 (Table 1) might make direct comparisons of data from the two sensors difficult from an applications
341 standpoint. However, the comparability between bands depicted in Figure 2 helps allay this concern, at
342 least for vegetated areas. It should be noted that the ranges displayed for the x and y axes for these
343 graphs vary among the bands, and are dependent on the actual range of observations for the
344 vegetation. Most vegetation has low reflectance in the visible portion of the spectrum, and thus the
345 range in values for the blue, green, and red bands is much lower than for what is shown for the near-
346 infrared and shortwave-infrared bands. Similar to Figure 2, the linear regression slope and r^2 values,
347 representing all pairwise scene comparisons (Figure 3), indicate that the band by band variation in
348 observations is greater at the shorter wavelength regions than at the longer wavelengths. That the
349 Landsat “7 vs. 7” and “8 vs. 8” observations are often towards the edges of the range of variability is

probably largely a function of the 16-day differences between the scenes being compared (as opposed to eight-day differences for the Landsat 7 vs. 8 comparisons), which creates greater discrepancies between the data sets.

There have been a limited number of other studies that have compared Landsat 8 data with Landsat 7 data using clear-sky observations for the same locations and using data acquired eight days apart (Flood, 2014; Li et al., 2014). Flood (2014) reported that the top-of-atmosphere reflectance difference between the two sensors was about 6% and surface reflectance difference was about 2%. NDVI was affected by about 5%, on average. Conversely, Li et al. (2014) concluded that the two sensors are similar enough so that they can be used together without major problems. Zhu et al. (submitted) used the CCDC algorithm to predict Landsat 8 surface reflectance based on all available Landsat 5 and 7 data acquired over Guangzhou, China, and noted biases in the visible bands, especially the blue band. The NDVI values were positively biased by about 0.04. In our study, we did not find any obvious consistent bias between Landsats 7 and 8 for any of the similar bands, although it is apparent that the variability between the compared data sets was highest for the bands characterized by the shortest wavelengths. Even though data were atmospherically corrected, we suspect that most of the visible band intra- and inter-sensor radiometric differences that we observed were related to differences in atmospheric conditions rather than actual sensor differences. The within-sensor comparisons (i.e. between Landsat 7 versus 7 and Landsat 8 versus 8) were mostly similar to those of the inter-sensor comparisons (i.e., between Landsat 7 versus 8). We note that the process used to correct for atmosphere has changed between Landsat 5/7 and 8. While we suspect that the new process likely improves the atmospheric correction of the Landsat 8 data, it is also probable that the process results in some discrepancies that we are observing between Landsat 7 and Landsat 8. Correcting for the atmosphere to surface reflectance continues to be a major challenge for time-series assessments, and precise corrections are especially important when

comparisons are made using the visible portion of the spectrum. Not only are atmospheric conditions more difficult to characterize at these shorter wavelengths, but in general, visible reflectance tends to be very low and relatively homogeneous for vegetated targets, with differences often being subtle. The combination of these characteristics can mean that small correction errors can have relatively large impacts on final results. We believe that the potential differences that can be caused by different atmospheric conditions are likely to be greater sources of error than differences in sensor characteristics. This is a topic that warrants continued research.

6. Examples of Gradual Change

6.1 Inter-annual Trends using Anniversary Date Imagery

Gradual changes can be easy to overlook in the midst of abrupt changes in the landscapes. We use an area in and around Crater Lake National Park, Oregon, USA, to illustrate how multiple forms of change can be occurring within relatively local proximity (Figure 4). These examples were generated using Landsat data acquired during late summer (usually one observation per year). Comparison of the trend NDVI data set (Figure 4B) with the RGB composite image (Figure 4A) indicates how the variability and magnitude of the trend patterns correspond to different land cover features across the landscape. The Pumice Desert (denoted by “1” in Figure 4) is a sparsely vegetated section of the park with widely dispersed, small herbaceous plants. It represents a spectrally stable area (Figure 5, blue line), exhibiting minimal inter-annual variability within a very narrow range of low NDVI values. Near the edge of the Pumice Desert, slow encroachment by coniferous vegetation is indicated by the gradual increase in greenness (increase of .003 NDVI per year; r-square = 0.607) in the NDVI profile (green line in Figure 5). This contrasts with a nearby area of conifer forest (denoted by “2” in Figure 4) showing a steady decline in greenness (black line in Figure 5; slope = -0.005 and r-square = 0.642). Orthoimagery in Google™

earth reveals many dead trees throughout the declining area, which appears to have fewer living trees in more recent orthoimagery than in past imagery. In our experience, it is relatively unusual to encounter areas of steady decline over such a long time period. More typically, declines last on the order of a decade or less before they start reverting (either because the agent of decline has left or lessened, enabling recovery, or because other vegetation species become established).

Two areas of major disturbance provide examples of abrupt change followed by gradual recovery. In Figure 5, the red line is for a pixel in an area with relatively high and stable NDVI until it burned in 2003, resulting in a marked decrease in NDVI followed by rapid growth of vegetation (slope of recovery line = 0.043) at a rate more than ten times that of the zone of encroachment along the edge of the Pumice Desert. The yellow profile in Figure 5 is for a pixel in a forest stand that was logged in 1988. The pre-logged NDVI was initially similar to that of the pre-burned NDVI (red line), and the drop in NDVI following forest harvest was also comparable, but recovery to similar levels of pre-disturbance greenness took twice as long for the logged site as for the burned site. Such observations can lead to a variety of ecological investigations, such as analyses of differences in site potentials, disturbance effects, land management practices, and impacts of climate on recovery rates.

The NDVI trajectories assembled for the data analyses shown in Figure 5 were from Landsats 5 and 7 (1985-2012) and 8 (2013-2014). As discussed earlier, there has been some concern whether the spectral properties of Landsat 8 data would be comparable with data from Landsats 5 and 7, and we had reason to believe that there might be differences between sensors (especially for the near-infrared band and the indices that use this band) that warranted attention (e.g., Figure 1). In this assessment we did not see

evidence of a significant bias in any direction, and it appeared that the temporal profiles we assembled had smooth transitions across sensors.

Direction, magnitude, pattern, and statistical significance all are ways of portraying gradual trends spatially (Vogelmann et al., 2012). A map of the NDVI trends described above is shown in Figure 4B, which is rendered based on the slope of the linear regression relation for each pixel from 1985 to 2014. Bright areas indicate where NDVI values have increased and dark areas show where values have decreased. Moderate grey areas, such as the Pumice Desert (labeled “1” in Figure 4B), indicate areas of little or no change over the time period. The ring of brightness fringing the Pumice Desert (visited in the summer of 2012) corresponds with the area of conifer encroachment discussed earlier. This area is not obvious when images from various years are inspected individually, and can better be discerned through analyses of time-series data, such as employed here.

The example of declining NDVI shown in Figure 5 corresponds with the dark area labeled “2” in Figure 4B. In contrast, areas labeled “3” and “4” in Figure 4 have been undergoing increased greenness at the tree line zone in the mountains. These mountain sites are interesting because they show patterns of change in areas largely devoid of direct human activity. An analysis whereby average NDVI trend information was segmented using 50-m elevation range thresholds for three mountains (two are shown in Figure 4 and a third is to the north of the region portrayed) revealed that, although all areas below tree line are exhibiting evidence of greening over the 30-year time frame, the greatest increase has been occurring around 2050–2200 m elevation (Figure 6), which is where conifer tree vegetation transitions to shrub and herbaceous alpine vegetation. At higher elevations, this alpine vegetation is replaced with rock and snow, and the greening trend diminishes towards zero. These patterns are intriguing, as the

greening in these tree line areas is reminiscent of the greening taking place in the Arctic (Pearson et al., 2013; Epstein et al., 2013). The most plausible explanation for the changes taking place at tree line in the mountain areas is that the climate is gradually becoming milder in these historically harsh settings. This is consistent with observations by Gottfried et al. (2012), in which vegetation samples above the tree line from summit sites in European mountain systems showed that ongoing climate change is gradually transforming mountain plant communities.

6.2. Intra- and Inter-annual Trends using All Available Imagery

Time-series data sets for individual pixels generated using the CCDC algorithm (Figures 7 and 8) display the high level of detailed spectral-temporal information characterizing sites when all available clear observations from Landsats 5–8 are used. Red, black, and blue points represent Landsat TM, ETM+ and OLI observations, respectively. Major land-cover changes are identified by the black circles (e.g. in Figure 7D near 1990) and time-series models are depicted by the sinusoidal curves. Compared with profiles generated using one Landsat data set per year over the Landsat 4–8 time-frame (e.g., Figure 5), these CCDC graphs depict an impressive amount of complex information, including detail related to both inter- and intra-annual trends. The graphs in Figure 7 represent different types of conditions for pixels from the Crater Lake National Park area described previously. As expected, the NDVI values from the Pumice Desert pixel are stable (Figure 7A), and show neither a significant increase nor decrease during the 30-year time interval. The second site (Figure 7B) is located at the edge of the Pumice Desert, where encroachment by conifers is occurring. This pixel shows a steady growth trend over the entire time period. This trend is more obvious than that depicted by a similar pixel located in the same area in Figure 5 (green line). The third site (Figure 7C) shows evidence of an abrupt reduction in greenness in 2008 that also is evident for the same pixel in Figure 5 (black line), but the CCDC algorithm sheds more

light on the actual timing of the forest disturbance event. The fourth site (Figure 7D) shows a strong growth trend at a site following an abrupt change caused by forest harvest.

Other types of changes, namely wetland changes, drought, and those related to a pine beetle outbreak, show different and unique spectral profiles (Figure 8). Figure 8A is a wetland pixel trajectory from the Prairie Pothole Region, North Dakota, USA. Depressional (“pothole”) wetlands in this region are largely dependent on precipitation for water input and evaporation for water loss (Winter and Rosenberry, 1998), and the region cycles through periods of drought and deluge at roughly decadal (or longer) time scales (Natural Resources Conservation Service 2014). Wetland vegetation cycles in response to climate, with water surfaces nearly devoid of vegetation during years of very high annual precipitation (due to drowning of plants), to successively more dense marsh and emergent vegetation cover in years of lower annual precipitation (Ballard et al., 2014). NDVI for the wetland shown in Figure 8A illustrates these cycles, showing a strong signal from aquatic vegetation from 1985 through 1993 during a series of dry years, followed by a gradual downward trajectory set in motion by wetter conditions through 2002, followed by an abrupt jump in greenness set off by another dry period through 2009, and another subsequent gradual downward trend with the onset of a wetter period.

A pixel from a forest in southern Arizona (Figure 8B), USA, represents an area that has been under severe drought for several decades. This pixel not only shows a downward trajectory signaling decreasing green biomass, but also shows increasing spectral variability as the drought progresses. Variability becomes noticeably higher at about the year 2000, and becomes further accentuated around 2007. This increased variability might be expected because normally stable vegetation communities,

which initially have relatively stable seasonal cycles of photosynthetic activity and predictable spectral properties, will become more variable as continued water stress alters phenology, decreases vegetation production, and increases browning, all of which can increase spectral variability (Huang and Anderegg, 2012; Venter et al., 2015; Walker et al., 2014). In addition, the NDVI values towards the latter part of the time-series tend to be lower than during the first part of the series, which is consistent with decreases in amounts of green vegetation as the drought progresses.

The final example (Figure 8C) represents a pixel in a forest infested by the mountain pine beetle in the Rocky Mountains of Colorado, USA. An initial beetle attack occurred around 2004, and NDVI decreased markedly. Afterwards, the NDVI values show steady increase with re-establishment of green vegetation cover.

We emphasize two main points from these examples. The first is that different types of changes have different spectral trends, and these can be effectively captured by the CCDC algorithm using dense time-series of Landsat observations. These different spectral trends enable us to describe and understand the types of changes taking place across our landscapes in much more detail than using the limited number of observations traditionally assembled for Landsat land-change applications. Not only are the characteristics of trends different, but the patterns of variability are different as well, with some systems showing minimal amounts of intra- and inter-annual variability (e.g., Figure 7A) and other systems showing especially high levels of variability (e.g., Figures 7D, 8A, and 8B). This variability can be problematic to understand and characterize when only a limited number of data sets are analyzed, which can lead to misclassifications and other types of errors. The second point is that Landsat 8 data

appear to be very consistent with the data from Landsat 5 and Landsat 7 for conducting trend analyses. We have not noticed any cases of significant spectral discrepancies between data from Landsats 7 and 8, and this, bolstered by our statistical analysis of Landsat 7 versus 8 data (Figure 2), gives us confidence that Landsat 8 data can be used in combination with previous Landsat data for assessing long-term trends. This is consistent with the conclusions by Mishra et al. (2014), who evaluated radiometric consistency between Landsat 8 and Landsat 7 reflective bands and concluded that reflectance observations were within 2.5% of each other.

7. Major challenges

Many of the algorithms that have been developed for assessing change with time-series data have focused on detecting breaks in the spectral continuum, after which a pixel is flagged as changed, with a time stamp and magnitude-of-change index associated with it. The Vegetation Change Tracker (Huang et al., 2010), Breaks for Additive Seasonal and Trend (Verbesselt et al., 2010), Landtrendr (Kennedy et al., 2010), and Continuous Change Detection and Classification (Zhu et al., 2012) algorithms are very effective at detecting these types of change features, but their abilities to assess change information associated with gradual change are less developed. In part, this is due to the variation in forms by which gradual change is manifest in the spectral data. The most straightforward trends to assess are those that (1) occur over long periods of time (e.g., over several decades), (2) have relatively steep spectral slopes, and (3) have low statistical inter-annual variability. Unfortunately, many of the trends that are ecologically meaningful do not exhibit these ideal characteristics. In reality, trends can be short-term (e.g., a few years or less), can be obscured at particular times of the year, and can have low-gradient

slopes with relatively high inter-annual variability. Development of appropriate algorithms to detect gradual changes must take into consideration all of these characteristics. To complicate the issue, there are problems regarding how best to visualize and characterize results. It is more problematic to characterize a region that has undergone several different forms of trends at different time intervals and with different slopes, variability, and start times, than it is to portray a straightforward long-term trend, such as forest growth following harvest. One possibility is to treat the different types of trends based on a stratification approach, such as analyzing trends by land-cover types (e.g., forests vs. grasslands) or perhaps ecoregions. This would simplify the interpretations and enable managers and scientists to develop better understanding of the trends that are taking place on a case by case basis. Another approach is to partition observations by time interval to learn how much of the landscape is undergoing gradual change during slices of time that coincide with particular drivers of interest. Research is needed to develop techniques for characterizing and visualizing information about gradual change.

Validating gradual change is a greater challenge. Providing validation and accuracy assessments for large-area cover-type maps and associated abrupt-change products has always been a difficult undertaking for the remote sensing community, and has been discussed in a number of studies (Cohen et al., 2010; Huang et al., 2010; Thomas et al., 2011). Validation is expensive and often undervalued, and practitioners of land-cover and land-change products may not fully appreciate the suite of considerations for designing a robust validation design (Olafsson et al., 2014). Longstanding issues with upscaling of field- or other fine-scaled validation data to the scale of land-cover products, and temporal inconsistencies in acquisition dates of validation data versus product data, continue to confound efforts to quantify the quality of thematic land-cover and land-change products. All these challenges are compounded for assessing the accuracy of gradual-change products. Traditional validation designs have focused on verifying thematic cover types and abrupt thematic conversions. Gradual changes occur

within-class and require more labor-intensive forms of validation data acquired over long periods of time; these might include measures of spatial density of plants, species composition, plant vigor/health, and soil moisture availability, among others. Historical ground-reference data on land-cover types can be hard to find, but historical information on vegetation condition is even rarer.

Researchers have begun addressing the complex demands of validating gradual change in a variety of ways, borrowing some approaches from those who study plant phenology. Collection of field validation data carries the usual challenges of mismatched spatial scales, but also requires obtaining observations through time (e.g., Lambert et al., 2013; Liang et al., 2011; Rautianinen et al., 2012; Serbin et al., 2013; Steinberg et al., 2006). Similarly, researchers can upscale remotely sensed data from higher spatial resolution sensors to validate gradual change detected with coarser-scaled sensors (e.g., Hutchinson et al. 2015; Steinberg et al., 2006; Wei et al., 2012). Complementary historical data, such as from weather station point data or derivative surfaces, have been used to provide evidence that corroborates observed gradual changes (e.g., Brandt et al., 2014; Shi and Liang, 2014). Classic space-for-time substitutions can be appropriate for validating certain applications of gradual change, such as tracking recovery from fire disturbance (e.g., Chen et al., 2005). Cross-validation has proven useful when suitable independent validation data are unavailable (e.g., Shi and Liang, 2014). Less traditional has been the use of citizen science/public source data, as with available camera networks (Graham et al., 2010) or phenological observation sites (Kross et al., 2011). A qualitative approach incorporating surveys of in-depth local knowledge can lend support and interpretive value to more quantitative findings (Brandt et al. 2014).

Olofsson et al. (2012) and Stehman et al. (2012) have given thought to developing a global data set for validating thematic products for land cover and abrupt land-cover change. They stress the importance of a probability sampling protocol, an ability to augment samples and produce accuracy estimates for multiple spatial units, and a need to maintain simple and consistent estimation protocols. Although these attributes could be used for validating gradual change, as well, the potential for populating the validation dataset with standardized measures for gradual-change variables would be much more challenging and harder to implement than for thematic land-cover change.

8. Summary and Conclusions

The 30+ years of Landsat TM, ETM+ and OLI data provide us with unprecedented opportunities for assessing landscape changes. The data sets provide us not only with the opportunity to assess major land-cover conversions, but also to assess the gradual changes that are taking place. Eventual expansion of time-series analyses to include data from the MSS archive will provide us with more than 43 years of continuous coverage at scales relevant to natural resource planners and managers. Although the individual Landsat sensors have changed through time, the spectral characteristics from Landsats 4-8 are reasonably comparable and support the generation of dense time-series spectral information. Factors such as intra- and inter-annual differences in phenology, moisture conditions, and atmospheric conditions such as haze and smoke are likely to have bigger impacts on the spectral signals than are the differences related to sensor characteristics.

As discussed throughout this paper, there are many ecological insights that can be gleaned from analyzing Landsat time-series data sets. Although sometimes it is reasonably straightforward to explain the trends we can observe with Landsat time-series data, such as rapid vegetation growth following

disturbance events or vegetation declines following insect outbreaks, many cases will require significant “sleuthing” activities to interpret. Steady declines or increases in greenness over long periods located in areas largely devoid of significant direct anthropogenic impact, such as areas of long-established national parks, will require ancillary data to test hypotheses and deduce explanations. Whereas the reasons for such changes could generally be explained with detailed field-based data sets, such information typically does not exist at the necessary spatial and temporal scales.

Historical land use and climate are two of the most important types of information to help explain the gradual changes we find in our Landsat time-series data sets. Many of the long-term spectral trends in the time-series data have their roots in a legacy of historical land-use changes, and it is important to understand a region’s history when we analyze data on trends. For example, logging and grazing in forested environments can set in motion a sequence of reforestation and successional stages that carry influence across multiple decades to centuries. It is important that we consider such historical legacies as we interpret the spectral data of gradual change. Climate also undeniably impacts vegetation spectral trends, and although we are making significant progress in understanding relations between climate variables and plant growth (e.g., Walther et al., 2002; Anderegg et al., 2013), there is much more to understand. Analyzing climate data in conjunction with gradual-change data sets will help to further our understanding of these relations. Moreover, the ability to detect early-warning signs with the onset of gradual change in vegetation communities will be an important step towards improving our abilities for biological forecasting. As discussed in Barnosky et al. (2012), anticipating biological surprises will be crucial for guiding the future of the global ecosystem and human societies. Determining where and when climate-induced gradual ecological changes are occurring using Landsat time-series data will play a key role for these purposes.

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Figure 1. Pixel by pixel comparison of Landsat 7 versus Landsat 8 atmospherically corrected reflectance values for homologous bands. Data were acquired on July 20, 2013 (Landsat 7), and July 28, 2013 (Landsat 8), and are for path 45, row 30 (Oregon, USA). Turquoise indicates the highest frequency of observations. The ideal case would be for turquoise points to be located on the “one-to-one” (red) line.

Figure 2. Comparisons showing the mean of Landsat 7 versus Landsat 8 linear regression results $\pm$ 1 standard deviation, for six reflectance bands generated using non-agricultural, non-urban vegetation pixels. Averages are based on results using four different World Reference System-2 path/rows (locations depicted in the inset), with two Landsat 7 versus 8 comparisons made per path/row. In the inset map: 1=path 45/row 30; 2=36/38; 3=35/32; and 4=31/27.

Figure 3. Comparisons between all individual scene pairs showing the relationship among the Landsat 7 vs 7, 8 vs 8, and 7 vs 8 observations. Top graph shows the slope values derived from the linear regressions, and the bottom graph shows the r^2 values. Comparisons are for the six reflectance bands, and were generated using the same pixels as used in Figures 1 and 2. NIR, SWIR-1 and SWIR-2 represent the near-infrared, shortwave-infrared 1 and shortwave-infrared 2 bands, respectively.

Figure 4. A. Shortwave-infrared 1/near-infrared/red RGB image from Landsat 8 acquired on September 1, 2013. Green represents dense conifer forest, pink represents sparse conifer forest, and light and dark purple areas are barren. 1=Pumice Desert; 2=Region of forest decline; 3=Mt. Bailey; 4= Mt. Thielsen. B.

1063 Image showing 1985–2014 NDVI trends. Bright areas indicate increased greenness over the period; dark
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1065 map shown in Figure 1.

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1067 Figure 5. NDVI temporal trajectories for selected pixels in an area near Crater Lake National Park,
1068 Oregon, USA. Linear regression lines, equations, and r-square values are shown for pixels that did not
1069 undergo a major disturbance during the 30-year time period. “L7” label near the x axis denotes the years
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1075 Figure 6. Mean 1985–2014 NDVI trends, as measured by linear regression of NDVI versus time for all
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1077 increased greenness over the time period. The highest greening tends to occur near tree line. The
1078 lowest values are located in barren areas above tree line.

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1080 Figure 7. NDVI temporal trends using all available clear observations from Landsats 5, 7, and 8 for
1081 individual pixels from an area near Crater Lake National Park, Oregon, USA. Red points are from Landsat
1082 5 TM; black points are from Landsat 7 ETM+; and blue points are from Landsat 8 OLI. Circles depict
1083 major change events. A. Pumice Desert. B. Forest growth on fringes of Pumice Desert. C. Forest decline
1084 east of Pumice Desert. D. Forest regrowth following harvesting in 1989.

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1086 Figure 8. NDVI temporal trends using all available clear observations from Landsats 5, 7, and 8 for
1087 individual pixels representing different types of change. Red points are from Landsat 5 TM; black points
1088 are from Landsat 7 ETM+; and blue points are from Landsat 8 OLI. Circles depict major change events.
1089 A. Wetland in North Dakota, USA. B. Drought area in southern Arizona, USA. C. Pine bark beetle
1090 infestation in Colorado, USA.

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1105 Table 1. Examples of types of gradual change and the users of such information.

Gradual Change	Examples	Example Stakeholders	Event Duration	References
Disturbance from pest infestations	Mountain pine beetle ¹ or western spruce budworm	Foresters	Several years	Meddens et al., 2013; Liang et al., 2014; Vogelmann et al., 2009
Climate-induced die-off	Climate-induced die-off in pinyon-juniper and aspen in southwestern US	Climate change community	Decades	Yang et al., 2012; Huang and Anderegg, 2012;
Shifts in phenological cycles	Longer growing seasons in Arctic	Climate change community	Decades or more	Zeng et al., 2013; Hamunyela et al., 2013;
Forest growth and succession	Succession after harvesting	Carbon community	Several years to decades or more	Czerwinski et al., 2014; Gomez et al., 2011
Invasive species	Cheatgrass and buffle grass	Range biologists, conservation groups	Several years to decades or more	Clinton et al., 2010; Marshall et al., 2014
Biome shifts	Vegetation changes at tree lines in mountains	Climate change community	Decades to centuries	Mathisen et al., 2014; Beckage et al., 2008
Shifting patterns of agriculture ¹	Increases in specific crops related to the ethanol industry	Commodity industry	Several years	Rudorff et al., 2010; Brown and Pervez, 2014
Wetland changes	Cyclical climate effects on water levels in North American Prairie Pothole region	Wetland ecologists	Several years or more	Klemas, 2011; Moser et al., 2014; Gomez-Rodriguez et al., 2010
Gradual impacts from pollution	Forest die-back; Water quality	Foresters, water quality managers	Years to decades	Tote et al., 2014; Bresciani et al., 2011
Overgrazing	Overgrazing in grass and shrub ecosystems	Rangeland managers	Several years	Liu et al., 2013; Wylie et al., 2012
Desertification and recovery processes	Degradation and greening in the Sahel	Global change community, pastoralists	Years to decades or more	Dardel et al., 2014; Albalawi and Kumar, 2013

1106 ¹These types of gradual change are principally observable at scales broader than the individual pixel.

1107 Table 2. Wavelength ranges (in micrometers) for the reflectance bands common to sensors on Landsats
 1108 4, 5, 7, and 8.

Spectral Band	Landsats 4, 5 TM	Landsat 7 ETM	Landsat 8 OLI
Blue (Band 1 TM/ETM+; Band 2 OLI)	0.45–0.52	0.45–0.52	0.45–0.51
Green (Band 2 TM/ETM+; Band 3 OLI)	0.52–0.60	0.52–0.60	0.53–0.59
Red (Band 3 TM/ETM+; Band 4 OLI)	0.63–0.69	0.63–0.69	0.64–0.67
Near-infrared (Band 4 TM/ETM+; Band 5 OLI)	0.76–0.90	0.76–0.90	0.85–0.88
Shortwave-infrared 1 (Band 5 TM/ETM+; Band 6 OLI)	1.55–1.75	1.55–1.75	1.57–1.65
Shortwave-infrared 2 (Band 7 TM/ETM+; Band 7 OLI)	2.08–2.35	2.09–2.35	2.11–2.29

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Figures

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