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EMPHASIZING NEW IDEAS TO STIMULATE RESEARCH IN ECOLOGY

A survival guide to Landsat preprocessing

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Abstract. Landsat data are increasingly used for ecological monitoring and research. These data often require preprocessing prior to analysis to account for sensor, solar, atmospheric, and topographic effects. However, ecologists using these data are faced with a literature containing inconsistent terminology, outdated methods, and a vast number of approaches with contradictory recommendations. These issues can, at best, make determining the correct preprocessing workflow a difficult and time-consuming task and, at worst, lead to erroneous results. We address these problems by providing a concise overview of the Landsat missions and sensors and by clarifying frequently conflated terms and methods. Preprocessing steps commonly applied to Landsat data are differentiated and explained, including georeferencing and co-registration, conversion to radiance, solar correction, atmospheric correction, topographic correction, and relative correction. We then synthesize this information by presenting workflows and a decision tree for determining the appropriate level of imagery preprocessing given an ecological research question, while emphasizing the need to tailor each workflow to the study site and question at hand. We recommend a parsimonious approach to Landsat preprocessing that avoids unnecessary steps and recommend approaches and data products that are well tested, easily available, and sufficiently documented. Our focus is specific to ecological applications of Landsat data, yet many of the concepts and recommendations discussed are also appropriate for other disciplines and remote sensing platforms.

Key words: atmospheric correction; change detection; decision tree; ecology; image; normalization; radiometric correction; remote sensing; review; satellite; topographic correction; workflow.

INTRODUCTION

Landsat data have become exceedingly integrated into Earth observation and monitoring applications, particularly within the last decade (Wulder et al. 2012, Turner et al. 2015). This recent increase is due in part to Landsat's free and global coverage; when Landsat data became freely available in 2009, the USGS saw a 50-fold annual increase in image downloads (Miller et al. 2011). The Landsat program's ever-expanding image archive is an invaluable data set for ecological monitoring, change detection, and biodiversity conservation (Cohen and Goward 2004, Loveland and Dwyer 2012, Kennedy et al. 2014, Turner et al. 2015, Vogelmann et al. 2016). Before these data can be used for certain ecological analyses,

they must be preprocessed to account for sensor, solar, atmospheric, and topographic effects. However, each preparation step further alters the data from their original values, increasing the potential to introduce error (Kennedy et al. 2009). Determining the appropriate level of preprocessing is a significant barrier to non-remote sensing scientists who lack expertise in the numerous and constantly changing techniques necessary to preprocess these data (Pettorelli et al. 2014). This difficulty is exacerbated by preprocessing approaches that are similar but distinct, each with numerous possible workflows that analysts must navigate. Furthermore, explanations of the specific preprocessing steps taken in ecological studies vary; some offer detailed technical accounts, while others provide just a few broad summary sentences. These inconsistencies result in confusion and ambiguity, particularly for researchers and managers who would like to use Landsat data in their work but do not have a clear roadmap for how to do so.

Terminology adds to the challenge of determining the most appropriate preprocessing workflow. The remote sensing community has made efforts to standardize its terminology (Schaepman-Strub et al. 2006), but terms are often conflated in more applied studies published in ecological journals. This contributes to the continued use of outdated or redundant terms, which creates confusion for researchers attempting to reproduce or expand on published research methods.

Our purpose is to clarify and synthesize the preparation of Landsat imagery for ecological applications. We begin with a concise overview of the Landsat missions. We then describe the different levels of preprocessing and the sequence in which preprocessing steps should be applied, while clarifying inconsistent remote sensing terminology (Appendix S1: Table S1). Finally, we present a decision tree to help analysts determine the level of preprocessing necessary for their study, and provide examples of its implementation in common ecological analyses. We stress that this paper does not contain the only available or appropriate approaches for all circumstances, nor is it meant to serve as an introduction to the field of remote sensing. Our aim is to address common questions that have repeatedly been raised during our collective experience as scientists working with Landsat data. As such, this paper is intended as a guide for novice users of Landsat imagery as well as a concise reference for those with more experience.

Overview and synthesis of the Landsat missions

The National Aeronautics and Space Administration (NASA) launched the first Landsat satellite in 1972 and has since followed with six successfully launched satellites (Fig. 1). While NASA builds and launches the satellites, the U.S. Geological Survey (USGS) has operated the missions since the 1990s. The Landsat program offers a near-continuous record of imagery, but there are a number of differences among the satellites and sensors that pose challenges for experts and non-experts alike (Table 1). For example, the spectral range of many bands have changed, which can create issues for time series analyses (e.g., Holden and Woodcock 2016). The Landsat satellites have been organized into three groups based on their sensor and platform characteristics (Chander et al. 2009) and in the following section, we modify this framework and include recent and upcoming Landsat missions.

The first group, Landsat 1–3, were equipped with the Multispectral Scanner (MSS), which recorded data in four spectral bands; two visible and two near-infrared (NIR; Table 1). The next group, Landsat 4–7, carried either the Thematic Mapper (TM) or Enhanced Thematic Mapper (ETM+) sensors, which featured finer spatial resolution (i.e., pixel size), and increased radiometric resolution (i.e., bit depth) than the MSS. This group also had expanded spectral coverage, adding bands in the middle-infrared and thermal-infrared wavelengths. It is worth noting that the middle-infrared is now often referred to as the shortwave infrared (SWIR). While middle-infrared and SWIR generally cover different, but largely overlapping, spectral ranges, the relevant Landsat bands fall within this overlap. For these reasons, we use the term SWIR.

The satellites in the TM/ETM+ group have slightly different characteristics from one another. In addition to the TM instrument, Landsat 4–5 also had an MSS scanner onboard. Landsat 7 included a panchromatic band with increased spatial resolution. The third group currently consists of Landsat 8, equipped with its Operational Land Imager (OLI) and Thermal Infrared (TIRS) sensors. The OLI augments the spectral resolution of the TM group with the addition of a deep blue and a cirrus band, while TIRS adds a second thermal band. These instruments also offer a number of sensor and calibration improvements over the previous Landsat missions (Roy et al. 2014). The other member of the third group, Landsat 9, is currently planned as an upgraded rebuild of Landsat 8 and is scheduled to be launched in 2020.

The data generated from the Landsat program offer a number of characteristics that can support ecological
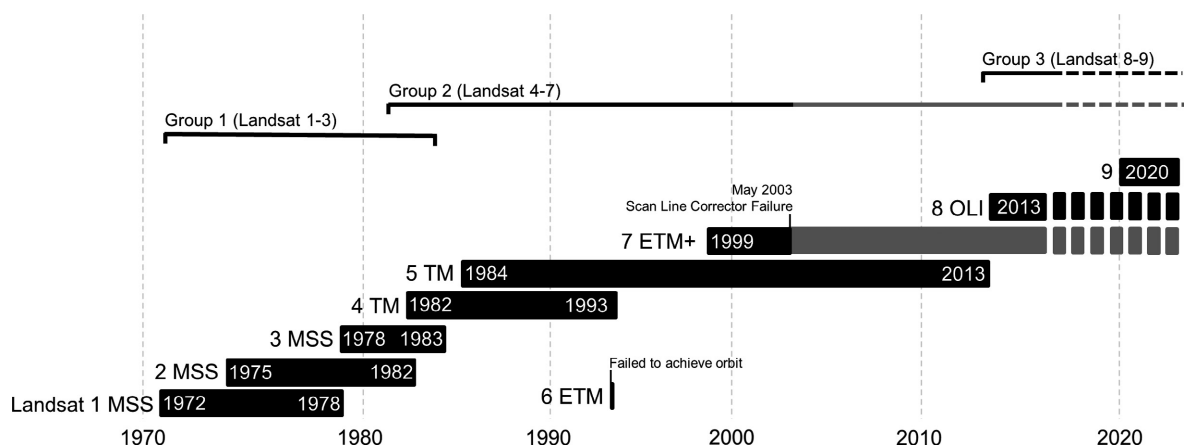

FIG. 1. A timeline of Landsat satellites and sensors. Landsat 9 launch date is based on recent congressional appropriations language.

TABLE 1. Summary of band designations and pixel size (m) for all Landsat satellites (LS) and sensors.

Landsat sensor	LS 1–5 MSS	LS 4–5 TM	LS 7 ETM+	LS 8 OLI/TIRS	Pixel size (m)
Coastal aerosol				B1 (0.43–0.45)	30
Blue		B1 (0.45–0.52)	B1 (0.45–0.52)	B2 (0.45–0.51)	30
Green	B1 (0.5–0.6)	B2 (0.52–0.60)	B2 (0.52–0.60)	B3 (0.53–0.59)	30 (60† for MSS)
Red	B2 (0.6–0.7)	B3 (0.63–0.69)	B3 (0.63–0.69)	B4 (0.64–0.67)	30 (60† for MSS)
NIR 1	B3 (0.7–0.8)				60
NIR	B4 (0.8–1.1)	B4 (0.76–0.90)	B4 (0.77–0.90)	B5 (0.85–0.88)	30 (60† for MSS)
SWIR 1		B5 (1.55–1.75)	B5 (1.55–1.75)	B6 (1.57–1.65)	30
SWIR 2		B7 (2.08–2.35)	B7 (2.09–2.35)	B7 (2.11–2.29)	30
Thermal		B6 (10.40–12.50)	B6‡ (10.40–12.50)	B10 (10.60–11.19) B11 (11.50–12.51)	30†
Pan-Chromatic			B8 (0.52–0.90)	B8 (0.50–0.68)	15
Cirrus				B9 (1.36–1.38)	30

Notes: The table shows each band number and the corresponding wavelength range (in parentheses, micrometers). The exact spectral range of each band varies among sensors, but are comparable for many applications. The MSS bands were originally numbered 4–7, but were relabeled 1–4 with the launch of Landsat 4. Empty cells occur where a particular sensor was not present in a satellite. This table was adapted from USGS (2015*a*).

† Data are recorded at a coarser pixel size, but upsampled and delivered at the size listed in table. Native pixel size of MSS data was 79 × 57 m. Native pixel size of thermal data has changed with the sensors: 60 m (TM), 120 m (ETM+), 100 m (TIRS).

‡ Landsat 7 thermal data are acquired at both high and low gain settings. The data are therefore delivered with two Band 6 files (USGS 2015*a*).

studies (Pasquarella et al. 2016). The multispectral bands enable local to regional-scale mapping of vegetation type and condition (Jones and Vaughan 2010). The NIR and SWIR bands are particularly useful for mapping plant and soil moisture characteristics, as well as water quality in wetlands, rivers, and coastal environments (Roy et al. 2014). The thermal infrared bands play an important role in mapping and understanding wildfire ecology (Wang et al. 2010), managing of water resources and monitoring of evapotranspiration (Anderson et al. 2012), and land cover classification (Sun and Schulz 2015). The majority of Landsat data are delivered at a pixel size of 30 m (Table 1). This pixel size prevents fine-scale mapping of surface features; however, it is often beneficial in ecology, as it accurately captures landscape-scale characteristics while avoiding the significant computational requirements associated with hyper-spatial and hyper-spectral sensors. This pixel size also tends to correspond well with many management-level activities. Landsat 4–8 have a revisit interval of 16 d (Schowengerdt 2007), which facilitates studies of landscapes through time (for a review, see Hansen and Loveland 2012, Willis 2015). Additionally, ecologists have increasingly incorporated Landsat imagery, Global Positioning System (GPS) field data, topographic data, and other ancillary variables in correlative spatial models over the last decade.

Data coverage and dissemination

Landsat satellites record data as they orbit the Earth; these data are then systematically partitioned into images based on scene location and date. The terms scene and image are often confused in the literature when referring to these data. We use the framework provided by Strahler et al. (1986) who define the scene as the extent, or footprint, that exists on the ground, while the image is the collection of spatially arranged measurements (i.e., bands) captured in the scene at a single time. Each scene has an assigned location that is defined by the Worldwide Reference System (WRS). This system assigns a path determined by the satellite's orbit (i.e., vertical, latitudinal) and a row (i.e., horizontal, longitudinal) for each scene, providing a global index for database cataloging, querying, and dissemination. Landsat data are distributed in two WRSs; Landsat 1–3 follow WRS1, while Landsat 4–8 follow WRS2 due to the differing orbit altitudes of the satellites.

The USGS manages Landsat data and disseminates them via a number of online portals (e.g., EarthExplorer; USGS 2015*b*). Although a number of Landsat-based data products are available at various levels of preprocessing (e.g., WELD; Roy et al. 2010), we focus on the current and primary Landsat archive processed by the USGS, with particular emphasis on the Level-1 and higher-level Climate Data Records (CDR) products. Level-1 products are a part of the Collection 1 data systematically processed by the USGS to standardized tiers based on data quality and processing level, while higher-level CDR products provide additional levels of preprocessing. These products are explained further in the following sections. At this time, former Landsat products (e.g., L1T) are being reprocessed to be included in the Collection 1 Level-1 data archive.

The USGS is working on a project to provide data in an alternative format called Analysis Ready Data (ARD) as an addition to the products already available. The initial purpose for these data is to provide standardized products for users of large data amounts over space and/or time and to reduce or eliminate the need for preprocessing. These efforts may provide a reasonable alternative to some or all of the preprocessing steps described below for

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certain users, but understanding the motivation and steps of preprocessing will still be valuable in determining whether Level-1 or ARD is appropriate.

<center>PREPROCESSING</center>

Images acquired by Landsat sensors are subject to distortion as a result of sensor, solar, atmospheric, and topographic effects. Preprocessing attempts to minimize these effects to the extent desired for a particular application. However, preprocessing steps are time-consuming, imperfectly address the artifacts to be removed, and have the potential to introduce additional sources of error. Many ecological applications require further preprocessing than that provided by Level-1 products or even CDR products before performing an analysis. These preprocessing steps can significantly impact analysis results (Sundaresan et al. 2007) and have a general order in which they should be performed. While methods sections in the literature commonly mention these steps, the justification or reasoning for performing them are often vague or omitted, creating confusion about which steps should be considered and what they accomplish for a particular application. In this section, we provide a description of the most common preprocessing steps applied to Landsat products and their importance.

Before preprocessing Landsat imagery, it is important to understand the units commonly associated with these data: digital number (DN), radiance, and reflectance for the visible to SWIR (vis-SWIR) bands and, for the thermal bands, DN, radiance, and temperature (Fig. 2). Initial sensor-recorded signals are calibrated to radiance values using gains and offsets that differ among sensors and over time due to sensor degradation. Radiance (watts·steradian^{-1}·m^{-2}·µm^{-1}) is the measure of energy flux recorded by the sensor. These values are then rescaled to digital number as 6-bit or 7-bit (MSS), 8-bit (TM, ETM+), or 12-bit (OLI, TIRS) unsigned integers

(Chander et al. 2009). Landsat Level-1 products are delivered as digital numbers, which can be converted to absolute units of radiance or reflectance. Reflectance is a unitless measure of the ratio of radiation reflected by an object relative to the radiation incident upon the object. Ecological studies most commonly use DN and reflectance. For the thermal bands, studies often use DN or temperature (degrees Kelvin).

Preprocessing to these specific units, along with correcting for radiometric artifacts, typically follows a general workflow (Fig. 3). Most of the steps can be classified into three broad groups: geometric, absolute, and relative. Some steps convert the imagery from one unit to another (e.g., at-sensor radiance to top-of-atmosphere reflectance via solar correction), while others specifically address potential artifacts (e.g., topographic correction). We present the workflow assuming the analyst is starting with either Level-1 or high-level surface reflectance CDR products. Although other products (e.g., Level 0 raw imagery) may be desired for a particular analysis, they are rarely used in ecological studies and require additional expertise and understanding to process. Note that Level-1 products have assumptions (e.g., the use of cubic convolution resampling vs. alternative resampling methods) that may need to be considered for some applications. The preprocessing steps presented in the workflow can be implemented using a variety of software packages that continue to develop and improve. Some free options include R packages 'RStoolbox' and 'landsat', as well as QGIS, GRASS GIS, Google Earth Engine, and MultiSpec. Proprietary software includes ENVI, ArcGIS, ERDAS IMAGINE, Geomatica, and MATLAB. Some of these software options provide a graphical user interface while others use command-line processing, which requires code input in various programming languages. Therefore, software selection is largely driven by the familiarity of the analyst and their collaborators with the software as well as the demands of a given analysis.
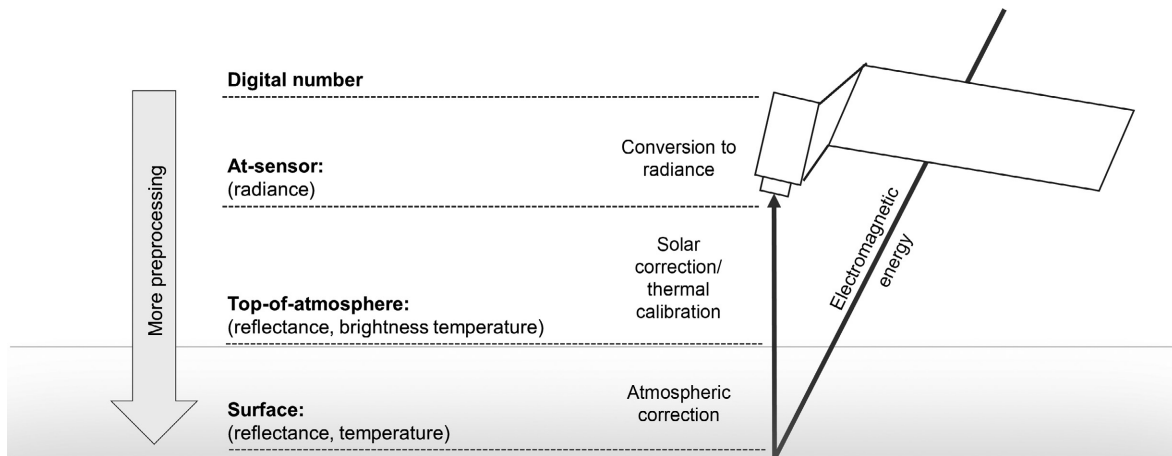

FIG. 2. The common units of Landsat imagery used in ecological analysis. The units change as each step of absolute correction is performed: conversion to radiance, solar correction/thermal calibration, and atmospheric correction.
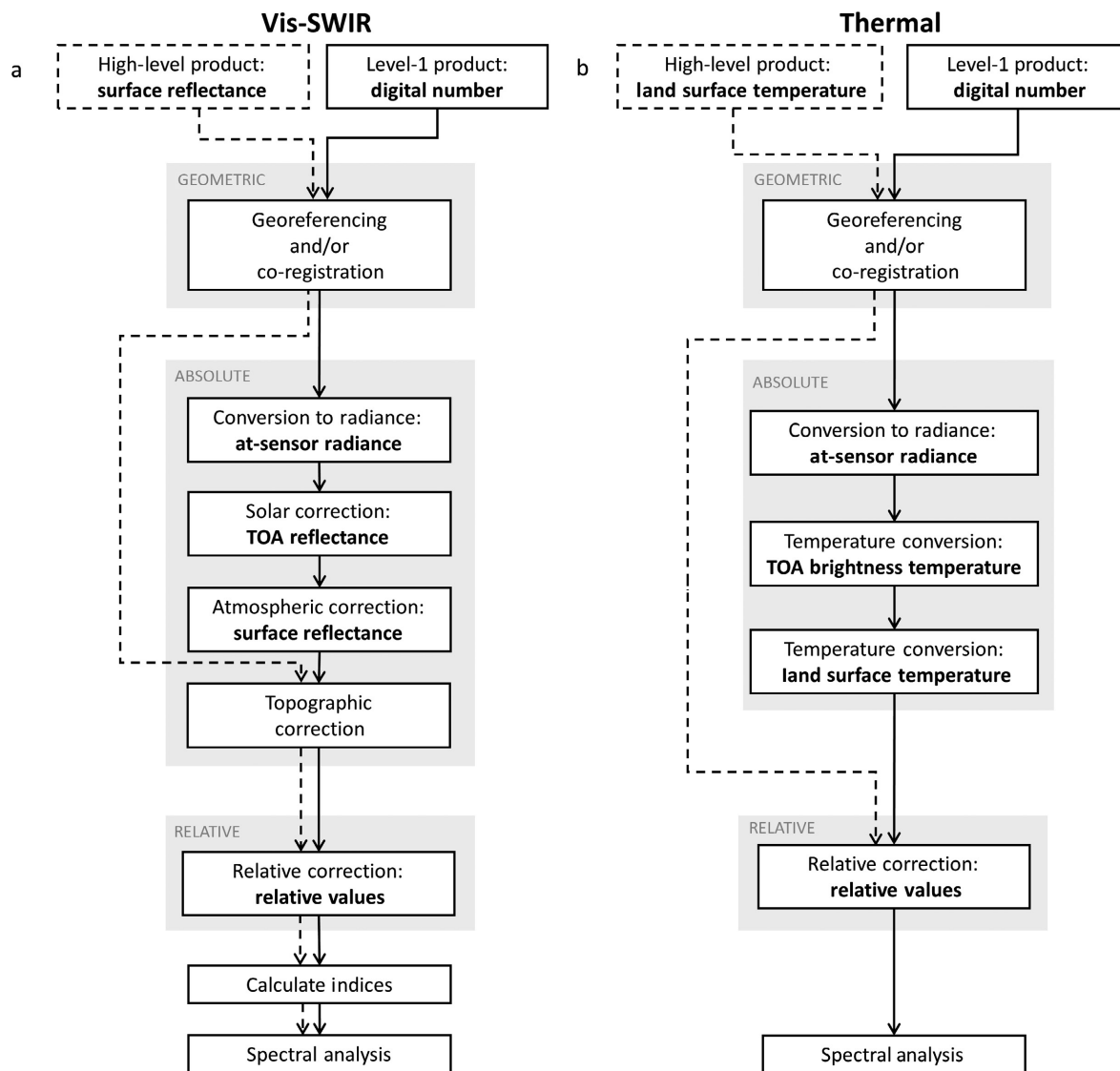
FIG. 3. Sequential workflow of potential preprocessing steps. Steps are presented in the recommended sequence, but not all steps are necessary for all analyses. Boldface type indicates preprocessing level. The two flowcharts show (a) general preprocessing steps for visual and shortwave infrared (vis-SWIR) data from both high-level data products (dashed line; e.g., Landsat surface reflectance CDR) and Level-1 Landsat products (solid line) and (b) the general preprocessing steps for thermal data. Note that a high-level land surface temperature product is not currently available, but is expected to be available soon. Refer to the section *Preprocessing* in the text for more detail and discussion of each step.

Geometric correction

The processes of georeferencing (alignment of imagery to its correct geographic location) and orthorectifying (correction for the effects of relief and view direction on pixel location) are components of geometric correction necessary to ensure the exact positioning of an image. Imagery can be positioned relative to the datum, topography, or other data types, including reference data and additional geospatial layers that might be used in the analyses. Landsat Level-1 products are precision registered and orthorectified through a systematic process that involves ground control points and a digital elevation

model (DEM). The Landsat Level-1 products are termed "terrain-corrected" and the majority of images can be used as delivered by the USGS (2015c). Collection 1 images are classified into tiers based on quality and processing level (USGS 2016c). Tier 1 products are consistently georegistered within ≤12 m radial root mean square error, making them suitable for time-series pixel-level analysis. The other tiers (currently Tier 2 and Real-Time) may not necessarily be as accurate and should be evaluated on a case-by-case basis. Comparatively, the geometric accuracy of Pre-Collection L1T products is approximately 30 m within the United States and about 50 m globally but the relative geolocation within an image

is much better (Loveland and Dwyer 2012). A small fraction of Tier 2 and Pre-Collection L1T images contain errors and there may be cases where specific Landsat images require additional georeferencing. For example, additional georeferencing is more likely to be needed when working across large spatial extents or timeframes, working with older imagery in the Landsat archive, or working in areas of the world where the USGS has not been able to obtain sufficient ground control points (although the USGS is continually improving its ground control; Bodart et al. 2011, Avitabile et al. 2012). When a workflow involves stacking multiple images, mosaicking adjacent images, compositing ancillary spatial layers, or using georeferenced ground data, the alignment of features in the images should be checked quantitatively with ground control points or, at the very least, through visual assessment. Discrepancies should be corrected prior to analysis using a process known as co-registration (often referred to as just registration). Registration involves aligning data layers relative to one another, while georeferencing involves aligning layers to the correct geographic location. Registration is a critical step in preprocessing Landsat imagery for ecological analysis, since a misregistration can result in significant errors, especially in change detection analyses (Sundaresan et al. 2007). When relating Landsat data to ancillary georeferenced data, such as GPS-marked plot data, images should be georeferenced rather than registered to maintain alignment between data. There are numerous approaches for both georeferencing and registering Landsat data, and the process might involve a simple pixel shift or a more complex automated feature detection and matching between images (for review, see Brown 1992, Zitová and Flusser 2003).

Absolute radiometric correction

Absolute radiometric correction (sometimes referred to as just absolute correction) can refer to a single preprocessing step or a collection of preprocessing steps that account for sensor, solar, atmospheric, and topographic effects. The term absolute is used to describe the process of obtaining "true" and comparable values, although the corrected values are still approximations. Values obtained from absolute correction can be compared (across time, space, or sensor) to images that have undergone the same level of correction. Some levels of absolute correction are better suited for comparing across images (e.g., surface reflectance/land surface temperature) than others (e.g., at-sensor radiance). The term absolute correction is heavily used in the Landsat preprocessing literature to clarify the interpretation of the resulting values, and is often contrasted with relative radiometric correction (see *Relative radiometric correction*).

Conversion to radiance

Significant efforts have been made to bring the data collected across the multiple Landsat missions and acquisition dates to a common scale for consistent Earth monitoring through time (Chander et al. 2009, Markham and Helder 2012). Digital numbers cannot be used to compare spectral values across time due to sensor degradation and differences between sensors. While DNs can be used effectively for many single-image analyses, absolute correction is needed to bring the values to a comparable scale. As described above, the DNs provided in Level-1 products are calibrated radiance values that have been scaled to varying bit depths. Conversion to radiance is the preprocessing step whereby the DNs are converted back to radiance (often termed at-sensor radiance) by using rescaling factors (i.e., calibration coefficients) associated with each band for a given sensor. The rescaling factors are stored in the metadata file associated with each image. Often this preprocessing step is described as sensor calibration, which specifically refers to the determination of the coefficients used to conduct the conversion, not the conversion itself. The conversion to radiance step is necessary before additional absolute correction steps; however, this level of preprocessing alone should rarely be used for analysis because the conversion is linear and therefore little additional information is gained relative to using DNs. Many of the available software programs will automatically perform this conversion, as well as an additional solar correction (see *Solar correction*), when supplied with the metadata file associated with the image (a text file with "MTL" in the name).

Solar correction

The next preprocessing step, solar correction, accounts for solar influences on pixel values. Solar correction converts at-sensor radiance to top-of-atmosphere (TOA) reflectance by incorporating exoatmospheric solar irradiance (power of the sun), Earth-Sun distance, and solar elevation angle. These vary with date, time, and latitude so their effects must be accounted for when working across multiple images, even within a single scene. Top-of-atmosphere reflectance is a measure of the proportion of incoming radiation reflected from a surface as detected from above the atmosphere. The solar correction step is often grouped with conversion to radiance in the literature. Similar to conversion to radiance, the solar correction values for Landsat data can be retrieved from the metadata files associated with each image or, in some cases, found in lookup tables. Landsat 8 provides coefficients to convert directly to a TOA reflectance product from DNs, but this should not be considered true TOA reflectance since the process does not provide a correction for the solar elevation angle (USGS 2014).

Atmospheric correction

The energy that is captured by Landsat sensors is influenced by the Earth's atmosphere. These effects include scattering and absorption due to interactions of the electromagnetic radiation with atmospheric particles (i.e.,
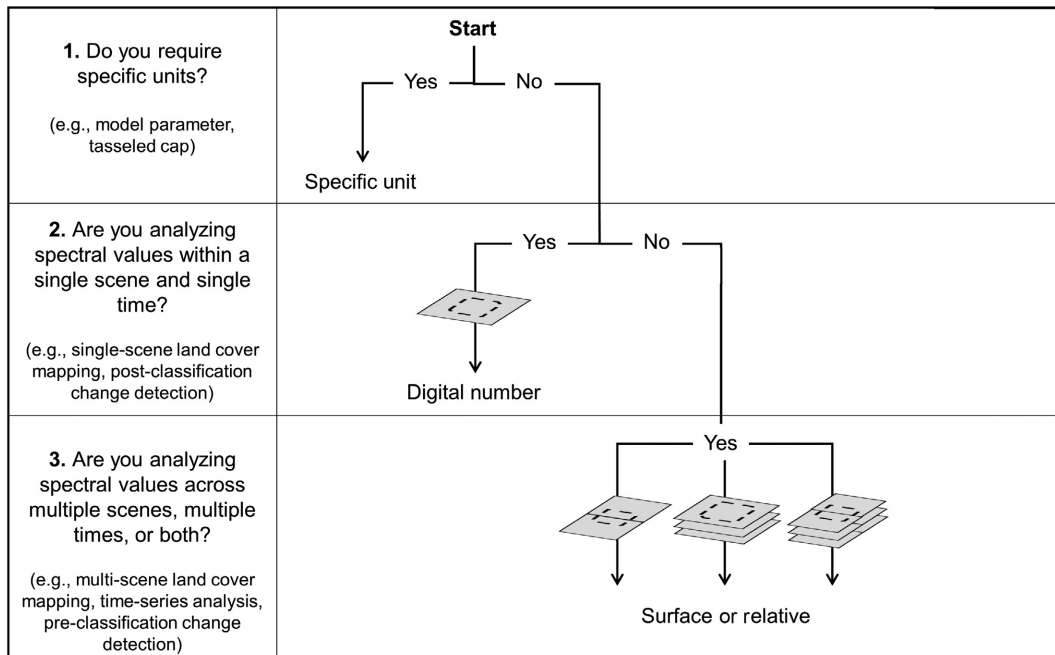
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FIG. 4. Dichotomous decision tree for determining the level of preprocessing necessary for most ecological applications, guided by the spatial and temporal extent of the study. The graphics on the tree branches represent images (gray squares) and the project study area (dashed lines). "Single time" refers to images captured on the same day (or closest day if adjacent paths) to represent one period in time, or images made into a mosaic to represent a single date. Normalization for multi-scene and multi-temporal studies should be done in two steps: horizontal (images from across multiple with same/similar dates) relative correction then vertical (images from across different times) relative correction.

gases, water vapor, and aerosols). Atmospheric correction attempts to account for these effects. However, some atmospheric effects are highly variable over the Earth's surface and can be difficult to correct in Landsat imagery. While it is not always necessary to atmospherically correct Landsat data to surface values, there are instances where this level of correction is needed. In general, absolute atmospheric corrections are needed when (1) an empirical model is being created for application beyond the data used to develop it, (2) there is a comparison being made to ground reflectance data such as a field-based spectroradiometer, or (3) as an alternative to relative correction when comparisons are being made across multiple images. All atmospheric correction methods have associated assumptions about the target and the nature of the atmospheric particles or emissivity (for land surface temperature). There are numerous atmospheric correction methods available, ranging from simple approaches that use only within-image information such as dark object subtraction (Chavez 1988), to more complex and data-intensive approaches such as the method used for the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) products (Masek et al. 2006). The complex methods are generally more accurate than simpler methods; however, they often require ancillary data about atmospheric conditions at the time of image collection and can be difficult to implement, especially for non-remote sensing experts. Further, these corrections can introduce additional errors (Schroeder et al. 2006). As

such, we recommend not performing atmospheric correction unless necessary (discussed in *Determining the appropriate level of preprocessing* and in Fig. 4) and to use freely available high-level products when needed (e.g., Landsat CDR; discussed in *High-level products*).

Topographic correction

Solar correction does not account for illumination effects from slope, aspect, and elevation that can cause variations in reflectance values for similar features with different terrain positions (Riaño et al. 2003). Topographic correction is the process used to account for these effects. While this correction is not always required, it can be especially important for applications in mountain systems or rugged terrain (Colby 1991, Riaño et al. 2003, Shepherd and Dymond 2003), which are common settings for satellite monitoring due to the difficulty of accessing these environments for field measurements.

An important distinction should be made between topographic and terrain correction. Topographic correction is a radiometric process while terrain correction is geometric in nature. Although Landsat Level-1 products are terrain corrected, this does not account for the same effects as a topographic correction. Terrain correction ensures each pixel is displayed as viewed from directly above regardless of topography or view angle, and, while important, does not account for the same effects as topographic correction.

Numerous methods exist for performing topographic correction. Band ratios are a simple way to partially reduce impacts from illumination effects without the use of a digital elevation model (DEM; Holben and Justice 1981, Colby 1991, Hale and Rock 2003). This method assumes reflectance will increase or decrease proportionally in both bands being used, however this assumption is demonstrably false for indirect radiation (i.e., diffuse irradiance; Leprieur et al. 1988, Conese et al. 1993). Conversely, more complex approaches can be used with a DEM to model the illumination effects by taking into account the specific slope and aspect of the terrain. Several methods are commonly used in the literature (Riaño et al. 2003, Vanonckelen et al. 2013), and numerous studies comparing these methods have been published with varying results depending on study location and application (e.g., Meyer et al. 1993, Lu et al. 2002, Hale and Rock 2003, Riaño et al. 2003, Richter et al. 2009, Hantson and Chuvieco 2011, Vanonckelen et al. 2013, Adhikari et al. 2015). While no specific topographic correction method is superior in all cases, the Minnaert Correction (Minnaert 1941) and C-correction (Teillet et al. 1982) methods have shown consistently good performance for removing topographic effects within Landsat imagery (Riaño et al. 2003, Gao and Zhang 2009, Richter et al. 2009, Hantson and Chuvieco 2011, Vanonckelen et al. 2013). Sola et al. (2016) provide a recent and thorough evaluation of many of these methods, which can be implemented in several open-source and commercial software products. Given the number of available approaches and the difficulty of their application by non-remote sensing experts, analysts should carefully consider whether a topographic correction is necessary for their study. While this preprocessing step can be more important than atmospheric correction for some applications in topographically complex regions (Vanonckelen et al. 2013), this step is not needed for every scenario.

Relative radiometric correction

Ecologists often conduct analyses that require consistent spectral values across space and time. However, such studies do not necessarily require the use of true surface reflectance values. A common preprocessing step when using multiple images is a relative radiometric correction or normalization (hereafter referred to as relative correction). Relative correction brings each band of an image to the same radiometric scale as the corresponding band of a reference image. This presumably accounts for sensor, solar, and atmospheric differences, but does not expressly account for vegetation phenological differences.

Similar to atmospheric and topographic correction, there are many approaches to relative correction, and there is no clear preferred method that consistently performs best across all applications (Chen et al. 2005). Relative correction typically uses the overlapping regions between a reference image and another image to be

transformed. Two general approaches are used to compare these overlapping regions. The first is histogram matching (also referred to as equalizing), which uses information from all pixels in the overlapping regions. We do not recommend histogram matching Landsat data, as this approach is generally used for relatively correcting multiple images from the same day when there is little variation in the solar and atmospheric conditions. Adjoining Landsat images collected on the same day (i.e., along the same path) can be mosaicked without a relative correction.

The second approach uses pseudo invariant features (PIF; generally consisting of one or more pixels) or pseudo invariant targets (PIT; generally a single pixel), where non-changing features or targets in the overlapping area are used to bring the images to a common scale (Schott et al. 1988). These pseudo invariant features/targets can be selected manually or automatically through statistical algorithms (Du et al. 2002, Bao et al. 2012). Comparisons have shown that performing a relative correction might provide more accurate results than an absolute atmospheric correction, especially when comparability is more important than the pixel value (Schroeder et al. 2006). Furthermore, some studies have performed relative correction of atmospherically corrected imagery to account for residual differences between images arising from imperfect preprocessing when surface reflectance is desired (Li et al. 2014). We suggest this approach only if both comparability between images and surface reflectance units are needed for a particular application. If the objective is to obtain images that are spatially or temporally consistent (and that is the only goal of the relative correction), then relative correction from a more basic preprocessing level, such as DN or TOA, would be the most appropriate option, as correcting to surface reflectance serves no purpose and injects a potential source of error.

Preprocessing for spectral indices

Spectral indices are transformations and reductions of spectral data that are used to highlight specific phenomena on the landscape. Indices facilitate data interpretation and comparison, both qualitative (e.g., pattern visualization) and quantitative (e.g., monitoring plant health). A plethora of spectral indices have been designed to highlight vegetation, hydrology, geology, burned areas, and snow, to name a few (for a review, see Jackson and Huete 1991, Bannari et al. 1995, Lozano et al. 2007). They can be particularly useful as relative measures where reference data do not exist to model such variables quantitatively.

The approach to preparing multiple bands for use in spectral indices should be the same as the approach for preparing individual bands for any analysis; the analyst should determine what level of preprocessing is necessary based on the characteristics and objectives of the study. Ratio-based indices account for multiplicative atmospheric artifacts, but do not correct additive effects and

atmospheric differences between bands. Therefore, when comparing spectral indices across multiple images (time or space), we recommend a correction to eliminate such effects. There are potential exceptions; notably, some indices have correction factors that are dependent on the data being in a specific unit, such as the soil adjusted vegetation index (reflectance) or the tasseled cap transformation (varies by sensor/method). Further, if image correction is not feasible, atmospherically resistant indices may be used to reduce some atmospheric effects (Pinty and Verstraete 1992, Huete et al. 1997).

High-Level Products

High-level Landsat products are data that have been preprocessed to a level beyond the specifications of Level-1 products and are directly available for download. These products eliminate the need for the user to complete certain preprocessing steps, a welcome advancement that simplifies the preprocessing workflow.

The USGS Landsat Surface Reflectance Climate Data Records (CDR) are the most notable of the current high-level data products. These are surface reflectance products that can be downloaded from multiple USGS sources (USGS 2015b, 2016a). The Landsat surface reflectance CDRs are processed to calibrate raw DNs to TOA reflectance (also available for download), and then corrected to surface reflectance using atmospheric parameters and a DEM. Furthermore, TOA brightness temperature, as well as masks for clouds, cloud shadows, adjacent clouds, land, and water are also available as high-level products from the USGS. Land surface temperature and MSS data are not currently included with the Landsat surface reflectance CDRs, however, the USGS has publicly stated its intent to release a land surface temperature product (Laraby 2016). The quality of the surface reflectance CDR products can be adversely affected by low sun angle, excessive clouds, high latitudes (>65 degrees north or south), or locations that are very arid or snow/water dominated (USGS 2015d). Moreover, the process to develop surface reflectance CDR products contains nonlinear elements, which can introduce error and unwanted data artifacts. Nevertheless, these data are the products of high-quality, well-documented approaches that are likely as reliable as any approach readily available to ecologists. Quality assurance layers are available as an additional USGS high-level product for pixel-level condition and validity flags.

The USGS continues to release additional high-level data and make improvements to the existing products. In addition to surface reflectance, the USGS has made available some of the most widely used spectral indices derived from Landsat Surface Reflectance high-level products (Masek et al. 2006). These products are generated from the surface reflectance data and therefore have the same caveats. However, they also carry additional assumptions inherent to the derivation of the indices themselves (e.g., coefficient values and correction factors; USGS 2016b). These are available through the USGS EROS Center Science Processing Architecture (ESPA) on demand interface (USGS 2016d). Furthermore, at the time of this writing, the USGS has expressed that they will deliver essential climate variables (ECVs) that will include land surface temperature, burned area extent, dynamic surface water, and snow cover area as additional high-level products in the near future. While these products will provide the data required to perform large extent and accurate ecological analyses with only a fraction of the preprocessing time, users will benefit from understanding the concepts and assumptions that are inherent in their creation.

Determining the Appropriate Level of Preprocessing

While understanding the levels and appropriate order of preprocessing steps provides a necessary foundation, the analyst is ultimately left with the question, "What level of correction is 'good enough' for my study?" To help answer this question, we start with the guiding principle that only the preprocessing steps necessary for a given analysis should be applied because each step may risk introducing artifacts and/or error into the data (Song et al. 2001, Riaño et al. 2003, Kennedy et al. 2009). Even with this core tenet, it can still be challenging to identify the appropriate level of preprocessing.

We designed a flexible decision tree to help navigate these choices (Fig. 4). The first row of the tree refers to analyses that require the data be converted to a specific value type, such as a parameter for an existing model. Beyond these scenarios, we recommend the analyst guide their decision by identifying how the spatial and temporal extent of their analysis relates to the existing scene boundaries. The questions in the decision tree specifically refer to when and where the *analysis of spectral values* is taking place within the broader workflow. Row two of the decision tree focuses on analyses taking place within a single image, and thus calls for the use of DNs to avoid unnecessary preprocessing. Row three considers analyses using multiple images. This could be multi-temporal (i.e., multiple images from different dates analyzed as separate time steps, also referred to as multi-date), multi-scene (i.e., images with different path/row designations), or a combination of the two. This row calls for either surface or relative units to account for differences between images resulting from sensor, solar, atmospheric, and topographic effects. In such cases, we recommend performing a relative correction to normalize values. Nevertheless, because relative corrections typically require more expertise than obtaining surface reflectance CDR products, these products can be a valid and convenient alternative with high accuracy (Vuolo et al. 2015), especially if the images are similar in time, phenology, or growing degree days. Caution should be exercised with this approach when the analysis spans different sensors (e.g., Landsat 7 ETM+ and Landsat 8 OLI) since systematic biases appear among their surface reflectance

values, and these biases can be magnified in products such as the normalized difference vegetation index (NDVI; Roy et al. 2016).

We illustrate these concepts in the following section by walking through three examples commonly encountered by ecologists working with Landsat data: specific value type, change detection, and correlative modeling. These examples are not intended to be exhaustive, but demonstrate the use and flexibility of the decision tree.

Example scenario 1: Specific value type

Landsat data are often used to measure specific physical properties of the Earth's surface. For example, a researcher may want to use Landsat data to measure surface albedo to evaluate post fire dynamics in a forest environment. Because surface reflectance is used to derive surface albedo, the researcher would require a specific value type (Fig. 4, row 1) and preprocess the data to surface reflectance. Another example is the tasseled cap transformation. The coefficients used for the tasseled cap transformation vary between Landsat sensors; some are intended to be used with reflectance data, while others require DNs. In this case, the researcher would again require a specific value type and identify the specific level of preprocessing required for their sensor.

Example scenario 2: Change detection

The Landsat program's historical archive makes it particularly useful for mapping environmental change. There are many approaches to change detection with remote sensing data, each with their own advantages and limitations. Most ecological studies addressing thematic change take either a pre-classification or post-classification approach.

Pre-classification change detection.—Pre-classification change detection involves comparing the spectral values from multiple dates and subsequently classifying the pixels by their change in values. Examples include image differencing (i.e., subtracting pixel values between each pair of bands) and multi-temporal principal component analysis, in which the bands of two images are combined into a single composite raster and the data are transformed to identify change classes. In these cases, the spectral values are being compared across images from multiple times, and the imagery should be preprocessed to either surface reflectance or relative values to ensure comparability (Fig. 4, row 3).

Post-classification change detection.—Post-classification change detection involves classifying images from multiple dates and subsequently comparing one categorical map to the other to identify changes. Consider a study designed to map forest loss by classifying the pixels of a 1980 Landsat image and a 2010 image of the same scene and subsequently calculating the changes in classes.

Although multiple times are used, the spectral values are being analyzed independently to create two categorical maps of forest cover because only one image is used for each classification. The analysis is detecting changes in the *cover classes* from each image, not the spectral values. It is therefore appropriate in this case to classify each image using its respective DN values (Fig. 4, row 2) and subsequently perform the change detection. If the analysis involved multiple scenes for each time period, then this would bring the user to the third row of the decision tree and preprocessing to relative values or using surface reflectance would be required (Fig. 4, row 3).

Example scenario 3: Mapping with correlative models

Landsat bands and derived spectral indices are increasingly used as variables in correlative models (e.g., regression tree analysis, random forests, MaxEnt). These are used to map continuous responses (e.g., percent cover, biomass, habitat suitability) as well as discrete classes (e.g., land cover type; He et al. 2015, Lawrence and Moran 2015). In such cases, if the study area is encompassed within a single image, DN is an appropriate preprocessing level to use (Fig. 4, section 2). However, including multi-temporal imagery in correlative models can significantly improve mapping of temporally dynamic features such as wetlands, vegetation, or deciduous forests (Baker et al. 2006, Evangelista et al. 2009, Savage et al. 2015). There are a variety of ways to include multi-temporal imagery in such models. Digital number is appropriate when bands or indices from multi-temporal images are included as individual model variables and the data are not combined in any way (e.g., differencing, ratioing). This is because the images are being treated as individual variables and no analysis is taking place between the spectral values prior to model development. However, if the bands or indices are planned to be combined to produce a new variable, the spectral analysis is taking place across time and the data should be corrected to surface or relative values before combination and subsequent model development (Fig. 4, row 3). If the study area spans multiple scenes for any of the scenarios above, surface reflectance or relative values are necessary (Fig. 4, row 3).

Conclusion

Landsat data are a rich resource for ecological analysis, but the literature and available resources to appropriately make use of these data are inconsistent, disjointed, and challenging to interpret for non-experts. Our overview and synthesis summarizes the Landsat sensor characteristics and clarifies key preprocessing steps necessary to work with the data. The workflow and decision tree can be used as guides for determining the necessary sequence of steps to achieve the appropriate level of image preprocessing for common ecological applications. Equipped with this knowledge, readers will be able

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to critically evaluate the approaches described in the literature and adapt them to their own application.

We recommend taking a parsimonious approach to preprocessing; correct the artifacts necessary for a particular application, but avoid unnecessary steps that may introduce additional artifacts without gaining additional value (Song et al. 2001, Riaño et al. 2003, Kennedy et al. 2009). When analyzing across multiple images, we recommend performing a relative correction to normalize values. However, the quality and availability of high-level surface reflectance products continue to improve (Vuolo et al. 2015) and we encourage readers to consider using these products while taking into account the assumptions inherent in their creation.

This survival guide reduces the potential for confusion and ambiguity that many scientists face when determining how to preprocess their imagery for analysis. A better understanding of Landsat preprocessing can improve reproducibility and accuracy as ecologists and others continue to develop new applications for remote sensing data. This will facilitate integration with other remote sensing programs, such as the European Space Agency's Sentinel-2 mission, which has similar spectral bands and is designed to integrate with the Landsat Program. Although there are still some issues when using these two data sources together (e.g., Storey et al. 2016), there are significant efforts underway (MuSLI, Multi-Source Land Imaging) to resolve them. This cross-platform consistency makes our conceptual workflow easily adaptable to current and future multispectral remote sensing missions, enabling unprecedented opportunities for comparative research and monitoring of ecological processes.

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