Remote sensing for studies of vegetation condition: Theory and application

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Citation:
Wulder, M.A., J.C. White, N.C. Coops, and S. Ortlepp, 2009. Remote sensing for studies of vegetation condition: Theory and application. Pages 357-367, Chapter 25 in: The SAGE Handbook of Remote Sensing, Edited by T.A. Warner, M.D. Nellis, and G.M. Foody, Sage Press, SAGE Publications Limited, London, United Kingdom, 504p. [peer reviewed]

DOI:
http://dx.doi.org/10.4135/9780857021052.n25

INTRODUCTION

Remotely sensed data is a proven source of information for detailed characterization of vegetation type (e.g., Gould, 2000; Luther et al., 2006), structure (e.g., Gamon et al., 2004; Healey et al., 2006), and condition (e.g., Rossini et al., 2006; Wulder et al., 2006a). The spatial, spectral, and temporal resolution at which the data is acquired is critical in how these vegetation properties are observed and may ultimately determine the success of a particular remote sensing application. Therefore, when undertaking applications with remotely sensed data, it is imperative to have a clear understanding of the information need that is to be satisfied, thereby allowing for the selection of the most appropriate imagery and analysis methods.

Previous Chapters have detailed the capture and characteristics of optical remotely sensed data (Ch. 2, 3, 7) over a range of spatial and spectral resolutions from both airborne and satellite platforms (Ch. 8-10, 14). Approaches to image processing (Ch. 15) and applications (Ch. 16-18, 20) have also been discussed. In this Chapter, we discuss the use of remotely sensed data for assessing vegetation conditions at landscape and tree levels, and the considerations that need to be made depending on a given information need. The goal of this chapter is to address the key issues that should be considered when using remotely sensed data to characterize vegetation, and through this, understand how operational applications may be undertaken.

IMAGE RESOLUTIONS AND DATA SELECTION

Remotely sensed data can be characterized by the image spatial resolution (pixel size), spectral resolution (wavelength ranges utilized), temporal resolution (when and how often are images collected), and radiometric resolution (the degree of differentiation within the dynamic range of the sensor). Vegetation is a complex target with a large amount of inherent spectral and spatial variability, and vegetation is typically characterized by strong absorption in the visible wavelengths, particularly the red wavelengths of the electromagnetic spectrum and high reflectance in the near-infrared (NIR) wavelengths. The amount of absorption or reflectance is controlled by vegetation type, amount, density, structure, and vigor. At the leaf scale, pigment concentrations, water content, and structure all contribute to variations in absorption, transmittance, and reflectance. In this section, we discuss the characteristics of remotely sensed data and consider how these various characteristics influence the remote sensing of vegetation.

Of the four resolutions typically used to characterize remotely sensed data, spatial resolution arguably has the greatest impact on the information content of remotely sensed data, particularly for vegetation targets. Strahler et al. (1986) posit a scene model, based on spatial resolution, for understanding the information content of remotely sensed data. In this model, there are either many objects per pixel (an L-resolution environment) or conversely, many pixels per object (an H-resolution environment) (Figure 1). The target objects of interest are therefore important for assessing the utility of a given spatial resolution for a selected application. Table 1 provides some examples of commonly used remotely sensed data sources and the type of vegetation information one may expect to extract from these data sources.

Recent advances in the development of satellites with fine to very fine spatial resolution (e.g. < 2 m), combined with the widespread availability of digital camera and scanning technologies, and increasingly sophisticated computer processing techniques, have contributed to an increase in the use of high spatial resolution imagery to estimate traditional and non-traditional vegetation attributes (Wulder et al., 2004a). However, with increased spatial resolution comes added complexity with respect to defining homogenous vegetation classes. While the increased textural information available in fine or very fine spatial resolution image data allows for improved interpretation based on the shape and texture of ground features, the current techniques used to process and analyze satellite image data, such as the use of standard vegetation indices or per-pixel based classifiers (e.g., maximum likelihood) may not be effective when applied to high spatial resolution image data (Goetz et al., 2003). In this H-resolution environment (Strahler et al., 1986), with many pixels per object (e.g. tree), there will be a large amount of spectral variability associated with individual trees (e.g., pixels representing sunlit crown, shaded crown, and the influence of factors such as branches, cones, and tree morphology). This variability confounds the development of unique spectral signatures for tree or vegetation classification (Culvenor, 2003).

Temporal resolution provides an indication of the time it takes for a sensor to return to the same location on the Earth's surface. The revisit time is a function of the satellite orbit, image footprint, and the capacity of the sensor to image off-nadir (e.g., not directly beneath the sensor, but at an angle). The timing of image acquisition should be linked to the target of interest; some disturbance agents may have specific bio-windows (*e.g.*, fire, defoliating or phloem feeding insects) during which imagery must be collected in order to capture the required information (Wulder et al., 2005), while other disturbances may be less time specific (e.g., harvest). For ongoing programs designed to monitor forest change before and after a disturbance event, the acquisition of images should occur in the same season, over a series of years (known as anniversary dates). Anniversary dates are critical to ensure the spectral responses of the vegetation remain relatively consistent over successive years (Lunetta et al., 2004). The reduction in image radiometric quality for off-season imagery resulting from low sun-angles and reduced illumination conditions compromises the ability to capture changes clearly. Selection of scenes captured at the same time each year may reduce issues related to sun angle, shadow, and overall scene brightness.

The temporal characteristics of an imaging system are also important. For some applications, the capacity to incorporate multi-temporal images can be advantageous. For example, analysis of vegetation at both leaf-on and leaf-off periods can provide important information on the land cover, especially for seasonally variable vegetation, such as deciduous species (Dymond et al., 2002). Aerial-acquisitions are in general more flexible regarding timing than satellite-acquisitions, with the ability to collect images on demand, for example, coincident with insect outbreaks or fires (Stone et al., 2001). For satellite images, there tends to be a trade-off between image spatial resolution and the typical repeat period for image acquisition. Generally, high spatial resolution imagery, including that from satellites such as IKONOS and QuickBird, is acquired from sensors that are able to view off-nadir, and therefore have the potential to revisit a location every 1 to 3.5, days depending on the latitude of the target location. Note however, that shorter revisit times come at the cost of off-nadir viewing. True-nadir image revisit time for QuickBird and IKONOS is 144 days, compared to 16 days for moderate resolution satellites such as Landsat.

Spectral resolution provides an indication of the number and the width of the spectral wavelengths (bands) captured by a particular sensor. Sensors with more bands and narrower spectral widths are described as having a higher spectral resolution. Currently, most operational remote sensing systems are multispectral and have a small number of broad spectral channels: Landsat-7 Enhanced Thematic Mapper Plus (ETM+) data has seven spectral bands in the reflective portion of the electromagnetic spectrum and one band in the thermal-infrared region. Hyperspectral data (*e.g.,* instruments with more than 200 narrow spectral bands (Lefsky and Cohen, 2003) are becoming more widely available (Vane and Goetz, 1993) both on spaceborne (such as the HYPERION sensor on the EO-1 platform) and airborne platforms such as HyMap (Cocks et al., 1998), CASI (Compact Airborne Spectrographic Imager) (Anger et al., 1994), and the NASA Advanced Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) (Vane et al., 1993). Since phenomena of interest (*e.g.* foliage discolouration) may be manifested in a specific portion of the electromagnetic spectrum, the number, width, and location of a particular sensor's spectral bands along the electromagnetic spectrum, will therefore determine whether the data from a given sensor is suitable for characterizing the phenomena.

Radiometric resolution may be interpreted as the number of intensity levels that a sensor can use to record a given signal (Lillesand and Kiefer 2000) and provides an indication of the information content of an image. Most remotely sensed data currently used for vegetation applications (e.g. Landsat, SPOT-5) have a minimum 8-bit radiometric resolution; if a sensor uses 8 bits to record data, there are 2^8 or 256 digital values available, ranging from 0 to 255. The finer the radiometric resolution of a sensor the more sensitive it is to detecting small differences in reflected or emitted energy (QuickBird has 11-bit data).

INFORMATION NEEDS AND APPLICATIONS CONSIDERATIONS

The growing number and types of remotely sensed data sources available simplify matching a data source to a particular information need. Since image characteristics determine the nature of the information that may be extracted from an image, this section demonstrates the importance of clearly defining the information need, as a precursor to the selecting appropriate data and analysis approaches. Methodological options may then be considered once the information need is clearly identified. Several logistical issues may emerge when acquiring remotely sensed data to address a specific information need. These issues include the scale at which the target must be measured (e.g., landscape-level or tree-level information); the attributes of interest (change, condition, spatial extent); cost; timeliness; and, repeatability. Independent of the information need defined, there will also be application specific data requirements. Many of these logistical issues stem from the acquisition and processing of these required data sources. While focused on a specific application, these issues may be considered as generic for remote sensing applications of vegetation.

The timing of image acquisition can have an impact on the quality of data extracted. Image acquisition characteristics often require compromise when images are being selected, since non-optimal years or seasons will have an impact on the nature and quality of information captured. Images collected during the winter months (e.g., October-March) can have a lower dynamic range (particularly true at more northerly latitudes), which can reduce spectral overlap between different cover types. Areas of shadow will also be larger, especially in areas of high topography, further reducing the dynamic range. Off-year imagery (that is, imagery from a different year than planned, even when creating a longer time interval) is typically preferred over off-season imagery, as off-season imagery generally requires more processing, includes phenological artifacts, and will reduce overall mapping quality (Wulder et al., 2004b).

Depending on the spatial extent of the area of interest and the required resolution, more than one scene may be needed to meet the information needs. For example, if the information need requires characterization of the temporal change in beetle damage over a large spatial extent, at least two dates of imagery will be required to measure the change, and multiple images will likely be required to fully cover the area of interest. By necessity, the infilling of image areas obscured by clouds and shadows could further increase the number of scenes required to facilitate complete spatial coverage of the area (Homer et al. 1997). Moreover, if the information need requires a high level of detail, the number of images further increases, given that remotely sensed data with a higher spatial resolution typically have a smaller image extent. Multiple images present several image processing challenges such as edge effects, geometric co-registration, image radiometric normalization, phenological and annual differences, and data handling issues.

The costs associated with the acquisition and processing of remotely sensed data are not insignificant. A landscape-level project generally requires the use of multiple scenes, presenting numerous image processing challenges. Tree-level characterization necessitates the use of higher spatial resolution imagery, which is generally much more expensive to acquire than data with a lower spatial resolution. While data acquisition will undoubtedly represent the bulk of the costs, additional costs may be associated with ancillary data processing (e.g., for calibration and validation), data management, and image analysis. Expertise in processing different types and potentially large volumes of remotely sensed and other geographic data, within a geographic information system (GIS) is also often required.

Ancillary data is required for calibration and validation of the analysis methods for most projects. Ancillary data sources are important for generating masks that will restrict the image analysis and aid in vetting the calibration and validation data points. Masks are often used to constrain the variability in spectral response resulting from cover types that are not of interest, such as water or cloud. The use of masks reduces the number of false positives and enables the processing of pixels where there is real change in the object of interest rather than a transition, for example, from cloud or shadow. The set of points remaining enables the interpretation of the results to be made under an assumption that the calibration and validation is not impacted by extraneous conditions. Rogan and Miller (2006) provide a summary of considerations and opportunities for integrating spatial and remotely sensed data to meet applications needs.

APPLICATION OPPORTUNITIES: SPECTRAL CHARACTERISTICS

Different portions of the electromagnetic spectrum may be exploited to satisfy different information requirements. In this section, we present some brief examples of how the visible, near-infrared, and shortwave-infrared portions of the spectrum have been used in a variety of applications, and how these various portions of the electromagnetic spectrum may be combined algorithmically in a vegetation index to further enhance feature discrimination. A more detailed of vegetation response in each portion of the electromagnetic spectrum may be found in Chapter 3.

Visible wavelengths

The visible portion of the electromagnetic spectrum spans 400nm-700nm with the spectral reflectance of vegetation in this part of the spectrum heavily influenced by leaf pigmentation, specifically chlorophylls a and b. These pigments reflect highly in the green portion of the spectrum (500nm) and absorbs the blue (450nm) and red (670nm) wavelengths (Hoffer, 1978). Other pigments that influence leaf absorption and thus reflectance include carotene, xanthophyll, and anthocyanins (Blackburn, 1998). Information on pigments, especially chlorophyll, has been used in applications ranging from agriculture to natural vegetation studies. Pigments are integral in the physiological function of a leaf, and can be used as indicators of its physiological state. For example, the amount of chlorophyll can be used as an indicator of plant productivity as it is linked to the amount of photosynthetically active radiation absorbed by the leaf, and thus to the photosynthetic rate (Gamon and Qiu, 1999).

A study by Zarco-Tejada et al. (2005) measured the chlorophyll content of the European grapevine at leaf and canopy levels to determine its physiological condition. For the leaf level, field based measurements of the pigment concentration were made, and a spectrometer was used to measure the reflectance properties of individual leaves. Concurrent canopy level data was acquired by three airborne hyperspectral imaging systems: CASI, ROSIS (Reflective Optics System Imaging Spectrometer), and DAID-7915 (Digital Airborne Imaging Spectrometer). Upon linking the leaf and canopy level data it was found that the best indictors of chlorophyll content used ratios calculated within the 700-750 nm range of the hyperspectral imagery.

Near-infrared wavelengths

The near infrared (NIR) portion of the electromagnetic spectrum ranges from 700nm-1200nm. Vegetation is characterized by high reflectance in the NIR, controlled primarily by leaf structure; reflectance in these wavelengths occurs at cell walls and at the interfaces between air and water within the leaf (Slaton et al., 2001). In a typical vegetation spectral response curve, the “red edge” is the steep portion of the curve in the transition from red to NIR wavelengths. The slope of this curve can indicate plant stress and chlorophyll concentration (Carter and Knapp, 2001). The red edge is followed by the NIR plateau, and this portion of the spectrum has been associated with changes at the cellular level, including hydration, health, and arrangement, as well as biomass (Rock et al., 1986). The NIR part of the spectrum has been shown to have a high correlation with hardwood forest biomass (Zheng et al., 2004), and as an indicator of leaf area index. Roberts et al. (1998) correlated leaf age with increasing NIR absorbance in tropical vegetation. Since the NIR can be used to assess vegetation health, it is also an important tool in monitoring tree defoliation due to pests or environmental conditions. For example, the NIR reflectance has been used to detect defoliation levels due to Jack Pine budworm in Wisconsin, USA (Radeloff et al, 1999) and a fungal pathogen in Australia (Coops et al., 2006).

Shortwave infrared wavelengths

The shortwave portion of the spectrum ranges from 1300nm – 2400nm, is strongly influenced by the absorption by water. The moisture contained within a leaf absorbs shortwave infrared radiation, making this range of the spectrum useful in estimating plant water content (Ustin et al., 2004). Vegetation water content is especially important when trying to assess forest fire risk (Maki et al., 2004), and for determining water deficiency in agricultural crops. Tian et al. (2001) used the SWIR reflectance (between 900-1850nm and 1700-2500nm) of wheat leaves to determine moisture stress.

Indices are commonly used with a wide range of remotely sensed data types to integrate multiple wavelength ranges that inform upon vegetation characteristics of interest (Asner et al., 2003). Studies have shown that spectral indices or ratios using the visible wavelengths are sensitive to changes in leaf pigmentation (Blackburn, 1998). For example, Chapelle et al., (1992), found that by using a ratio of soybean reflectance spectra and reference spectra, corresponding to the absorption bands of individual pigments, they were able to estimate the concentration of chlorophyll and carotene in the soybean plants. Recent research has resulted in the development of a function for assessing the sensitivity of spectral vegetation indices to biophysical parameters (Lei and Peters, 2007).

APPLICATIONS EXAMPLE: SPATIAL CHARACTERISTICS

Based on differing information needs for differing management objectives, digital satellite remote sensing offers a complementary technology for detection and mapping of a range of vegetation related phenomena. Remotely sensed data can facilitate mapping of individual trees or small groups of trees, as well as providing the capacity to cover large spatial areas - ensuring a census, rather than a sample of areas of interest (Wulder et al., 2006b). In addition, remotely sensed data can be easily integrated with other spatial data (such as roads, elevation and climate data) (Dial et al., 2003; Tao et al., 2004) and forest inventory data (Wulder et al., 2005). Furthermore, through the use of more automated processing and interpretation functions, there may be a reduction in interpreter subjective bias (White et al., 2005), which may increase the consistency and reliability of mapping between different areas or dates (Wulder et al., 2006a).

In this section, we present two examples of applications that have used remotely sensed data to map mountain pine beetle (*Dendroctonus ponderosae*) damage to lodgepole pine (*Pinus contorta* Dougl. ex Loud. var. *latifolia* Engelm.) forests in British Columbia, over two different spatial extents. The first example is mapping damage caused by epidemic levels of infestation over very large areas at the landscape level using remotely sensed data with a spatial resolution of 30 m, while the second example is mapping low levels of infestation, at the forest stand level, where individual trees or groups of trees have been infested and killed by the beetle.

Landscape level application example

Over large areas, information on the location, extent, and severity of mountain pine beetle damage is required to determine the resources needed to address the infestation and to allocate those resources effectively. This information is also used for timber supply review, forest inventory update, biodiversity conservation, land use planning, and as baseline information to parameterize and validate the assumptions associated with predictive models. Landscape-level information is also used to direct the location and intensity of more detailed surveys, designed to satisfy operational information needs.

When mountain pine beetles attack and kill a healthy pine tree, the tree's foliage will initially remain green, eventually fading to red (typically within six to eight months after the initial attack). The red coloration of the foliage is characteristic of beetle damage and is termed as the red attack stage; this dramatic change in foliage colour enables detection and mapping of beetle damage (Figure 1 provides examples of red attack trees). Provided appropriate imagery is selected to coincide with the manifestation of the red attack stage, the damage can be mapped over large areas in an accurate and timely fashion using Landsat Thematic Mapper (TM) or ETM+ imagery and change detection methods (Skakun et al., 2003; Wulder et al., 2006b).

The creation of a large-area product detailing the location and spatial extent of red attack damage involves the consideration of several logistical issues related to the mapping of a large area, many of which are not often faced in small, research-driven projects. Generating a consistent product over large areas involves the use of multiple scenes collected on different dates and potentially in non-optimal seasons. Other considerations are data availability and quality of available imagery. Imagery that is suitable for the detection and mapping of mountain pine beetle red attack damage must be acquired during the appropriate bio-window for mountain pine beetle (Wulder et al., 2006a).

The Enhanced Wetness Difference Index (EDWI) has been effectively used to detect a range of forest disturbance types (Franklin et al., 2001; 2002; 2003; 2005; Skakun et al., 2003; Wulder et al., 2006b). The EDWI is based on the Tasseled Cap Transformation (TCT) coefficients developed by Huang et al. (2002a), which compress Landsat spectral data into a reduced number of bands associated with physical scene characteristics (Crist and Cicone 1984). Though this transformation was originally constructed for agricultural applications, it has been used to reveal some key forest attributes (Cohen et al, 1995). The EDWI is calculated based on a combination of two dates of Landsat images, making geometric matching of multiple scenes a critical pre-processing step, even with orthorectified imagery, to ensure that the images are properly co-registered.

The mapping approach developed to capture red attack damage involves a sequence of steps including pre-planning, image scene selection, image pre-processing, and analysis (Figure 2). The EWDI approach performs best over areas with more homogeneous and extensive attack. Scenes with excessive cloud and haze should be avoided, and any areas of cloud, cloud shadows, haze, topographic shadows, or snow cover should be masked out. Masks must also be generated from forest inventory and harvesting data to identify areas of suitable hosts.

Generally speaking, when applying the EWDI large positive values indicate wetness loss while small EWDI values show no change of wetness, and large negative EWDI values represent wetness gain. Therefore, the areas with large positive values in the EWDI image are likely to be the mountain pine beetle red attacked areas (Skakun et al., 2003). Mountain pine beetle red attack, however, is not the only disturbance that results in a loss of wetness, as other forest management activities will also manifest as decreases in moisture (e.g. forest harvesting).

The EWDI values of the attacked and non-attack pixels can be approximated by a Gaussian distribution, and can be separated by thresholding (Skakun et al. 2003). To determine the EWDI thresholds, calibration and validation data are required for both red attack and non-attacked pine stands. Once the threshold has been set, the accuracy of the output can be verified using reserved validation data. An accuracy assessment provides information on the success of the detection methods used and identifies possible sources of error, and is also valuable for comparing and evaluating different mapping techniques and in the development of new methods.

Tree-level application example

Successful mitigation of mountain pine beetle attack relies on accurate detection of infested trees, and information on the number and location of attacked trees. This detailed information is critical for a range of activities, including sanitation logging, the implementation of silvicultural regimes designed to reduce the susceptibility of host trees, as well as treatments to directly control populations. In all of these cases, information on the location and health status of individual tree crowns is critically important.

The advent of high spatial resolution satellite data, since the launch of the IKONOS satellite in 1999, has resulted in an increased capacity to detect individual trees from space. Airborne digital imagery, such as that obtained by digital cameras sensitive to both the visible and near infrared regions of the spectrum, also provides the capacity to deliver this detailed individual tree information. This spatially driven data is useful for identifying small disturbances focused over a limited spatial extent and can aid as a surrogate for field based measurements (Asner and Warner, 2003) or validation efforts (Morisette et al., 2003).

White et al. (2005) use IKONOS 4 m multi-spectral data to detect mountain pine beetle red attack damage using image classification. In their study, an unsupervised clustering technique was applied to detect red attack damage in forest stands with low and moderate levels of attack, and then compared these estimates to red attack damage estimates generated from air photo interpretation. Results indicate that within a one-pixel buffer (4 m) of identified damage pixels, the accuracy of red attack detection was 70.1% for areas of low infestation (stands with less than 5% of trees damaged) and 92.5% for areas of moderate infestation (stands with between 5% and 20% of trees damaged). Analysis of red-attack trees that were missed in the classification of the IKONOS imagery indicated that detection of red-attack was most effective for larger tree crowns (diameter >1.5 m) that were <11 m from other red attack trees.

In mountain pine beetle infested forest stands, Kneppeck and Ahern (1989) compared manually derived counts of red attack trees from airborne scanner imagery (with a 1.4 m and 3.4 m spatial resolution) to counts estimated by manual interpretation of 1:10,000 air photos. Counts of red attack trees from the 1.4 m resolution imagery were higher (136%) than those derived from the air photo interpretation, while counts from 3.4 m resolution imagery were lower (71%). The results from this study indicated that detailed surveys can benefit from a multi-stage sampling approach where a small sample of ground counts is used to adjust estimates generated from other data sources.

Coops et al. (2006) used helicopter GPS survey measurements of beetle infested pine trees in north-central British Columbia to indicate areas of attack and non-attack stands on QuickBird 2.4 m multispectral data (blue, green, red, near-infrared). The authors tested the ANOVA separability of four classes: sunlit non-attacked crowns, dense red-attack crowns, fader crowns, and shadowed crowns, using four QuickBird spectral bands and the NDVI and red/green spectral ratios. Spectral thresholds were used to generate a binary map of red-attack and non-attack. The results show that the ratio of the red to green QuickBird spectral bands was the most significant band combination for detecting red-attack beetle damage and the information derived from the QuickBird imagery showed good correspondence with both forest health survey data and trends derived from broader spatial resolution Landsat imagery.

CONCLUSION

In this Chapter, we have described the capacity of remotely sensed data to characterize and monitor vegetation condition and have demonstrated how information needs influence the choice of remotely sensed data and analysis methods. Regardless of whether the scope of the application is over large areas or at the level of individual trees, there are several logistical issues related to data acquisition and processing that must be addressed. The focus on meeting information needs using remotely sensed data poises the remote sensing community to support sustainable forest management and to play a role in informing policy makers.

The use of remotely sensed data for vegetation characterization has matured rapidly from scientific investigations to operational usage. It is this very success that is producing some of the grand challenges that remain and continue to emerge. The ability to make subtle characterizations of vegetation condition and structure at fine scales has created a demand for this detailed information over large areas. As we described in this chapter, a contradiction in what is desired and what is available may develop, with the typical economies associated with remote sensing being lost if highly detailed characterizations are desired over large areas. A means of addressing this desire for large-area characterizations of finely detailed information is through sampling and modeling; whereby, fine resolution imagery (with high spatial and spectral resolution) is strategically sampled to enable large-area extrapolations with moderate spatial resolution imagery (or other spatial data sources). These and other forms of data integration will aid in meeting increasingly demanding needs for characterizing vegetation over a wide range of scales.

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TABLE CAPTIONS

Table 1. Example instrument-related spatial resolution ranges and levels of plant recognition in to be expected across a range of image scales (after Wulder, 1998). Note, as a heuristic, coarse, moderate, and fine spatial resolution ranges may be considered as pixels sided > 1000 m, 1000 – 100 m, and < 10 m, respectively.

FIGURE CAPTIONS

Figure 1. Examples of image spatial resolution over a forested scene with crowns of varying condition. Superimposed pixel sizes range from 30 m (Landsat) (L-resolution model with many objects per pixel) to 4 m (IKONOS multispectral) to 1 m (IKONOS panchromatic) (H-resolution model with many pixels per object).

Figure 2. Summary of steps included in the processing flow to generate a map of mountain pine beetle red attack damage from two dates of Landsat TM/ETM+ imagery.

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Type or Photo Scale	**Approximate Range of Spatial Resolution (m)**	**General Level of Forest Vegetation Discrimination**
Coarse Resolution Satellite Images	1000 (AVHRR) 250 - 1000 (MODIS)	Broad land cover patterns (regional to global mapping)
Moderate Spatial Resolution Satellite Images	30 (Landsat) 20 (SPOT multispectral) 10 (SPOT panchromatic)	Separation of extensive masses of evergreen versus deciduous forests (stand level characteristics)
Fine Spatial Resolution Satellite images (e.g. IKONOS)	> 1 (panchromatic); > 4 (multispectral)	Recognition of large individual trees and of broad vegetative types
Airborne Multispectral Scanners	> 0.3	Initial identification of large individual trees and stand level characteristics
Airborne Video	> 0.04	Identification of individual trees and large shrubs
Digital Frame Camera	> 0.04	Identification of individual trees and large shrubs
1:25,000 to 1:100,000 Photo	0.31 to 1.24*	Recognition of large individual trees and of broad vegetative types
1:10,000 to 1:25,000 Photo	0.12 to 0.31	Direct identification of major cover types and species occurring in pure stands
1:2,500 to 1:10,000 Photo	0.026 to 0.12	Identification of individual trees and large shrubs
1:500 to 1:2,500 Photo	0.001 to 0.026	Identification of individual range plants and grassland types

*based upon a typical aerial film and camera configuration utilizing a 150 mm lens

REQUIRED DATA CHECKLIST

Remotely Sensed Imagery

- ❑ **1 pre-infestation scene**
- ❑ **1 post-infestation scene (preferably with 2 year lag)**

Calibration and Validation Data

- ❑ **Locations of known red attack damage (e.g., derived from helicopter GPS surveys or air photo interpretation)**
- ❑ **Locations of pine forest with no mountain pine beetle attack (e.g., information from ground based sources are preferred; however, image derived alternatives may be used in the absence of ground data)**

Forest Data

- ❑ **Forest inventory information**
- ❑ **Forest harvesting information**

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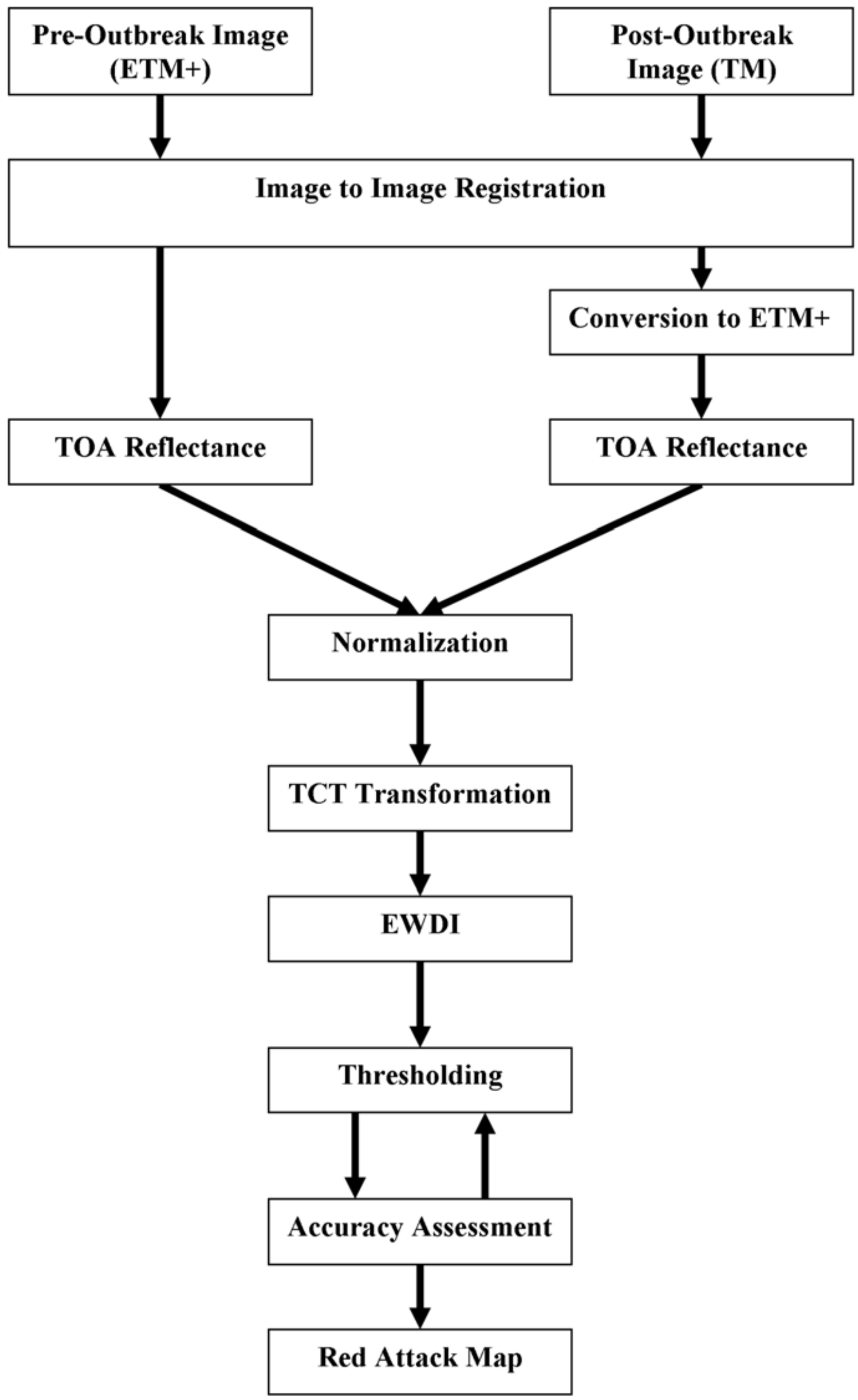

Figure 2. Summary of steps included in the processing flow to generate a map of mountain pine beetle red attack damage from two dates of Landsat TM/ETM+ imagery.