

TECHNICAL REPORT

Remote sensing for restoration planning: how the big picture can inform stakeholders

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The use of remote sensing in ecosystem management has transformed how land managers, practitioners, and policymakers evaluate ecosystem loss, gain, and change at multiple spatial and temporal scales. Less developed is the use of these spatial tools for planning, implementing, and evaluating ecosystem restoration projects and especially so in multifunctional landscapes. We use a case study approach in a multistakeholder tropical dryland restoration project to highlight the potential of remotely sensed products to quantitatively and economically guide often conflicting restoration priorities with stakeholder objectives. High-resolution digital elevation models derived from an airborne remote sensing platform informed land managers tasked with endangered species restoration by guiding their efforts to highly suitable areas of the landscape where plant growth, performance, and survival should be greater. In turn, satellite-based monitoring offered a temporal approach to broadly quantify vegetation fire risk in order to restrict fire promoting activities in dry landscapes most modified by fire promoting invasive grasses. Together, the delineation of high suitability areas for plant-based restoration and low suitability areas for wildfire management ultimately releases moderate suitability land for alternative land uses deemed important in multistakeholder landscapes. We review the benefits of using remotely sensed data for restoration planning, and highlight the costs and benefits of various data sources.

Key words: LiDAR, multiuse landscapes, restoration planning, scale dependent, spatial analysis, stakeholders

Implications for Practice

- Remote sensing tools can help land managers and practitioners identify priority areas for restoration; identify and quantify existing and emerging threats to restoration; and define restoration goals and monitor progress towards them.
- Spatial tools based on project scale, resolution, and cost offer a quantitative approach towards land management decision making in multifunctional landscapes.

Introduction

The use of Earth observation systems to monitor and assess ecological parameters has transformed the fields of natural resource management and conservation biology (Turner et al. 2003; Corbane et al. 2015). Now, with some limitation, evaluation of changes in biodiversity, biophysical parameters, and ecosystem function can be regularly examined at multiple spatial scales. Further, remote sensing has played an increasingly important role in quantifying ecosystem degradation and conservation-management outcomes towards recovery (see review by Cabello et al. (2012)). For example, remote sensing technology can relate the degrading factors of fire, invasive species, and other anthropogenic forces of land use change to biophysical and geomorphic variables. Further, changes in forest productivity, biodiversity, basal area, tree density, or canopy

closure can directly convey ecosystem recovery or restoration success (Duro et al. 2007; Vierling et al. 2008; Wang et al. 2009; Calders et al. 2015). In fact, remotely sensed estimates of change in forest dynamics are now often adopted as measures of restoration success at community, regional, national, and global scales and serve as a foundation for natural resource decision making (Global Observation of Forest and Land Cover Dynamics [GOFC-GOLD] 2008).

Less developed is the direct use of remote sensing technology for planning and monitoring of target-based ecological restoration. This may be due to the typical spatial extent of restoration ecology practice, which has historically been conceived and conducted primarily at a site-specific scale. Now with global and cross-ecosystem issues, such as climate change, invasive species, and pervasive land use, more landscape-scale projects

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are becoming the norm. Recent advances in using Light Detection and Ranging (LiDAR) to characterize objectives associated with restoration, such as plant and animal habitat associations (Holbrook et al. 2015; Scott et al. 2015), imaging spectroscopy to identify species and plant functional performance (Asner et al. 2015; Roth et al. 2015), and the use of spatial data to assess resource variables and stakeholder interests (Brown et al. 2015; Gonzalez-Redin et al. 2016) are examples of new tools that can help to guide the field and practice of ecological restoration.

The purpose of this article is to highlight the need for, and utility of, remotely sensed data for restoration planning, particularly across large multiuse/multistakeholder landscapes where spatial data can provide an objective and quantitative approach to landscape management. We use Hawai'i Island as a case study to outline some of the relevant tools needed for restoration planning in a landscape where ecological gradients and socio/political/economic boundaries are compressed, and where landowner needs and objectives may conflict or overlap between relevant stakeholders and issues.

Remote Sensing Background — Promises and Trade-offs

Remote sensing is the process of gathering information about an object from a distance, and uses a sensor to record information and a platform that positions the sensor over the object of interest. Sensors typically detect electromagnetic energy that is emitted or reflected by objects on the surface of the Earth. A platform can be anything that holds a sensor including satellites, airplanes, unmanned aerial vehicles (UAVs), balloons, or even a tall pole. Sensors are either active or passive in the method by which the data are collected. Active sensors emit a pulse of radiation and detect the amount of radiation reflected back to the sensor. LiDAR is an example of an active sensor that emits a laser pulse and detects the return of the pulse to record information about the elevation of the land surface as well as objects such a vegetation canopies and built structures (Lefsky et al. 2002). Other common active sensing technologies are radar and sonar. Passive optical and thermal sensors measure radiation reflected and/or emitted by a surface. Passive sensors may measure radiation at a number of wavelengths in the electromagnetic spectrum, each recording a portion of potential wavelength range (often called a spectral "band" or "channel"). For example, a digital camera is a sensor that detects wavelengths in the range of visible light (0.4–0.7 μm), usually in three spectral bands centered on the red (0.650 µm), green (0.550 µm), and blue (0.450 µm) wavelengths. Satellite multispectral sensors also include, e.g., the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) that measures Earth in 36 spectral channels between 0.405 and 14.385 µm, and the Landsat sensors that measure 4–10 channels spanning the visible and infrared wavelength regions. Imaging spectrometers, also known as hyperspectral imagers, record in many more spectral channels (>200) than multispectral sensors, and critically, these channels are precisely positioned in wavelength to provide continuous and overlapping coverage of a large portion of the solar-reflected spectrum (e.g. $0.4-2.5~\mu m$). For example, the NASA Airborne Visible Infrared Imaging Spectrometer (AVIRIS) records data in 0.01- μm -width channels $0.35-2.51~\mu m$. The spectral data are distributed in a matrix of picture elements (pixels) that are projected onto the Earth's surface, so they can be viewed and analyzed in a digital map format. The dimension of each pixel when projected to the ground, also called the ground sampling distance (GSD) or spatial resolution, determines the granularity or spatial information content of the image.

Restoration scientists and practitioners will be interested in data products that can inform aspects of restoration planning, including high-resolution terrain data for site or plot selection such as areas with suitable microtopography (Questad et al. 2014); identifying important features at a landscape scale associated positively with restoration success (e.g. trees, wetlands, stream channels [James et al. 2007; McKean et al. 2008; Mollot & Bilby 2008]), restoration project monitoring, and invasive species monitoring postrestoration or management (Asner & Vitousek 2005; Huang & Asner 2009; Kellner et al. 2011). For example, three-dimensional information generated by a LiDAR sensor is usually processed into digital terrain models (DTMs) of the ground surface and also models of vegetation canopy height above the ground (Lefsky et al. 2002). Both of these data products can assist with restoration planning. There are a number of postprocessed products available from spectral data, including vegetation indices that measure vegetation "greenness" (e.g. Normalized Difference Vegetation Index [NDVI], Enhanced Vegetation Index [EVI]), evapotranspiration, and maps of recent fires. These data can be used for frequent monitoring of larger managed or restored areas, including monitoring for new plant invasions (Huang & Geiger 2008; Huang & Asner 2009; Huang et al. 2009; Martín-Alcón et al. 2015) or used to document success metrics.

There are trade-offs that must be made in selecting GSD, map coverage area, frequency of sampling, the variable costs of processing compared to the more fixed costs of obtaining the image, and cost associated with all remote sensing platforms and sensors (Table 1). The GSD is an important trade-off to consider, with UAV platforms able to provide fine-grained pixel sizes (1-10 cm) and satellites providing larger-grained pixel sizes (e.g. Landsat and MODIS: 30-1,000 m). For example, Landsat data can be collected over a typical restoration site, but not often for smaller areas such as individual trees or plots. The size of the area covered by the data will also differ among products. Some satellite products are available for the entire Earth, whereas airborne products are only available for specific regions. Products from battery powered, micro-UAVs are geographically limited to landscapes up to a few km² due to limited battery power and short flight times. However, for small restoration projects and experiments occurring within a defined site, traditional airborne or micro-UAV platforms would provide adequate coverage. Frequency of sampling is another important consideration. For some types of data, such as elevation data used to map wetland depressions, one image may suffice. Other types of data may require repeat imaging, such as when "greenness" indices are used to monitor the growth and senescence of vegetation or

the invasion of non-native species. Satellite imagery is collected repeatedly, every 16 days for Landsat and every day for MODIS. Traditional airborne remote sensing can be more costly to collect repeatedly, making it a less attractive option for frequent monitoring. There is, however, a strong economy-of-scale effect whereby using traditional airborne sensors for high-resolution (0.5–1.0 m GSD) mapping of representative samples of whole countries is less expensive per unit area than traditional field efforts (Asner et al. 2014).

The issues of scale are critically important for deciding what platform to use, which then greatly affects the type and quality of the sensors carried. For example, LiDAR and hyperspectral imagers onboard UAVs are miniaturized, which currently leads to a reduction in the quality of the data produced, but which may be warranted for small restoration projects (<1,000 ha). In contrast, airborne LiDAR and hyperspectral sensors can be large-format instruments (e.g. AVIRIS), which can result in much higher quality data, yet their use is best scoped for large areas (thousands to millions of ha). Many satellite products are freely available, but some newer images require a small fee and some high-resolution satellite imagery, such as WorldView-3, are more expensive. While airborne and UAV platforms provide the most flexibility in terms of sensors and areas sampled, satellite data are the most cost effective especially if repeated sampling is needed across large areas. These trade-offs can be considered for each restoration project to choose an appropriate source of data. In our case, we used airborne hyperspectral and LiDAR.

For small restoration projects, UAVs may provide a low cost platform for collecting useful digital elevation data (Zahawi et al. 2015). Micro-UAVs that can carry a digital camera are now inexpensive and ubiquitous and can collect data to help with setting up plots, creating planting plans, delineating key features, such as wetlands, and monitoring projects postrestoration. Cost versus quality decisions will always be an important part of the discussion for restoration planning of large landscapes and those with limited budgets.

Case Study

Our study system is the highly endangered tropical dryland vegetation communities on the U.S. Army Pohakuloa Training Area (PTA) on the island of Hawai'i. PTA is biologically rich encompassing 24 vegetation communities. Twenty-two rare plant species have been documented with 11 of those listed as federally endangered and 9 as species of concern. Mean annual precipitation is low (<500 mm) and highly variable from year to year. Outplanting efforts of these species have had limited success (Kawakami unpublished data). Non-native invasive species such as ungulates, rodents, and insects are abundant in this ecosystem, but it is the non-native grasses that are particularly problematic because they change fire regimes by increasing the frequency, intensity, and size of fires (D'Antonio et al. 2000). Further, ecosystems in Hawai'i are small, compressed in scale, and close-knit, and where multiple stakeholder interests can produce conflicting perspectives on restoration. In the PTA case study, stakeholder interests include mandated protection of threatened and endangered species and their associated habitat, military training, public recreation (hunting), and public safety (wildfire).

Given that the land represents a very limited resource, it is important to optimize usage via an objective and quantifiable approach. The most overt challenge in this ecosystem is between protection of biodiversity and public hunting of non-native animals. Threatened and endangered species can likely only persist in areas protected from non-native animals (Cole et al. 2012), but these same animals depend on forested habitat. Complicating these opposing interests, federally mandated critical habitat for threatened and endangered species generally encompass large areas of historical habitat, forcing land managers to protect vast tracts of land for potential species recovery. This strategy is problematic because much of the landscape has been so altered and degraded that native species recovery is virtually impossible without active restoration. This policy reduces other land use activities such as military training opportunities and hunting areas, thereby fueling a long-lasting and currently unresolved conflict.

To address these complex dynamics, our approach was to use high-resolution remote sensing tools to identify areas of the landscape where stakeholder activities are prioritized based on biophysical and geomorphic characteristics. We suggest that areas deemed high priority for restoration can be more intensively managed, thereby releasing low priority areas for hunting and military training and areas with high risk of fire should be targeted for appropriate fire reduction activities.

Description of Mapping Tools

First, we created map layers of *restoration potential* based on canopy cover and topographic suitability and fire *fuel accumulation* for the 49,000 ha PTA installation using LiDAR and spectroscopic measurements from the Carnegie Airborne Observatory (CAO) (Asner et al. 2007). Second, we combined the layers to identify areas of the landscape where different stakeholder interests could be met. Third, we used NASA MODIS satellite data to develop a tool to monitor near real-time fire fuel conditions to provide additional assistance with fire management. Here, we present examples of our approach from two plant communities, a shrubland dominated by *Dodonaea viscosa* (Sapindaceae) and a forest dominated by *Metrosideros polymorpha* (Myrtaceae).

We wanted our maps of *restoration potential* to show areas of the landscape with microclimates that will promote plant growth and establishment during restoration (i.e. protected from desiccating winds and areas of expected resource accumulation). We used LiDAR data to derive a DTM of the ground and a digital surface model (DSM) of the vegetation canopy (for methods, see Kellner et al. 2011). The GSD, or pixel size, of these models was 2.2 m. This fine-scale mapping allowed us to model relatively small features important for plant growth and establishment, including microtopography and individual trees. We defined restoration potential in the *Dodonaea* shrubland using the DTM to identify topographic features that can

Table 1. Comparison of tradeoffs for different types of remote sensing data and applications for restoration. It is important to note that costs reflect image acquisition only. Data processing costs can be minimal to large and are dependent upon the needs and objectives of the user. ^aCosts are based on image acquisition, which are somewhat fixed per unit area, and do not include the cost of image processing or analysis, which are variable based on the end products and needs of individual users. ^bCost is based on a LiDAR survey in Malheur National Forest. Costs would vary with type of sensor, ground sampling distance, data processing needs, and size of area surveyed (Hummel et al. 2011). ^cCost is based on a large-scale carbon mapping project in Peru (Asner et al. 2014). ^dCost is based on a professional series ready-to-fly UAV package including camera. Actual costs would vary with model of UAV and sensors purchased.

| ready-to-fly UAV package 1 | including camera. A | Actual costs would vary | ready-to-fly UAV package including camera. Actual costs would vary with model of UAV and sensors purchased. | ensors purchased. | | | |
|-------------------------------------|---------------------|-------------------------|---|---------------------|---|---|---|
| | Pixel Size | Extent of Imagery | Frequency | Spectral Resolution | $Cost^a$ | Data Products Useful for Restoration | Restoration Applications |
| Airborne sensor | 0.5-5 m | Established by user | Single image with repeatability (e.g. daily, monthly, or yearly) | Low-high | \$0.01 ^b to \$6.50/ha ^c | Detailed topography or vegetation mapping of a specific area | Site selection Identifying features |
| Landsathttp://landsat. usgs.gov | 15-100 m | Global | 16 days | Moderate | Free of charge | Measures of vegetation "greenness" | Larger-scale monitoring of restoration projects Monitoring plant invasions |
| MODIShttp://modis. gsfc.nasa.gov | 500-1,000 m | Global | 8 days | Moderate | Free of charge | Measures of vegetation "greenness" Evapotranspiration Recent fires | Larger-scale monitoring of restoration projects Monitoring plant invasions |
| UAV | 0.01-0.1 m | Established by user | Single image with high repeatability (<1 hour) | Low-high | \$1,000 and up ^d | Detailed topography or vegetation mapping of a specific, small area Flexibility for repeated sampling at low cost | Site selection Identifying features Restoration monitoring (e.g. plant health) Monitoring plant invasions in a small area |

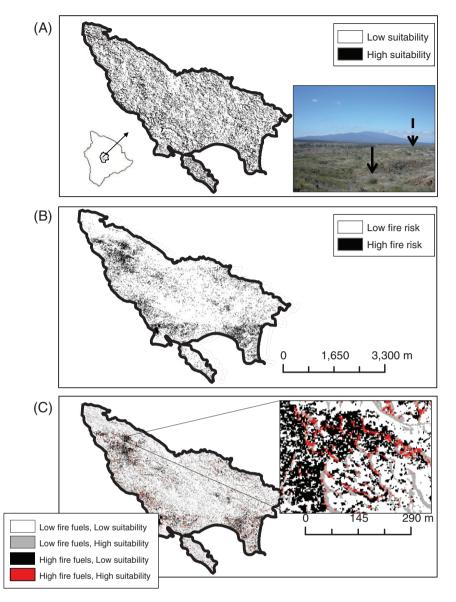


Figure 1. Restoration potential maps of the *Dodonaea viscosa* shrubland at PTA. (A) Map of suitability for restoration based on microtopography, the photo illustrates an area of high suitability with a solid arrow and low suitability with a dashed arrow; (B) map of fire risk based on the accumulation of fine, flashy fuels (NPV < 2 m in height); (C) map combining A and B to assist with decision-making.

improve plant establishment (Questad et al. 2014). Areas with high restoration potential met two criteria: (1) they are in topographic depressions; and (2) they are protected from the prevailing winds by an existing topographic feature (Fig. 1A). High restoration potential in the *Metrosideros* forest was defined as areas with more canopy cover. Canopy cover reduces solar radiation and wind exposure to restored seedlings, and should improve plant establishment compared to more open, exposed areas (Uhl & Kauffman 1990; Freifelder et al. 1998; Scowcroft & Jeffrey 1999; Cordell & Questad unpublished data). We used the LiDAR-based DSM to calculate the density of pixels with canopy greater than 2.5 m in height (e.g. trees) in a 22 × 22 m² area (10 × 10 pixels in the DSM). Areas that we defined as

having high restoration potential had canopy cover in the top 10% of the distribution across the *Metrosideros* forest (Fig. 2A). High suitability areas contained 28% or greater tree cover. Our maps of *fuel accumulation* focused on fine, fire-prone fuels in a spatial context (i.e. from one area to another in the landscape) because fires in Hawai'i are driven mainly by invasive grasses (Smith & Tunison 1992). The abundance of standing, senescent biomass is the main source of fuel from these perennial grasses. We modeled these fuels using spectroscopic measurements and LiDAR data from the CAO to quantify the fractional abundance of nonphotosynthetic vegetation (NPV) less than 2 m in height (Asner & Lobell 2000; Varga & Asner 2008). Values in the upper 10% of the distribution of pixels in each study area

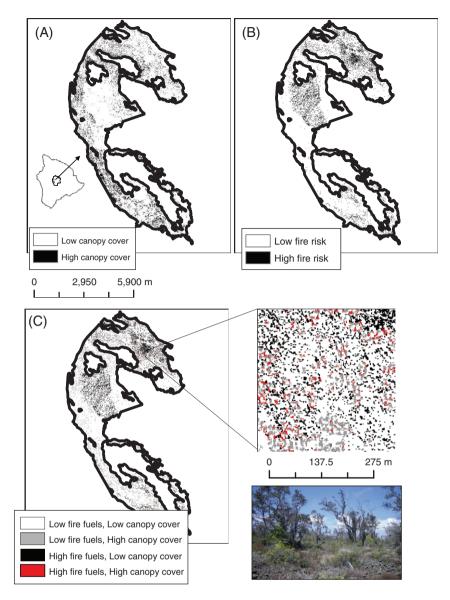


Figure 2. Restoration potential maps of the *Metrosideros polymorpha* forest at PTA. (A) Map of suitability for restoration based on canopy cover; (B) map of fire risk based on the accumulation of fine, flashy fuels (NPV < 2 m in height); (C) map combining A and B to assist with decision-making.

were considered areas at greatest risk of fire (Figs. 1B & 2B). Areas in the shrubland and forest with the greatest fuel accumulation had 51.6 and 40% cover of NPV, respectively (Kellner et al. 2011).

We mapped fuel conditions using data from the MODIS sensor that provides sufficient spectral information on an 8-day repeat cycle to allow for coarse-scale temporal modeling (Elmore & Asner 2006). The data are limited to a 250-m pixel size or GSD, thus they serve only as a broad indicator of fire hazard conditions. Nonetheless, this modeling technique corresponds with both aircraft and field-based measurements of dry fuel cover and moisture content (Elmore & Asner 2006). This product is available as a web tool, and has been effectively introduced to the U.S. Department of Defense (DoD) and other Hawai'i-based land managers (http://hawaiifire.stanford.edu).

This product, combined with the one-time high-resolution *fuel accumulation* map, provides the most complete depiction of spatial and temporal variations in fuel conditions in this region.

Remotely Sensed Data as a Planning Tool for Restoration

Using our case study as an example, we describe potential uses of remote sensing data products to help guide the restoration planning process:

(1) Map layers of restoration potential and fuel accumulation can be used to identify areas of the landscape where particular restoration activities are likely to be the most effective. For example, physical fire barriers such as fuel breaks cleared of vegetation can be added to areas with high fire risk and low restoration potential (Figs. 1C & 2C);

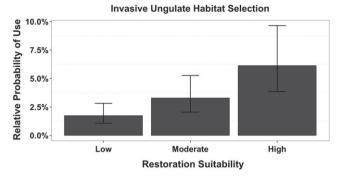


Figure 3. Predicted probability of use values of three categorical habitat types (low, moderate, and high restoration suitability) by non-native feral goats at PTA tracked from 8 July, 2010 to 2 July, 2011. Values were generated based on logistic regression in a Resource Selection Function modeling framework. To visualize model estimates and predictions for the Restoration Suitability variable, we generated predicted use values while holding all other variables at mean values. Error bars represent empirical ±95% confidence intervals for model predictions. Ungulates are more likely to use high suitability areas despite the low abundance of these areas in the landscape.

- (2) Native plant restoration to reduce fire fuels (green fuel breaks) could be the most effective in areas with high fire risk and high suitability for plant growth;
- (3) A MODIS-based fuel monitoring tool can help plan management activities throughout the year. For example, fuel breaks can be inspected and expanded during times of high fuel accumulation, and areas focused on ecosystem process level restoration can be monitored for fire risk during these times;
- (4) Restoration of endangered plant populations can be focused in areas with low fire risk and high restoration potential (Figs. 1C & 2C). These areas would have the best microclimatic conditions for successful outplanting and would have the lowest risk of losing the plants to a fire.
- (5) Areas of high suitability for restoration can be prioritized for excluding ungulates because non-native ungulates are more likely to occur in these areas (see Fig. 3 where we modeled resource selection using a logistic regression of feral goats based on the restoration suitability layer). However, because animals also occur in areas of moderate suitability, these areas could be managed for recreational hunting. This mixed-use approach would satisfy desires of local stakeholders while benefiting the underlying mission of restoration ecologists.

Summary

The case study in Hawai'i focuses on a region that is important for the conservation of species at risk of extinction. Effectively partitioning the landscape for focused management activities in the areas of highest conservation value could substantially reduce costs. In this case study, we set thresholds for defining areas with high fuel accumulation and high restoration potential. Thus, the maps we present here are just one example

of how the data can be used to visualize a landscape. Each restoration project will have to consider the trade-offs between data quality, area covered, and cost (Table 1). Results from this case study show the potential of using remote sensing tools as a planning guide in ecosystem restoration to increase capacity and knowledge to restore ecosystems through wild-fire reduction, protection of high value habitats, and conflict resolution between multiuse stakeholders. This opportunity could potentially redefine the way land managers accomplish multiuse missions on their landscapes by providing a set of quantitatively based and spatially explicit tools to ensure effective and compliant land use management.

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