Predicting Risk of Invasive Species Occurrence—Remote-Sensing Strategies

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Chapter 6 of

Early Detection of Invasive Plants—Principles and Practices

Edited by Bradley A. Welch, Paul H. Geissler, and Penelope Latham

Scientific Investigations Report 2012–5162

U.S. Department of the Interior
U.S. Geological Survey

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Chapter 6. Predicting Risk of Invasive Species Occurrence—Remote-Sensing Strategies

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Why Use Remotely Sensed Data?

Knowledge of invasive species occurrence, distribution, and potential invasion pathways is important in developing appropriate long-term monitoring protocols. Costs associated with ground-based visits, however, preclude the National Park Service from inventorying all associated park lands to determine invasive species presence. One potentially cost-effective approach in identifying potential occurrences of invasive species is to predict their distributions by using remotely sensed data and knowledge of species ecology and environmental tolerances (Everitt and others, 1996; Goslee and others, 2003; Osborn and others, 2002; Parker-Williams and Hunt, 2004).Once potential areas of invasive species occurrences are predicted, ground reconnaissance can be more effectively used and applied to an early-detection context for monitoring, verification, and control.

Remote sensing is a means to describe characteristics of an area without physically sampling the area. Remote sensors can be mounted on a satellite, plane, or other airborne structure. Remotely sensed data allow for landscape perspectives on management issues. Sensors measure the electromagnetic energy reflected from an object or area on the Earth's surface (fig. 6.1). These sensors measure energy at wavelengths that are beyond the range of human vision. The guiding principal is that different objects (for example, soils, plants, buildings, water) reflect and absorb light differently at varying wavelengths. Graphically plotting the amount of radiation reflected at a given wavelength provides a unique signature for an object, especially if there is sufficient spectral resolution to distinguish its spectrum from those of other objects (fig. 6.2). Reflectance of clear water is typically low, with initial higher reflectance values in the blue end of the spectrum, which decreases as wavelength increases. Vegetation reflectance is typically low in both the blue and red regions of the spectrum due to absorption by chlorophyll. Because reflectance values peak at the green region, vegetation appears green. In the near infrared (NIR) region, reflectance is much higher than that in the visible bands due to leaf cellular structure. Therefore, vegetation can be identified by the high NIR but generally low visible reflectance. Spectral reflectance curves can be used to discriminate between vegetation types or plant species.

Many Geographic Information System (GIS) data sets are created from remotely sensed data. For example, digital elevation models (DEMs) are derived from space or aircraft-borne sensors. Most GIS software packages can calculate slope and aspect from a DEM. Remotely sensed data can also be used to augment GIS data sets by allowing visual interpretation of images for roads, waterways, fence lines, buildings, and other features. These features can be readily digitized and placed into a GIS environment.

Box 6.1. Use of remotely sensed data. Remotely sensed data are most appropriate for species whose biological characteristics, habitat composition and structure, and landscape context combine to offer a data quality and logistical advantage to ground-based methods (Landenberger and others, 2003).

Remote sensing and GIS technologies were initially developed for different purposes. Traditionally, the two disciplines worked independently, developing new uses for spectral or spatial data (Atkinson and Tate, 1999). Recently, there has been a merging of these two disciplines, as scientists learn the benefits of integrating remote sensing with GIS (Hinton, 1999). Current computer software and hardware facilitate the easy integration of these data sources. Most GIS software packages allow remotely sensed data to be analyzed, or at least viewed. This ability allows the analyst to overlay remote sensing data layers with other spatial data layers. Both spectral and spatial data can provide information about the invasive species occurrences within national parks. As such, integrating remotely sensed data with GIS data shows promise in modeling invasive plant habitats in national parks (Anderson and others, 1996).

Over the last decade, the number of publications pertaining to modeling invasive species by using remotely sensed

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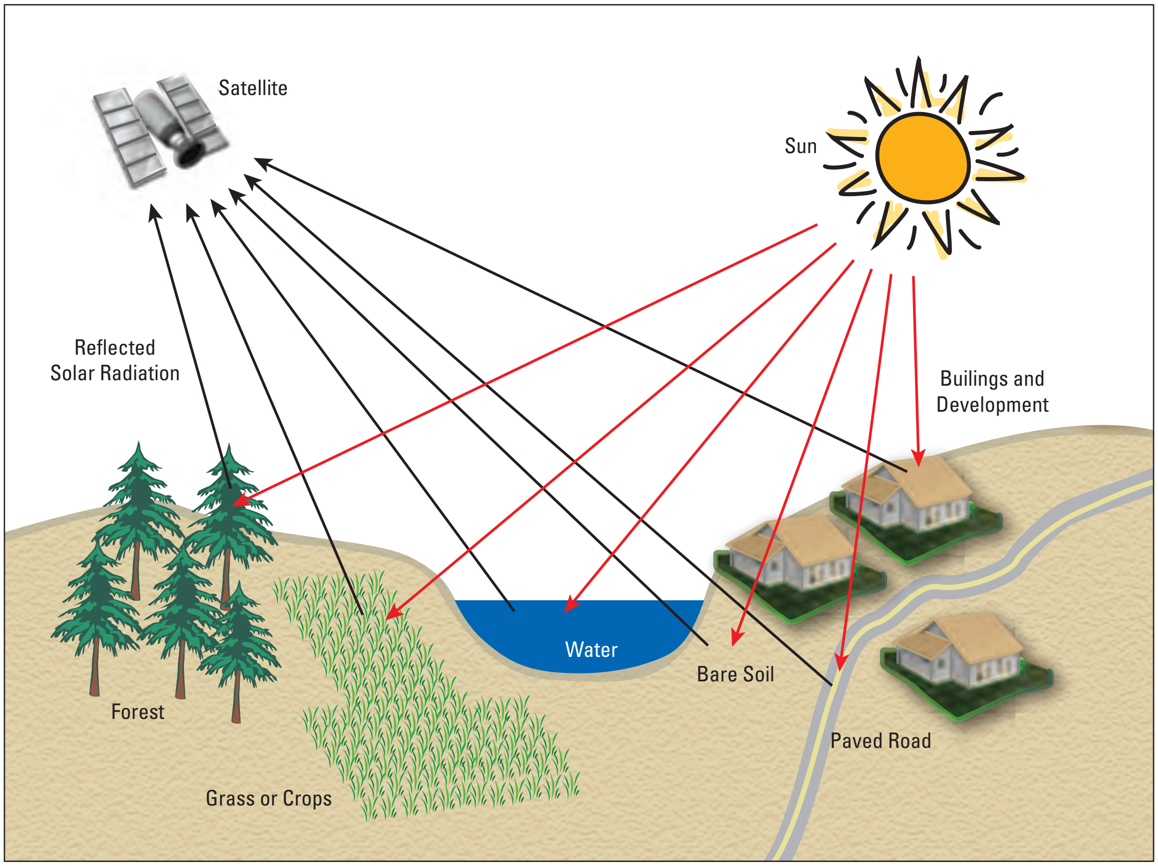

Figure 6.1. Reflected solar radiation, for example, electromagnetic energy, captured by space or aircraft-borne sensors.

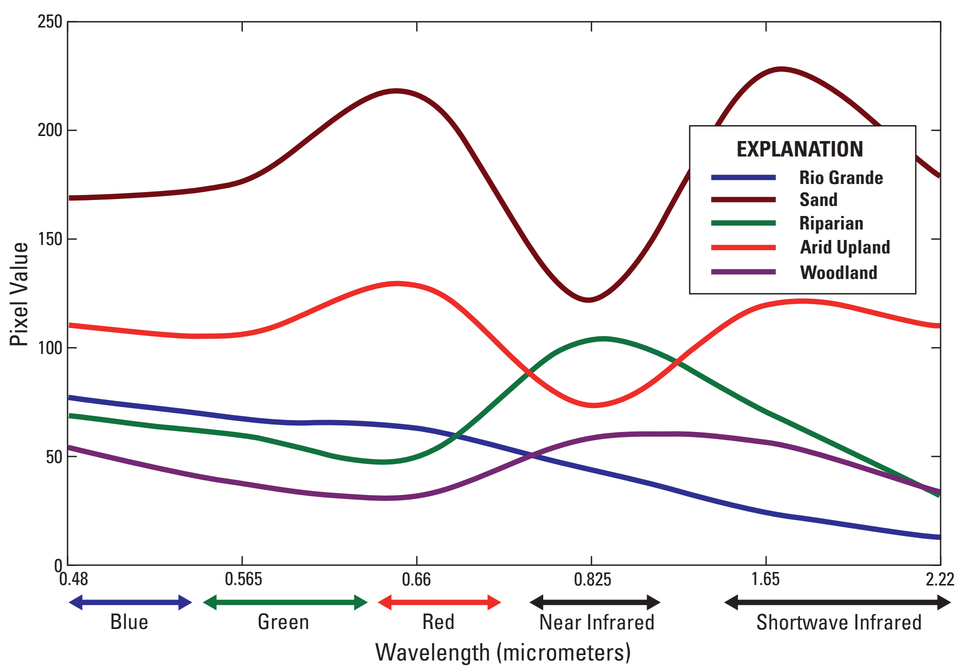

Figure 6.2. Spectral reflectance curves derived from Landsat 7 Enhanced Thematic Mapper Plus for vegetation types in Big Bend National Park, Texas.

data has increased substantially (Chudamani and others, 2004). Information can be found in a variety of journals, technical reports, symposia and workshops, and on the Internet. Journals that support remote sensing publications for invasive species include: Weed Technology, Weed Science, Photogrammetric Engineering and Remote Sensing, Remote Sensing of Environment, International Journal of Remote Sensing, Journal of Ecology, Journal of Range Management, and Journal of Arid Environments.

We provide a review of the utility of using remotely sensed data in modeling the potential distribution of invasive plant species. A complete description of all remote sensing applications for invasive species is beyond the scope of this document. Chudamani and others (2004) and Lass and others (2005) also provide recent overviews on the utility of using remotely sensed data for early detection of invasive plants. For an application of remote sensing techniques to invasive plant early detection in Big Bend National Park, see Chapter 12.

When to Use Remotely Sensed Data

Remotely sensed data may not always be the most effective approach for early detection of invasive plants. There are still limitations associated with the data resolution, processing, and costs. Nevertheless, our ability to detect, map, and monitor invasive plant populations or suitable habitats with remotely sensed data has greatly increased over the last decade. Remotely sensed data could assist in early-detection protocols if:

- The area of consideration is large (park, network, region, or area too large for effective ground surveys).
- Resource managers or contractors have access to GIS capabilities.
- One or a few invasive plants of interest exhibit unique phenological or habitat associations.
- There is a need to prioritize ground survey efforts. Remote sensing can gather information over a wide geographic area in a short amount of time to assist ground surveys.
- There is a need to estimate the likelihood of invasive plant or suitable habitat presence in areas not easily accessible by ground.
- There is a need to evaluate areas where an existing population may spread (early detection in new or adjacent areas). This may arise if an invasive plant occurs outside of a park, network, or other management unit and resource managers need to locate where the plant may start to occur inside the park.
- There is a need to understand which land parcels are most at risk to plant invasion. Risk analyses using GIS and remotely sensed data sets allow for estimates that can cross jurisdictional boundaries.
- There is a need to describe landscape trends prior to invasions or the initiation of monitoring programs. Multiple years of imagery can be analyzed to create a multitemporal data set.

Conversely, resource managers may wish to consider other modeling approaches that assist in early detection (see Chapter 7) if:

- Invasive plant populations are known to be sparse, small, or diffuse patches, which may be the case for early-detection programs. Remote sensing techniques may not be cost effective.
- Complete census for invasive plants is feasible for the area of concern.
- Degree or severity and location of the invasive population are already well known.
- Invasive plant populations are obscured by the overstory vegetation (for example, canopy trees).
- Invasive plant populations do not exhibit unique phenological differences from the surrounding landscape or unique habitat associations.
- There is no access to GIS capabilities or contractors.

NASA Office of Earth Science and the U.S. Geological Survey are developing a National Invasive Species Forecasting System. This system is for early detection and management of invasive species and includes the use of satellite data for invasive species modeling (accessed March 25, 2014, at *http://earthdata.nasa.gov/our-community/community-data-system-programs/reason-projects/invasion-species*). Initiatives such as this will help develop methodologies and models that will overcome existing challenges in using remotely sensed data for invasive plant detection and management.

Spatial, Spectral, and Temporal Scale Issues

The efficacy of remote sensing data for detecting invasive plants or associated habitat is a function of the sensors' spatial and spectral (bandwidth) resolution, and the sensors' repeat cycle. When planning remotely sensed projects, these factors need to be considered with respect to project objectives (Hobbs, 1990). It is often a challenge to balance the scale and resolution of the source data with the information need.

Spatial Considerations

Spatial resolution describes the amount of detail an image contains across a given distance, typically a cell size. The ability to "resolve" or describe small details or objects is one way of describing spatial resolution. As such, smaller objects are typically better "resolved" or detected with high-resolution images. IKONOS and QuickBird images have spatial resolutions less than 5 meters and thus are considered high-resolution images. Conversely, Advanced Very High Resolution Radiometer (AVHRR) is considered a low-resolution image with a spatial resolution of 1.1 kilometers.

Spectral Considerations

There are three generalized categories for sensors with different bandwidths. Panchromatic sensors are sensitive to radiation within a broad wavelength range. The physical quantity measured is the brightness of the object. When the wavelength ranges coincide with the visible range, the resulting image resembles a "black-and-white" photograph. In this case, "color" information is lost. IKONOS, SPOT, and Landsat 7 Enhanced Thematic Mapper Plus (ETM +) each have a panchromatic bandwidth. Multispectral sensors are sensitive to radiation within several narrow wavelength bands. These sensors register reflectance in a number of spectral bands throughout the visible, near- to far-infrared portions of the electromagnetic spectrum. The result is a multilayer image that contains both the brightness and spectral color information of the landscape. These broadband scanners have been successfully applied to discriminate between broad land-cover types. Multispectral sensors include Landsat 7 Enhanced Thematic Mapper Plus (ETM +), SPOT, IKONOS, and QuickBird, among others. Hyperspectral sensors acquire data in more (10 to several 100) but narrower (from 10 to a few nanometers wide) spectral bands than broadband sensors. This precise spectral information allows for capturing finer spectral characteristics (less variability per bandwidth) that yield better identification of objects. NASA Jet Propulsion Laboratory Airborne Visible/Infrared Imaging Spectrometer and the Probe-1 are examples of hyperspectral systems.

Sensors that yield high spatial-resolution data and have hyperspectral capabilities have the highest likelihood of detecting microhabitats or rare plants (Marcus, 2002; Marcus and others, 2003; Lass and others, 2005; Lawrence and others, 2006). However, these data also tend to be expensive, and their relatively small swath size (ground area of the image) requires extensive computer processing time and storage for analyses of large areas. As such, large parks will likely need to compromise bandwidth and spatial resolution to model invasive species occurrences across large landscapes.

Temporal Considerations

Although remotely sensed data are often used for mapping vegetation and general land-cover types, mapping individual plant species imposes many challenges. Similar spectral signatures between the target plant and the surrounding environment, changes in soil color or moisture, and low plant densities hinder discrimination efforts. However, seasonal differences in plant phenology may help in detecting invasive plants. Some invasive plants flower or green-up at a different time than the surrounding vegetation. Multiple image dates allow for detecting these phenological differences between target plants and the surrounding landscape. For example, remote sensing data that coincided specifically with flowering events aided in the detection of yellow starthistle (*Centaurea solstitalis*) (Lass and others, 1996) and leafy spurge (*Euphorbia esula*) (Anderson and others, 1996; Parker-Williams and Hunt, 2002). Likewise, Peters and others (1992) found that broom snakeweed (*Gutierrezia sarothrae*) could be differentiated from grassland species because of its distinct phenological characteristics. As such, the repeat cycle of the sensor may be a key criterion to consider when selecting imagery. Imagery dates should correspond to critical recognition phases of the target plant (Hobbs, 1990; McGowen and others, 2001; Chudamani and others, 2004).

Types of Remotely Sensed Data

There are a variety of remotely sensed data that may be used to detect invasive plants or potential invasive plant habitats (table 6.1). The data chosen for individual projects or parks will depend on several variables, including:

- fiscal considerations,
- goals and objectives,
- park size,
- distribution and patch sizes of current (known) invasive plants,
- invasive species (that is, species phenologically different than the surrounding land cover),
- availability of computing resources, and
- availability of a Remote Sensing Analyst or consultant for image manipulations.

Figure 6.3 provides a general guide to selecting a potential group of sensors to detect invasive species or model their habitats based on park size, differences in plant phenology (target plants that exhibit unique physical characteristics compared to surrounding vegetation), amount of area infested by invasive plants, and the amount of canopy cover of invasive plants. Other considerations may apply when selecting an appropriate remote sensor.

Multispectral, Low Spatial Resolution Sensors

Multispectral, low spatial resolution sensors have limited ability to detect individual invasive plants or small populations. AVHRR sensor is an example. This sensor is a broadband, 4- or 6-channel scanning radiometer, sensing in the visible, near-infrared, and thermal infrared portions of the electromagnetic spectrum. Ground resolution is 1.1 kilometers, which precludes its ability to detect small invasive plant populations.

The AVHRR sensor has useful temporal data, with fairly continuous global coverage since 1979. Two acquisitions are available daily (morning and afternoon).

Table 6.1. Spatial and spectral resolution of remote sensors that may be useful for detecting potential invasive plants or modeling their habitats. This list is not inclusive of all possible remote sensors available as of December 2006.

[µm, micrometers; km, kilometers; m, meters; <, less than]

Sensor	Spatial resolution	Bands	Wavelength (µm)	Color	Swath	Repeat path
Advanced Very High Resolution Radiometer (AVHRR)						
	1.1 km	1	0.58–0.68	Red	2,399 km	2 per day
	1.1 km	2	0.73–1.10	Near infrared	2,399 km	
	1.1 km	3a	1.58–1.64	Mid infrared	2,399 km	
	1.1 km	3b	3.55–3.93	Mid infrared	2,399 km	
	1.1 km	4	10.30–11.30	Thermal infrared	2,399 km	
	1.1 km	5	11.50–12.50	Thermal infrared	2,399 km	
Multispectral Scanner (MSS)						
	80 m	1	0.45–0.52	Blue	185 x 170 km	16 days
	80 m	2	0.52–0.60	Green	185 x 170 km	
	80 m	3	0.63–0.69	Red	185 x 170 km	
	80 m	4	0.76–0.90	Near infrared	185 x 170 km	
Landsat 7 Enhanced Thematic Mapper Plus (ETM +)						
	15 m	Panchromatic	0.52–0.90		185 km	16 days
	30 m	1	0.45–0.52	Blue	185 km	
	30 m	2	0.53–0.61	Green	185 km	
	30 m	3	0.63–0.69	Red	185 km	
	30 m	4	0.75–0.90	Near infrared	185 km	
	30 m	5	1.55–1.75	Shortwave infrared	185 km	
	60 m	6	10.40–12.50	Thermal infrared	185 km	
	30 m	7	2.09–2.35	Shortwave infrared	185 km	
SPOT (5)						
	2.5 or 5 m	Panchromatic	0.48–0.71		60–80 km	26 days
	10 m	1	0.50–0.59	Green	60–80 km	
	10 m	2	0.61–0.68	Red	60–80 km	
	10 m	3	0.78–0.89	Near infrared	60–80 km	
	20 m	4	1.58–1.75	Mid infrared	60–80 km	
IKONOS						
	1 m	Panchromatic	0.53–0.93		70.3 km	Various
	4 m	1	0.45–0.52	Blue	23.9 km	
	4 m	2	0.51–0.60	Green	23.9 km	
	4 m	3	0.63–0.70	Red	23.9 km	
	4 m	4	0.76–0.85	Visible and near infrared	23.9 km	
QuickBird						
	60 cm	Panchromatic	0.45–0.90		16.5 km	3–7 days
	2.4 m	1	0.45–0.52	Blue	16.5 km	
	2.4 m	2	0.52–0.60	Green	16.5 km	
	2.4 m	3	0.63–0.69	Red	16.5 km	
	2.4 m	4	0.76–0.90	Near infrared	16.5 km	
NASA Jet Propulsion Laboratory Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)						
	20 m	224	0.40–2.45 inch	Blue-shortwave infrared	11 km	By request
PROBE-1 Hyperspectral Instrument						
	1–10 m	128	0.40–2.45 inch	Blue-shortwave infrared	<1–6 km	By request

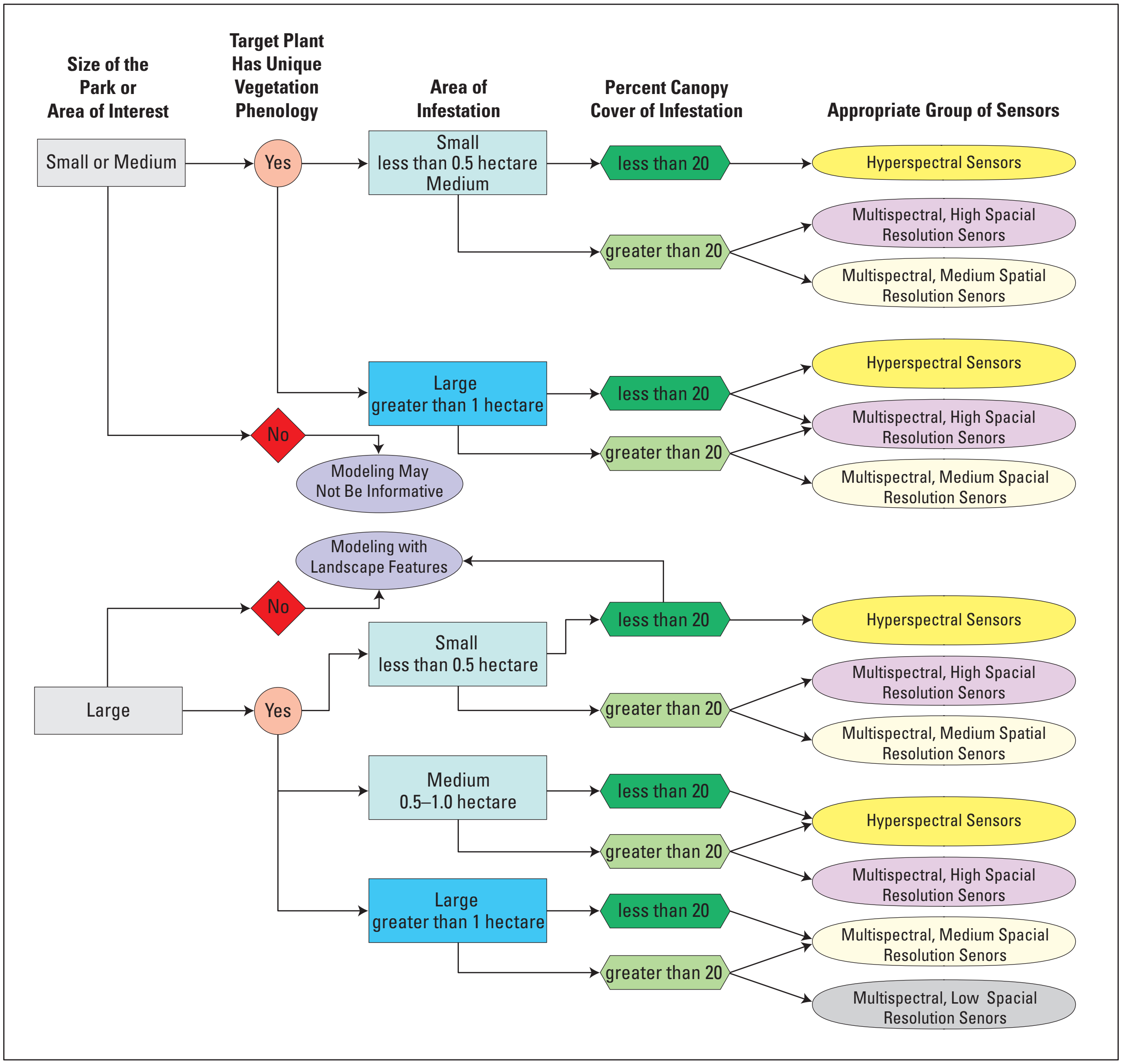

Figure 6.3. General guide to selecting a potential group of sensors to detect invasive species or model their habitats based on park size, differences in plant phenology (target plants that exhibit unique phenology compared to surrounding vegetation), amount of area infested by invasive plants, and the amount of canopy cover of invasive plants. Other considerations may apply when selecting an appropriate remote sensor.

Although AVHRR data cannot detect small invasive plant populations, these data may be useful for detecting landscape changes or evaluating degraded landscapes (Eve and others 1999). Bradley and Mustard (2005) used AVHRR data, time series analyses, to estimate cheatgrass (*Bromus tectorum*) area in the Great Basin. Further, large dense patches of broom snakeweed were detected using this sensor (Peters and others, 1992).AVHRR data are primarily used for investigation of clouds, land-water boundaries, snow and ice extent, cloud distribution, and land and sea surface temperatures. AVHRR data can also be used for studying and monitoring vegetation conditions in ecosystems, including forests, tundra, and grasslands, with applications that include land cover mapping and production of large-area image maps.

Multispectral, Medium Spatial Resolution Sensors

Multispectral, medium spatial resolution sensors such as Multispectral Scanner (MSS), Landsat TM and ETM+, and SPOT have been used extensively to model landscape vegetation types and conduct landscape change analyses. MSS is a multispectral scanning radiometer that was carried onboard Landsats 1 through 5. The instruments provided temporal coverage from July 1972 to October 1992. MSS image data consist of four spectral bands. The resolution for all bands was 79 meters, and the approximate scene size was 185 x 170 kilometers (115 x 106 miles). Due to the spatial resolution, MSS data cannot detect small populations of invasive plants. However, this dataset may be useful for detection of landscape changes and attributes that promote invasive plant establishment (Pickup and others, 1993; Chavez and MacKinnon, 1994; Lass and others, 2005).

The sensors onboard Landsat satellites have varied as technologies have improved and certain types of data proved more useful than others. The sensor on Landsat 7, the Enhanced Thematic Mapper Plus (ETM+), replicates the capabilities of the Thematic Mapper (TM) instruments on Landsats 4 and 5. Landsat 7 ETM+ has the same spectral bands as the previous Landsat sensors, but the ETM+ also features a panchromatic band with 15-meter spatial resolution and a thermal IR channel with 60-meter spatial resolution. A mechanical failure of the scan line corrector onboard Landsat 7 in May 2003 resulted in data gaps from this sensor. Landsat TM and ETM+ data are still available and reasonably priced.

SPOT satellite imaging system was launched in 1986, and currently collects data in green, red, near-infrared, and mid-infrared spectrum. By combining imagery from other SPOT satellites, data are generated at four levels of resolution (20, 10, 5, and 2.5 meters). This multiresolution approach offers users the geospatial information for regional and local analyses. The SPOT imaging system can collect stereo image pairs that contain topographic (3-D) information. SPOT satellites can also be programmed to revisit a given geographic area at any specific time. Imagery required specifically for a vegetation phenology event may be obtained from this service.

Landsat TM and ETM+ have been extensively used to model broad vegetation types. In some cases, these sensors can identify individual plant species with unique spectral or temporal characteristics (Parker-Williams and Hunt, 2002). Dewey and others (1991) compared dyers woad (*Isatis tinctoria*) locations with 60 spectral classes created from Landsat 5 TM data in northern Utah. The authors found strong associations between 10 spectral classes and dyers woad locations. They concluded that their remotely sensed predictive model provided resource managers with a powerful tool for estimating potential dyers woad distributions. Several authors have suggested that Landsat TM and ETM+ data are best used for detecting invasive plants that have patch sizes around 0.5 hectare (1 acre) or larger (Anderson and others, 1993; Everitt and Deloach, 1990; Everitt and others, 1992). McGowen and others (2001) used Landsat 5 TM to map serrated tussock (*Nassella trichotoma*) and scotch thistle (*Onopordum spp*.) in Australia. Detections were limited to areas with infestations greater than 20 percent groundcover. Cheatgrass in the Great Basin was modeled using Landsat TM and ETM+ data (Bradley and Mustard, 2005).

Multispectral, High Spatial Resolution Sensors

Multispectral, high spatial resolution sensors such as IKONOS and QuickBird have less than 5-meter spatial resolution. QuickBird's panchromatic band has a spatial resolution of 60 centimeters. These high spatial resolution sensors show promise for detecting individual species and capturing plant phenological state (Asner and Warner, 2003; Turner and others, 2003; Wang and others, 2004) and mapping shallow aquatic habitats (Mumby and Edwards, 2002). Tsai and others (2005) used QuickBird imagery to accurately map the spatial extent of the invasive horse tamarind (*Leucaena leucocephala*) in southern Taiwan.

Data from these sensors are more expensive than medium spatial resolution sensors. IKONOS and QuickBird also have relatively small swath sizes (around 20 kilometers). Thus, analyses of large areas require extensive computer processing time and storage.

Aerial Photography

Perhaps the oldest remote sensing method is aerial photography (Sabins, 1987; Lillesand and Kiefer, 1994). Historically, the use of aerial photographs was limited to small areas because of the high cost of data acquisition (Lass and others, 2005). Advances in digital aerial photography have improved both the spectral and spatial resolution. Digital cameras can be attached to a variety of aircraft, providing greater flexibility with resolution and timing. However, image preprocessing of raw digital photography presents many challenges (Lass and others, 2005).

There are wide choices of photography with varying degrees of spectral sensitivity (visible and infrared part of the spectrum). Color infrared photography is often called "false-color" photography. Surface objects that are normally red appear green; green objects (except vegetation) appear blue; and "infrared" objects, which typically are not seen with the human eye, appear red. A major use of color infrared photography is for vegetation studies. Green vegetation with active photosynthesis is a strong reflector of infrared radiation and appears bright red on color infrared photographs.

Digital Orthophoto Quadrangles (DOQs) are aerial images produced by the U.S. Geological Survey (USGS). These computer-generated images have been corrected for image displacement caused by terrain relief and camera tilt. DOQs are either grey-scale, natural color, or color-infrared images with 1-meter ground resolution. They cover an area approximately 8 kilometers on each side and have between 50- and 300-meter overlap with adjacent images. This overlap facilitates tonal matching and mosaicking of adjacent images. DOQs have been used for georegistering other imagery or GIS data, visual image interpretation, and on-screen digitizing of landscape features (Coulter and others, 2000; Lawrence and others, 2006). The National Agriculture Imagery Program (NAIP) acquires imagery during the agricultural growing seasons, which enables DOQ acquisition within the same year. NAIP imagery has a

1-meter spatial resolution and is available at *http://www.apfo.usda.gov*. There are also a variety of commercial developers that specialize in obtaining aerial photographs and videography (Lass and others, 2005). The cost of aerial photographs and videography varies depending on the type and resolution of the image and the amount of area surveyed.

Aerial photographs or videography have been found to be useful in detecting saltcedar (*Tamarix ramosissima*) (Everitt and others, 1992, 1996) and leafy spurge (Everitt and others, 1995; Anderson and others, 1996). Further, aerial photographs were used as a tool to estimate the rate of spread for giant hogweed (*Heracleum mantegazzianum*) in the Czech Republic (Mullerova and others, 2005) and for mimosa (Mimosa pigra) in northern Australia (Lonsdale, 1993). Color digital aerial photographs flown in a helicopter 100 meters above ground level were used to census Haleakala silversword (*Argyroxiphium sandwicense*) within a remote volcano crater in Hawaii (Landenberger and others, 2003). The authors found higher errors of commission and omission with aerial photograph census compared to ground census. However, aerial photograph analyses were favorable because they allowed for a larger area to be surveyed with less time than ground-based surveys (Landenberger and others, 2003).

Hyperspectral Sensors

Hyperspectral sensors are perhaps the most helpful group of remote sensors for detecting small populations of invasive plants. These sensors sample the electromagnetic spectrum in narrow, continuous increments, which allows for improved identification of species. There are many hyperspectral sensors available from both governmental and commercial use. Sensors are airborne and may be attached to a variety of aircraft. NASA Jet Propulsion Laboratory Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) (*http://aviris.jpl.nasa.gov/*) has 224 spectral bands that measure light from the blue through the shortwave infrared (0.4 to 2.5 µm with 0.01-µm increments), with a 20-meter resolution. As such, each 20-meter pixel in the image has 224 spectral attributes of data. Likewise, the Hyperion sensor has 220 spectral bands (0.4 to 2.5 µm), with a 30-meter resolution, and the Probe-1 sensor (accessed November 26, 2010 at *http://www.earthsearch.com/index.php*) has 128 spectral bands ranging from 0.4 to 2.5 µm. Spatial resolution varies between 1.0 and 10 kilometers depending on altitude of the aircraft.

Several invasive plants have been detected with the hyperspectral sensors. DiPietro (2002) used AVIRIS data to discriminate riparian vegetation from giant reed (*Arundo donax*) in California. Likewise, AVIRIS data were used to estimate leafy spurge canopy cover and distribution in Wyoming (Parker-Williams and Hunt, 2002, 2004). Lawrence and others (2006) experienced high accuracy using the Probe-1 sensor to detect spotted knapweed (*Centaurea maculosa*) and leafy spurge. Other hyperspectral sensors have been used to detect spotted knapweed (Lass and others, 2002, 2005), yellow starthistle (Miao and others, 2006), and babysbreath (*Gypsophila paniculata*) (Lass and others, 2005). Small infestations of leafy spurge were identified in southeastern Idaho using HyMap (accessed March 22, 2012 at *http://www.hyvista.com/?page_id=440*) hyperspectral data (Glen and others, 2005).

Fiscal and Technical Considerations

Our ability to detect invasive plants over large landscapes is greatly improved by the use of remotely sensed data. The optimal remote sensing data, or combination of data, would have characteristics of hyperspectral sensors and high spatial resolution sensors. Although hyperspectral data facilitates detection of individual plants, hyperspectral data has approximately 75 times greater data volume than an equivalent area using Landsat ETM+ (Thenkabail and others, 2004). Likewise, multispectral, high spatial resolution sensors (for example, IKONOS or QuickBird) also show promise in detecting invasive plants with spatial resolutions less than 5 meters. These sensors are also encumbered by large data volumes over large areas. The new challenge is to develop methods that integrate the required spectral resolution with the ideal spatial resolution and are efficient with the high-dimensional data sets for large area analyses. Remote sensing data sets also come with fiscal and technical expertise considerations. Higher spectral and spatial resolution data are substantially more expensive than multispectral, medium spatial resolution sensors and require greater technical expertise for image processing (fig. 6.4).

Data Processing Considerations

Preprocessing Considerations

Box 6.2. Computational power needed for data processing.

- Fast processor (minimally a 2.0 GHz processor)
- At least 1.0 GB of RAM
- Multiple hard drives (2 or 3 hard drives optimize efficiency)
- At least 5 times the amount of hard drive storage space needed to store 1 copy of the imagery
- Virtual memory directory should have 5 times the amount of space as the RAM.

One of the first considerations to evaluate when beginning a remote sensing project is the availability of ample computation power and storage capacity. Image processing is computationally intensive, in terms of storage (hard drive space and RAM), and CPU(central processing unit) usage. There are no specific rules for the correct processor speed or amount of RAM (random access memory) needed to process and analyze

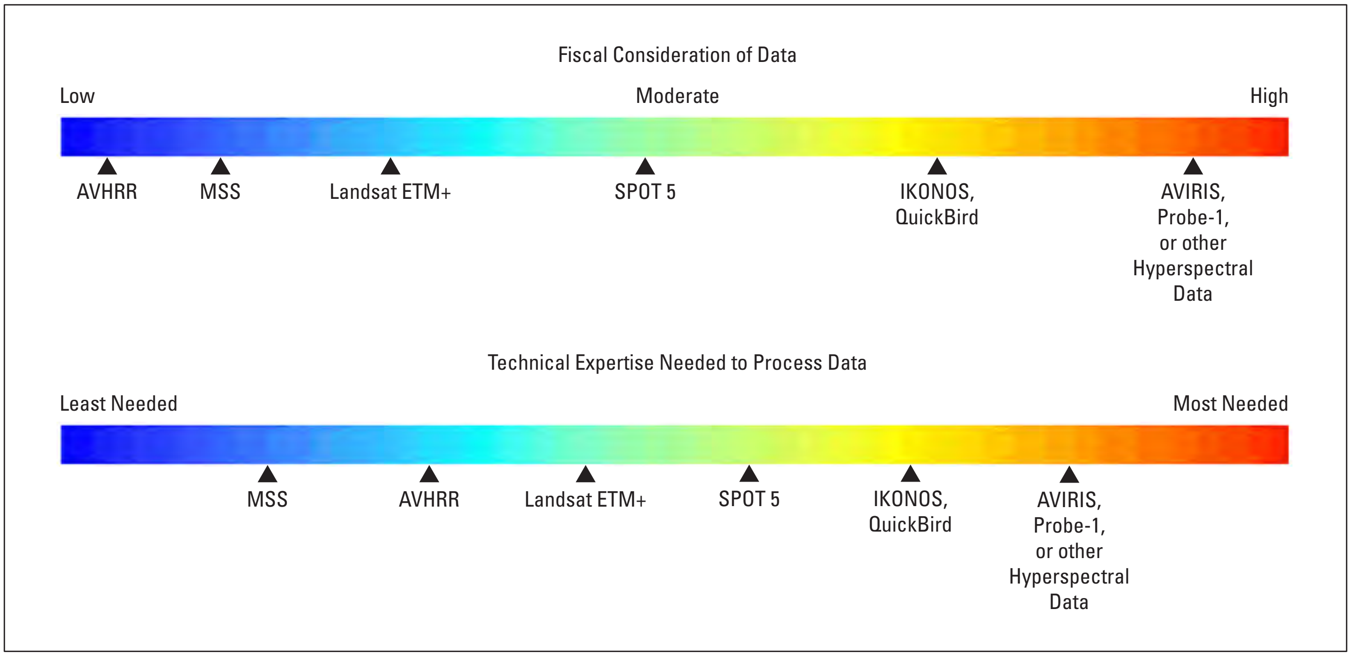

Figure 6.4. Fiscal and technical consideration associated with various types of remotely sensed data (accurate in 2006) (AVHRR, Advanced Very High Resolution Radiometer; MSS, Multispectral Scanner; ETM+ Landsat 7 Enhanced Thematic Mapper Plus; SPOT, Satellite Pour l'Observation de la Terre; AVIRIS, Visible/Infrared Imaging Spectrometer).

remotely sensed data. Generally, the computer should have at least a 2.0 GHz (gigahertz) processor (higher capacity CPUs are better) and at least 1.0 GB (gigabyte) of RAM. To allow for sufficient processing space, the computer used for image analyses should have at least five times the amount of hard drive storage space needed to store one copy of the imagery needed for the area of interest. Computers that contain more than one hard drive will optimize efficiency. One hard drive should be used as the "read from" drive and another as the "write to" drive. If possible, the operating system and virtual memory location should be on a separate hard drive from the processing drives. This would require a third hard drive but would increase processing efficiency. Further, the amount of space on the virtual memory directory should be increased to at least five times the amount of space as the physical memory (RAM).

Box 6.3. Preprocessing steps.

- Extract imagery from storage format
- Consolidate files
- Georeference imagery
- Standardize images, for example, atmospheric standardization
- Mosaic or reduce imagery to area of interest

No matter what remote sensing platform/imagery is chosen to meet research needs, several processing steps may be needed to facilitate the use of the imagery for invasive species analyses. These steps, commonly referred to as "preprocessing" techniques, place imagery in a format that facilitates analyses and reduces errors. Procedures used will vary depending on imagery selected and software used for analyses and processing. Most software packages have designed specific tools to facilitate preprocessing satellite images. Therefore, we discuss general preprocessing steps instead of specific procedures for any one software package. More information regarding the specific preprocessing procedure can be found in the software manuals. Typically, imagery "metadata" will describe processes that have been completed for each dataset and, therefore, indicate steps that remain to be accomplished. Explanations of preprocessing procedures can be found in Lillesand and Kiefer (1994) and Jensen (2005). Aspinall and others (2002) provide an overview to pre-processing and processing considerations with hyperspectral data.

Acquire and Extract Imagery

Box 6.4. Common image software packages.

- ArcView and ArcGIS - *http://www.esri.com/*
- Erdas Imagine - *http://www.hexagongeospatial.com/products/ERDAS-IMAGINE/details.aspx*
- ENVI - *http://www.exelisvis.com/ProductsServices/ENVIProducts.aspx*
- PCI - *http://www.pcigeomatics.com/*
- Idrisi - *http://www.clarklabs.org/*

Satellite imagery can be acquired from numerous sources in various file formats. Common methods of distribution include CD–ROM, DVD, and FTP or HTTP download. Imagery for a particular satellite sensor can be available in several formats that are directly compatible with various imagery manipulation software packages. Flat binary multiband formats are the most common form of storing remotely sensed data. This "generic binary" format is generally accepted by all software packages. The correct choice of format is dictated by the requirements and capabilities of the software used for analyses. Multiple steps commonly are required to place imagery in a format that is suitable for analyses. Typically, the first step is to "import" or extract imagery from a compressed transportation format into a format that the software can understand and display. Some software packages may require an intermediate format, requiring a second conversion from the storage format into a readable format, and then into an analysis format. For example, imagery may arrive in a .bil format (binary, band interleaved by line). This format can be imported and saved (first conversion) in an .img format (Erdas Imagine format). Depending on the software capabilities, the .img format may need a second conversion to a grid (ArcGIS format) for analyses. Although these steps are often trivialized, a considerable amount of time can be expended to extract imagery from its storage media or transportation format into a usable form.

Consolidate and Georeference Imagery

Satellite images may be received in several discrete files, one file for each band of data represented in a scene. For example, one file may represent the red spectrum of an image, another file representing the blue spectrum, and another file representing the green spectrum. Many software packages allow users to combine or "layer stack" these discrete bands of data into one file that contains all layers of information simultaneously. For example, Landsat ETM+ data often come with each band in a separate file. Once these files are combined, the resulting image contains attributes for each band. This consolidation of several data bands into one usable file allows users to efficiently manipulate multispectral data in subsequent processing steps.

Georeferencing is a generic term for the process of defining a spatial coordinate system to each pixel of an image so that it is precisely represented in the location where it is intended to be. The process of defining coordinates to pixels will vary in complexity depending on the precision required for analyses and the type and format of imagery used. In some cases adequate precision can be achieved throughout the image by defining coordinates to each of the corners of the image, such as in Landsat ETM+ imagery. In other cases, such as in the use of some aerial photography, several "ground control points" will need to be acquired to achieve precision within the entire image. Often DOQs are used to geo-reference other remotely sensed data. Defining a coordinate system accurately is essential if several image dates or other GIS data sets are to be analyzed simultaneously.

Atmospheric Standardizations

Procedures to compensate for variations in atmospheric conditions across multiple images and dates are referred to as atmospheric standardization. There are many types of atmospheric standardization routines available to users that, like georeferencing, vary in complexity depending on the precision desired and the type and format of imagery used. Most of the effective procedures attempt to compensate for differences in sun illumination intensity, atmospheric effects (for example, absorptions and refraction), and instrument calibration. These procedures typically normalize pixel values among adjacent image scenes or across multiple dates. Atmospheric standardization procedures can often improve the ability to conjoin adjacent imagery as well as enhance comparisons of multiple images in the same location (time series).

Mosaic or Reduce Imagery

Often, several satellite images will have to be joined because they were acquired in spatial sizes that did not completely represent the desired area for analyses. Several small adjacent scenes can be combined into one large, seamless mosaic image for analyses. The specific routines used for this procedure vary by software package; but in general, this task is accomplished by comparing overlapping pixels in adjacent images and adjusting the values so that each will closely coincide when combined. For this procedure to be effective, adjacent imagery should be acquired within the same day or within the shortest possible time period. It is also advisable to perform some form of image standardization prior to this procedure for the best results.

When one satellite image represents more land area than is required for analyses, it is often desirable to reduce the spatial extent of the image through a "clipping" process. Smaller images will expedite processing and analyses and reduce storage requirements. Clipping can be accomplished with GIS vector data or other raster data. Other related procedures, referred to as "masking," will also reduce required file sizes and subsequent processing time for analysis. Masking is the elimination of unwanted or unneeded pixels within an image. For example, areas that are contaminated by excessive cloud cover or cloud-shadowed areas, or areas that may corrupt analysis, such as snow cover or sun glint on water bodies, can be removed through a masking process. Areas that are removed to enhance image processing time and analyses are dependent on specific goals and objectives of each project.

Box 6.5. File formats.

- Flat binary multiband formats (common form of storing raster data)
  - .BIL (band interleaved by line)
  - .BIP (band interleaved by pixel)
  - .BSQ (band sequential)
- HDF-EOS format (standard data format for all NASA Earth Observing System)
- GeoTIFF format (commonly used generic image format that has spatial information) has spatial.
- ERDAS Imagine (one of the standard remote sensing formats)
  - .LAN format (old image format)
  - .IMG format
- Grid (ArcGIS, Arc/Info)
  - ArcGrid (integer data)
  - GridFloat (Arc floating point data)
- CEOS format (standard data format for radar data)
- MrSID format (Multi-resolution Seamless Image Database)
- Fast L7 (used for Landsat data where each band is self-contained in its own file)
- CAP or DIMAP format (used for SPOT data; may require software package with SPOT data interface)
- SDTS format (Spatial Data Transfer Standard)
- ESRI shape files (standard for vector data)

Attributes for Predictive Models

Box 6.6. Potential attributes for predictive models.

- Spectral reflectance
- Vegetation indices
- Elevation
- Slope
- Aspect
- Habitat associations
- Soil information
- Climatic conditions
- Landscape heterogeneity or degradation
- Anthropogenic locations (roads, fences, building)
- Species traits (flowers, early or late green-up, or senescence)

Many of the examples previously discussed used spectral characteristics as a means to identify invasive plants. Some authors used straightforward visual photograph interpretation methods (Mullerova and others, 2005; Anderson and others, 1996), while others used computer technology and various classification algorithms to classify remotely sensed images. These algorithms are based on spectral reflectance values. Because the spectral reflectance of a given pixel is influenced by the mixture of ground components in that pixel, remote sensing scientists have designed a wide variety of analyses to discriminate spectrally distinct vegetation types. Parker-Williams and Hunt (2002, 2004) applied the Mixture Tuned Matched Filtering (MTMF) classification algorithm to AVIRIS hyperspectral imagery to discriminate leafy spurge with as little as 10 percent canopy cover. Likewise, Glen and others

(2005) used the MTMF algorithm using HyMap hyperspectral imagery. Aspinall and others (2002) provide a summary of hyperspectral imagery classification algorithms used for discriminating invasive plants.

Vegetation indices are classification algorithms commonly used to discriminate plant populations. Most indices assess landscapes in terms of vegetation greenness, soil reflectance, and soil moisture. Examples of vegetation indices that may be useful in discriminating plant populations or attributes that favor invasive plant establishment include:

1. the Normalized Difference Vegetation Index (NDVI) (Lauver and Whistler, 1993),
2. Soil Adjusted Vegetation Index (SAVI) (Huete, 1988),
3. Modified Soil Adjusted Vegetation Index (MSAVI) (Qi and others 1994),
4. tasseled cap transformation,
5. simple band ratios, and
6. the wide dynamic range index (Andries and others, 1994; Tanser and Palmer, 1999; Schmidt and Karnieli, 2000; Gitelson, 2004).

Unfortunately, there is not one index that works best for all vegetation communities. Parks will need to evaluate multiple indices to determine which is most useful for their area and objectives. Vegetation indices can be derived from a variety of sensors, including AVHRR (Bradley and Mustard, 2005), Landsat TM (McGowen and others, 2001; Goward and others, 2003), IKONOS and QuickBird (Asner and Warner, 2003; Goward and others, 2003; Tsai and others, 2005), and hyperspectral data (Thenkabail and others, 2004).

Recent technologies in discriminating landscape features include texture analysis and object-oriented analysis. Image texture analysis investigates the structural and statistical properties of spatial patterns on images (Tsai and others, 2005). Object-oriented analyses classify an image based on attributes of an image object rather than attributes of individual pixels (Benz and others, 2004). Homogeneous pixels are aggregated into image objects using their spatial (size, shape, location) or spectral characteristics (Laliberte and others, 2004). These relatively new approaches show great promise for detecting invasive plants, especially when combined with spectral data.

While remotely sensed data can detect plant species and populations, some researchers have combined remotely sensed data with other spatial data sets to enhance predictive models. Anderson and others (1996) used aerial photograph interpretation, roads, trails, hydrographic data, slope, and aspect to model leafy spurge in Theodore Roosevelt National Park. The authors noted that using GIS and remote sensing data together proved to be a powerful combination of tools. Yellow starthistle was predicted using landscape variables such as elevation, slope, aspect, and Landsat land-use classifications (Shafii and others, 2003).

Remotely sensed data can also be used to assess attributes associated with invasive plant presence. For example, many invasive plants are associated with fragmented or degraded landscapes (Sakai and others, 2001; With, 2004). Tanser and Palmer (1999) used a measurement of landscape heterogeneity to assess degradation. A moving standard deviation filter was passed over Landsat TM imagery creating a moving standard deviation index (MSDI). Degraded landscapes exhibited higher MSDI values than undisturbed landscapes. Other environmental variables that are associated with landscape heterogeneity and appear to have high potential for remote sensing include total vegetation cover, relative proportion of grass and shrub cover, and organic soil cover (Warren and Hutchinson, 1984; Schmidt and Karnieli, 2000).

Species characteristics have been used to explain invasion patterns (Rejmanek and Richardson, 1996; Goodwin and others, 1999). For example, vegetative propagation, leaf size, flowering period, and wind dispersal were associated with invasive plant abundances on five Mediterranean islands (Lloret and others, 2005). However, inclusion of species characteristics into spatially explicit predictive models is hindered by the lack of strong associations between species characteristics and spatial data (see Chapter 7). Some species traits may be detected by remotely sensed data. For example, invasive species that have flowers and (or) bracts, green-up or senesce at a different time than plants in the surrounding environment, have a unique canopy architecture or growth form, or have a unique coloration are good candidates for using species-related traits in predictive modeling.

Attributes chosen to predict invasive species distributions may be direct, indirect, or "models of models" (see Chapter 7). In terms of landscape studies, ecological parameters are generally sampled from GIS or remotely sensed data. Close scrutiny of coarse resolution variables may be warranted, as these variables may introduce spatial uncertainties from interpolation errors, lack of sufficient ground data, and poor associations with causal factors (Guisan and Zimmermann, 2000). Variables that have little to no direct physiological relevance for a species' performance (slope, aspect, elevation, or topographic position) are easily measured from field or spatial data sets and are often used because of their good correlation to observed species patterns. Models constructed with these resource variables are typically general but are applicable over larger areas. Given the complexity of natural landscapes, spatially explicit predictive habitat models are generally a compromise between precision and generality (Guisan and Zimmermann, 2000). Chapter 7 provides greater discussion on attributes for species distribution models and their interpretation limitations.

Building Predictive Models

A variety of analytical methods could be used to construct predictive models for invasive species, ranging from simple overlays to more statistically driven models. Simple models can be developed directly within a GIS by using overlays of environmental variables. Boolean approaches are modeling methods that use overlay rules (where individual layers are added, subtracted, or multiplied together). These approaches have been widely used in wildlife habitat relation (WHR) models (for example, GAP models). WHR models describe resources and conditions present in areas where a species persists and reproduces or otherwise occurs. These modeled relations predict, and spatially depict, areas of potentially suitable habitat. While these types of models are informative, they may lack the ability to make statistical inferences.

Statistical approaches to constructing species distribution models (SDMs) will be discussed in Chapter 7. These approaches also apply to remote sensing and GIS data and can be more desirable than simple overlay models. Statistical approaches to model building allow enhanced accuracy and predictive power. Unfortunately, GIS software packages still lack important statistical procedures for predictive purposes. Some software packages have modules for classification and regression trees (CART), clustering analyses, logistic regression, and various other supervised classification procedures. However, statistical analyses in the GIS environment may be limited by the current lack of model selection procedures available in the software (for example, stepwise selection procedure for logistic regression) (Guisan and Zimmermann, 2000). Many statistical software analyses can be easily implemented into a GIS. For example, Generalized Linear Models (GLMs) and logistic regression analyses can be placed in a GIS by multiplying each regression coefficient with its related predictor variable layer. Most GIS software packages allow users to write algorithms for image manipulations. Alternatively, spatial data sets can be exported as ASCII files and analyzed in a variety of spatial programs. Guisan and Zimmermann (2000) and Scott and others (2002) provide additional insights into predictive model approaches. Unfortunately, there is no one analytical method that works for all scenarios. The appropriate analytical method for constructing predictive species models will be a function of park goals and objectives, the type and structure of the data, software availability, and expertise in statistical and GIS modeling.

The analytical method used to construct predictive models will dictate the type of model produced. Predictive models may display:

- probabilities of occurrence (derived from logistic GLM analyses),
- the most probable abundance (derived from ordinal GLM analyses),
- predicted occurrence (based on nonprobabilistic metrics), or
- the most probable entity (from hierarchical analyses) (Guisan and Zimmermann, 2000).

Regardless of the type of model, assessing model performance is essential in preparing adequate models. There are three forms of assessment for spatial models:

- draft models that are verified,
- committed (final) models that are assessed for accuracy, and
- final models subjected to user validation.

Draft models are produced during an evolutionary and refinement process that involves iterative collection and testing with verification data. **Model verification** does not examine the accuracy of the model or the usefulness of the model. Model verification examines only the model’s internal consistency (Conroy and Moore, 2002). This is analogous to “measures of model fit” discussed in Chapter 9. Subsequent to this iterative process, models are committed to a final form, which is the version that is subjected to accuracy assessment. No further alteration of a committed model is permitted after accuracy assessment; if further alterations are performed, then the model is a new version that requires additional assessment to provide an applicable accuracy statement. Final models and associated accuracy statements are published for use by others. Model validation is performed by, and arises from, judgments of intended users. Model validation depends primarily on the goals of the users rather than on statistics alone (Guisan and Zimmermann, 2000). See Chapter 9 for a greater discussion on model validation.

Model performance can be evaluated by:

- using two independent sets of data for building and evaluation (often called “training” and “evaluation” data),
- cross-validation procedures where the dataset is separated into two sets, a training set, and evaluation set,
- jack-knife procedures that resample the dataset based on deleting a portion of the original observations or input model variables in subsequent samples,
- bootstrap techniques that perform repeated random sampling with replacement from an original sample,
- randomization procedures where random samples are obtained by sampling without replacement, and
- resubstitution procedures where the same dataset is used for training and testing, with no partitioning of data.

Detailed explanations on these procedures, and others, are provided by Efron and Tibshirani (1993), Fieldings and Bell (1997), and Guisan and Zimmermann (2000). See also Chapter 9 for more information on model evaluation and assessment.

From an applied perspective, there are two ways a habitat model can be inaccurate:

- the model can overpredict, rating locations suitable although the location is unsuitable, or the species has not been detected in the predicted location (type I error),

- or the model can fail to predict the presence of a species where it is indeed present (type II error) (Shrader-Frechette and McCoy, 1993).

The first represents an error of commission. The second case represents an error of omission. Both types of errors undermine the defensibility of the model. However, errors of omission are less acceptable than errors of commission if we wish to implement a precautionary principle in biological conservation (Shrader-Frechette and McCoy, 1993). For example, if the predictive model and field assessment conclude an area is suitable, and the species was not present, then the area would be a good candidate to monitor for potential expansion of the species. Errors of commission and omission are often summarized in confusion or error matrices that cross-tabulate the observed and predicted presence/absence patterns (see Chapter 9). These matrices can be summarized into percent agreement and disagreement or further analyzed to evaluate the association between observed and predicted. For example, the correlation coefficient often is used to measure the strength of a relation between two variables that are normally distributed. The kappa statistic (Cohen, 1960) provides a measurement of the proportion of chance or expected agreement. The gamma coefficient, Spearman *R*, or Kendall *tau* are nonparametric equivalents to the standard correlation (Goodman and Kruskal, 1979; Zar, 1984). Other model performance assessments are discussed in Chapter 9, including threshold-dependent and threshold-independent measures.

Nature is heterogeneous and often difficult to predict accurately from a single, although complex, model. As such, model assessments over a wider range of situations (in space and time) will provide a better definition of the range of applications for which the model predictions are suitable (Guisan and Zimmermann, 2000).

Landscape Risk Assessments to Prioritize Areas for Conservation Efforts

Understanding where to concentrate survey efforts to find new species or expanding populations of existing species is paramount to early-detection protocols. Most natural resource managers prioritize survey efforts based on management considerations and documented predictors of invasiveness. However, given the variability associated with species traits, climatic events, and landscape characteristics, no set of conditions or traits exists that can be universally applied to accurately characterize all successful invasions (Alpert and others, 2000). Risk-assessment procedures can assist natural resource managers in prioritizing areas for conservation efforts. Risk assessment for invasive species is the process of obtaining quantitative or qualitative measures of risk levels by incorporating a broad array of information describing factors that may influence the distribution of invasive species (Allen and others, 2006). There are several approaches to modeling risk of invasions. For example, neutral landscape models, which evaluate flows through spatially heterogeneous landscapes, were used to assess the risk of invasions in fragmented landscapes (With, 2004). Landis (2004) describes a relative risk model that incorporates a system of numerical ranks and weighting of factors that may influence the distribution of invasive species. The Landis (2004) risk model takes into account the spatial relations of the locations of species introductions, migration paths, and the habitat structure or suitability. As such, modeling potentially suitable habitat and migration paths (potential vectors and pathways) for the introduction or spread of invasive species is an important component in conducting risk assessments in parks and other natural areas. Vectors refer to the mechanism of plant introduction, while pathways refer to the route taken. Examples of vectors include wind, water, and animals (Sakai and others, 2001). Examples of pathways include roads, trails, and waterways. Discussions on invasive plant vectors and pathways are presented in Chapter 2. Remote sensing and GIS data sets can model potential habitats, vectors, and pathways to allow for landscape-scale risk assessments.

Few communities are impenetrable to invasion by non-native species, but communities differ in their susceptibility to invasion (Sakai and others, 2001). Although it is difficult to generalize about invasive species dispersal across landscapes (Tackenberg, 2003), repeated introductions increase the chances of establishment (Sakai and others, 2001; Perrings and others, 2002). In many parks and other natural areas, roads and waterways are perhaps the pathways of most concern. These pathways enhance species invasions by acting as dispersal corridors, providing suitable habitat, and containing reservoirs of propagules (Parendes and Jones 2000). Disturbance along roads by vehicle traffic and maintenance activity (for example, road grading, ditch clearing, and trimming of overhanging vegetation) is often the source of repeated introductions. Waterway disturbances occur from floods and associated transport of sediment.

GIS data sets for invasive species pathways are readily accessible. Many parks and natural areas already have road, trail, and waterway GIS layers. Road and hydrologic layers are available from a variety of GIS data clearinghouses, Federal agencies, and private companies. Digital line graphs (DLGs) (digital vector data derived from USGS maps), Digital Raster Graphics (DRGs) (scanned digital images of USGS topographic quadrangles), and National Hydrography Data sets (NHD) can be downloaded from the USGS Website *http://eros.usgs.gov/*.

Spatial data sets on potential invasive species vectors are not as readily accessible and would likely have to be created specifically for the target species and the area of interest. Many authors have analytically modeled potential vectors, especially seed dispersal by wind. Schurr and others (2005) created a mechanistic model for secondary seed dispersal by wind (the wind-driven movement of seeds along the ground surface). The authors found a relation between seed dispersal and seed size but noted that the model tended to underestimate dispersal rates. Tackenberg (2003) also modeled seed dispersal by wind and found that long-distance dispersal was primarily influenced by weather conditions that yielded thermal turbulence and convective updrafts. Tackenberg (2003) noted that the inclusion of topography in estimating dispersal rates is important, even in landscapes that exhibit only small differences in elevation and slight slopes. In addition, Campbell and others (2002) simulated landscape-scale invasions of plants that use rivers to transport propagules.

Box 6.7. Benefits of remote sensing.

- Remote-sensing technologies look beyond the human view in the electromagnetic spectrum, which allows better detection of vegetation.
- Remote sensors allow for regional analyses.
- Cost savings for large parks.
- Provides a means for prioritizing ground surveys.
- Facilitates repeat analyses and change detections.

Few studies have created spatial models of vectors or pathways. Favorable predictive spatial models incorporate:

- invasive species distribution data,
- population rates,
- factors influencing the number of propagules,
- dispersal modes,
- landscape structure,
- ecological processes, and
- statistically explained patterns (Moody and Mack, 1998; Higgins and others, 1996; Higgins and Richardson, 1999; Wadsworth and others, 2000; Sakai and others, 2001).

Summary

Remotely sensed images have a number of features that make them ideal for predicting invasive species in parks and other natural areas. Remote-sensing technologies look beyond the human view, in the electromagnetic spectrum, which allows better detection of vegetation. Remote sensors allow for regional analyses that would be cost-prohibitive using ground-based visits. Regional analyses allow for prioritizing ground-reconnaissance visits to survey, control, or eradicate potential invasive plant populations. Further, the ease of securing temporal data allows for repeat analyses and change detections.

Our ability to detect invasive plants using remotely sensed data has increased with improved sensors, computer technology, and classification techniques (Lass and others, 2005). Although integrating remotely sensed data with other spatial data sets enhances our abilities to model invasive plants, detecting small or sparse plant populations is still hampered by spatial and spectral resolution and by our limited ability to analyze large data sets. Data sets that have the highest likelihood of detecting invasive plants come with high fiscal and technical considerations. Overall, the use of remotely sensed data will be most appropriate for species whose biological characteristics, habitat composition and structure, and landscape context combine to offer a data quality and logistical advantage to ground-based methods (Landenberger and others, 2003).

Parks and other natural areas need predictive models that can help in setting priorities for control of invasive species and predicting the potential of future invasions. Remotely sensed data can aid in the development of spatially explicit predictive habitat models and estimates of distributional vectors and pathways (see Chapter 12 for an example). This information will provide land managers with early-detection tools, a means to evaluate current and future control needs, and a means to prioritize conservation efforts. Early-detection methods increase our ability to eradicate invasive plants and reduce costs of control (Rejmanek and Pitcairn, 2002).

Recommended Reading

- Introductory digital image processing—A remote sensing perspective (Jensen, 2005).
- Introduction to Remote Sensing (Campbell, 2002).
- Remote sensing and image interpretation (Lillesand and Kiefer, 1994).

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