Improving Potential Geographic Distribution Models for Invasive Plants by Remote Sensing

Authors: Hunt,, E. Raymond, Gillham, John H., and Daughtry, Craig S. T.

Source: Rangeland Ecology and Management, 63(5) : 505-513

Published By: Society for Range Management

URL: https://doi.org/10.2111/REM-D-09-00137.1

Rangeland Ecol Manage 63:505–513 | September 2010 | DOI: 10.2111/REM-D-09-00137.1

Improving Potential Geographic Distribution Models for Invasive Plants by Remote Sensing

E. Raymond Hunt, Jr.,[1] *John H. Gillham,*[2] *and Craig S. T. Daughtry*[3]

Authors are [1]*Research Physical Scientist and* [3]*Research Agronomist, US Department of Agriculture (USDA) Agricultural Research Service, Hydrology and Remote Sensing Laboratory, Beltsville, MD 20705, USA; and* [2]*Computer Specialist, USDA Forest Service, Remote Sensing Applications Center, Salt Lake City, UT 84119, USA.*

Abstract

Remote sensing is used to map the actual distribution of some invasive plant species, such as leafy spurge (*Euphorbia esula* L.), whereas geospatial models are used to indicate the species' potential distribution over a landscape. Geographic data layers were acquired for Crook County, Wyoming, and the potential distribution of leafy spurge presence or absence were predicted with the use of the Weed Invasion Susceptibility Prediction (WISP) model. Hyperspectral imagery and field data were acquired in 1999 over parts of the study area. Leafy spurge presence or absence was classified with the use of the Spectral Angle Mapper with a 74% overall accuracy. However, the user accuracy was 93%, showing that where leafy spurge was indicated in the image, leafy spurge was usually found at that location. With the use of Kappa analysis, there was no agreement between WISP model predictions and either the field data or the classified hyperspectral image. Kappa analysis was then used to compare predictions based on single geographic data layers, to increase the power to detect subtle relationships between independent variables and leafy spurge distribution. The WISP model was revised for leafy spurge based on the remote-sensing analyses, and only a few variables contributed to predictions of leafy spurge distribution. The revised model had significantly increased accuracy, from 52.8% to 61.3% for the field data and from 30.4% to 80.3% for the hyperspectral image classification, primarily by reducing the areas predicted to have potential for invasion. It is generally more cost effective to deal with the initial stages of invasion by only a few plants, compared to an invasion that is large enough to be detected by remote sensing. By reducing the potential area for monitoring, management of invasive plants could be performed more efficiently by field crews.

Resumen

La teledetección se utiliza para mapear la distribución efectiva de algunas especies de plantas invasoras tales como la *Euphorbia esula* L., mientras que los modelos geoespaciales se utilizan para indicar la distribución potencial de esta especie en el paisaje. Se obtuvieron capas de datos geográficos para el condado de Crook, Wyoming, y la distribución potencial de presencia o ausencia de *E. esula* se predijo utilizando el modelo de Predicción de Susceptibilidad a la Invasión por Malezas (PSIM). Se obtuvieron imágenes hiperespectrales y datos de campo de 1999 de porciones del área de estudio. Se clasificó la presencia o ausencia de *E.esula* utilizando el Mapeador Espectral de Angulo con un 74% de exactitud general. Sin embargo, la exactitud del observador fue del 93% demostrando que donde *E.esula* era indicada en el mapa, generalmente era encontrada en el terreno. El uso de la Prueba de Kappa demostró la ausencia de correspondencia entre las predicciones del modelo PSIM y los datos de terreno o la imagen hyperespectral clasificada. La Prueba de Kappa se utilizó luego para comparar predicciones basadas en capas geográficas individuales con la finalidad de aumentar el poder de detección de relaciones sutiles entre las variables independientes y la distribución de *E. esula*. Se realizó una revisión del modelo PSIM para ajustarlo a *E. esula* basado en el análisis de teledetección, y solamente unas pocas variables contribuyeron a predecir la distribución de *E. esula*. La exactitud del modelo revisado aumentó significativamente de 52.8% a 61.3% para datos de campo y de 30.4% a 80.3% para la clasificación hiperespectral de imágenes, debido principalmente a la reducción de aéreas con potencial predicho de invasión. Generalmente es más económico intervenir durante los estadíos tempranos en los que la invasión consiste de unas pocas plantas comparado con una invasión que es lo suficientemente grande como para ser detectada mediante teledetección. La reducción del área potencial de monitoreo, permitiría a los equipos de campo realizar un manejo más eficiente de plantas invasoras.

Key Words: AVIRIS, *Euphorbia esula*, hyperspectral remote sensing, Kappa analysis, leafy spurge, Weed Invasion Susceptibility Prediction model

INTRODUCTION

Invasive species are a world-wide problem affecting maintenance of biodiversity and production of food and fiber. In the United States, annual economic losses from invasive species are about $120 billion (Pimentel et al. 2005). Understanding the potential geographic distribution of an invasive species is important because regions that have not yet been infested require different management strategies compared to regions that are already infested (Rouget et al. 2004). An active area of research is the development of potential distribution models, both as a scientific methodology to understand species' niches (Jackson et al. 2009) and to predict changes in distribution with

Correspondence: Raymond Hunt, USDA Agricultural Research Service Hydrology and Remote Sensing Laboratory, Building 007 Room 104 BARC-West, 10300 Baltimore Avenue, Beltsville, MD 20705, USA. Email: Raymond.Hunt@ars.usda.gov

Manuscript received 24 September 2009; manuscript accepted 27 May 2010.

climate change (Pearson and Dawson 2003; Thuiller et al. 2008). Niche models require a different set of parameters for each invasive species based on its specific ecological characteristics (Peterson 2003; Austin 2007; Hoffman et al. 2008; Stohlgren et al. 2010). A general problem with potential distribution models is that these models are usually tested with only species-presence data, which can result in model errors (Fielding and Bell 1997; Engler et al. 2004; Tsoar et al. 2007). Other studies have shown that using only species-presence data can result in accurate distribution models (Evangelista et al. 2008, 2009; Kumar et al. 2009). On the other hand, species-absence data can be unreliable because a given location can be either unfavorable for the species occurrence or simply the propagules for the species haven't arrived yet at that location.

A major application of remote sensing is to map the actual distribution of invasive species (Everitt et al. 2002; Underwood et al. 2003; Lass et al. 2005). Remotely sensed imagery is often used to provide variables for the prediction of invasive weed distribution (Morisette et al. 2005; Rew et al. 2005). Furthermore, remote sensing can be used to map the locations of plant species that have spectral or phenological differences from the co-occurring native vegetation, which then can be used in lieu of field plots to develop potential geographic distribution models (Bradley and Mustard 2006; Andrew and Ustin 2008, 2009).

Leafy spurge (*Euphorbia esula* L.) is an invasive weed that renders large amounts of rangeland unfit for horses or cattle (Anderson et al. 2003). For four states, Wyoming, Montana, North Dakota, and South Dakota, the direct economic losses exceed $37 million annually and the indirect economic losses are about $83 million annually (Leistritz et al. 2004). The flower-bracts are distinctively yellow green (Hunt et al. 2004), which can be remotely sensed either with high-spatial-resolution sensors or imaging spectrometers/hyperspectral sensors (Everitt et al. 1995; Anderson et al. 1996; Everitt et al. 2002; Casady et al. 2005; Glenn et al. 2005). The success is mixed for moderate-resolution, multispectral sensors such as Landsat Thematic Mapper (Hunt and Parker Williams 2006; Mladinich et al. 2006; Stitt et al. 2006; Mitchell and Glenn 2009). Therefore, the ability of remote sensing to detect leafy spurge is probably dependent on high amounts of flower-bract cover in a pixel (Hunt et al. 2007), which in turn may be related to leafy spurge's vegetative propagation via adventitious buds on the root system (Messersmith et al. 1985).

Gillham et al. (2004) developed the Weed Invasion Susceptibility Prediction (WISP) model, which uses simple thresholds and categorical variables relating species occurrence to geographic distribution in a landscape. Furthermore, the WISP model was parametrized for leafy spurge with the use of only presence data acquired in Wyoming's Bighorn River Basin, and model performance was assessed with the use of only producer accuracy (Gillham et al. 2004). In this study, the WISP model was used to predict the occurrence of leafy spurge at a new site, Devils Tower National Monument in northeastern Wyoming. Parker Williams and Hunt (2002, 2004) and Hunt et al. (2007) determined the distribution of leafy spurge at Devils Tower National monument with the use of imagery from NASA's Airborne Visible Infrared Imaging Spectrometer (AVIRIS; Green et al. 1998). Over a landscape, the unreliability of absence data may be ameliorated by acquiring a large number of pixels. Similar landscape units that are potentially unfavorable will have relatively few occurrences of leafy spurge, whereas for the similar landscape units that are potentially favorable, some will have leafy spurge and some will not. Both presence and absence data from remote sensing are then used to test and then revise the WISP model.

METHODS

Study Area

The original study was conducted as part of The Ecological Area-Wide Management Leafy Spurge project (Anderson et al. 2003; Hodur et al. 2006). The study area was around Devils Tower National Monument in Crook County, Wyoming, between lat 44.4° and 44.6° N and long from 104.6° to 104.9° W (Fig. 1). Elevations range from 1 219 m to 1 584 m and vegetation is a mosaic of conifer woodlands, northern mixed-grass prairie, riparian zones with deciduous shrubs and trees, and sagebrush shrub lands. Leafy spurge is well established throughout the area (Parker Williams and Hunt 2002, 2004).

There were two sets of field plots established for validation of remotely sensed imagery. The first set were circular plots (46 m in diameter; $n = 109$) used for determining the amount of cover, where all plots had some leafy spurge (Parker Williams and Hunt 2002). The second set were square plots (50 m on a side; $n = 246$) used for classification accuracy of spurge presence or absence (Parker Williams and Hunt 2004). The positions of the center point or corner points were obtained with a Rockwell Precision Federal Global Positioning System (Rockwell International, Cedar Rapids, IA) with a positional accuracy of 5 m. The two sets of plot data were acquired during June and July 1999 (Parker Williams and Hunt 2002, 2004) and were combined for the accuracy assessment of WISP model.

Weed Invasion Susceptibility Prediction Model (WISP)

The WISP model uses a geographic information system (GIS) to predict suitable areas for five invasive plant species with the use of commonly available geospatial data layers and a look-up table of parameters (Gillham et al. 2004). Vector data layers are converted into raster formats. Pixels that are unsuitable for a specific geospatial data layer are labeled with a zero and pixels that are suitable are labeled with a one. Then, the sum of all zeros and ones from the various data layers is calculated for each pixel.

Gillham et al. (2004) used expert opinion to determine the model parameters for leafy spurge (Table 1). Furthermore, because they used nine data layers, pixels with sums of eight or nine were defined as having high susceptibility for invasion by leafy spurge. The GIS data layers for the WISP model were obtained from the Wyoming Geographic Information Science Center, University of Wyoming (http://www.uwyo.edu/wygisc/). The map scale of the data was 1:100 000, and the positional accuracy was about 51 m. To match the resolution of the remote-sensing data, the geospatial data layers were converted into 20-m pixels.

Image Acquisition and Classification

NASA's AVIRIS was flown in an ER2 aircraft at high altitude (resulting in 20-m pixels) over the study area on 6 July 1999

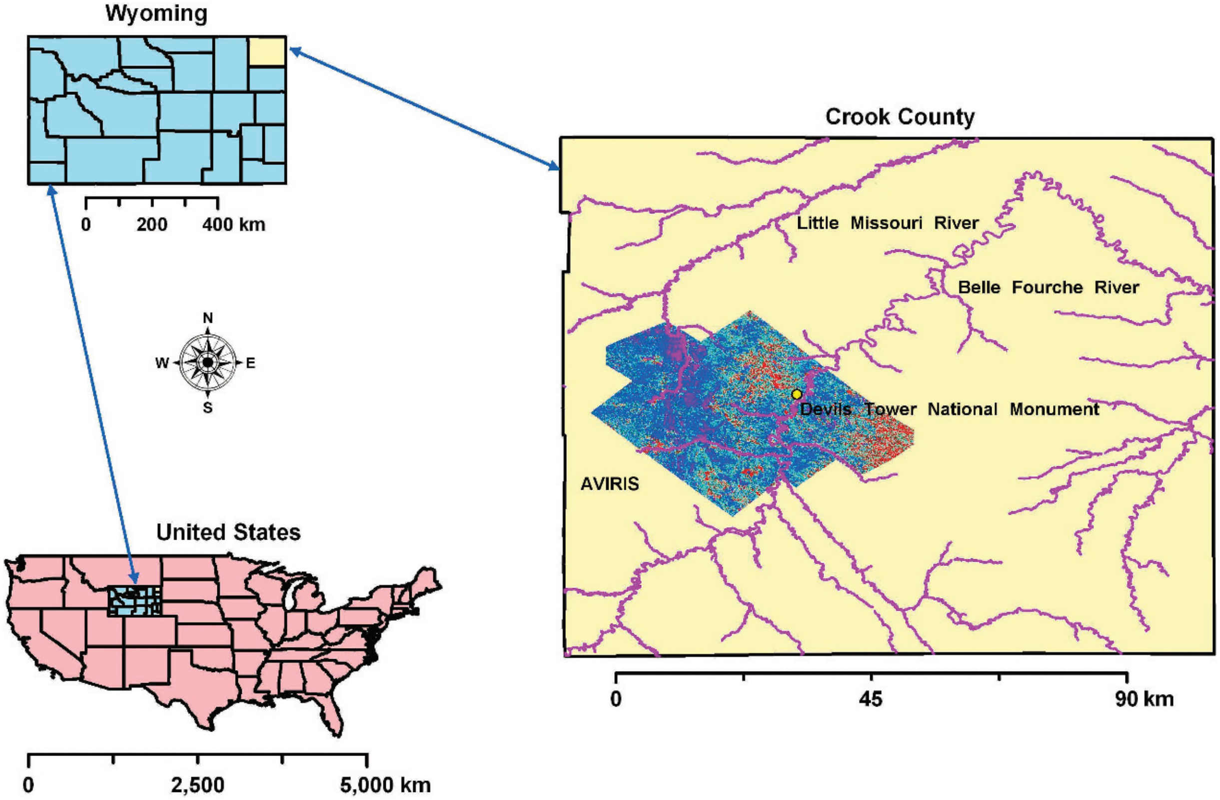

Figure 1. Location of Crook County, Wyoming, and coverage of the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) overflights. The two major rivers are the Little Missouri and the Belle Fourche. The location of Devils Tower National Monument is indicated with a dot.

(Parker Williams and Hunt 2002, 2004). The AVIRIS data were atmospherically corrected to land-surface reflectance with the use of the Atmospheric Correction Now (ACORN) model from ImSpec LLC (Seattle, Washington). Atmospheric spectral transmittance was estimated in the ACORN model by using gas and water vapor absorption bands (Gao et al. 1993, 2009). Then the ACORN model output for each pixel was smoothed with the use of the measured reflectance spectra of a large talus field at the base of Devils Tower (Parker Williams and Hunt 2002). In 1999, high-altitude AVIRIS flights did not have global positioning system and inertial motion sensor data recorded with each scan line of data; hence, the three flight lines were registered to a geospatially rectified SPOT 4 image (20-m pixels) acquired on 11 July 2000. The root-mean-square error between the AVIRIS and SPOT 4 images was 26 m. However, inspection of the overlap between adjacent flight lines showed that some areas were misregistered by up to eight pixels (160 m), which occurred because atmospheric turbulence affected the ER2 aircraft during the overflights.

Table 1. Original Weed Invasion Susceptibility Prediction (WISP) model variables and parameter values for leafy spurge presence from Gillham et al. (2004).

Variable	Parameter values
Distance to water	<500 m
Distance to disturbance (roads)	<400 m
Aspect	South, east, west
Slope	$<36^\circ$
Elevation range	1 200–2 400 m
Precipitation	>200 mm
Soil texture class	Loam, sandy loam, silt loam, clayey loam
Vegetation cover type	Shrublands, grasslands, woodlands, riparian, nonvegetated
Soil pH	6.8–8.4

Kruse et al. (1993) defined the spectral angle between two reflectance spectra based on vector algebra:

$$\cos\Theta = \mathbf{R}\cdot\mathbf{T}/(\|\mathbf{R}\|\|\mathbf{T}\|) \quad [1]$$

where Θ is the spectral angle (degrees), $\mathbf{R}$ and $\mathbf{T}$ are the reference and target spectra, the numerator is the dot product of two vectors, and the denominator is the product of the normalized vectors. A large field (7.2 ha in size, 182 pixels) with approximately 100% cover of flowering leafy spurge (ocular estimate) located just outside of Devils Tower National Monument was selected as the training area for the reference spectrum of leafy spurge. Classification with the use of the spectral angle mapper (SAM) requires some threshold value of Θ, so spectral angles less than the threshold are classified as leafy spurge present and spectral angles greater than the threshold are classified as leafy spurge absent. A low threshold will increase the number of false negatives (errors of omission), which will lower the producer accuracy, whereas a high threshold will increase the number of false positives (errors of commission), which will lower the user accuracy. The threshold value of Θ was determined to be 3.5°, with the use of

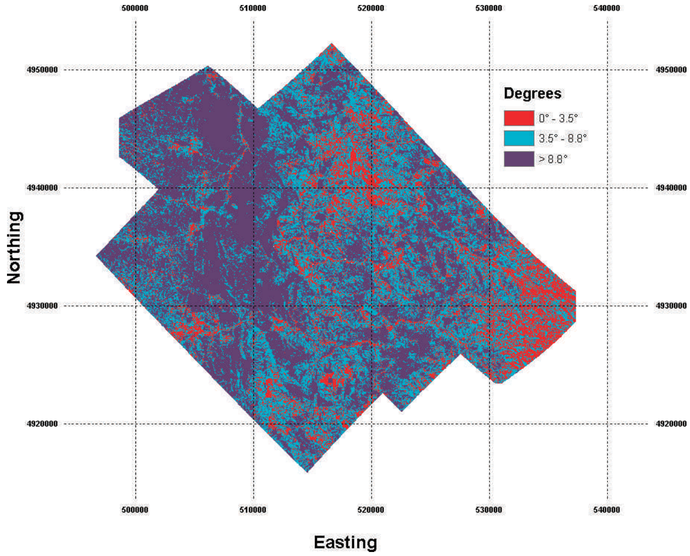

Figure 2. Spectral angle mapper (SAM) classification for three Airborne Visible Infrared Imaging Spectrometer (AVIRIS) flight lines acquired on 6 July 1999. The spectral angles were divided into three classes: leafy spurge present (red), high vegetation cover with leafy spurge absent (cyan), and low vegetation cover with leafy spurge absent (violet).

simulations from the scattering by arbitrarily inclined leaves model and plot spectral reflectance data (Hunt et al. 2007).

Kappa Analysis

Cohen (1960, according to Congalton and Green 2009) originally proposed Kappa analysis for testing categorical data. The Kappa statistic ($\hat{\kappa}$) is defined:

$$\hat{\kappa} = (P_c - P_e)/(1 - P_e) \qquad [2]$$

where P_c is the percentage of correct predictions (overall accuracy) and P_e is the percentage of correct predictions attributable to chance, which is calculated from the false-positive and false-negative errors (Congalton and Green 2009). One important feature of Kappa analysis is that the variance of $\hat{\kappa}$ can be estimated, so inference tests (Z statistic) can be used to test hypotheses about differences among various classifications (Congalton and Green 2009).

We used the AVIRIS SAM classification of leafy spurge presence and absence to test the WISP model predictions pixel-by-pixel over the landscape around Devils Tower National Monument. However, with 808 557 pixels, there was too much statistical power to accept the null hypothesis, possibly causing a Type II error. Sims and Wright (2005) generally suggested sample sizes up to about 1 600 in order to detect small differences of $\hat{\kappa}$, so 1 000 pixels were selected at random for calculating $\hat{\kappa}$ and its variance.

The significance of each WISP model variable was tested with the use of the presence/absence predicted by that variable alone with the AVIRIS SAM classification. For the variables distance to water (defined as streams and rivers) and distance to disturbance (defined as roads), we increased the threshold distance incrementally to determine the value that maximized accuracy. New parameters were selected to create a revised model, which was then tested with the field data and AVIRIS classification.

Table 2. Accuracy assessment of the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) Spectral Angle Mapper (SAM) classification of leafy spurge presence/absence with the use of the plot data of Parker Williams and Hunt (2002, 2004).

	Field data	
AVIRIS classes	Present	Absent
Present	139	10
Absent	83	122

Total = 354
Overall accuracy = (139 + 122)/354 = 0.737
Producer accuracy = 139/(139 + 83) = 0.626
User accuracy = 139/(139 + 10) = 0.933
$P_e = [(222 \times 149) + (205 \times 132)]/(354)^2 = 0.480$
Kappa ($\hat{\kappa}$) = (0.737 − 0.480)/(1.0 − 0.480) = 0.495
$Z = 10.62$

RESULTS AND DISCUSSION

AVIRIS Image Classification

For the three AVIRIS flight lines, about 8% of the area was classified as leafy spurge with the use of the Spectral Angle Mapper (Fig. 2). Three classes of vegetation cover were separated by the value of Θ: high vegetation cover with leafy spurge, high vegetation cover without leafy spurge, and low vegetation cover without leafy spurge. The SAM classification of the AVIRIS data was only 74% accurate, the user accuracy was 93%, and the Kappa statistic was highly significant (Table 2). The high user accuracy indicated that where leafy spurge was by the classified image, it was usually found at that location. Nonflowering leafy spurge has spectral reflectances similar to that of other green vegetation (Hunt et al. 2004), so some of the errors in overall accuracy (Table 2) were probably due to variation in the cover of flowering of leafy spurge (Parker Williams and Hunt 2002).

The SAM classification results were not as good as previously reported with a classification based on mixture tuned matched filtering, which uses two subsets of the same AVIRIS and ground data (Parker Williams and Hunt 2002, 2004). Mixture tuned matched filtering separates a single spectral class from an image by comparing the reference and pixel spectra with respect to the variance calculated from all pixels. Because the entire AVIRIS data set was used in this analysis, there were probably many more spectral classes; thus the variance was much larger (J. W. Boardman, personal communication, May 2004), with the result that the classification of leafy spurge was not significantly better than chance ($Z = 0.75$). However, the SAM classification was significantly better ($Z > 3.0$) than alternative supervised methods such as Mahalanobis distance and maximum likelihood (data not shown).

WISP Model Results

For Crook County, about 57% of the area was predicted to have high susceptibility to invasion by leafy spurge with the use of the original WISP model (Fig. 3). Accuracy assessment using the field plots in the study area ($n = 354$) resulted in an overall accuracy of 53%, which was not significantly different from

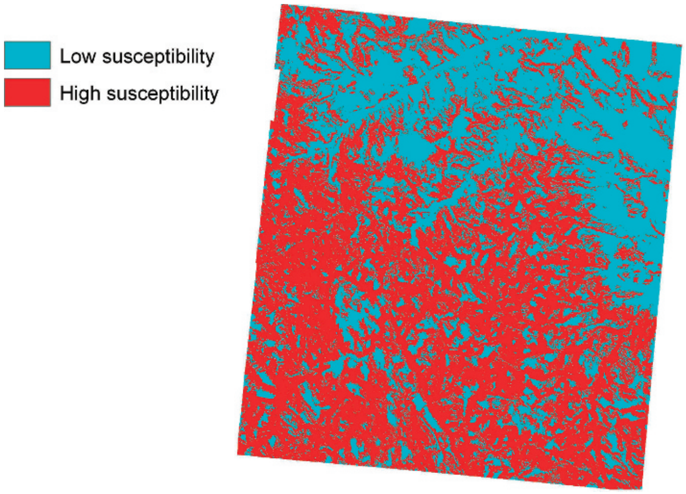

Figure 3. Weed Invasion Susceptibility Prediction (WISP) model predictions for leafy spurge in Crook County, Wyoming, with the use of the original model developed by Gillham et al. (2004). Data layers include elevation, slope, aspect, precipitation, soil texture, soil pH, distance to streams and rivers, distance to roads or other disturbed areas, and land-cover class. Susceptibility to leafy spurge invasion is the sum of favorable factors for each data layer, so a sum of 8 or 9 factors indicates high susceptibility for leafy spurge (dark gray or red) and sums < 8 indicate low susceptibility for leafy spurge (light gray or cyan).

Table 3. Accuracy assessment of Weed Invasion Susceptibility Prediction (WISP) model predictions for leafy spurge in Crook County, Wyoming, compared to field data and the classified Airborne Visible Infrared Imaging Spectrometer (AVIRIS) image.

	Data	
WISP predictions	Present	Absent
Field data		
Present	160	105
Absent	62	27
Overall accuracy = 0.528		
Producer accuracy = 0.721		
User accuracy = 0.604		
$\hat{\kappa} = -0.080$		
$Z = -1.36$		
AVIRIS		
Present	67 627	532 015
Absent	30 364	178 551
Overall accuracy = 0.304		
Producer accuracy = 0.690		
User accuracy = 0.113		
$\hat{\kappa} = -0.018$[1]		
$Z = -0.864$[1]		

[1]Based on 1 000 randomly selected pixels.

random chance (Table 3). The producer accuracy was 72%, which is somewhat lower than the producer accuracy determined by Gillham et al. (2004). In that study, the WISP model was validated in the Worland District of the Bureau of Land Management, located in Wyoming's Bighorn River Basin. Various state and local agencies collected leafy spurge presence data with global positioning system location ($n = 6461$).

Testing the WISP model predictions using the AVIRIS data for the study area resulted in an overall accuracy of 30%, which also was not significantly different from random chance (Table 3). Producer accuracy is similar to that for the field data; however, the user accuracy was only 11%, indicating that the original WISP model could not be used to predict potential habitat for leafy spurge.

WISP Model Evaluation and Modification

Presence or absence of leafy spurge was predicted for each data layer, which was then compared to the AVIRIS SAM classification with the use of Kappa analysis. Based on the parameters of the WISP model, leafy spurge was expected to occur on loamy soil textures; however, loamy soils had a significant negative association with leafy spurge (Table 4). Furthermore, leafy spurge was expected to occur on east-, west-, and south-facing slopes, but there was no significant association with aspect. Also, leafy spurge was expected to occur in grassland and shrub land cover types, which was not found (Table 4). Contrary to expectations, leafy spurge occurrence was significantly associated with clay and silty clay loam soil textures, and riparian and woodland land cover classes (Table 4). Other data layers had little or no variation over the study area precipitation, soil pH, elevation, and maximum slope, so these variables could not be tested for association with leafy spurge. Distance to disturbance (roads) was negatively associated with the occurrence of leafy spurge for all threshold distances from 25 m to 1 000 m (data not shown).

Distance to water was inversely related to leafy spurge susceptibility as expected, with areas close to water having higher occurrence of leafy spurge. The threshold distance to water was varied incrementally from 20 m to 1 000 m (Fig. 4). As the threshold value of distance increased, the $\hat{\kappa}$ reached a maximum at 100 m. At a threshold distance of 200 m, $\hat{\kappa}$ had the highest level of significance even though the value of $\hat{\kappa}$ was lower (Fig. 4). As the threshold distance to water increased, more total area was predicted to have potential for leafy spurge to occur, up to a distance of 1 000 m, where 98% of the area was predicted to be susceptible (Fig. 4). Also shown on Fig. 4 is the producer accuracy from the AVIRIS SAM classification; as the total area increased from thresholds from 20 m to 400 m, the producer accuracy was larger than the fractional area. At larger thresholds, the producer accuracy was about equal to the fractional area (Fig. 4), and the result was high producer accuracies for model prediction simply because of random chance.

If a large area is predicted to be susceptible, then the producer accuracy will be high even if model accuracy is not significant. Producer accuracies of 100% can be obtained by predicting the entire study area as susceptible to leafy spurge, which could provide some insight to its biology, but then the model would not be useful for prediction. Therefore, the problem with presence-only data for potential distribution models is the possibility that model parameters are determined without respect to total area predicted to be susceptible.

The WISP model was revised with the use of the results of the Kappa analyses. Three of the nine GIS data layers were used in the revised model; the new model parameters were 1) distance

Table 4. Associations between geospatial class and classified Airborne Visible Infrared Imaging Spectrometer (AVIRIS) imagery for three geographic variables with the use of Kappa analysis.

Variable	Class	$\hat{\kappa}$[1]	Z[1]
Soil texture	Loam	−0.084	−2.368
	Clay loam	−0.006	−0.101
	Silt loam	0.002	−0.052
	Clay	0.071	1.972
	Silty clay loam	0.084	1.746
Aspect	East	−0.009	−0.236
	South	−0.020	−0.576
	West	−0.006	−0.139
	North	0.036	0.941
Land cover	Grassland	−0.056	−1.177
	Shrubland	−0.085	−3.939
	Riparian	0.209	4.022
	Woodland	0.122	2.856

[1]Based on 1 000 randomly selected pixels.

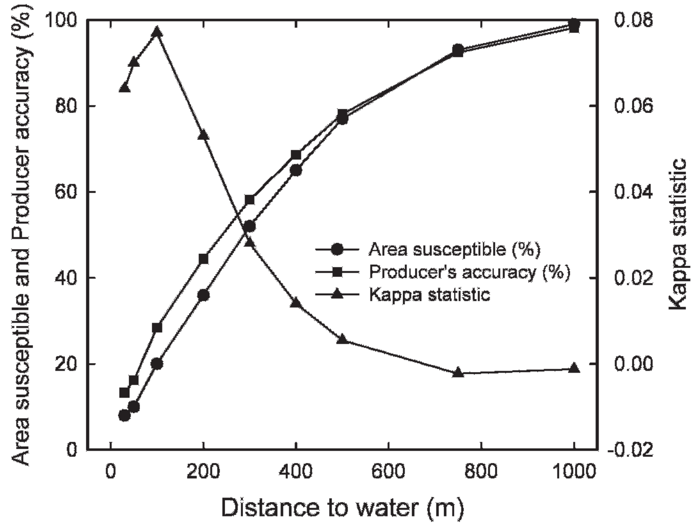

Figure 4. Variation in Weed Invasion Susceptibility Prediction (WISP) model accuracy for changes in the threshold distance parameter for the data layer, distance to water. Distances to water less than the threshold are predicted to be leafy spurge present and distances greater than the threshold are predicted to be leafy spurge absent. As the distance to water increases, more area is predicted to be susceptible. Producer accuracy is a measure of false negative errors.

to water $\leq$ 200 m, 2) riparian/woodland land cover, and 3) clay or silty clay loam soil textures. A sum of three was used to identify susceptible pixels. The area of Crook County estimated to be susceptible to leafy spurge was reduced from 43% to 13% (Fig. 5). A few new areas were predicted to be susceptible to leafy spurge compared to the original WISP model.

For both the field data and AVIRIS SAM classification, the revised model had lower producer accuracies and much higher overall accuracies, which were highly significant (Table 5). With the AVIRIS SAM classification, the revised model had a very low user accuracy of 22%, because there were a large number of pixels where the revised model predicted leafy spurge but the classification indicated leafy spurge was not present (Table 5). These areas could actually have leafy spurge, but the cover of leafy spurge was not high enough to be detected in the AVIRIS SAM classification (Table 2). Also, not all areas that were potentially susceptible for leafy spurge would actually have leafy spurge. Ranchers and farmers in the area have been applying herbicides and biological control methods to reduce the amount of leafy spurge in some areas. Therefore, the low user accuracy of the revised model could be in part attributed to the unreliability of absence data. Use of remote sensing imagery was important for WISP model revision because the large number of pixels allowed associations between leafy spurge and geographic data layers to be detected even when leafy spurge did not occupy all of the potential area.

On the other hand, there were about 3 times more pixels classified as leafy spurge in the areas predicted not to be susceptible to leafy spurge, i.e., low producer accuracy (Table 5). These are errors either by the revised WISP model or the geographic data layers. For example, there was a negative association between loamy soil texture and pixels classified as leafy spurge; however, there were some pixels classified as leafy spurge that occurred on loamy soils. Possibly, plants of other species may have had higher productivity on loamy soils, which reduced the cover leafy spurge and created an apparent negative association. This hypothesis may be tested during a drought year, when the deep root system of leafy spurge would increase its relative competitive ability.

The WISP model is a simple version of a potential distribution model in which the probability of occurrence is either 0 or 1. In reality, the probabilities vary between 0 and 1, perhaps with loamy soil textures having a lower probability than clayey soil textures. Advanced potential distribution models use various algorithms to determine the probability of occurrence for an invasive plant's ecological niche (Guisan and Zimmermann 2000; Peterson 2003; Guisan and Thuiller 2005; Austin 2007; Stohlgren et al. 2010). Another general type of potential distribution models are climatic envelope models (Sutherst 2003; Morisette et al. 2005), in which climate or remote sensing variables associated with current invasive plant distributions are used to predict potential distribution globally. One of the potential applications of climatic envelope models is predicting the effects of climatic change (Pearson and Dawson 2003; Thuiller et al. 2008). The original WISP model incorporated a few ideas from climatic envelope models (i.e., precipitation, Table 1), but there was little spatial variation in climatic variables at the county level.

A problem with invasive-species models is the possibility that the models are overtuned to specific locations, increasing agreement between data and model predictions at one location, but sacrificing applicability to other locations. Remotely sensed images, particularly from imaging spectrometers/hyperspectral sensors (Andrew and Ustin 2009), can be acquired at different locations and used to test model performance. However, not all invasive plant species can be detected with remote sensing, and those species that could be detected at some sites may not be detectable at other sites even with imaging spectrometer/hyperspectral data (Andrew and Ustin 2008). The positive and negative associations between geographic variables and classifications of species presence or absence by remote sensing may provide insight into the ecology of those invasive plants that are detectable, which could then be applied to other invasive species.

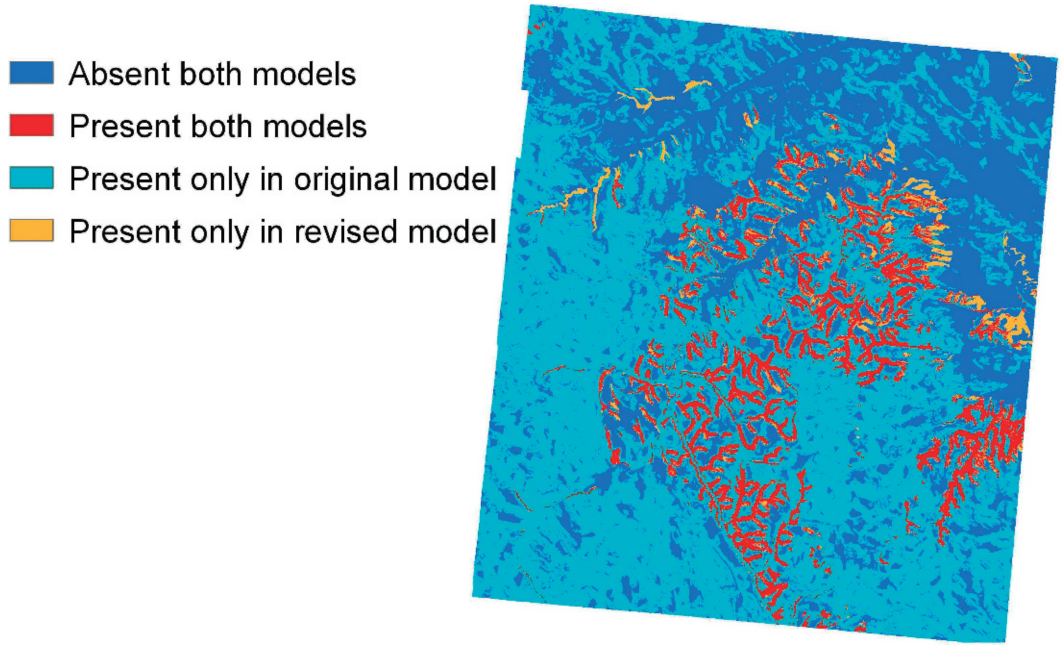

Figure 5. Comparison of the original Weed Invasion Susceptibility Prediction (WISP) model predictions and the revised WISP model predictions for potential areas of leafy spurge. Variables for the revised WISP model are distance to water, land cover type, and soil texture. New areas predicted by the revised WISP model (orange) had little effect on accuracy; the largest improvement in accuracy was from the reduction of area predicted to be susceptible to leafy spurge (cyan).

MANAGEMENT IMPLICATIONS

Imaging spectroscopy/hyperspectral remote sensing has compelling advantages when the target is spectrally distinct from the background, such as the yellow-green flower bracts of leafy spurge (Hunt et al. 2007). There are several different aircraft-borne hyperspectral sensors (besides AVIRIS), and plans are in place for a new generation of satellites deploying hyperspectral sensors (Schaepman et al. 2009). Schaepman et al. (2009) suggest one of the roles of hyperspectral imagery is to serve as a tool to scale field observations to larger scales, a task currently performed with the use of moderate-resolution multispectral satellites (Mladinich et al. 2006). Although software for atmospheric correction and image processing is available, analysis of hyperspectral data requires a high degree of expertise that is not routinely available to land managers. GIS and geographic data layers are routinely available. The results from this study suggest that remote sensing data should be used to test models of potential geographic distribution of invasive species at different locations, and make the GIS models available for land management.

Table 5. Accuracy assessment for revised Weed Invasion Susceptibility Prediction (WISP) model predictions compared to field data and the classified Airborne Visible Infrared Imaging Spectrometer (AVIRIS) image.

	Data	
WISP predictions	Present	Absent
Field data		
Present	103	18
Absent	119	114
Overall accuracy = 0.613		
Producer accuracy = 0.464		
User accuracy = 0.851		
$\hat{\kappa} = 0.284$		
$Z = 4.90$		
AVIRIS		
Present	23 971	85 151
Absent	74 020	625 415
Overall accuracy = 0.803		
Producer accuracy = 0.244		
User accuracy = 0.220		
$\hat{\kappa} = 0.119$[1]		
$Z = 8.79$[1]		

[1]Based on 1 000 randomly selected pixels.

It is generally less expensive to manage an invasive plant species when there are just a few individual plants. Because the cover of a few plants is well below the threshold for detection by remote sensing at moderate spatial resolution, it will still be necessary to look for new infestations of invasive plants by field crews or by very-large-scale aerial photography (Blumenthal et al. 2007). With validated potential distribution models, areas that are more likely to have leafy spurge can be monitored more frequently and areas that are less likely to have leafy spurge can be monitored less frequently, increasing the efficiency of field crews.

ACKNOWLEDGMENTS

We thank Amy E. Parker Williams for providing the field data, Ralph T. Roberts for performing the WISP model simulations, and Randy M. Hamilton for discussions. The Wyoming Geographic Information Science

Center (University of Wyoming, Laramie, Wyoming) provided the geographic data layers used in the WISP model. Furthermore, we thank the two anonymous reviewers and the associate editor for their comments.

LITERATURE CITED

Anderson, G. L., E. S. Delfosse, N. R. Spencer, C. W. Prosser, and R. D. Richard. 2003. Lessons in developing successful invasive weed control programs. *Journal of Range Management* 56:2–12.

Anderson, G. L., J. H. Everitt, D. E. Escobar, N. R. Spencer, and R. J. Andrascik. 1996. Mapping leafy spurge (*Euphorbia esula*) infestations using aerial photography and geographic information systems. *Geocarto International* 11:81–89.

Andrew, M. E., and S. L. Ustin. 2008. The role of environmental context in mapping invasive plants with hyperspectral imagery. *Remote Sensing of Environment* 112:4301–4317.

Andrew, M. E., and S. L. Ustin. 2009. Habitat suitability modeling of an invasive plant with advanced remote sensing data. *Diversity and Distributions* 15:627–640.

Austin, M. 2007. Species distribution models and ecological theory: a critical assessment and some possible new approaches. *Ecological Modelling* 200:1–19.

Blumenthal, D., D. T. Booth, S. E. Cox, and C. E. Ferrier. 2007. Large-scale aerial images capture details of invasive plant distributions. *Rangeland Ecology & Management* 60:523–528.

Bradley, B. A., and J. F. Mustard. 2006. Characterizing the landscape dynamics of an invasive plant and risk of invasion using remote sensing. *Ecological Applications* 16:1132–1147.

Casady, G. M., R. S. Hanley, and S. K. Seelan. 2005. Detection of leafy spurge (*Euphorbia esula*) using multidate high-resolution satellite imagery. *Weed Technology* 19:462–467.

Cohen, J. 1960. A coefficient of agreement for nominal scales. *Educational and Psychological Measurement* 20:37–40.

Congalton, R. G., and K. Green. 2009. Assessing the accuracy of remotely sensed data: principles and practices. 2nd ed. Boca Raton, FL, USA: CRC Press. 183 p.

Engler, R., A. Guisan, and L. Rechsteiner. 2004. An improved approach for predicting the distribution of rare and endangered species from occurrence and pseudo-absence data. *Journal of Applied Ecology* 41:263–274.

Evangelista, P. H., S. Kumar, T. J. Stohlgren, C. S. Jarnevich, A. W. Crall, J. B. Norman, and D. T. Barnett. 2008. Modelling invasion for a habitat generalist and a specialist plant species. *Diversity and Distributions* 14:808–817.

Evangelista, P. E., T. J. Stohlgren, J. T. Morisette, and S. Kumar. 2009. Mapping invasive tamarisk (*Tamarix*): a comparison of single-scene and time-series analyses of remotely sensed data. *Remote Sensing* 1:519–533.

Everitt, J. H., G. L. Anderson, D. E. Escobar, M. R. Davis, N. R. Spencer, and R. J. Andrascik. 1995. Use of remote sensing for detecting and mapping leafy spurge (*Euphorbia esula*). *Weed Technology* 9:599–609.

Everitt, J. H., C. Yang, D. E. Escobar, and M. R. Davis. 2002. Using remote sensing to detect and map invasive plant species. *Annals of Arid Zone* 41:321–342.

Fielding, A. H., and J. F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* 24:38–49.

Gao, B. C., K. B. Heidebrecht, and A. F. H. Goetz. 1993. Derivation of scaled surface reflectances from AVIRIS data. *Remote Sensing of Environment* 44:165–178.

Gao, B. C., M. J. Montes, C. O. Davis, and A. F. H. Goetz. 2009. Atmospheric correction algorithms for hyperspectral remote sensing data of land and ocean. *Remote Sensing of Environment* 113(Supplement 1):S17–S24.

Gillham, J. H., A. L. Hild, J. H. Johnson, E. R. Hunt, Jr., and T. D. Whitson. 2004. Weed Invasion Susceptibility Prediction (WISP) model for use with geographic information systems. *Arid Land Research and Management* 18:1–12.

Glenn, N. F., J. T. Mundt, K. T. Weber, T. S. Prather, L. W. Lass, and J. Pettingill. 2005. Repeat hyperspectral data processing for the detection of small infestations of leafy spurge. *Remote Sensing of Environment* 95:399–412.

Green, R. O., M. L. Eastwood, C. M. Sarture, T. G. Chrien, M. Aronsson, B. J. Chippendale, J. A. Faust, B. E. Pavri, C. J. Chovit, M. Solis, M. R. Olah, and O. Williams. 1998. Imaging spectroscopy and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). *Remote Sensing of Environment* 65:227–248.

Guisan, A., and W. Thuiller. 2005. Predicting species distribution: offering more than simple habitat models. *Ecology Letters* 8:993–1009.

Guisan, A., and N. E. Zimmermann. 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* 135:147–186.

Hodur, N. M., F. L. Leistritz, and D. A. Bangsund. 2006. Evaluation of the TEAM Leafy Spurge project. *Rangeland Ecology & Management* 59:483–493.

Hoffman, J. D., S. Narumalani, D. R. Mishra, P. Merani, and R. G. Wilson. 2008. Predicting potential occurrence and spread of invasive plant species along the North Platte River, Nebraska. *Invasive Plant Science and Management* 1:359–367.

Hunt, E. R., Jr., C. S. T. Daughtry, M. S. Kim, and A. E. Parker Williams. 2007. Using canopy reflectance models and spectral angles to assess potential of remote sensing to detect invasive weeds. *Journal of Applied Remote Sensing* 1: article no. 013506. Available at: http://dx.doi.org/10.1117/1.2536275. Accessed 29 July 2010.

Hunt, E. R., Jr., J. E. McMurtrey III, A. E. Parker Williams, and L. A. Corp. 2004. Spectral characteristics of leafy spurge (*Euphorbia esula*) leaves and flower bracts. *Weed Science* 52:492–497.

Hunt, E. R., Jr., and A. E. Parker Williams. 2006. Detection of flowering leafy spurge with multispectral satellite imagery. *Rangeland Ecology & Management* 59:494–499.

Jackson, S. T., J. L. Betancourt, R. K. Booth, and S. T. Gray. 2009. Ecology and the rachet of events: climate variability, niche dimensions, and species distributions. *Proceedings of the National Academy of Science* 106(Supplement 2):19685–19692.

Kruse, F. A., A. B. Lefkoff, J. W. Boardman, K. B. Heidebrecht, A. T. Shapiro, P. J. Barloon, and A. F. H. Goetz. 1993. The spectral image processing system (SIPS)–interactive visualization and analysis of imaging spectrometer data. *Remote Sensing of Environment* 44:145–163.

Kumar, S., S. A. Spaulding, T. J. Stohlgren, K. A. Hermann, T. S. Schmidt, and L. L. Bahls. 2009. Potential habitat distribution for the freshwater diatom *Didymosphenia geminata* in the continental US. *Frontiers in Ecology and the Environment* 7:415–420.

Lass, L. W., T. S. Prather, N. F. Glenn, K. T. Weber, J. T. Mundt, and J. Pettingill. 2005. A review of remote sensing of invasive weeds and example of the early detection of spotted knapweed (*Centaurea maculosa*) and babysbreath (*Gypsophila paniculata*) with a hyperspectral sensor. *Weed Science* 53:242–251.

Leistritz, F. L., D. A. Bangsund, and N. M. Hodur. 2004. Assessing the economic impact of invasive weeds: the case of leafy spurge (*Euphorbia esula*). *Weed Technology* 18:1392–1395.

Messersmith, C. G., R. G. Lym, and D. S. Galitz. 1985. Biology of leafy spurge. *Monograph Series of the Weed Science Society of America* 3:42–56.

Mitchell, J. J., and N. F. Glenn. 2009. Leafy spurge (*Euphorbia esula*) classification performance using hyperspectral and multispectral sensors. *Rangeland Ecology & Management* 62:16–27.

Mladinich, C. S., M. Ruiz Bustos, S. Stitt, R. Root, K. Brown, G. L. Anderson, and S. Hager. 2006. The use of Landsat 7 Enhanced Thematic Mapper Plus for mapping leafy spurge. *Rangeland Ecology & Management* 59:500–506.

Morisette, J. T., C. S. Jarnevich, A. Ullah, W. Cai, J. A. Pedelty, J. E. Gentle, T. J. Stohlgren, and J. L. Schnase. 2005. A tamarisk habitat suitability map for the continental United States. *Frontiers of Ecology and the Environment* 4:11–17.

Parker Williams, A. E., and E. R. Hunt, Jr. 2002. Estimation of leafy spurge cover from hyperspectral imagery using mixture tuned matched filtering. *Remote Sensing of Environment* 82:446–456.

Parker Williams, A. E., and E. R. Hunt, Jr. 2004. Accuracy assessment for detection of leafy spurge with hyperspectral imagery. *Journal of Range Management* 57:106–112.

Pearson, R. G., and T. P. Dawson. 2003. Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? *Global Ecology and Biogeography* 12:361–371.

Peterson, A. T. 2003. Predicting the geography of species' invasions via ecological niche modeling. *Quarterly Review of Biology* 78:419–433.

Pimentel, D., R. Zuniga, and D. Morrison. 2005. Update on the environmental and economic costs associated with alien-invasive species in the United States. *Ecological Economics* 52:273–288.

Rew, L. J., B. D. Maxwell, and R. Aspinall. 2005. Predicting the occurrence of nonindigenous species using environmental and remotely sensed data. *Weed Science* 53:236–241.

Rouget, M., D. M. Richardson, J. L. Nel, D. C. Le Maitre, B. Egoh, and T. Mgidi. 2004. Mapping the potential ranges of major plant invaders in South Africa, Lesotho and Swaziland using climatic suitability. *Diversity and Distributions* 10:475–484.

Schaepman, M. E., S. L. Ustin, A. J. Plaza, T. H. Painter, J. Verrelst, and S. Liang. 2009. Earth system science related imaging spectroscopy—an assessment. *Remote Sensing of Environment* 113(Supplement 1):S123–S137.

Sims, J., and C. C. Wright. 2005. The kappa statistic in reliability studies: use, interpretation, and sample size requirements. *Physical Therapy* 85:257–268.

Stitt, S., R. Root, K. Brown, S. Hager, C. Mladinich, G. L. Anderson, K. Dudek, M. Ruiz Bustos, and R. Kokaly. 2006. Classification of leafy spurge with Earth Observing-1 Advanced Land Imager. *Rangeland Ecology & Management* 59:507–511.

Stohlgren, T. J., P. Ma, S. Kumar, M. Rocca, J. T. Morisette, C. S. Jarnevich, and N. Benson. 2010. Ensemble habitat mapping of invasive plant species. *Risk Analysis* 30:224–235.

Sutherst, R. W. 2003. Prediction of species geographic ranges. *Journal of Biogeography* 30:805–816.

Thuiller, W., C. Albert, M. B. Araujo, P. M. Berry, M. Cabeza, A. Guisan, T. Hickler, G. F. Midgely, J. Paterson, F. M. Schurr, M. T. Sykes, and N. E. Zimmermann. 2008. Predicting global change impacts on plant species' distributions: future challenges. *Perspectives in Plant Ecology, Evolution and Systematics* 9:137–152.

Tsoar, A., O. Allouche, O. Steinitz, D. Rotem, and R. Kadmon. 2007. A comparative evaluation of presence-only methods for modelling species distribution. *Diversity and Distributions* 13:397–405.

Underwood, E., S. L. Ustin, and D. Dipietro. 2003. Mapping nonnative plants using hyperspectral remote sensing. *Remote Sensing of Environment* 86:150–161.