ABSTRACT

DETECTING AN INVASIVE SHRUB IN DECIDUOUS FOREST UNDERSTORIES USING REMOTE SENSING

by Bryan N. Wilfong

Remote sensing has been used to directly detect and map invasive plants, but has not been used for forest understory invaders because they are obscured by a canopy. However, if the invasive species has a leaf phenology distinct from native forest species, then temporal opportunities exist to detect the invasive. *Lonicera maackii*, an Asian shrub that invades North American forests, expands leaves earlier and retains leaves later than native woody species. I explored whether Landsat 5 TM and Landsat 7 ETM+ imagery could predict *L. maackii* cover across woodlots in Darke and Preble Counties in south western Ohio and Wayne County, Indiana. The best predictor of *L. maackii* cover was Normalized Difference Vegetation Index (NDVI) from November 2005, with a quadratic function providing a better fit ($R^2 = 0.75$) than a linear function. This predictive model was verified with 15 other woodlots. With refinement, this approach can map understory invasion by *L. maackii*.

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REMOTE SENSING

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Bryan N. Wilfong
Miami University
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Advisor _____
(David L. Gorchov)

Reader _____
(Mary C. Henry)

Reader _____
(Jerry E. Green)

Contents

List of Tables	iii
List of Figures	iv
Acknowledgements	v
Introduction	1
Methods	3
Study Area	3
<i>Lonicera maackii</i>	3
Site Selection	4
Vegetation Sampling and Analysis	4
Seasonal Patterns of Leaf Abscission	6
Remote Sensing Data	6
Preprocessing	7
Processing	8
Image Differencing	8
Statistical Analysis of Image Data	9
Results	9
Seasonal Patterns of Leaf Abscission	9
Training Data and Model Development	10
Regression of <i>L. maackii</i> cover on spectral data	10
Image Differencing	11
Model Verification	11
Influence of Other Variables on Model Performance	12
Discussion	12
Works Cited	16
Appendix I	34
Appendix II	38
Appendix III	39

List of Tables

Table 1 <i>Lonicera maackii</i> cover classes and number of ground plots within each level of <i>L. maackii</i> cover.	22
Table 2 Spectral and spatial characteristics of Landsat 5 TM and Landsat 7 ETM+ where IR=infra red (modified from Jensen 2007).	22
Table 3 Conversion equations for Landsat 5 image DN values to Landsat 7 equivalents (USGS 2001).	22
Table 4 Image and band specific equation values for DN to radiance conversion.	23
Table 5 Individual COST model equations for each band and image date.	23
Table 6 Pearson's correlation coefficients for the four SVIs most strongly correlated with amount of <i>L. maackii</i> cover for the November 12, 2005 training data (N = 35).	24
Table 7 R^2 and p-values from the least squares regression analysis of the November 12, 2005 training data (N = 35) where <i>L. maackii</i> cover was regressed on individual SVI and reflectance band values.	24
Table 8 R^2 and p-values from linear regression analyses of various data transformations applied to the November 12, 2005 training data (N = 35), where <i>L. maackii</i> was regressed on NDVI.	24
Table 9 Comparison of RMSE, R^2 , and p-values of the OLS regression model to the quadratic polynomial regression model for the November 12, 2005 training data (N = 35) where <i>L. maackii</i> cover was regressed on NDVI.	25
Table 10 Stepwise multiple regression models and analysis values for the November 12, 2005 training data (N = 35) where Y = <i>L. maackii</i> percent cover and the various SVIs and reflectance bands are the dependent variables. Mallows $C_{(p)}$ statistic is related to the mean square error of a fitted value and identifies parsimonious models with good predictive power. The better model is one where Mallows' C_p is small and close to the number of predictors in the model plus the constant (p).	25
Table 11 Results of the linear and quadratic polynomial regression analyses of <i>L. maackii</i> on the top performing SVI from the January 28, 2002 minus November 12, 2005 training data values (N = 35) and the June 11, 2007 minus November 12, 2005 training data values	25
Table 12 R^2 and p-values from the regression analysis of the November 12, 2005 verification data (N = 15) (Y = observed <i>L. maackii</i> cover, X = the predicted <i>L. maackii</i> cover).	25

List of Figures

Figure 1 Distribution of plots represented with black circles within the study area. The inset window displays the location and extent of Landsat Path 20 Row 32 coverage and the location of the study area within that extent.	26
Figure 2 Polygons drawn in ArcMap over suitable woodlots using mosaiced DOQQs.....	27
Figure 3 Fall 2006 canopy and shrub layer in sites with high <i>L. maackii</i> abundance (ERC and Kramer) versus sites with no <i>L. maackii</i> presence (Sugarbush and Bigwoods), where solid line is shrub layer and dashed line is canopy.....	28
Figure 4 Fall 2007 canopy and shrub layer in sites with high <i>L. maackii</i> abundance (ERC and Kramer) versus sites with no <i>L. maackii</i> presence (Sugarbush and Bigwoods), where solid line is shrub layer and dashed line is canopy.....	29
Figure 5 Linear regression of <i>L. maackii</i> cover on NDVI of the November 12, 2005 training data. Different color circles distinguish plots with different graminoid cover (high = black, medium = grey, and low = white).....	30
Figure 6 Quadratic polynomial regression of <i>L. maackii</i> cover on NDVI of the November 12, 2005 training data. Different color circles distinguish plots with different graminoid cover (high = black, medium = grey, and low = white).	30
Figure 7 Linear regression of observed <i>L. maackii</i> cover on predicted <i>L. maackii</i> cover values. Predicted values were calculated from the November verification data using the quadratic polynomial regression model of NDVI. Different color circles distinguish plots.....	31
Figure 8 Linear regression of observed <i>L. maackii</i> cover on predicted <i>L. maackii</i> cover values. Predicted values were calculated from the November 12, 2005 verification data using the linear regression model of NDVI. Different color circles distinguish plots with.....	31
Figure 9 Linear regression of <i>L. maackii</i> cover on NDVI using the November training data. Different color circles distinguish plots with differences in disturbance (evident disturbance = black and no apparent disturbance = white).....	32
Figure 10 Quadratic regression of <i>L. maackii</i> cover on NDVI using the November training data. Different color circles distinguish plots with differences in disturbance (evident disturbance = black and no apparent disturbance = white).	32
Figure 11 Linear regression of <i>L. maackii</i> cover on NDVI using the November training data. Different color circles distinguish between plots with <i>Quercus</i> species and <i>F. grandifolia</i> comprising > 20% of basal area (black = high <i>Quercus</i> and <i>F. grandifolia</i> and white = low <i>Quercus</i> and <i>F. grandifolia</i>).....	33
Figure 12 Quadratic regression of <i>L. maackii</i> cover on NDVI using the November training data. Different color circles distinguish between plots with <i>Quercus</i> species and <i>F. grandifolia</i> comprising > 20% of basal area (black = high <i>Quercus</i> and <i>F. grandifolia</i> and white = low <i>Quercus</i> and <i>F. grandifolia</i>).....	33

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Introduction

Invasion of native ecosystems by exotic species is a major threat to global biodiversity and is considered a significant cause of ecological change at multiple scales (Hooper et al. 2005). In the United States, invasion by exotic species has been identified as a significant threat to the survival of indigenous species (Wilcove et al. 1998). Invasive exotic species are estimated to cost the U.S. economy over \$137 billion per year in damages and control costs (Pimentel et al. 2000). Within the U.S. it is estimated that exotic plants invade 700,000 hectares of wildlife habitat annually and that 5,000 exotic plant species have become established in native ecosystems (Pimentel et al. 2000).

Exotic plants typically exert negative impacts on invaded systems and significantly alter ecosystem processes, plant community composition, and influence the structure of trophic levels (Vitousek 1990; Eiswerth and Johnson 2002; Levine et al. 2003; Chornesky et al. 2005). The problems associated with invasive species are expected to worsen as the anthropogenic factors that have greatly accelerated the rate of exotic propagule introduction and the disturbance activities that facilitate invasion of native ecosystems are increasing (Eiswerth and Johnson 2002; Levine et al. 2003). In recognition of the deleterious effects of invasive species, research on the dynamics of ecosystem invasion and management efforts to control the spread of exotic species have been identified as priorities at the global and national level (Andersen et al. 2004; Leung et al. 2005).

Information about the distribution of exotic plant populations is essential in the formulation of effective ecological conservation policies, the development of management and control efforts, and to gain insight into the dynamics of ecosystem invasion (Byers et al. 2001; Eiswerth and Johnson 2002; Rew et al. 2005; Bradley and Mustard 2006). Quantification of the spatial distribution of exotic plants within an invaded system is the primary parameter used to evaluate the efficacy of control efforts (Cooksey and Sheley 1997). Information about the spatial distribution of invasive plant populations improves the accuracy of attempts to measure the economic and ecological impacts of invasive species, informs predictions about future population densities, and likely pathways of dispersal (Parker et al. 1999; Andersen et al. 2004; Cohen and Goward 2004). Furthermore, information on the current and historical distributions of invasive plant populations across the landscape can provide insight into mechanisms that facilitate invasion.

Those involved in the study and control of invasive species expend considerable resources to gather information about the current spatial distribution and population abundances of invasive species (Byers et al. 2001; Rew et al. 2005; Deckers et al. 2005). Traditional ground-based methods for gathering this information are high in resource costs; thus, research and management activities are often constrained by financial and/or logistical costs (Caughlan and Oakley 2001; Anderson et al. 2003; Lawrence et al. 2006; Rew et al. 2005). Remote sensing can provide information on the spatial and temporal distributions of plant populations (Kerr and Ostrovsky 2003; Shaw 2005) in an efficient and cost-effective way (Rew et al. 2005; Patil et al. 2001).

For example, the ability to accurately identify the spatial distribution of an invasive exotic plant species would enhance the efficacy of control and management efforts by enabling land managers to more accurately direct eradication programs, develop better predictive models about future dispersal, and coordinate management programs across multiple scales. Furthermore, enhancing our ability to detect plant communities that have been invaded by an exotic species and those that have not will aid research into what characteristics make ecosystems susceptible to invasion by exotic species. The identification of such characteristics has been identified as being of critical importance in the control of invasive species and in mitigating the impacts of exotic species invasion (Hobbs and Humphries 1995).

Remote sensing has been used to detect and map the distribution of invasive plants in a variety of ecosystems where the invasive was not beneath a canopy. Examples include semi-arid grasslands (Bradley and Mustard 2005; Lass et al. 2005; Peterson 2005), wetlands (Pengra et al. 2007; Laba et al. 2008) and riparian communities (Hamada et al. 2007; Noonan and Chafer 2007). Forest understory invaders are difficult to detect because they are obscured by the canopy. However, if the invasive species has a leaf phenology that differs from native forest species, then temporal opportunities may exist to detect the invader. Exotic shrubs, such as *Lonicera maackii*, often leaf out earlier in the spring and retain leaves longer in the fall than native deciduous species (Trisel and Gorchoff 1994). As a result of this phenological difference remote sensing platforms should be able to detect such invasive shrubs in forest understories in the early spring and late fall when native deciduous species are leafless.

Phenological differences have been used in numerous studies to derive ecological information from remote sensing data. Differences in phenology between native species and the

invasive grass *Bromus tectorum* were exploited to map the distribution of *B. tectorum* using Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data (Bradley and Mustard 2005; Peterson 2005). Resasco et al. (2007) demonstrated that it might be possible to use Landsat images and differences in leaf phenology to identify dissimilarity in spectral reflectance values of stands with *L. maackii* versus non-invaded stands in images captured after forest canopy leaves had fallen.

The objective of this study is to test the hypothesis that differences in leaf phenology between *L. maackii* and native tree species can be used to estimate the cover abundance of *L. maackii* in forest understories through the analysis of remote sensing data.

Methods

Study Area

The study area was approximately 1,200 km² (Figure 1) in Darke and Preble Counties in southwestern Ohio and neighboring Wayne County, Indiana. The landscape of the study area is a patchwork of small woodlots with varying degrees of connectivity surrounded by agricultural fields, farm houses, and small towns. Darke County was identified by Bartuzevige et al. (2006) as an area that is on the front of an advancing *L. maackii* invasion, where forest patches exhibit a range of *L. maackii* abundance.

Lonicera maackii

Lonicera maackii is a perennial shrub originating in northeastern Asia. It was introduced into the U.S. in 1898 and has been widely cultivated for a variety of purposes (Luken and Thieret 1995). The plant escaped cultivation and has now established naturalized populations in at least 24 eastern states (Trisel and Grochov 1994) and 35 Ohio counties (Trisel 1997). Propagule pressure of *L. maackii* is high, as the shrub's fruit has been incorporated into the diets of numerous avian species that disperse viable *L. maackii* seeds to habitats suitable for the shrub's establishment (Batuszevige and Gorchov 2006).

Lonicera maackii impacts forest ecosystems at multiple levels and the shrub exhibits the potential to alter natural patterns of forest succession and influence trophic structure. *Lonicera maackii* reduces growth and fecundity of native annual and perennial herbs due to competitive effects (Gould and Gorchov 2000; Miller and Gorchov 2004), fecundity of annual and biennial herbs from potential allelopathic effects (Dorning and Cipollini 2006; Cipollini et al. 2008), and

survival and growth of native tree seedlings (Gorchov and Trisel 2003; Hartman and McCarthy 2004). Under *L. maackii* canopies the species richness and abundance of native herbs and tree seedlings are reduced (Collier et al. 2002). In forest stands with established populations of *L. maackii* overstory trees have significantly lower rates of radial growth (Hartman and McCarthy 2007). Comparisons among stands with differing levels of *L. maackii* abundance revealed a negative relationship between *L. maackii* density and the density of *Acer saccharum* (Hutchinson and Vankat 1997). *Lonicera maackii* also has the potential to influence the trophic structure of invaded ecosystems, since songbird nests in *L. maackii* suffered higher predation than nests constructed in native species (Schmidt and Whelan 1999).

Site Selection

I located woodlots of sufficient spatial extent using ArcMap and digital orthophotos (DOQQs) of the study area, obtained from the Darke County Geographic Information Office and the Preble County Planning Department. Woodlots greater than 120m by 120m in extent were identified for the location of a 100m by 100m study plot with at least a 15m buffer on all sides. The perimeters of woodlots that met the size requirement (Figure 2) were digitized and saved as shapefiles with a projection in UTM WGS 1984 Zone 16 North. Pathfinder Office was used to load the shapefiles into a handheld Trimble GPS unit with sub-meter accuracy.

Vegetation Sampling and Analysis

The woodlot polygon layer was used in conjunction with the GPS unit to identify woodlots suitable for the placement of ground plots (GPs). Once permission was granted by property owners, potential woodlots were reconnoitered and those found suitable for inclusion were sampled. An attempt was made to select woodlots that had similar stand characteristics (e.g. basal area, species composition), relatively flat topography, and a range of *L. maackii* cover densities. However, great difficulty was encountered in finding woodlots with medium to high densities of *L. maackii* invasion; as a result it was not always possible to place GPs in woodlots that had similar stand characteristics.

Once a woodlot was selected for the placement of a GP, I selected an anchor point for the start of the mainline transect that ensured all transect lines remained within the woodlot and did not extend into the 15m edge buffer. The woodlot polygon layer and the Trimble GPS unit were

used to aid in the placement of the anchor point and to determine the azimuths for the mainline and line intercepts.

A total of 50 GPs were obtained across of range of *L. maackii* cover (Appendix III). In each GP I established one 100m baseline transect with four 100m parallel line intercept transects spaced 25m apart. The four parallel transects served a dual purpose as line intercepts to quantify *L. maackii* cover and as anchor lines for point-quarter plots (PQPs). Whenever a *L. maackii* individual intercepted a vertical projection of a line intercept transect, the start and end point of the interception was recorded to the nearest cm. These distances were then summed to calculate the total portion of the 4 lines covered by *L. maackii*. The GPS unit was used to collect the geographic coordinates of the anchor and end points of each main transect line.

The PQPs were used to collect basic forest stand community characteristics. There were 4 PQPs per transect line for a total of 16 PQPs per GP. The first PQP was located randomly within the first 25m, with the other three PQPs spaced at 25 m intervals. The nearest tree $\geq$ 10cm in diameter at breast height (dbh) in each quadrant of the PQP was identified to species and its dbh and distance from the PQP center recorded. I also recorded large treefall gaps, topographical variation, graminoid cover and indications of observable disturbance such as recent timber harvests, livestock grazing, vehicle trails, or trash dumps. Data from the PQPs were used to calculate stand density, stand basal area, and total basal area, as well as absolute basal area, relative basal area, absolute density, and relative density of individual tree species, as described by Smith and Smith (2001).

Graminoid cover abundances for each woodlot were recorded in three categories; high, medium, and low. Low cover plots had very little graminoid cover in the understory. Medium cover plots had a patchy distribution of dense graminoid cover (e.g. in canopy gaps and on roads/skid trails). High cover plots were those woodlots that had substantial amounts of graminoid cover throughout the understory.

GPs were divided into eight groups based upon the percent *L. maackii* cover observed (Table 1). In each of these groupings approximately two-thirds were used as training and one-third as verification data. The random number generating function within Excel was used to assign a random value to each letter and the plots with highest randomly generated values in each group were placed in the verification pool.

Seasonal Patterns of Leaf Abscission

In order to confirm the differences in phenology between native species and *L. maackii* and to identify the optimal dates for image acquisition it was necessary to quantify fall leaf senescence. Sampling was conducted in two plots with high levels of *L. maackii* abundance (the Ecology Research Center (ERC) of Miami University with 57% *L. maackii* cover and Kramer Woods, Miami University Natural Areas with 37% *L. maackii* cover) and two plots with no *L. maackii* (the Sugarbush and Bigwoods stands in Hueston Woods State Park) all plots are in Butler County, Ohio.

Sample plots consisted of four 50m transect lines that were spaced 25m apart. Pin flags were spaced every 5m along transects. In the 2006 sampling 54 sample points per plot were placed and in the 2007 sampling 50 sample points were placed. The corner coordinates of the plots established by Resasco et al. (2007) were used to establish the anchor points for line transects.

Measurements of the forest canopy and the shrub layer were taken with a vertical densitometer using the procedure described by Stumpf (1993). Overstory canopy measurements were taken approximately 3.5m from the ground surface through the use of a stepladder. Measurements of the understory were from the same position, but with the vertical densitometer pointing downwards. In 2006, sampling was begun on October 21st and ended on December 2nd with measurements collected every seven days. In 2007, canopy sampling was begun September 9th and finished December 1st with measurements collected every seven days.

Remote Sensing Data

I used images from Landsat Path 20 Row 32. Two images from the Landsat 5 Thematic Mapper (TM) platform, one captured on June 11, 2007 and the other on November 12, 2005 for full leaf and canopy leaf off, respectively. A Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image captured on January 28, 2002 was used for canopy and understory leaf off. This combination was necessary to find cloud free and snow free images of the desired dates, and in an effort to use the most current and complete images available. Georectified images for these three dates were acquired from OhioView.org and the metadata for each image was obtained from USGS's EarthExplorer website (<http://edcsns17.cr.usgs.gov/EarthExplorer/>).

The June image established a baseline for green biomass when both the overstory and understory are photosynthetically active. The November image was collected when overstory

leaves had senesced and the majority had abscised while in the understory *L. maackii* still had green leaves. This assumption was based on the canopy sampling conducted in the fall of 2006, observed patterns of fall leaf abscission collected by the Ohio Department of Natural Resources (available at <http://www.dnr.state.oh.us>), and Trisel and Gorchov (1994). The January image would have been captured when deciduous plants in the overstory and understory were no longer photosynthetically active and virtually devoid of leaves. All preprocessing and processing of the remote sensing data were performed using Leica Geosystems' ERDAS Imagine software.

Preprocessing

OhioView.org provides Landsat 5 and Landsat 7 data in a georectified Tagged Image File Format (tiff) with each spectral band available in separate tiff files. For the purposes of this study Landsat 5 and Landsat 7 bands one through five and seven were used (Table 2). Landsat 5 and Landsat 7 store image data in a digital number (DN) format which is a measure of at-satellite radiance. It was necessary to convert the Landsat 5 images into Landsat 7 equivalents, as these values are not directly comparable between satellite platforms. The conversion of DN values was performed using the conversion equation (Table 3) developed by the USGS (2001) and the Imagine Model function.

DN values must be converted to equivalent at-satellite radiance values for further processing and this is accomplished through the use of the equation:

$$L_{\lambda} = L_{min\lambda} + \frac{(L_{max\lambda} - L_{min\lambda})}{255} \times DN$$

$L_{min\lambda}$ and $L_{max\lambda}$ are standard values derived from the Landsat7 ETM+ radiometric calibration curve and represent the post-calibration dynamic ranges where the $L_{min\lambda}$ value corresponds to the minimum DN value of zero and $L_{max\lambda}$ corresponds to the maximum DN value of 255 (Chander et al. 2007). The individual band equations for each image are in Table 4.

The next phase of image preprocessing involves the conversion of radiance values to reflectance values and the correction of atmospheric effects on the reflectance values. The radiance values must be converted to reflectance before analysis of ecological parameters can be performed (Jensen 2007) and radiometric correction is necessary because at-satellite radiance is affected by the scattering, absorption, and refraction of light in the atmosphere (Chavez 1996). The cosine approximation model (COST) developed by Chavez (1996) was used to correct for atmospheric effects using the following formula:

$$Reflectance = \frac{\pi \times (Image - L_{haze}) \times d^2}{Esun(\cos Z)}$$

Image specific models using the appropriate values for each image date and band (Table 5) were created using the Imagine Modeler tool. Once processed, each image's radiance values were transformed to reflectance and atmospheric effects on reflectance were reduced.

Processing

Image values were transformed to obtain spectral vegetation indices (SVIs), which are combinations of spectral information from multiple bands that produce an image which exhibits increased sensitivity to plant biophysical variables while external and internal effects (e.g. background soil reflectance) are reduced (Jensen 2007). It was predicted that in the November image there would be a positive correlation between SVI values and *L. maackii* abundance; more specifically, woodlots with a high abundance of *L. maackii* in the understory would exhibit higher SVI values compared to woodlots with low to no *L. maackii* presence.

Seven SVIs image transformations were performed: 1) Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), 2) Enhanced Vegetation Index (EVI) (Huete et al. 1997), 3) Simple Ratio (SR) (Birth and McVey 1968; Cohen 1991), 4) Kauth-Thomas Transformation or Tasseled Cap (TCap) (Kauth and Thomas 1976; Crist and Cicone 1984; Huang et al. 2002), 5) Visible Atmospherically Resistant Index (VARI) (Gitelson et al. 2002), 6) Soil Adjusted Vegetation Index (SAVI) (Huete 1988), and 7) Normalized Difference Moisture Index (NDMI) (Hardisky et al. 1983).

Following image transformation, ArcMap 9.2 was used to extract the mean values for pixels that fell within the delineated plots. ArcCatalog was used to create two separate shapefiles, one containing the verification plots and the other containing training plots. Value extraction was accomplished through the use of the Spatial Analyst tool within ArcMap. Mean values for each plot were extracted from all SVI images, as well as the six reflectance bands (RB) for each image date.

Image Differencing

Image differencing was performed with the expectation that emphasizing seasonal changes in *L. maackii* cover could enhance the ability to detect *L. maackii* cover. For example, image differencing of Landsat TM data has been used to detect changes in vegetative cover due

to anthropogenic disturbance (Norberg and Evertson 2003). Imagine was used to subtract the November image from the June image and the January image from the November image. This process was repeated for each SVI image transformation and for all six reflectance images. Plot pixel values were extracted from these images using the Spatial Analyst tool in ArcMap.

Statistical Analysis of Image Data

Correlation and regression analyses were performed using SAS 9.1 to evaluate the ability of the different SVIs to accurately predict *L. maackii* cover. The training data was used to develop models that predict *L. maackii* cover. Three different regression methods were utilized: ordinary least squares linear, multiple predictors stepwise, and quadratic polynomial. The November 12, 2005 training data was used to develop the best model for predicting *L. maackii*. In all model iterations *L. maackii* cover served as the response variable and the extracted pixel values of the different SVI transformations and individual reflectance images were the predictor variables. Correlation and regression analyses were also performed on the PQP data to determine if any quantified woodlot parameters exerted a detectable influence on reflectance values.

The verification data was used to test the validity of the top performing regression models created with the training data. The extracted pixel values for the 15 verification plots were used to generate predicted *L. maackii* cover based on each model. The observed *L. maackii* cover values were then regressed against the predicted *L. maackii* cover to evaluate model performance.

Results

Seasonal Patterns of Leaf Abscission

The results of the 2006 (Figure 3) and 2007 (Figure 4) canopy sampling confirm that there was approximately a four week period in which the leaves of the native deciduous trees had abscised while those of *L. maackii* were still green. In 2006 the heavily *L. maackii* invaded ERC and Kramer Woods stands had a significant amount of green leaves in the shrub layer in November, while their main canopies were mostly devoid of leaves. Whereas, the canopies and shrub layers of the Sugarbush and Bigwoods stands, with no *L. maackii* present, exhibited a

virtual absence of green leaves. This condition persisted from approximately November 04 to November 30, when *L. maackii* leaves abscised.

In 2007 the temporal difference in leaf abscission between native canopy and exotic shrub species (Figure 3) was repeated; however, abscission dates were later than in 2006. In 2007 the optimal time to detect *L. maackii* in the understory using satellite imagery began on November 22, 18 days later than in 2006.

Training Data and Model Development

A correlation analysis of SVIs and reflectance bands revealed a high degree of correlation between virtually all indices and reflectance bands, while no significant correlations were found to exist between the remote sensing data for any of the three dates and stand density or stand basal area (Appendix I). *L. maackii* cover was correlated with four SVIs, with NDVI having the highest correlation value (Table 6). No other SVI or individual reflectance band had a correlation value with *L. maackii* greater than 0.5 (Appendix I).

Regression of *L. maackii* cover on spectral data

Univariate linear regression from the November 12, 2005 image revealed that NDVI and SR were the best predictors of *L. maackii* cover (Table 7). The strongest performing SVI in the linear regression analyses was NDVI with a coefficient of determination (R^2) equal to 0.6259 (Figure 5; Appendix II, Table AII-1). Numerous transformations of both the dependent and independent variables were performed in an effort to normalize the data and improve the fit of the linear model. None of the transformations improved model fit (Table 8).

A quadratic regression was performed in which *L. maackii* cover was regressed against NDVI and $NDVI^2$ (Table AII-2). The quadratic model proved a better predictor of *L. maackii* cover compared to the linear model having a lower root mean square error (RMSE) and a higher R^2 value (Table 9; Figure 6).

Stepwise regression was also performed to test the possibility that a combination of reflectance and/or SVIs would improve the detection of *L. maackii*. Based upon the results of the correlation analysis the available combinations of noncorrelated predictor variables were limited. Predictor variables were selected for inclusion if there was no strong correlation between them, the strength of performance in the linear regression, and their spectral properties. For example, in the model $L. maackii \text{ cover} = -110 + 444(NDVI) + 21.2(VARI) - 694(RB1)$ none

of the predictors were strongly correlated, NDVI performed best in the linear regression, and NDVI's predictive power lies within the red and near infra-red bands, VARI in the green, red, and blue bands, and RB1 band is the blue reflectance band. Predictors were allowed to enter the model if they were significant at the 0.25 level and were retained in the model with a p-value <0.15 . Three multiple regression models achieved a minimal improvement in R^2 values over the single predictor NDVI model, but all were inferior to the quadratic NDVI model (Table 10).

Image Differencing

The results of the regression analyses of the November 12, 2005 minus January 28, 2002 (Nov-Jan) image values were similar to the results attained from using the November image alone. Of the regression models based upon Nov-Jan SVI and reflectance band training data, NDVI proved to be the best predictor of *L. maackii* cover (Table 11). The linear regression of *L. maackii* percent cover on Nov-Jan NDVI proved to be a slightly better predictor ($R^2 = 0.65$) than using the NDVI values derived from November 12, 2005 image alone ($R^2 = 0.63$). However, the quadratic polynomial regression of *L. maackii* cover on NDVI of the Nov-Jan values ($R^2 = 0.747$) was no stronger than the quadratic regression model using the single date November image values ($R^2 = 0.750$).

The June 11, 2007 minus November 12, 2005 image values returned slightly different results. In both the linear and quadratic polynomial regressions, SR performed marginally better than the NDVI. The other SVIs performed as poorly in predicting *L. maackii* presence as in previous regression analyses. The linear regression of *L. maackii* cover on SR ($R^2 = 0.52$) and the quadratic polynomial regression of *L. maackii* cover on SR ($R^2 = 0.63$) (Table 12) both had less predictive power than the quadratic regression model of *L. maackii* on NDVI using November data.

Model Verification

The validity of the linear and quadratic models (*L. maackii* cover to NDVI) was tested with the 15 verification plots. The quadratic polynomial model was an adequate predictor of *L. maackii* cover, with $R^2 = 0.56$ (Figure 7; Table 12) and was superior to that of the linear model $R^2 = 0.43$; Figure 8).

Influence of Other Variables on Model Performance

The scatterplots from the linear (Figure 5) and quadratic (Figure 6) regression of *L. maackii* on NDVI revealed a high amount of scatter around the regression line at low *L. maackii* cover abundances. The high NDVI values of some of these points were not expected based upon the low *L. maackii* cover. I explored whether the unexpected distribution of these points could be due to inter-plot variation in graminoid cover abundance, anthropogenic disturbance, or abundance of *Quercus* species and *Fagus grandifolia* in the canopy.

Plots were classified as having high, medium, or low graminoid cover and plotted for the linear (Figure 5) and the quadratic (Figure 6) models. There were 19 woodlots with medium to high graminoid cover and 16 woodlots with low graminoid cover. Twelve of the medium to high graminoid cover plots were to the right of the linear regression line and 11 of these were to the right of the line in the quadratic regression.

The distribution of woodlots with evident anthropogenic disturbance was plotted for the linear (Figure 9) and quadratic (Figure 10) regression of *L. maackii* on NDVI. There were 12 woodlots with evidence of recent disturbance. In the linear regression 10 of these plots were to the right of the line and in the quadratic regression eight plots were to the right of the line.

Quercus species and *Fagus grandifolia* do not immediately abscise senesced leaves and retain senesced leaves longer in the fall than other main canopy species (e.g. genera *Acer*, *Fraxinus*, and *Juglans*). The distribution of plots with a combined relative basal area of all *Quercus* species and *Fagus grandifolia* equal to or greater than 20% in the scatterplots from the linear regression (Figure 11) and the quadratic regression (Figure 12) suggests that *Quercus* and *Fagus* abundance did not significantly influence NDVI values.

Discussion

The differences I found in leaf abscission between *L. maackii* and native tree species confirm that the opportunity exists to use late fall remote sensing data to detect *L. maackii* in the understory of deciduous forest. Late fall Landsat images predicted *L. maackii* cover with relative accuracy, because NDVI was not influenced by tree biomass at this time, when the majority of overstory leaves had abscised.

The observed inter-annual variability in leaf fall could complicate efforts to use satellite imagery to detect *L. maackii* in the understory for years in which the date of overstory canopy

leaf fall is not known. The observed inter-annual variation in autumn leaf senescence may be due to differences in weather between 2006 and 2007. However, there is no conclusive evidence that temperature plays a major role in governing autumn leaf senescence, but some research indicates that autumn chilling may influence the onset of leaf senescence (Richardson et al. 2006). Observations conducted by Lee et al. (2003) in a mixed northern hardwood forest in Massachusetts over an eight year period found high consistency in the timing of leaf abscission, with only a 6 to 9 day difference between years. Therefore, it may be possible to reliably predict the optimal temporal window for *L. maackii* detection based upon past observations of leaf abscission, weather data, and/or remote sensing data.

The regression analyses of the SVIs and reflectance bands revealed that NDVI was the best predictor of *L. maackii* cover. The quadratic polynomial model proved superior to the linear model in predicting *L. maackii* cover. However, the wide variation in NDVI values for plots with low *L. maackii* cover indicated that other variables in the woodlots influenced NDVI values. NDVI is sensitive to the reflectance properties of background material. For example, in agricultural settings NDVI is highly influenced by soil reflectance (Baret and Guyot 1991). The poor performance of the EVI and SAVI as predictor variables suggested that background soil reflectance did not influence NDVI values. However, in forested woodlots dominated by deciduous trees one would expect there to be more non-photosynthetically active biomass (i.e. plant litter) than bare soil. NDVI values are influenced by senescent leaves (DiBella et al. 2004) and leaf litter (Van Leeuwen and Huete 1996) and the influence of background material is greater the lower the green biomass cover (Nemani et al. 1993). The wide scatter of NDVI values at low *L. maackii* cover observed (Figures 5 and 6) may have been a result of the influence of plant litter.

Another possible explanation for the wide scatter of NDVI values at low *L. maackii* cover is variation in green vegetation cover other than *L. maackii*. The presence of green biomass in forest understories has been demonstrated to influence reflectance values and interfere in deriving information on forest canopy attributes from remote sensing data using NDVI (e.g. Chen and Cihlar 1996; Turner et al. 1999). The high NDVI values of plots with little *L. maackii*, but medium to high graminoid cover suggests that graminoids and perhaps other green vegetation reduces the ability of NDVI to predict *L. maackii* cover, especially at low *L. maackii* cover values (Figures 5 and 6).

The distribution of points that exhibited evidence of anthropogenic disturbance (Figures 9 and 10) was similar to the pattern of points with medium to high graminoid cover (Figures 5 and 6) with the majority of disturbed plots to the right of the linear and quadratic regression lines. However, all of the plots with evidence of recent disturbance were also plots with medium or high graminoid abundance and this may indicate that disturbance promotes the presence of graminoids. Disturbance may also facilitate the establishment of other invasive plants (e.g. *Rosa multiflora*, *Berberis thunbergii*), as these were more frequently encountered in woodlots with evident anthropogenic disturbance. Furthermore, disturbance activity was primarily timber harvesting and to a lesser extent livestock grazing, both of these could result in changes that would facilitate the establishment of understory vegetation. Therefore, disturbance may influence NDVI values by promoting the presence of green vegetation other than *L. maackii*. Timber harvesting could also influence NDVI values by reducing canopy cover, stand structure, and reducing shadow effects, which would result in increased NDVI values (MacDonald et al. 1998).

The availability of Landsat 5 TM data for this study was limited to one suitable image that was free of cloud cover over the study area from the period 2001 to 2007. Fall Landsat 7 ETM+ was not considered due to the scan line corrector failure that occurred in May 2003. Different remote sensing platforms could offer additional opportunities for the acquisition of cloud free images. For example, the SPOT platform could acquire an image of the study area for any day specified.

The accuracy of the quadratic NDVI model could be improved by increasing the spectral resolution of the remote sensing data and the amount of field data collected. Combining higher spectral resolution remote sensing data with field measurements of *L. maackii* green leaf reflectance could increase the level of discrimination between *L. maackii* and other green vegetation. If the spectral reflectance characteristics of *L. maackii*, as well as other vegetation present in the study area were collected, then these values could be used to develop a predictive model with improved discrimination between *L. maackii* and other vegetation cover types (Lass et al. 2005). The collection of quantitative data pertaining to the spectral reflectance properties of all above ground biomass (green leaf, litter, bark) would provide information about other factors influencing the reflectance values of study plots and enable one to reduce the influence of background reflectance on the predictive model (Van Leeuwen and Huete 1996).

Improvements in the detection of *L. maackii* cover may be achieved through the use of multiple remote sensing platforms, as this technique has been used to achieve improved model performance for the estimation of above ground biomass (Lu 2006). By combining information from a broadband platform with information from a hyperspectral platform the degree of discrimination between vegetation cover types would be expected to increase and an improvement in predictive power achieved.

Improvements in the predictive model may also be realized by the collection of more field data. There were 35 training plots and only eight of those had *L. maackii* cover greater than 20%. A greater number of high cover plots could reduce the influence of outliers and improve model fit for the training data. The weakness of fit in the verification model may be due to the small data set. There were only 15 verification plots and only two of those had greater than 20% *L. maackii* cover.

It is plausible that the spatio-temporal distribution of *L. maackii* could be mapped using remote sensing data. The Landsat 1 platform began collecting data in 1972 and SPOT 1 was launched in 1986. Mapping the distribution of *L. maackii* populations across the landscape over a 20 to 36 year period would provide insight into mechanisms that facilitate *L. maackii* invasion.

The results of this study demonstrate that NDVI may be used to predict the cover of the exotic shrub *L. maackii* in the understory of deciduous woodlots in the study area. Such a predictive model could be used to map the temporal and spatial distribution of *L. maackii* within the Eastern Broadleaf Ecoregion, as models developed in one study area may be used in other areas with similar biophysical environments if atmospheric correction methods are properly applied (Lu 2006). This model could also be used to predict the presence of other exotic invasive species that have similar leaf phenology characteristics (e.g. *Lonicera tatarica*, *Ligustrum sinense*, *Berberis thunbergii*) in the understories of eastern deciduous forests.

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Table 1 *Lonicera maackii* cover classes and number of ground plots (GPs) within each level of *L. maackii* cover.

Percent <i>L. maackii</i> cover	Total GPs within each cover class	Training GPs	Verification GPs
40-80	4	3	1
30-39.9	3	2	1
19-29.9	4	3	1
10-18.9	7	5	2
6-9.9	12	8	4
2-5.9	5	4	1
.1 -1.9	7	5	2
0	8	5	3
TOTALS	50	35	15

Table 2 Spectral and spatial characteristics of Landsat 5 TM and Landsat7 ETM+ where IR=infra red (modified from Jensen 2007).

Band	Spectral Resolution (μm)	Spatial Resolution (m)
1 (blue)	0.45 – 0.52	30x30
2 (green)	0.52 – 0.60	30x30
3 (red)	0.63 – 0.69	30x30
4 (near IR)	0.76 – 0.90	30x30
5 (mid IR)	10.4 – 12.5	30x30
7 (mid IR)	2.08 – 2.35	30x30

Table 3 Conversion equations for Landsat5 image digital number values to Landsat7 equivalents (USGS 2001).

Band/Layer	Values for Landsat 5 conversion to Landsat 7
1/1	(layer1) * 0.9398 + 4.2934
2/2	(layer2) * 1.7731 + 4.7289
3/3	(layer3) * 1.5348 + 3.9796
4/4	(layer4) * 1.4239 + 7.032
5/5	(layer5) * 0.9828 + 7.0185
7/6	(layer6) * 1.3017 + 7.6568

Table 4 Image and band specific equation values for digital numbers (DN) to radiance conversion.

Band/ Layer	DN to Radiance Equation Values for June 11, 2007	DN to Radiance Equation Values for November 12, 2005 and January 28, 2002
1/1	$-6.2 + ((191.6 + 6.2)/255) * (\text{layer } 1)$	$-6.2 + ((191.6 + 6.2)/255) * (\text{layer } 1)$
2/2	$-6.4 + ((196.5 + 6.4)/255) * (\text{layer } 2)$	$-6.4 + ((196.5 + 6.4)/255) * (\text{layer } 2)$
3/3	$-5 + ((152.9 + 5)/255) * (\text{layer } 3)$	$-5 + ((152.9 + 5)/255) * (\text{layer } 3)$
4/4	$-5.1 + ((241.1 + 5.1)/255) * (\text{layer } 4)$	$-5.1 + ((157.4 + 5.1)/255) * (\text{layer } 4)$
5/5	$-1 + ((31.06 + 1)/255) * (\text{layer } 5)$	$-1 + ((31.06 + 1)/255) * (\text{layer } 5)$
7/6	$-0.35 + ((10.8 + 0.35)/255) * (\text{layer } 6)$	$-0.35 + ((10.8 + 0.35)/255) * (\text{layer } 6)$

Table 5 Individual COST model equations for each band and image date.

Band/ Layer	COST Equation Values for June 11, 2007
B1/L1	$(3.14159 * (\text{layer } 1) - 35.5312) * 1.030852365481 / (1969 * 0.822849376737328)$
B2/L2	$(3.14159 * (\text{layer } 2) - 25.9196) * 1.030852365481 / (1840 * 0.822849376737328)$
B3/L3	$(3.14159 * (\text{layer } 3) - 8.6681) * 1.030852365481 / (1551 * 0.822849376737328)$
B4/L4	$(3.14159 * (\text{layer } 4) - 8.5891) * 1.030852365481 / (1044 * 0.822849376737328)$
B5/L5	$(3.14159 * (\text{layer } 5) - 0.0462) * 1.030852365481 / (225.7 * 0.822849376737328)$
B7/L6	$(3.14159 * (\text{layer } 6) - 0) * 1.030852365481 / (82.07 * 0.822849376737328)$
Band/ Layer	COST Equation Values for November 12, 2005
B1/L1	$(3.14159 * (\text{layer } 1) - 18.7470) * 0.97971948 / (1969 * 0.238347103014051)$
B2/L2	$(3.14159 * (\text{layer } 2) - 10.8962) * 0.97971948 / (1840 * 0.822849376737328)$
B3/L3	$(3.14159 * (\text{layer } 3) - 1.5348) * 0.97971948 / (1551 * 0.238347103014051)$
B4/L4	$(3.14159 * (\text{layer } 4) - 1.2270) * 0.97971948 / (1044 * 0.238347103014051)$
B5/L5	$(3.14159 * (\text{layer } 5) - 0) * 0.97971948 / (225.7 * 0.238347103014051)$
B7/L6	$(3.14159 * (\text{layer } 6) - 0) * 0.97971948 / (82.07 * 0.238347103014051)$
Band/ Layer	COST Equation Values for January 28, 2002
B1/L1	$(3.14159 * (\text{layer } 1) - 28.2620) * 0.969809965 / (1969 * 0.202426144)$
B2/L2	$(3.14159 * (\text{layer } 2) - 36.4992) * 0.969809965 / (1840 * 0.202426144)$
B3/L3	$(3.14159 * (\text{layer } 3) - 15.7755) * 0.969809965 / (1551 * 0.202426144)$
B4/L4	$(3.14159 * (\text{layer } 4) - 9.8441) * 0.969809965 / (1044 * 0.202426144)$
B5/L5	$(3.14159 * (\text{layer } 5) - 0.6923) * 0.969809965 / (225.7 * 0.202426144)$
B7/L6	$(3.14159 * (\text{layer } 6) - 0.3181) * 0.969809965 / (82.07 * 0.202426144)$

Table 6 Pearson's correlation coefficients for the four SVIs most strongly correlated with amount of *L. maackii* cover for the November 12, 2005 training data (N = 35).

SVI	Pearson's Correlation Coefficient	p-value
NDVI	0.791	<.0001
SR	-0.782	<.0001
EVI	0.609	<.0001
NDMI	0.604	<.0001

Table 7 R² and p values from the least squares regression analysis of the November 12, 2005 training data (N = 35) where *L. maackii* cover was regressed on individual SVI and reflectance band (RB) values.

SVI	Linear Regression Model	R ²	p-value ($\alpha=.05$)
NDVI	<i>L. maackii</i> cover = -207 + 484(NDVI)	0.626	<0.0001
SR	<i>L. maackii</i> cover = 207 - 516(SR)	0.612	<0.0001
EVI	<i>L. maackii</i> cover = -116 - 389(EVI)	0.371	0.0001
NDMI	<i>L. maackii</i> cover = 40.7 + 290(NDMI)	0.365	0.0001
TCap wetness	<i>L. maackii</i> cover = 128 + 329(TCapW)	0.322	0.0004
RB 7	<i>L. maackii</i> cover = 115 - 481(COST7)	0.311	0.0005
SAVI	<i>L. maackii</i> cover = -118 + 418(SAVI)	0.305	0.0006
RB 3	<i>L. maackii</i> cover = 109 - 816(COST3)	0.303	0.0006
RB 5	<i>L. maackii</i> cover = 134 - 320(COST5)	0.292	0.0008
TCap greenness	<i>L. maackii</i> cover = -29.7 + 642(TCapG)	0.260	0.0017
RB 1	<i>L. maackii</i> cover = 160 - 2043(COST1)	0.245	0.0025
TCap brightness	<i>L. maackii</i> cover = 81.6 - 163(TCapB)	0.083	0.0936
RB 2	<i>L. maackii</i> cover = 46.2 - 1380(COST2)	0.021	0.0025
VARI	<i>L. maackii</i> cover = 6.5 - 4.9(VAR)	0.001	0.9021
RB 4	<i>L. maackii</i> cover = 13.7 - 1(COST4)	0.000	0.9924

Table 8 R² and p-values from linear regression analyses of various data transformations applied to the November 12, 2005 training data (N = 35), where *L. maackii* was regressed on NDVI.

Transformation	R ²	p-value ($\alpha=.05$)
log NDVI	0.619	0.0001
NDVI ²	0.635	0.0001
√NDVI	0.594	0.0001
1/√NDVI	0.105	0.0580
1/NDVI	0.583	0.0001
Log (<i>L. maackii</i> +1)	0.408	0.0001
√ <i>L. maackii</i>	0.532	0.0001
√NDVI and √ <i>L. maackii</i>	0.515	0.0001

Table 9 Comparison of RMSE, R², and p-values of the linear regression model to the quadratic polynomial regression model for the November 12, 2005 training data (N = 35) where *L. maackii* cover was regressed on NDVI.

Regression Model	RMSE	R ²	p-value ($\alpha=.05$)
<i>L. maackii</i> %cover=1165 - 5397(NDVI)+6273(NDVI ²)	8.96	0.750	<.0001
<i>L. maackii</i> %cover= -207 + 484(NDVI)	10.80	0.626	<.0001

Table 10 Stepwise multiple regression models and analysis values for the November 12, 2005 training data (N = 35) where Y = *L. maackii* percent cover and the various SVIs and reflectance bands are the dependent variables. Mallows C_(p) statistic is related to the mean square error of a fitted value and identifies parsimonious models with good predictive power. The better model is one where Mallows' Cp is small and close to the number of predictors in the model plus the constant (p).

Regression Model	R ²	p-value ($\alpha=.05$)	Mallow's C _(p)
Y= -110 + 444(NDVI) + 21.2(VARI) - 694(Reflectance1)	0.656	0.0001	2.7
Y= -167 + 468(NDVI) - 77.7(TCapBrightness)	0.644	<0.0001	2.6
Y= -185 + 497(NDVI) - 89(Reflectance4)	0.643	0.0001	2.5
Y= -23.2 + 425(SAVI) - 828(Reflectance3)	0.618	0.0001	3.0
Y= 90.8 + 331(EVI) - 333(Reflectance5) + 44.8(VARI)	0.617	<0.0001	4
Y= 29.7 + 384 (EVI) - 2000(Reflectance1)	0.606	<0.0001	3
Y= 1165.3 -5397(NDVI) + 6273.3(NDVI ²)	0.750	0.0009	3

Table 11 Results of the linear and quadratic polynomial regression analyses of *L. maackii* on the top performing SVI from the January 28, 2002 minus November 12, 2005 training data values (N = 35) and the June 11, 2007 minus November 12, 2005 training data values

Regression Model	Image Dates	RMSE	R ²	p-value ($\alpha=.05$)
<i>L. maackii</i> % cover = NDVI NDVI ²	Nov-Jan	9.02	0.747	<.0001
<i>L. maackii</i> % cover = NDVI	Nov-Jan	10.45	0.650	<.0001
<i>L. maackii</i> % cover = SR SR ²	Jun-Nov	10.94	0.628	<.0001
<i>L. maackii</i> % cover = SR	Jun-Nov	12.17	0.525	<.0001

Table 12 R² and p-values from the regression analysis of the November 12, 2005 verification data (N = 15) (Y = observed *L. maackii* cover, X = predicted *L. maackii* cover).

SVI	Training Data Regression Model	Verification Data Model	RMSE	R ²	p-value ($\alpha=.05$)
NDVI	OLS	Y = -1.20 + 1.02(x)	14.91	0.426	0.008
NDVI	Quadratic	Y = -2.99 + 1.317(x)	13.11	0.556	0.001

Figure 1 Distribution of plots represented with black circles within the study area. The inset window displays the location and extent of Landsat Path 20 Row 32 coverage and the location of the study area within that extent.

Figure 2 Polygons drawn in ArcMap over suitable woodlots using mosaiced DOQQs.

Figure 3 Fall 2006 canopy and shrub layer in sites with high *L. maackii* abundance (ERC and Kramer) versus sites with no *L. maackii* presence (Sugarbush and Bigwoods), where solid line is shrub layer and dashed line is canopy.

Figure 4 Fall 2007 canopy and shrub layer in sites with high *L. maackii* abundance (ERC and Kramer) versus sites with no *L. maackii* presence (Sugarbush and Bigwoods), where solid line is shrub layer and dashed line is canopy.

Figure 5 Linear regression of *L. maackii* cover on NDVI of the November 12, 2005 training data. Different color circles distinguish plots with different graminoid cover (high = black, medium = gray, and low = white).

Figure 6 Quadratic polynomial regression of *L. maackii* cover on NDVI of the November 12, 2005 training data. Different color circles distinguish plots with different graminoid cover (high = black, medium = gray, and low = white).

Figure 7 Linear regression of observed *L. maackii* cover on predicted *L. maackii* cover values. Predicted values were calculated from the November verification data using the quadratic polynomial regression model of NDVI. Different color circles distinguish plots with different graminoid cover (high = black, medium = gray, and low = white).

Figure 8 Linear regression of observed *L. maackii* cover on predicted *L. maackii* cover values. Predicted values were calculated from the November 12, 2005 verification data using the linear regression model of NDVI. Different color circles distinguish plots with different graminoid cover (high = black, medium = gray, and low = white).

Figure 9 Linear regression of *L. maackii* cover on NDVI using the November training data. Different color circles distinguish plots with differences in disturbance (evident disturbance = black and no apparent disturbance = white).

Figure 10 Quadratic regression of *L. maackii* cover on NDVI using the November training data. Different color circles distinguish plots with differences in disturbance (evident disturbance = black and no apparent disturbance = white).

Figure 11 Linear regression of *L. maackii* cover on NDVI using the November training data. Different color circles distinguish between plots with *Quercus* species and *F. grandifolia* comprising > 20% of basal area (black = high *Quercus* and *F. grandifolia* and white = low *Quercus* and *F. grandifolia*).

Figure 12 Quadratic regression of *L. maackii* cover on NDVI using the November training data. Different color circles distinguish between plots with *Quercus* species and *F. grandifolia* comprising > 20% of basal area (black = high *Quercus* and *F. grandifolia* and white = low *Quercus* and *F. grandifolia*).

Appendix I

Correlation tables with Pearson's correlation coefficients and p-values for *L. maackii* cover, stand density (SD), stand basal area (BA), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Simple Ratio (SR), Tasseled Cap Brightness (TCapB), Tasseled Cap Wetness (TCapW), Tasseled Cap Greenness (TCapG), Visible Atmospherically Resistant Index (VARI), Soil Adjusted Vegetation Index (SAVI), Normalized Difference Moisture Index (NDMI), and reflectance bands (RB) for the training data (N=35) from the three image dates.

Table AI-1 Pearson's correlation coefficients and p-values for the January 28, 2002 image.

	SD	BA	RB1	RB2	RB3	RB4	RB5	RB7	EVI	NDMI	NDVI	SAVI	SR	Tcap(B)	Tcap(W)	Tcap(G)
RB1	-0.151 0.294	-0.127 0.378														
RB2	-0.139 0.336	-0.27 0.057	0.773 0													
RB3	-0.265 0.063	-0.176 0.221	0.773 0	0.83 0												
RB4	0.079 0.584	-0.05 0.732	0.158 0.274	0.338 0.016	0.023 0.872											
RB5	-0.344 0.014	-0.2 0.164	0.639 0	0.756 0	0.633 0	0.556 0										
RB7	-0.304 0.032	-0.225 0.115	0.745 0	0.866 0	0.829 0	0.209 0.145	0.871 0									
EVI	0.146 0.312	-0.001 0.995	0.07 0.631	0.157 0.277	-0.207 0.15	0.961 0	0.41 0.003	0.031 0.83								
NDMI	0.468 0.001	0.191 0.185	-0.599 0	-0.579 0	-0.725 0	0.257 0.072	-0.66 0	-0.827 0	0.396 0.004							
NDVI	0.251 0.079	0.124 0.392	-0.623 0	-0.621 0	-0.906 0	0.387 0.006	-0.355 0.011	-0.683 0	0.587 0	0.775 0						
SAVI	0.144 0.319	0.002 0.99	-0.064 0.659	0.083 0.564	-0.268 0.06	0.956 0	0.351 0.012	-0.042 0.772	0.988 0	0.46 0.001	0.639 0					
SR	-0.234 0.102	-0.112 0.438	0.613 0	0.624 0	0.903 0	-0.371 0.008	0.364 0.009	0.691 0	-0.573 0	-0.773 0	-0.998 0	-0.625 0				
Tcap(B)	0.005 0.975	-0.094 0.518	0.32 0.024	0.503 0	0.207 0.149	0.979 0	0.704 0	0.399 0.004	0.904 0	0.065 0.652	0.21 0.144	0.882 0	-0.195 0.176			
Tcap(W)	0.132 0.36	-0.008 0.954	0.001 0.995	0.169 0.24	-0.151 0.294	0.983 0	0.411 0.003	0.031 0.831	0.979 0	0.41 0.003	0.54 0	0.99 0	-0.524 0	0.925 0		
Tcap(G)	0.397 0.004	0.216 0.132	-0.672 0	-0.774 0	-0.727 0	-0.31 0.029	-0.958 0	-0.954 0	-0.149 0.3	0.835 0	0.546 0	-0.085 0.557	-0.554 0	-0.487 0	-0.147 0.309	
VARI	0.296 0.037	-0.069 0.635	-0.168 0.244	0.161 0.264	-0.386 0.006	0.436 0.002	0.094 0.515	-0.024 0.869	0.526 0	0.286 0.044	0.501 0	0.521 0	-0.472 0.001	0.386 0.006	0.466 0.001	0.012 0.935

Table AI-2 Pearson's correlation coefficients and p-values for the November 12, 2005 Landsat image.

	<i>L. mackii</i>	SD	BA	RB1	RB2	RB3	RB4	RB5	RB7	EVI	NDMI	NDVI	SAVI	SR	Tcap(B)	Tcap(W)	Tcap(G)
RB1	-0.449 0.001	-0.151 0.294	-0.127 0.378														
RB2	-0.176 0.221	-0.139 0.336	-0.27 0.057	0.773 0													
RB3	-0.551 0	-0.265 0.063	-0.176 0.221	0.773 0	0.83 0												
RB4	-0.051 0.723	0.079 0.584	-0.05 0.732	0.158 0.274	0.338 0.016	0.023 0.872											
RB5	-0.575 0	-0.344 0.014	-0.2 0.164	0.639 0	0.756 0	0.633 0	0.556 0										
RB7	-0.535 0	-0.304 0.032	-0.225 0.115	0.745 0	0.866 0	0.829 0	0.209 0.145	0.871 0									
EVI	0.545 0	0.146 0.312	-0.001 0.995	0.07 0.631	0.157 0.277	-0.207 0.15	0.961 0	0.41 0.003	0.031 0.83								
NDMI	0.594 0	0.468 0.001	0.191 0.185	-0.599 0	-0.579 0	-0.725 0	0.257 0.072	-0.66 0	-0.827 0	0.396 0.004							
NDVI	0.748 0	0.251 0.079	0.124 0.392	-0.623 0	-0.621 0	-0.906 0	0.387 0.006	-0.355 0.011	-0.683 0	0.587 0	0.775 0						
SAVI	0.483 0	0.144 0.319	0.002 0.99	-0.064 0.659	0.083 0.564	-0.268 0.06	0.956 0	0.351 0.012	-0.042 0.772	0.988 0	0.46 0.001	0.639 0					
SR	-0.737 0	-0.234 0.102	-0.112 0.438	0.613 0	0.624 0	0.903 0	-0.371 0.008	0.364 0.009	0.691 0	-0.573 0	-0.773 0	-0.998 0	-0.625 0				
Tcap(B)	-0.32 0.023	0.005 0.975	-0.094 0.518	0.32 0.024	0.503 0	0.207 0.149	0.979 0	0.704 0	0.399 0.004	0.904 0	0.065 0.652	0.21 0.144	0.882 0	-0.195 0.176			
Tcap(W)	0.439 0.001	0.132 0.36	-0.008 0.954	0.001 0.995	0.169 0.24	-0.151 0.294	0.983 0	0.411 0.003	0.031 0.831	0.979 0	0.41 0.003	0.54 0	0.99 0	-0.524 0	0.925 0		
Tcap(G)	0.585 0	0.397 0.004	0.216 0.132	-0.672 0	-0.774 0	-0.727 0	-0.31 0.029	-0.958 0	-0.954 0	-0.149 0.3	0.835 0	0.546 0	-0.085 0.557	-0.554 0	-0.487 0	-0.147 0.309	
VAR1	-0.126 0.383	0.296 0.037	-0.069 0.635	-0.168 0.244	0.161 0.264	-0.386 0.006	0.436 0.002	0.094 0.515	-0.024 0.869	0.526 0	0.286 0.044	0.501 0	0.521 0	-0.472 0.001	0.386 0.006	0.466 0.001	0.012 0.935

Table AI-3 Pearson's correlation coefficients and p-values for the June 11, 2006 Landsat image.

	<i>L. maculii</i>	SD	BA	RB1	RB2	RB3	RB4	RB5	RB7	EVI	NDMI	NDVI	SAVI	SR	Tcap(B)	Tcap(G)	Tcap(W)
RB1	-0.513 0.002	-0.197 0.256	-0.157 0.366														
RB2	-0.316 0.064	-0.121 0.488	-0.329 0.054	0.775 0													
RB3	-0.403 0.016	-0.236 0.173	-0.267 0.121	0.778 0	0.851 0												
RB4	-0.289 0.092	-0.018 0.92	-0.094 0.59	0.235 0.175	0.33 0.053	0.058 0.743											
RB5	-0.489 0.003	-0.346 0.042	-0.281 0.102	0.656 0	0.744 0	0.668 0	0.587 0										
RB6	-0.358 0.035	-0.265 0.124	-0.296 0.084	0.736 0	0.879 0	0.872 0	0.253 0.143	0.876 0									
EVI	-0.224 0.196	0.039 0.824	-0.009 0.959	0.132 0.449	0.13 0.455	-0.185 0.287	0.958 0	0.418 0.013	0.042 0.811								
NDMI	0.331 0.052	0.404 0.016	0.259 0.133	-0.591 0	-0.618 0	-0.772 0	0.167 0.339	-0.699 0	-0.846 0	0.341 0.045							
NDVI	0.213 0.218	0.192 0.268	0.182 0.296	-0.608 0	-0.656 0	-0.907 0	0.352 0.038	-0.386 0.022	-0.718 0	0.566 0	0.793 0						
SAVI	-0.176 0.311	0.052 0.767	-0.015 0.932	-0.002 0.993	0.058 0.742	-0.252 0.145	0.951 0	0.362 0.033	-0.025 0.886	0.988 0	0.401 0.017	0.624 0					
SR	-0.189 0.276	-0.177 0.31	-0.163 0.35	0.598 0	0.657 0	0.903 0	-0.338 0.047	0.394 0.019	0.725 0	-0.553 0.001	-0.791 0	-0.998 0	-0.611 0				
Tcap(B)	-0.364 0.032	-0.083 0.637	-0.153 0.381	0.393 0.019	0.499 0.002	0.25 0.147	0.978 0	0.734 0	0.445 0.007	0.894 0	-0.032 0.855	0.164 0.347	0.87 0	-0.151 0.388			
Tcap(G)	-0.215 0.215	0.031 0.859	-0.038 0.828	0.074 0.671	0.154 0.378	-0.129 0.461	0.981 0	0.438 0.008	0.067 0.704	0.981 0	0.332 0.051	0.518 0.001	0.99 0	-0.504 0.002	0.919 0		
Tcap(W)	0.439 0.008	0.365 0.031	0.296 0.084	-0.673 0	-0.776 0	-0.766 0	-0.365 0.031	-0.964 0	-0.953 0	-0.175 0.315	0.852 0	0.571 0	-0.116 0.506	-0.578 0	-0.543 0.001	-0.197 0.258	
VAR1	0.387 0.022	0.322 0.06	0.036 0.837	-0.163 0.35	0.159 0.362	-0.345 0.042	0.36 0.033	0.016 0.925	-0.056 0.747	0.442 0.008	0.298 0.082	0.434 0.009	0.443 0.008	-0.405 0.016	0.305 0.074	0.394 0.019	0.069 0.693

Appendix II

Output from the SAS 9.1 regression analyses for the November 12, 2005 training data.

Table AII-1 Linear regression of *L. maackii* cover on NDVI.

Model: Linear regression						
Dependent Variable: <i>L. maackii</i> percent cover						
Number of Observations Read			35			
Number of Observations Used			35			
Analysis of Variance						
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	
Model	1	6439.02907	6439.02907	55.21	<.0001	
Error	33	3848.41688	116.61869			
Corrected Total	34	10287				
Root MSE		10.79901	R-Square	0.6259		
Dependent Mean		13.30129	Adj R-Sq	0.6146		
Coeff Var		81.18774				
Parameter Estimates						
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	Intercept	1	-206.99119	29.70265	-6.97	<.0001
NDVI	NDVI	1	484.22147	65.16553	7.43	<.0001

Table AII-2 Quadratic polynomial regression of *L. maackii* cover on NDVI.

Model: Quadratic polynomial regression						
Dependent Variable: <i>L. maackii</i> percent cover						
Number of Observations Read			35			
Number of Observations Used			35			
Analysis of Variance						
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	
Model	2	7718.26869	3859.13435	48.07	<.0001	
Error	32	2569.17725	80.28679			
Corrected Total	34	10287				
Root MSE		8.96029	R-Square	0.7503		
Dependent Mean		13.30129	Adj R-Sq	0.7347		
Coeff Var		67.36409				
Parameter Estimates						
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	Intercept	1	1165.27066	344.66422	3.38	0.0019
NDVI	NDVI	1	-5396.93812	1474.35242	-3.66	0.0009
ndvi2		1	6273.31693	1571.60471	3.99	0.0004

Appendix III

Information for the ground plots including: data set (Training data = T and Verification data = V), *Lonicera maackii* (percent cover), stand basal area (BA) expressed in meters² per hectare, graminoid cover abundance (H = high, M = medium, and L = low), plot disturbance (No disturbance = 0 and Disturbance = 1), and the X,Y coordinate values for plot centers expressed in decimal degrees.

Plot Number	Data Set	<i>Lonicera maackii</i>	Stand BA (m ² /ha)	Graminoid Cover	Plot Disturbance	X	Y
44	T	0.85	24.91	L	0	698424	4423380
46	V	0	22.17	L	0	694422	4430820
55	V	8.11	32.48	M	1	695126	4432080
58	T	0.75	38.43	L	0	692450	4431340
124	T	0	27.33	L	0	690982	4435300
129	T	0	28.08	M	0	689348	4436790
137	V	6.75	27.16	H	1	702818	4429950
143	T	0	21.08	H	1	686369	4402220
314	T	30.81	14.40	H	1	692085	4423630
332	V	0	31.01	L	0	693862	4428400
352	T	0	25.13	M	1	692598	4406130
456	V	24.04	25.50	L	0	705165	4425450
464	V	0.13	15.60	M	0	698029	4424590
470	T	11.76	25.18	L	0	692056	4423080
480	V	7.10	29.13	H	1	690533	4424150
498	V	1.27	20.65	L	0	691637	4425080
510	T	2.79	2.91	L	0	696183	4423350
515	V	6.32	38.71	H	1	694556	4389840
516	T	3.13	36.14	H	0	689581	4405020
517	T	9.28	28.97	L	0	690817	4408330
519	T	14.15	11.89	L	0	695430	4424330
610	T	0	27.75	M	0	691704	4427260
119P	T	59.40	55.63	L	0	696105	4432960
128ps	T	72.90	18.70	L	0	692536	4428380
269-270	V	14.08	15.93	M	1	687633	4407440
279p	T	8.43	26.87	M	1	693747	4427360
28ps	T	8.92	28.93	L	0	700748	4407440
361p	T	0.63	22.16	M	1	693841	4423830
366p	T	8.61	44.75	M	1	691571	4408980
374p	T	12.67	25.19	L	0	696998	4397940
377p	T	22.24	33.16	M	1	696353	4425780
378p	T	23.92	32.52	L	0	692563	4397730
379p	T	7.44	30.94	L	0	692596	4425520
380p	V	35.41	31.74	L	0	689199	4406770

Plot Number	Plot Division	<i>Lonicera maackii</i>	Stand BA (m²/ha)	Graminoid Cover	Plot Disturbance	X	Y
382p	T	12.55	15.89	M	0	687308	4410150
383p	T	4.64	18.25	M	0	693393	4395600
387p	T	5.05	42.76	M	1	699514	4434560
3i	V	0	25.06	H	0	694676	4428370
453-454	V	8.63	31.29	M	0	693008	4396940
457-458	V	0.85	11.43	L	0	692398	4425920
475-476	V	19.78	27.69	L	0	688405	4408980
478-479	T	6.54	12.39	M	0	687860	4408880
50-51ps	T	14.55	32.90	M	1	693910	4423490
511-512	T	36.35	22.17	M	1	692750	4433830
513-514	V	72.22	21.68	L	1	689474	4407450
525-526	T	0.24	30.27	L	0	694615	4425200
52ps	V	9.88	27.70	L	0	681691	4400930
5i	T	47.57	31.49	M	0	687921	4414070
66ps	V	13.48	46.53	L	0	694345	4424980
144ps	V	4.31	32.78	L	0	699935	4391220