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Detecting an Invasive Shrub in Deciduous Forest Understories Using Remote Sensing

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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. Amur honeysuckle, an Asian shrub that invades North American forests, expands leaves earlier and retains leaves later than native woody species. This research project explored whether Landsat 5 TM and Landsat 7 ETM+ imagery could predict Amur honeysuckle cover in woodlots across Darke and Preble Counties in southwestern Ohio and Wayne County in adjacent eastern Indiana. The predictive abilities of six spectral vegetation indices and six reflectance bands were evaluated to determine the best predictor or predictors of Amur honeysuckle cover. The use of image differencing in which a January 2001 image was subtracted from a November 2005 image provided better prediction of Amur honeysuckle cover than the use of the single November 2005 image. The Normalized Difference Vegetation Index (NDVI) was the best-performing predictor variable, compared to other spectral indices, with a quadratic function providing a better fit (R^2 = 0.75) than a linear function (R^2 = 0.65). This predictive model was verified with 15 other woodlots (R^2 = 0.77). With refinement, this approach could map current and past understory invasion by Amur honeysuckle.

Nomenclature: Amur honeysuckle, *Lonicera maackii* (Rupr.) Herder.
Key words: Landsat, TM, ETM+, leaf phenology, Normalized Difference Vegetation Index, NDVI.

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, invasive species have been identified as a significant threat to threatened and endangered species (Wilcove et al. 1998) and are estimated to cost over $137 billion per year in economic damages and control costs (Pimentel et al. 2000). Exotic plants frequently exert negative impacts on invaded systems and significantly alter ecosystem processes and plant community composition, and influence the structure of higher trophic levels (Chornesky et al. 2005; Eiswerth and Johnson 2002; Levine et al. 2003; Vitousek 1990). Within the United States, it is estimated that exotic plants invade 700,000 hectares of native plant communities annually and that 5,000 exotic plant species have become established in native ecosystems (Pimentel et al. 2000). 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 (Bradley and Mustard 2006; Byers et al. 2001; Eiswerth and Johnson 2002; Rew et al. 2005). 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 (Andersen et al. 2004; Cohen and Goward 2004; Parker et al. 1999), helps determine which characteristics make ecosystems susceptible to invasion (Hobbs and Humphries 1995), and can provide insight into the mechanisms that facilitate invasion.

Those involved in the study and control of invasive species often expend considerable resources to gather information about the current spatial distribution and population abundances of invasive species (Byers et al. 2001; Deckers et al. 2005; Rew et al. 2005). Traditional ground-based methods for gathering this information are high in resource costs, which often constrain research and management activities (Anderson et al. 2003; Caughlan and Oakley 2002; 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 (Patil et al. 2001; Rew et al. 2005).

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 semiarid grasslands (Bradley and Mustard 2005; Lass et al. 2005; Peterson 2005), wetlands (Laba et al. 2008; Madden, 2004; Pengra et al. 2007), 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 might exist to detect the invasive. Exotic shrubs such as Amur honeysuckle leaf out earlier in the spring and retain leaves longer in the fall than native deciduous species (Trisel and Gorchov 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 (Resasco et al. 2007).

Phenological differences have been used in numerous studies to derive ecological information from remote sensing data. Differences in phenology between native grasses and the invasive downy brome (*Bromus tectorum* L.) were used to map

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the distribution of downy brome using Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data (Bradley and Mustard 2005; Peterson 2005) in Great Basin rangelands. Resasco et al. (2007) demonstrated the possibility of using Landsat images to exploit phenological differences to identify a difference in spectral reflectance values of woodlots with Amur honeysuckle vs. noninvaded woodlots. Other researchers have demonstrated that multitemporal satellite images can detect phenological variation between species with a high degree of accuracy (e.g., Dymond et al. 2002) and reveal elevational gradients in canopy leaf expansion in deciduous forest landscapes (Fisher et al. 2006).

Study Species. Amur honeysuckle is a tall shrub from northeastern Asia that was introduced into the United States in 1898 and has been widely cultivated for a variety of purposes (Luken and Thieret 1995). Since its introduction, the shrub has established naturalized populations in at least 24 eastern states (Trisel and Gorchov 1994) and 35 Ohio counties (Trisel 1997). Propagule pressure of Amur honeysuckle is high, because the shrub's fruit has been incorporated into the diets of numerous bird species, some of which disperse viable seeds to habitats suitable for establishment (Bartuszevige and Gorchov 2006).

Amur honeysuckle impacts forest ecosystems at multiple levels and may alter natural patterns of forest succession. Amur honeysuckle reduces growth and fecundity of native annual and perennial herbs due to competitive effects (Gould and Gorchov 2000; Miller and Gorchov 2004), germination of annual and biennial herbs from potential allelopathic effects (Cipollini et al. 2008; Dorning and Cipollini 2006), and survival and growth of native tree seedlings (Gorchov and Trisel 2003; Hartman and McCarthy 2004). Under Amur honeysuckle canopies the species richness and abundance of native herbs and tree seedlings are reduced (Collier et al. 2002). Overstory trees have lower rates of radial growth in stands with Amur honeysuckle (Hartman and McCarthy 2007). Sugar maple (*Acer saccharum* Marsh.) seedling density was negatively correlated with Amur honeysuckle density among stands (Hutchinson and Vankat 1997). Amur honeysuckle also has the potential to influence the trophic structure of invaded ecosystems; for example, songbird nests in Amur honeysuckle suffered higher predation than nests in indigenous species (Schmidt and Whelan 1999).

The objective of this study was to test the hypothesis that differences in leaf phenology between Amur honeysuckle and native woody species could be exploited to estimate the cover abundance of Amur honeysuckle in forest understories using remote sensing data. We used regression analyses to determine how well Landsat acquired reflectance values from different dates explained variation in understory Amur honeysuckle cover among forested plots.

Materials and Methods

Study Area. The study area (39°38′ to 40°3′N, 84°35′ to 84°52′W) was approximately 1,200 km^2 with plots located in Darke and Preble counties in southwestern Ohio and in neighboring Wayne County, Indiana (Figure 1). The landscape is rural, mostly cropland, with many small (3 to 15 ha) woodlots, a few larger forests, farm houses, and small towns. Darke County was identified by Bartuzevige et al. (2006) as an area on the front of an advancing Amur honeysuckle invasion, where forest patches exhibit a range of Amur honeysuckle abundances, with many uninvaded. Nearly all canopy trees in these woodlots are deciduous (primarily oaks [*Quercus* spp.], ash [*Fraxinus* spp.], sugar maple, and American beech [*Fagus grandifolia* Ehrh]), although the evergreen Eastern redcedar (*Juniperus virginiana* L.) also was common. Understory plant composition varied across the study woodlots, but Amur honeysuckle was the only common woody plant with an extended leaf phenology.

Seasonal Patterns of Leaf Abscission. In order to characterize the differences in phenology between native species and Amur honeysuckle and to identify the optimal dates for image acquisition it was necessary to quantify fall leaf senescence. Sampling was conducted in Butler County, Ohio (just south of the main study area) on two plots with high levels of Amur honeysuckle abundance (the Ecology Research Center [ERC] of Miami University with 57% Amur honeysuckle cover and Kramer Woods, Miami University Natural Areas with 37% cover) and two plots with no Amur honeysuckle (the Sugarbush and Big Woods stands in Hueston Woods State Park).

Percent cover of the tree and the shrub layers were determined using a vertical densitometer in a manner similar to that described by Stumpf (1993). Readings were taken every 5 m along four 50-m transect lines that were spaced 25 m apart. Tree cover was scored as the presence of leaves observed when looking up from approximately 3.5 m from the ground surface through the use of a stepladder. Shrub cover was scored as the presence of leaves on shrubs observed from the same position but with the vertical densitometer pointing downward; herbs were occasionally present but not scored. In 2006, 54 points were sampled per plot and in 2007, 50 points were used. Observations were made weekly October 21 to December 2, 2006 and September 9 to December 1, 2007.

Field Sampling. Field sampling was conducted June to Sept. 2007 to quantify Amur honeysuckle cover and stand characteristics in woodlots. Woodlots larger than 120 m by 120 m were identified using digital orthophotos of the study area obtained from the Darke County Geographic Information Office and the Preble County Planning Department; this was the minimum size to accommodate a 100 m by 100 m study plot with ≥ 10 m buffer on all sides. A total of 50 ground plots (GP) that represented a wide range of cover of Amur honeysuckle (0% to 73%) were selected. Each GP consisted of one 100-m baseline transect with four 100-m parallel line intercept transects spaced 25 m apart. Transects were used to quantify Amur honeysuckle cover and as anchor lines for point-quarter plots (PQPs). A handheld global positioning system (GPS) with submeter accuracy was used to record the spatial location of the anchor and end points of each main transect line.

PQPs were used to collect basic forest stand community characteristics as described in Smith and Smith (2001). There were 16 PQPs per GP, 4 per transect line. The first PQP was located randomly within the first 25 m, with the other three PQPs spaced at 25-m intervals. The nearest tree ≥ 10 cm 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.

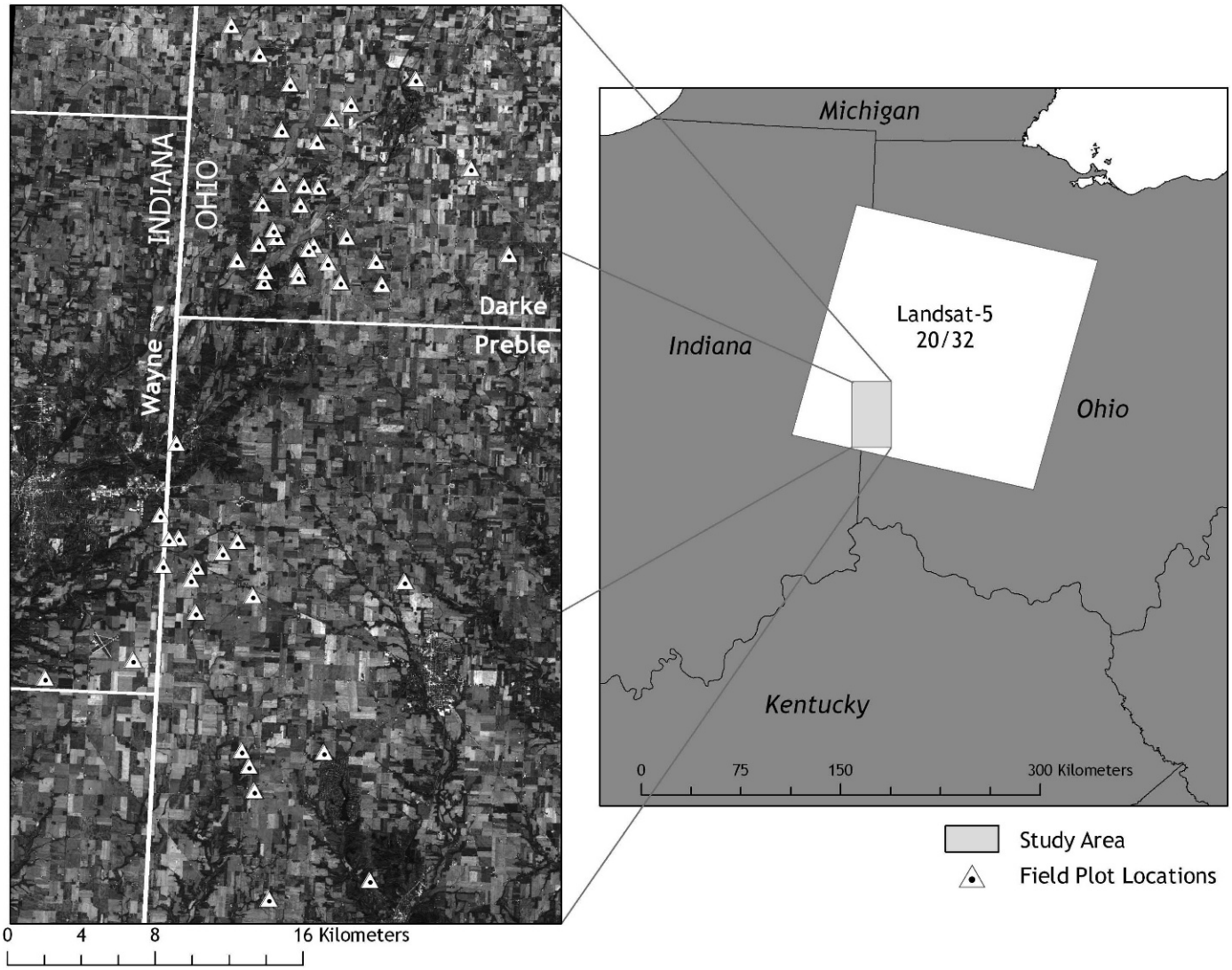

Figure 1. Location of study. Large map shows location and extent of Landsat Path 20 Row 32 coverage with the study area (gray rectangle) within that extent. Inset shows a SPOT-5 satellite image (red band) of study area with the 50 ground plots.

Graminoid cover for each woodlot was subjectively classified as high, medium, or low. Common graminoid species in these woodlots include hairy wildrye (*Elymus vilosus* Muhl. ex Willd.), eastern bottlebrush grass (*E. hystrix* L.), Gray's sedge (*Carex grayi* Carey), and fescue (Festuca spp.; S. M. Castellano, unpublished data). 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. We also noted whether the woodlot had been recently disturbed (e.g., timber harvest, livestock grazing, trash dumping).

Ground plots were divided into eight groups based upon the percent Amur honeysuckle cover observed. Within each group, plots were randomly assigned to either the validation or training data pool. Approximately two-thirds were used as training (35) and one-third (15) as validation data.

Remote Sensing Data. Three georectified Landsat images from Path 20 Row 32 were acquired from Ohioview.org (http://www.ohioview.org) in a GeoTIFF format: Landsat 5 TM images captured on June 11, 2007 and November 12, 2005 and a Landsat 7 ETM+ image captured on January 28, 2002. A combination of TM and ETM+ data from different years was necessary to find cloud- and snow-free images of the study area. The June image was captured when both the overstory and understory were in full leaf. The November image was collected when overstory leaves had senesced and the majority had abscised, whereas in the understory Amur honeysuckle still had green leaves. This assumption was based on the tree cover sampling conducted in the fall of 2006 and from Trisel and Gorchov (1994). The January ETM+ image was captured when deciduous plants in the overstory and understory were virtually devoid of leaves; no cloud-/snow-free midwinter images were available for dates closer to the November 2005 image from TM or ETM+.

Processing of the remote sensing data was performed using Leica Geosystems ERDAS Imagine 9.1 and ESRI ArcMap 9.2. The two Landsat 5 images were converted into Landsat 7 equivalent digital numbers (DN) using the conversion coefficients provided by the USGS (2001). The DN values of the three images were then converted to reflectance and corrected for atmospheric haze using the COST Model (Chavez 1996).

Seven spectral vegetation indices (SVIs) were calculated: (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; Crist and Cicone 1984; Huang et al. 2002; Kauth and Thomas, 1976), (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). Due to longer fall leaf-retention of Amur honeysuckle, it was predicted there would be a positive correlation between SVI values and Amur honeysuckle cover in the November-based SVIs. Although some plants in these woodlots, particularly graminoids, have green leaves in November, and thus would contribute to November SVIs, we wished to test whether the "signal" from Amur honeysuckle was sufficiently strong to be detectable over this "noise."

Image differencing was performed to investigate the possibility that it would emphasize seasonal changes in green biomass and enhance the ability to distinguish Amur honeysuckle cover by reducing interference from other variables. Each TM/ETM+ band and SVI from each image date was subtracted from the corresponding band and SVI from another image date. In an attempt to represent the green biomass of native deciduous trees, we subtracted November SVIs and bands from June SVIs and bands. In an attempt to represent Amur honeysuckle cover and remove reflectance due to evergreens, we subtracted January SVIs and bands from November SVIs and bands.

For each training and validation plot we created a 100 m by 100 m polygon using the recorded spatial coordinates of the start and endpoints of the mainline transects and the azimuths of the line intercepts for each ground plot. The mean pixel values of each plot polygon were then extracted for analysis.

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 Amur honeysuckle cover. Three different regression methods were utilized: ordinary least squares linear, multiple predictors stepwise, and quadratic. The training data were used to develop the best models for predicting Amur honeysuckle cover and the validation data were used to test the regression model derived using the training data.

In all training model iterations, Amur honeysuckle cover served as the response variable and the extracted pixel values of the training plots from the different SVI transformations and individual reflectance images were the predictor variables. Extracted pixel values for the 15 validation plots were then used to generate predicted Amur honeysuckle cover based on training models. Observed Amur honeysuckle cover values were then regressed against the predicted Amur honeysuckle cover to evaluate model performance.

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.

Results

Seasonal Patterns of Leaf Abscission. The results of the 2006 and 2007 tree and shrub cover sampling confirmed there was an approximately 4-wk period in which the leaves of the native deciduous trees had senesced and the majority abscised, while those of Amur honeysuckle were still green (Figure 2). In 2006, the ERC and Kramer Woods stands had a significant amount of green shrub cover in November when their canopies were almost devoid of leaves. At the same time the canopies and shrub layers of the Sugarbush and Big Woods stands showed an absence of leaves. This condition persisted from approximately November 4 to November 30, when Amur honeysuckle leaves abscised.

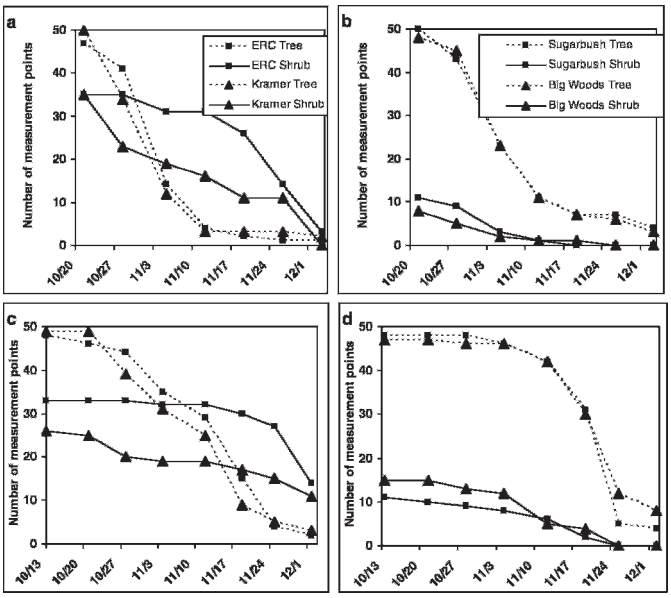

Figure 2. Number of points with leaf cover in the tree and shrub layers during the period of leaf drop in 2006 (a) and (b) and 2007 (c) and (d). Sites with high Amur honeysuckle abundance (ERC and Kramer) are shown in (a) and (c), sites with no Amur honeysuckle presence (Sugarbush and Big Woods) are shown in (b) and (d).

In 2007 there was a similar phenological difference in leaf senescence and abscission between the native tree and exotic shrub layer (Figure 2c); however, both senescence and abscission occurred later in 2007 than in 2006. In 2007 the optimal time to detect Amur honeysuckle in the understory using satellite imagery began approximately November 18, 2 wk later than in 2006.

Regression of Amur honeysuckle Cover on Spectral Data. Univariate linear regression from the November image revealed that NDVI was the best predictor of Amur honeysuckle cover (Table 1). The strongest-performing SVI in the linear regression analyses was NDVI from the November − January image with a coefficient of determination (R^2) equal to 0.649 (Figure 3; Table 2). Regressions using values derived from the June − November image differencing had lower R^2 than those using either the November or November − January data (Wilfong 2008), indicating no support for our expectation that high Amur honeysuckle cover would be associated with low change in summer-to-fall reflectance.

A quadratic regression was performed in which Amur honeysuckle cover was regressed against NDVI and NDVI^2 for both the November (Figure 4) and the November − January (Figure 3) images. For both images, the quadratic model proved a better predictor of Amur honeysuckle cover compared to the linear model having lower root mean square error (RMSE) and a higher R^2 values (Table 2).

Table 1. Statistics for linear regression of summer 2007 Amur honeysuckle cover on individual TM/ETM+ bands (RB) and spectral vegetation indices (SVI) from the November 2005 Landsat 5 TM image on the 35 training data plots.

SVI[a]	Linear Regression Model	R^2	P value
NDVI	Amur honeysuckle cover = −207 + 484 (NDVI)	0.626	< 0.0001
SR	Amur honeysuckle cover = 207 − 516 (SR)	0.612	< 0.0001
EVI	Amur honeysuckle cover = −116 − 389 (EVI)	0.371	0.0001
NDMI	Amur honeysuckle cover = 40.7 + 290 (NDMI)	0.365	0.0001
TCap Wet	Amur honeysuckle cover = 128 + 329 (TCapW)	0.322	0.0004
RB 7	Amur honeysuckle cover = 115 − 481 (RB7)	0.311	0.0005
SAVI	Amur honeysuckle cover = −118 + 418 (SAVI)	0.305	0.0006
RB 3	Amur honeysuckle cover = 109 − 816 (RB3)	0.303	0.0006
RB 5	Amur honeysuckle cover = 134 − 320 (RB5)	0.292	0.0008
TCap Green	Amur honeysuckle cover = −29.7 + 642 (TCapG)	0.260	0.0017
RB 1	Amur honeysuckle cover = 160 − 2043 (RB1)	0.245	0.0025
TCap Bright	Amur honeysuckle cover = 81.6 − 163 (TCapB)	0.083	0.0936
RB 2	Amur honeysuckle cover = 46.2 − 1380 (RB2)	0.021	0.0025
VARI	Amur honeysuckle cover = 6.5 − 4.9 (VAR)	0.001	0.9021
RB 4	Amur honeysuckle cover = 13.7 − 1 (RB4)	0.000	0.9924

[a] Abbreviations: NDVI, Normalized Difference Vegetative Index; SR, Simple Ratio; EVI, Enhanced Vegetation Index; NDMI, Normalized Difference Moisture Index; Tcap, Tasselized Cap; SAVI, Soil Adjusted Vegetation Index; VARI, Visible Atmospherically Resistant Index.

Stepwise regression also was performed using the November and November − January training data to test the possibility that a combination of reflectance and/or SVIs would improve the detection of Amur honeysuckle. Because most of the SVIs and TM/ETM+ bands were intercorrelated (Wilfong 2008), the available combinations of noncorrelated predictor variables were limited. Predictor variables were selected for inclusion based on the predictive power in linear regression, avoiding other variables that were strongly correlated with these. No multiple regression model performed better than the linear regression model developed from the November − January NDVI values.

None of the SVIs or TM/ETM+ bands from any of the three images were significantly correlated with stand density or basal area (Wilfong 2008), despite the fact that spectral indices are useful predictors of stand biomass (Zeng et al. 2004 and references cited within).

Training Model Validation. The performance of the linear and quadratic models (Amur honeysuckle cover on NDVI) was tested with the 15 validation plots (Table 3). The linear regression model developed from the November − January training data was a slightly better predictor of Amur honeysuckle cover of the validation points (R^2 = 0.62, Figure 5), than the November NDVI quadratic regression model (R^2 = 0.56). The quadratic model developed from the November − January NDVI training data proved to be the best predictor of Amur honeysuckle cover with an R^2 = 0.77.

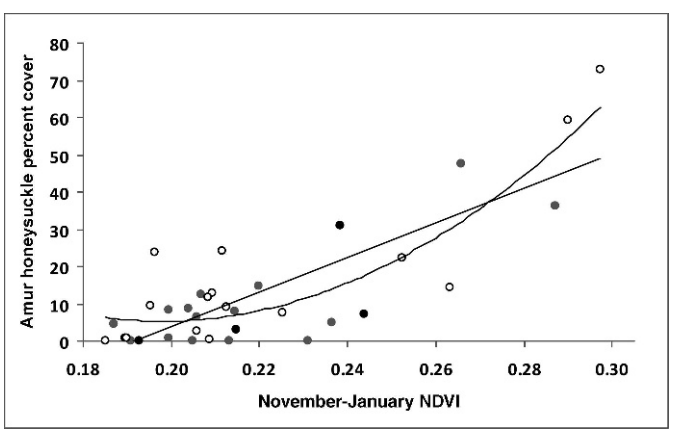

Figure 3. Linear and quadratic regressions of Amur honeysuckle on Normalized Difference Vegetation Index (NDVI) using the November − January training data (n = 35). Different color circles distinguish plots with differing amounts of graminoid cover (high = black, medium = gray, and low = white).

Influence of Graminoid Cover on NDVI. The scatterplots from the linear and quadratic regressions of Amur honeysuckle on NDVI reveal a high amount of scatter around the regression line at low Amur honeysuckle cover. We explored whether the distribution of these points could be due to interplot variation in graminoid cover.

Three of the four plots with high graminoid cover were to the right of the quadratic regression line of Amur honeysuckle cover on November NDVI (Figure 4), indicating a higher NDVI than expected based on Amur honeysuckle cover, whereas the fourth was on the line. In the January image, when Amur honeysuckle was leafless, plots with high graminoid cover had significantly higher NDVI (mean = 0.248) than did plots with medium or low graminoid cover (mean = 0.239; ANOVA F = 4.81, P = 0.033).

Discussion

The observed differences in leaf abscission between Amur honeysuckle and native tree species in 2006 and 2007 confirms that the opportunity exists to use late fall remote sensing data to detect Amur honeysuckle in the understory of deciduous forest. Reflectance of green vegetation (specifically NDVI) from late fall Landsat images correlated well with Amur honeysuckle cover, presumably because by this date most overstory leaves had abscised.

The interannual variability in leaf fall could complicate efforts to use satellite imagery to detect Amur honeysuckle in the understory for years in which the date of overstory canopy leaf fall is not known. The later leaf drop in 2007 compared to 2006 might have been due to warmer early autumn temperatures (mean monthly temperatures of 20.4 C and 13.8 C in Oxford, OH, for September and October 2007, compared to 16.5 C and 8.0 C for the same months in 2006, based on data obtained from www.epa.gov/CASTNET). Cool autumn temperature, as quantified by "chilling degree-days" (based on 20 C base temperature), is the best predictor of autumn leaf senescence date for three hardwood species in

Table 2. Statistics from the univariate linear and quadratic regressions of Amur honeysuckle cover on NDVI for the November 12, 2005 image and the November − January image difference, using the training data (n = 35).

Image	Regression Model[a]	R^2	P value	RMSE
November	Amur honeysuckle cover = −207 + 484 (NDVI)	0.626	< 0.0001	10.80
November	Amur honeysuckle cover = 1,165 − 5,397 (NDVI) + 6,273 ($NDVI^2$)	0.750	< 0.0001	8.96
November − January	Amur honeysuckle cover = −86.23 + 463.1 (NDVI)	0.649	< 0.0001	10.45
November − January	Amur honeysuckle cover = 220.6 − 2,234 (NDVI) + 5,795 ($NDVI^2$)	0.747	< 0.0001	9.02

[a] Abbreviation: NDVI, Normalized Difference Vegetative Index.

New England (Richardson et al. 2006), although Lee et al. (2003) found high consistency in the timing of leaf abscission, with only a 6- to 9-d difference between years, for tree species in another New England forest. Less is known about the timing of Amur honeysuckle leaf drop, but our observations (Figure 2) suggest it is consistent across years. Therefore, it might be possible to improve the detection of understory Amur honeysuckle by using remote-sensed imagery from the optimal date, based upon models relating direct or remote-sensed observations of leaf abscission with weather data.

The regression analyses of the SVIs and TM/ETM+ bands revealed that NDVI was the best predictor of Amur honeysuckle cover, the quadratic model was superior to the linear model in predicting Amur honeysuckle cover, and that NDVI values derived from the November − January image were superior to the November image alone.

However, the wide variation in NDVI values for plots with low Amur honeysuckle cover indicated that variables other than Amur honeysuckle influenced NDVI values. Previous research has shown that NDVI is affected by the reflectance properties of background materials such as soil (Huete et al. 1985), senescent leaves (DiBella et al. 2004), and leaf litter (Van Leeuwen and Huete, 1996), in addition to green biomass. The influence of such "background material" increases as green plant cover decreases (Nemani et al. 1993). Although the variation in NDVI among plots with low Amur honeysuckle cover might have been due to variation in the composition and/or abundance of such background materials (e.g., Huete et al. 1985), we argue this is unlikely because NDVI was nevertheless a better predictor of Amur honeysuckle cover than other spectral indices, such as EVI and SAVI.

The wide scatter of NDVI values at low Amur honeysuckle cover was more likely due to variation among plots in green vegetation other than Amur honeysuckle. 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). The high November NDVI values of plots with little Amur honeysuckle but high graminoid cover suggest that graminoids remained green active late in the year. Thus it appears that graminoids reduce the ability of November NDVI to predict Amur honeysuckle cover, especially at low Amur honeysuckle cover values. Our finding that November − January NDVI was a better predictor of Amur honeysuckle cover than November NDVI suggests that "correcting" for biomass that remains green in the winter reduces unexplained variation in November NDVI. Evidence that graminoids likely comprise most of this winter green biomass includes our finding that plots with high graminoid cover had higher January NDVI than plots with medium-low graminoid cover.

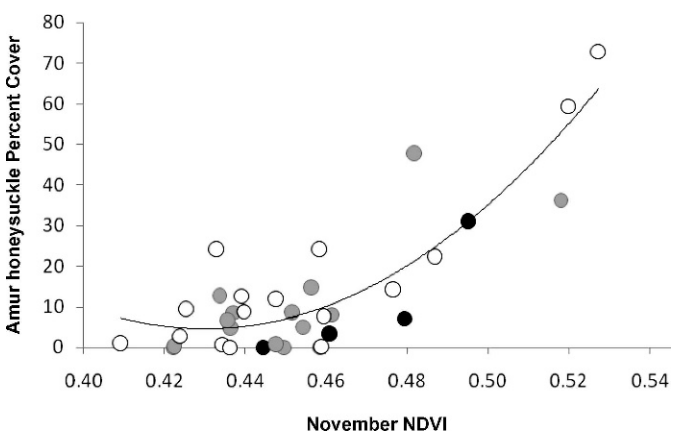

Figure 4. The quadratic regression of Amur honeysuckle cover on Normalized Difference Vegetation Index (NDVI) using the November training data (n = 35). Different color circles distinguish plots with differing amounts of graminoid cover (high = black, medium = gray, and low = white).

Two other factors were explored as to their possible influence on NDVI values: (1) species composition of canopy trees and (2) recent anthropogenic disturbance. Oak species and American beech retain senesced leaves longer in the fall than other main canopy species (e.g., maples, ashes, and walnuts). However, plots with a combined relative basal area of American beech and all oak species ≥ 20% did not tend to fall to the right of the regression of Amur honeysuckle cover on November NDVI or to have higher November NDVI than the other plots (Wilfong 2008).

Plots with evidence of anthropogenic disturbance tended to fall to the right of the linear and quadratic regression lines of Amur honeysuckle cover on NDVI. However, disturbance was confounded with graminoid cover, because 14 of the 16 woodlots with disturbance had medium to high graminoid cover. Disturbances in this system, primarily timber harvesting and secondarily livestock grazing, likely influence NDVI values by facilitating the establishment of graminoids and other forest floor plants, including the invasive shrubs multiflora rose (*Rosa multiflora* Thunb.) and Japanese barberry (*Berberis thunbergii* DC.). Graminoid cover might turn out to be a reliable correlate of past disturbance; if so, there is potential to use remote-sensed graminoid cover as a proxy to map disturbance in deciduous forests. Woody invasive species other than Amur honeysuckle were more frequently encountered in woodlots with evident anthropogenic disturbance, but were less abundant than Amur honeysuckle. Timber harvesting could also influence NDVI values by reducing canopy cover, stand structure, and 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

Table 3. Statistics from the regression analyses of observed Amur honeysuckle cover of the 15 validation plots on predicted Amur honeysuckle cover (= x) using Landsat images and training models specified in Table 2.

Training Model	Validation Model	R^2	P value	RMSE[a]
November Quadratic	Amur honeysuckle cover = −2.99 + 1.02 (x)	0.556	< 0.0001	13.11
November − January Linear	Amur honeysuckle cover = −1.943 + 1.053 (x)	0.620	< 0.0001	12.13
November − January Quadratic	Amur honeysuckle cover = −1.806 + 1.074 (x)	0.768	< 0.0001	9.47

[a] Abbreviation: RMSE, Root Mean Square Error.

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 NDVI model could be improved by using hypersectral remotely sensed data and the collection of additional field data to better discriminate Amur honeysuckle from other green vegetation (Lass et al. 2005). The collection of quantitative data pertaining to the spectral reflectance properties of all aboveground 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).

Additional improvements might be achieved through the use of multiple remote sensing platforms as described by Lu (2006) to achieve improved estimation of aboveground biomass. By combining information from a multispectral sensor with information from a hyperspectral system, the degree of discrimination between vegetation cover types would be expected to increase and an improvement in predictive power achieved.

The results of this study demonstrate that remote sensing data, and in particular NDVI, could be used to predict the cover of the exotic shrub Amur honeysuckle in the understory of deciduous woodlots in the study area, where other species with extended fall leaf phenology are rare. If a better model can be developed, one that accurately predicts current Amur honeysuckle distribution, it could be used to "map" the distribution of Amur honeysuckle in the recent past. The Landsat 1 platform began collecting data in 1972 and SPOT 1 was launched in 1986. This approach also could be used to map other exotic invasives with extended leaf phenology [e.g., Tatarian honeysuckle (*Lonerica tatarica* L.), Chinese privet (*Ligustrum sinense* Lour.), Japanese barberry] in the understories of eastern deciduous forests. However, in areas where more than one such species was common, it would be difficult to distinguish among them using our approach. If the distribution of an invader such as Amur honeysuckle can be mapped across the landscape over a 20- to 36-yr period, this would provide insight into mechanisms that facilitate invasion and help predict which sites are at greatest risk of colonization.

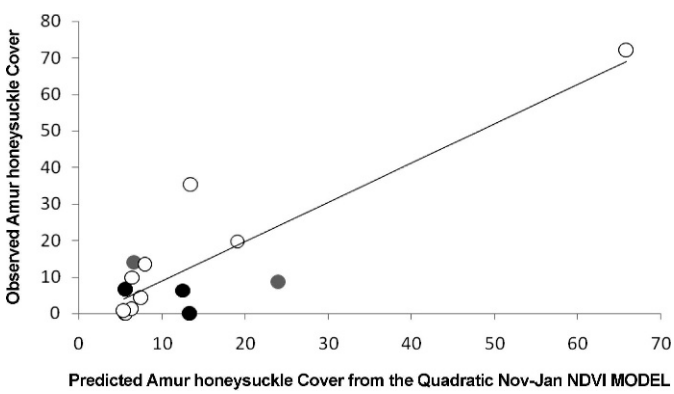

Figure 5. Linear regression of observed Amur honeysuckle cover on predicted Amur honeysuckle cover (n = 15). Predicted cover values were calculated using values from the November − January validation data and the quadratic model of the November − January Normalized Difference Vegetation Index (NDVI) training data. Different color circles distinguish plots with differing amounts of graminoid cover (high = black, gray = medium, and white = low).

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