Using Advanced Land Imager (ALI) and Landsat Thematic Mapper (TM) for the Detection of the Invasive Shrub *Lonicera maackii* in Southwestern Ohio Forests

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Abstract: We tested how accurately image data from the Advanced Land Imager (ALI) sensor vs. the Landsat Thematic Mapper (TM) predict the land cover of *Lonicera maackii* in the forest understory, taking advantage of this invasive shrub's extended leaf retention in the fall when the canopy is leafless. Percent cover of *L. maackii* in 20 woodlots in southwestern Ohio was regressed on values for spectral vegetation indices (SVIs) derived for each image. The land cover of *L. maackii* was best explained by the Simple Ratio (SR) using TM data ($R^2 = 0.537$). The regression results for SVIs from TM vs. ALI suggest that the ALI image was acquired too late in the fall to accurately detect this invasive shrub.

INTRODUCTION

Invasive species, those that spread rapidly outside their native range, are reported to be a major cause of species decline and loss of biodiversity (Wilcove et al., 1998) and result in an estimated $120 billion in environmental damages and losses in the United States each year (Pimentel et al., 2005). Invasive plants have a variety of negative impacts on native populations, communities, and ecosystems (Vitousek et al., 1997; Mack et al., 2000; Sakai et al., 2001; Levine et al. 2003).

Documenting distributions of invasive plants in the landscape is important for understanding and managing invasive species, and remote sensing in many cases provides a cost-effective approach (Peterson, 2005; Bradley and Mustard, 2005; Rew et al. 2005, Groeneveld and Watson, 2008; Swain et al. 2011). Detecting forest understory plants is problematic, however, due to the obstruction caused by the forest canopy. However, several understory plants have leaf phenologies that extend earlier and/or later than deciduous forest trees, providing an opportunity for detection when the canopy is leafless. We compared the effectiveness of two remote sensor systems to quantify one such understory invasive, *Lonicera maackii*.

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Lonicera maackii is an exotic shrub that was brought to North America in 1898 from Asia for ornamental purposes, wildlife food and cover, and erosion control (Luken and Thieret, 1996). *Lonicera maackii* reduces the survival and reproduction of native forest annuals (Gould and Gorchov, 2000), growth and reproduction of forest perennials (Miller and Gorchov, 2004), germination of annual and biennial herbs (Cipollini et al., 2008; Dorning and Cipollini, 2006), survival and growth of native tree seedlings (Gorchov and Trisel, 2003; Hartman and McCarthy, 2004), and increases nest predation on songbirds (Schmidt and Whelan, 1999) and mortality of amphibian larvae (Watling et al., 2011).

Lonicera maackii expands leaves earlier in the spring than native woody species (McEwan et al., 2009) and retains green leaves later in the fall (Wilfong et al., 2009), providing two opportunities to acquire remotely sensed data when *L. maackii* is one of few photosynthetically active plants in forests. Extended leaf phenology is also found in some invasive non-native shrubs, such as *Rosa multiflora*, which co-occurs with *L. maackii* in our study area.

Resasco et al. (2007) found that fall Landsat Thematic Mapper (TM) images were more useful for distinguishing *L. maackii*–invaded woodlots versus non-invaded woodlots than were spring images, and suggested this was because there is more photosynthetically active non–*L. maackii* cover in spring. Wilfong et al. (2009) found that the difference between the January and November Normalized Difference Vegetation Index (NDVI), using Landsat TM and ETM+, was a very good predictor of *L. maackii* cover.

The purpose of this research is to test how accurately image data from the Advanced Land Imager (ALI) sensor identifies *L. maackii* cover in comparison to Landsat Thematic Mapper (TM). Research questions include: (1) Will the additional bands of ALI provide a better combination of spectral vegetation indices (SVIs) than Landsat TM for the detection of *L. maackii* cover? (2) Which SVI best detects the percent cover of *L. maackii*? (3) Will the SVIs better represent *L. maackii* or a combination of *L. maackii* and *Rosa multiflora*?

SPECTRAL VEGETATION INDICES

When using remote sensing for vegetation studies, the use of spectral vegetation indices (SVIs) is a good approach. SVIs are sensitive to biophysical quantities such as canopy cover, leaf area index, and biomass (Jensen, 2005). There are many different SVIs that transform different band combinations into a single measure sensitive to vegetation characteristics (Table 1). The Simple Ratio (SR) is a vegetation index that is the ratio of red and near infrared reflectance. The Normalized Difference Vegetation Index (NDVI) is a very widely used vegetation index that is a normalized ratio of red and near infrared reflectance (Rouse et al., 1974). Densely vegetated areas have high and positive NDVI values, whereas sparsely vegetated areas have lower or negative NDVI values. The Enhanced Vegetation Index (EVI) is a variant of the NDVI that adjusts for atmospheric and soil effects and is the SVI used by the MODIS program (NASA, 2011). In this study, we were able to calculate several variations of each of these SVIs using the additional near infrared and mid-infrared bands of the ALI sensor.

Previous research used Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) sensors to identify *L. maackii* –invaded and non-invaded

Table 1. Spectral Vegetation Indices Used in the Research[a]

Index	Abbreviation	Formula	Reference
Simple Ratio	SR	$SR = \frac{Red}{NIR}$	Birth and McVey, 1968
Normalized Difference Vegetation Index	NDVI	$NDVI = \frac{NIR - Red}{NIR + Red}$	Rouse et al., 1974
Infrared Index	II	$II = \frac{NIR - MIR}{NIR + MIR}$	Hardisky et al., 1983
Mid-infrared Index	MIRI	$MIRI = \frac{MIR}{NIR}$	Musick and Pelletier, 1988
Enhanced Vegetation Index	EVI	$EVI = \frac{(NIR - Red)*2.5}{1 + NIR + 6*Red - 7.5*Blue}$	Huete et al., 1997

[a]Red = red band; NIR = near infrared band; MIR = mid-infrared band; blue = blue band.

Table 2. Landsat TM and ALI Bands

Spectral region	TM band number	TM wavelength range, µm	ALI band number	ALI wavelength range, µm
Visible	–	–	PAN	0.48–0.69
Blue	–	–	1p	0.433–0.453
Blue	1	0.45–0.52	1	0.45–0.515
Green	2	0.52–0.60	2	0.525–0.605
Red	3	0.63–0.69	3	0.63–0.69
Near IR	4	0.76–0.90	4	0.755–0.805
Near IR	–	–	4p	0.845–0.89
Mid-IR	–	–	5p	1.2–1.3
Mid-IR	5	1.55–1.75	5	1.55–1.75
Mid-IR	6	20.8–2.35	7	2.08–2.35
Thermal IR	7	10.40–12.50	–	–

woodlots (Resasco et al., 2007; Wilfong et al., 2009). The Landsat satellites carry the TM (Landsat 5) and ETM+ (Landsat 7) sensors, which acquire data that include visible, near infrared, and shortwave infrared bands with moderate spatial resolution (30 meters) (Table 2). The EO-1 satellite carries the Advanced Land Imager (ALI) sensor, which has the same spatial resolution as Landsat TM and ETM+ of 30 meters. However, the ALI data provide more spectral bands (nine) and also have better radiometric resolution, with 16-bit data within each band compared to Landsat TM and ETM+, which have 8-bit radiometric resolution. Bryant et al. (2003) compared the

ALI sensor to Landsat TM and ETM+ and found that ALI bands 4p (near infrared) and 5p (mid-infrared) provide different information than similar Landsat TM or ETM+ bands. Elmore and Mustard (2003) used ALI images for vegetation studies in comparison to Landsat TM and ETM+. These authors compared percent green cover estimates from ALI to field data estimates and to Landsat ETM+ data estimates. They concluded that the use of ALI image data for vegetation studies can be substituted for the use of Landsat TM or ETM+, as the ALI vegetation estimates have the same quality as those produced by TM or ETM+. Bryant et al. (2003) advocate the use of ALI image data instead of Landsat TM or ETM+, due to the continuity of the data and the different information that the ALI band 5p acquires. Using ALI data, we calculated a total of 21 SVIs, including three NDVIs, three SRs, six Infrared Indices (IIs), six Mid-infrared Indices (MIRIs), and three EVIs. For the Landsat TM image, seven SVIs were calculated.

METHODS

Leaf Drop Data

Leaf drop timing varies from year to year, so we measured canopy and shrub cover at two locations near our study site (farther south, in Butler County, Ohio) in the fall of 2009. The locations were at Miami University's Ecological Research Center (ERC) and Kramer Woods. Tree composition at ERC was primarily *Fraxinus* spp., *Acer saccharum*, and *Carya tomentosa*, and at Kramer Woods primarily *Fraxinus*, *A. saccharum*, and *Liriodendron tulipifera* (Resasco et al., 2007). At each site we marked four parallel 80 m transects, 25 meters apart. Along each transect we marked points every 5 meters, and at each point a vertical densitometer, held 2.5 meters above the ground, was used to assess whether the space above the point was at least half covered with leaves. The same procedure was followed while looking down at the forest floor with the densitometer to assess shrub cover. These data were recorded at the ERC on October 1, 12, 27 and November 3, 10, and 17, 2009, and at Kramer Woods on October 6, 20, 29 and November 5, 12, and 17, 2009.

Study Site

Southern Darke County and eastern Preble County, Ohio (Fig. 1) were chosen as the study area for this research project because it is on the front of a *L. maackii* invasion (Bartuszevige et al., 2006; Wilfong et al., 2009). This area of Darke and Preble counties is largely rural and contains fragmented forest patches of varying size and proximity to other forest patches.

Field plot sites were chosen by size of woodlot (at least 130 m × 130 m) and permission from the property owner(s). One 100 m × 100 m plot was sampled in each of 20 different woodlots.

Field Data

A point intercept sampling method was used to measure *L. maackii* cover in each plot. One transect was established for each of several random starting points in each

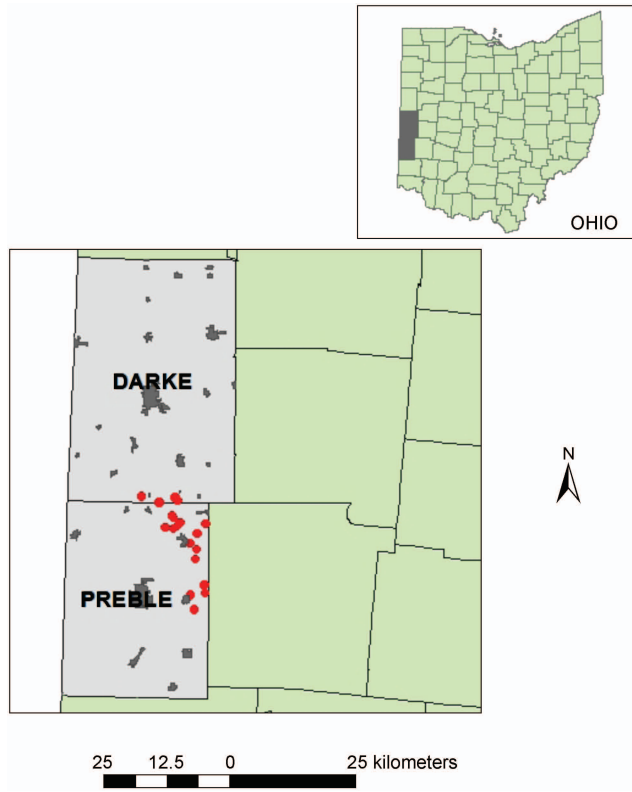

Fig. 1. State of Ohio with Darke and Preble counties shaded in grey and labeled. Study areas are indicated in red, and cities are shaded in dark grey.

woodlot (Etchberger and Krausman, 1997). The starting loci were determined using random numbers for the X and Y axes from random.org. Bearings (in degrees) for the transects were also randomly generated. Each transect continued until it reached within 5 meters of the edge of the plot; thus transect length varied. Additional transects were sampled to achieve 400 m in total transect length for each plot.

At 5-meter intervals on each transect, we recorded the presence or absence of *L. maackii* and of *R. multiflora*. These were used to calculate the percent cover for each species separately, as well as "TOTAL"' invasive shrub cover (either species present).

Image Data

The ALI image data for this research project were acquired November 21, 2009 (Entity ID of EO1A0200322009325110PK_PF1_01). The image contains substantial cloud cover on its west side, and plots were carefully located to avoid that area. We also used a Landsat TM image (Path 20, Row 32) acquired November 7, 2009 (Entity ID: LT50200322009311ED00). Preprocessing of both the ALI and TM images included radiometric calibration of digital numbers to reflectance (Markham et al.,

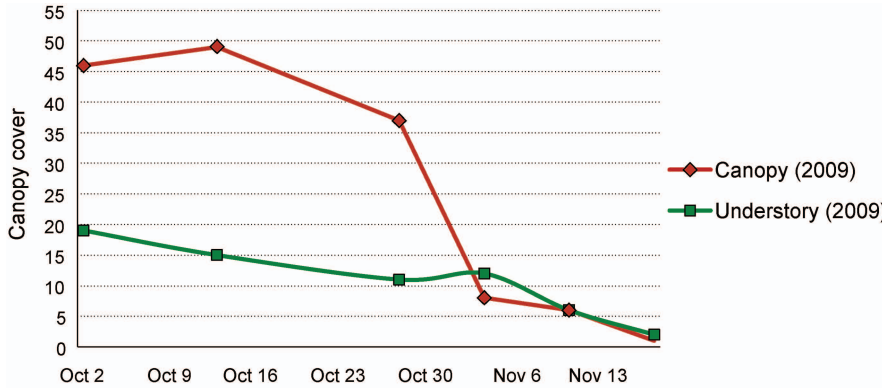

Fig. 2. Canopy and understory leaf drop during fall 2009 at the Ecology Research Center (ERC).

2005; Chander et al., 2009) and haze correction using the COST model (Chavez, 1996). Variations of five different SVIs were calculated using the corrected TM and ALI data. Regressions were calculated between percent cover of each species (*L. maackii* and *R. multiflora* and TOTAL) and each SVI using the SAS JMP 8.0.2 program for both images separately.

RESULTS

Leaf Drop Data

The temporal pattern of leaf drop data was slightly different between the two locations. At ERC the most rapid decline in canopy cover occurred between October 27 and November 3, with most understory leaf drop being recorded between November 3 and 17 (Fig. 2). In Kramer Woods, the majority of canopy leaf drop occurred between October 20 and November 5, and understory leaf drop occurred between October 29 and November 12 (Fig. 3).

Shrub Cover

Of the 20 plots, 11 had > 0% cover of *L. maackii* (max. 55%), and 15 had > 0% cover of *R. multiflora* (max. 13.75%; Lawlor, 2011). Two plots had 0% cover for both invasive shrubs. Of the 11 plots that had *L. maackii*, eight also had measurable *R. multiflora*. Seven plots had *R. multiflora*, but not *L. maackii*.

RELATIONSHIP BETWEEN *L. maackii* AND SVIS

Advanced Land Imager (ALI)

Regressions of *L. maackii* percent cover on individual SVIs calculated from the ALI image were significant for 11 of the 21 SVIs (Table 3; Lawlor, 2011). Regressions of TOTAL cover (*L. maackii* and *R. multiflora*) were significant for the same 11 SVIs

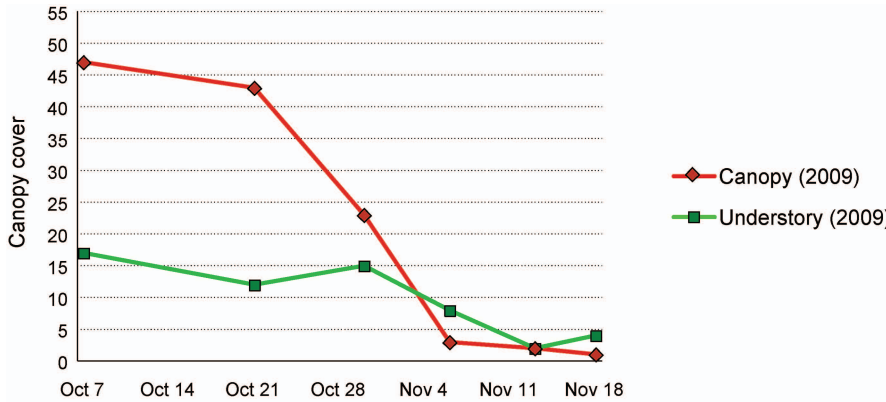

Fig. 3. Canopy and understory leaf drop during fall 2009 at Kramer Woods.

Table 3. Significant Linear Regression Equations for *L. maackii* (LOMA6) and TOTAL (*L. maackii* and *R. multiflora)* Percent Cover on Spectral Vegetation Indices (SVIs) from ALI

SVI	ALI linear regression equations (R^2)	
II_4	LOMA6 = 61 + 291*II_4 (0.242)	TOTAL = 68 + 316*II_4 (0.292)
II_4P	LOMA6 = 34 + 310*II_4p (0.268)	TOTAL = 38 + 328*II_4P (0.307)
II_5P	LOMA6 = –27 + 514*II_5P (0.473)	TOTAL = –23 + 493*II_5P (0.446)
II_4_7	LOMA6 = –10 + 244*II_4_7 (0.267)	TOTAL = –9 + 260*II_4_7 (0.310)
II_4P_7	LOMA6 = –39 + 271*II_4P_7 (0.289)	TOTAL = –39 + 283*II_4P_7 (0.323)
II_5P_7	LOMA6 = –125 + 420*II_5P7 (0.434)	TOTAL = –118 + 407*II_5P_7 (0.416)
MIRI_5_4	LOMA6 = 164 – 108*MIRI_5_4 (0.265)	TOTAL = 179 – 116*MIRI_5_4 (0.314)
MIRI_5_4P	LOMA6 = 172 – 138*MIRI_5_4P (0.275)	TOTAL = 184 – 146*MIRI_5_4P (0.315)
MIRI_5_5P	LOMA6 = 268 – 297*MIRI_5_5P (0.461)	TOTAL = 260 – 285*MIRI_5_5P (0.435)
MIRI_7_4	LOMA6 = 142 – 155*MIRI_7_4 (0.287)	TOTAL = 152 – 163*MIRI_7_4 (0.328)
MIRI_7_4P	LOMA6 = 147 – 198*MIRI_7_4P (0.295)	TOTAL = 156 – 206*MIRI_7_4P (0.328)

(Table 3). Of those 11, all were variations of the Infrared Index and Mid-Infrared Index. The Normalized Difference Vegetation Index, Simple Ratio, and Enhanced Vegetation Index equations did not have significant relationships with *L. maackii*, *R.*

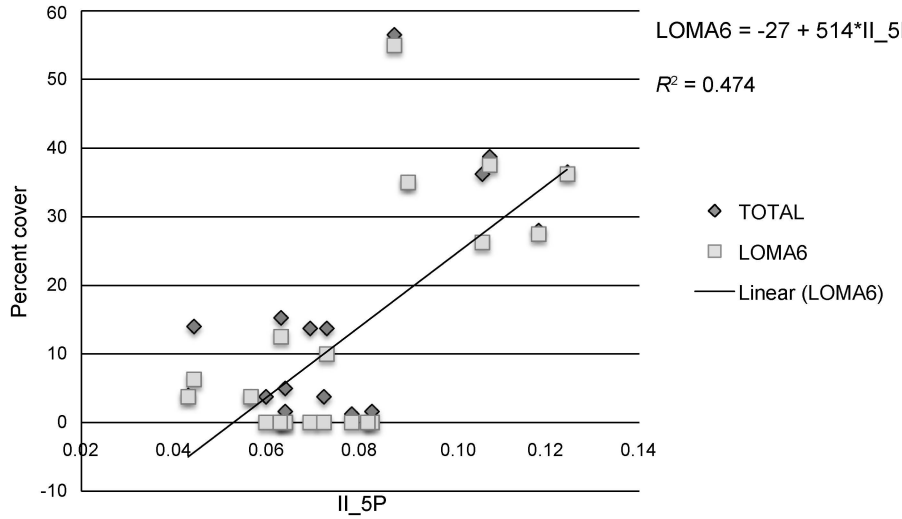

Fig. 4. Regression of *L. maackii* cover on Infrared Index 5P. Total (*L. maackii* and *R. multiflora*) cover is also plotted; the regression equations and statistics for both response variables are presented in Tables 3 and 4.

multiflora, or TOTAL percent cover. It was expected that the regressions of *L. maackii* on SVIs would have lower coefficients of determination (R^2) than the regressions of TOTAL on SVIs; this was the case for most, but not all SVIs.

The best predictor of *L. maackii* cover was the Infrared Index 5P, with $R^2 = 0.473$ (Fig. 4). All of the Infrared Indices that had significant regressions for *L. maackii* and TOTAL include ALI band 7, which is the longer mid-infrared wavelength. All regressions involving *L. maackii* or TOTAL cover and Infrared Index had positive slopes.

All but one Mid-Infrared Index (MIRI) were significant predictors of both *L. maackii* and TOTAL cover, with negative slopes. MIRI made use of all the near infrared and mid-infrared bands.

Landsat TM

Results from the Landsat TM image, acquired earlier in November than the ALI image, were compared to the results from the ALI image. Regressions of *L. maackii* cover on each of the SVIs calculated for this sensor were significant, as were regressions of TOTAL cover on all but EVI (Table 4).

NDVI, SR, and the Infrared Index (II) 5 and 7 all showed positive relationships with *L. maackii* cover and TOTAL cover; EVI also had a significant positive regression with *L. maackii* (Table 4). The best predictor of both cover variables was SR (Table 4, Fig. 5). Both Mid-Infrared Indices (MIRI) had significant regressions for both *L. maackii* and TOTAL. MIRI variation 7 (mid-infrared) had a positive relationship with both cover variables, while MIRI variation 4 (near infrared) had a negative relationship.

Table 4. Significant Linear Regression Equations for *L. maackii* (LOMA6) and TOTAL (*L. maackii* and *R. multiflora)* Percent Cover on Spectral Vegetation Indices (SVIs) from Landsat TM

SVI	Landsat TM linear regression equations (R^2)	
NDVI	LOMA6 = –121 + 318*NDVI (0.494)	TOTAL = –114 + 308*NDVI (0.475)
SR	LOMA6 = –120 + 54*SR (0.537)	TOTAL = –112 + 52*SR (0.510)
II_5	LOMA6 = 62 + 260*II_1 (0.442)	TOTAL = 59 + 226*II_1 (0.342)
II_7	LOMA6 = 6.20 + 214.58*II_2 (0.460)	TOTAL = 9.88 + 188.35*II_2 (0.363)
MidIR_4	LOMA6 = 139 – 85*MIRI_4 (0.440)	TOTAL = 125 – 74*MIRI_4 (0.341)
MidIR_7	LOMA6 = –333 + 221*MIRI_7 (0.273)	TOTAL = –301 + 202*MIRI_7 (0.234)
EVI	LOMA6 = –47 + 391*EVI (0.225)	n.s.

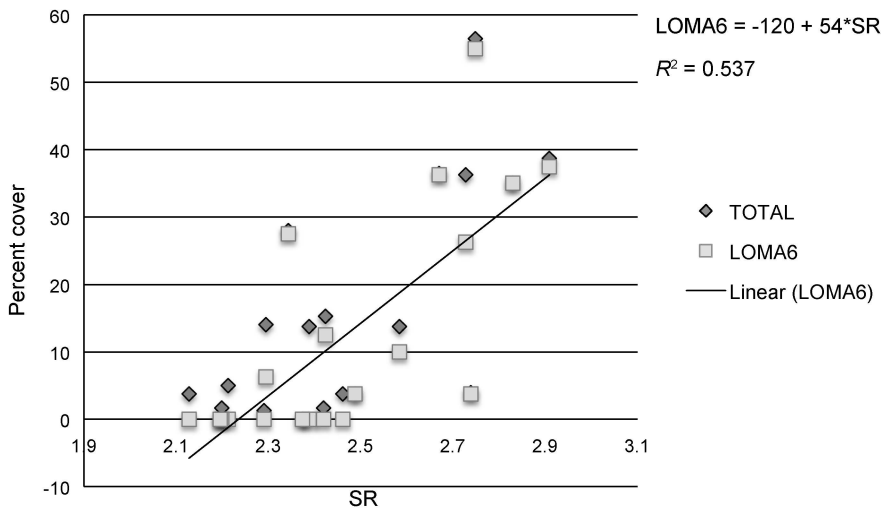

Fig. 5. Regression of *L. maackii* cover on Landsat TM's Simple Ratio. Total cover is also plotted; the regression equations and statistics for both response variables are presented in Tables 3 and 4.

DISCUSSION

Comparison of ALI vs. Landsat TM for Prediction of *L. maackii* Cover

Although more SVIs can be calculated from the ALI image, because of the multiple near infrared and mid-infrared bands (USGS, 2010), these were not as good at predicting *L. maackii* cover as SVIs from Landsat TM. We hypothesize that the weaker predictive power of SVIs from ALI was because the ALI image was acquired too late

in the growing season to accurately capture *L. maackii* cover. As noted above, the ALI image was from November 21; by this date the *L. maackii*–dominated understories at ERC and Kramer Woods had lost nearly all of their leaves (Figs. 2 and 3). The woodlots for which the relationship between *L. maackii* cover and SVIs were investigated were about 50 km farther north, and thus likely lost leaves about one week earlier.

The TM image was acquired 14 days earlier, on November 7; on this date the understories of both ERC and Kramer had most of their leaf cover, while the tree canopy was mostly leafless (Figs. 2 and 3). This later loss of *L. maackii*–dominated understory cover compared to canopy cover was documented at the same two sites in 2006 and 2007 (Wilfong et al., 2009). However, in those years understory leaves were retained later than in 2009, providing a longer period during which *L. maackii* shrubs could be detected under a leafless canopy. Temporal patterns of leaf drop are expected to vary annually due to temperature (Richardson et al., 2006) and storm events.

Which SVI Best Detects the Cover of *L. maackii*?

The best predictor of *L. maackii* cover was the Simple Ratio from the Landsat TM image, which was calculated as near infrared/red (NIR/R). This ratio would be expected to correlate positively with vegetation because the red radiation is absorbed by chlorophyll, and near infrared radiation is scattered by mesophyll tissue (Turner et al., 1999). We had hypothesized that NDVI would be the best predictor of *L. maackii*, since Wilfong et al. (2009), using similar methods but a different set of woodlots, found that the best predictor of *L. maackii* was the change in NDVI between a November 2005 (TM) and a January 2002 Landsat (ETM+) image.

Detection of *L. maackii* vs. a Combination of *L. maackii* and *R. multiflora*

Because *R. multiflora* retains green leaves late in the growing season, it could potentially confound detection of *L. maackii*, leading us to investigate whether the combined cover of these two invasive shrubs (TOTAL) could be predicted better than *L. maackii* alone. While *R. multiflora* was present in most of our study sites, its cover was not significantly predicted by any of the SVIs from either image. Furthermore, regressions of *L. maackii* on Landsat TM SVIs were always stronger (higher R^2) than regressions of TOTAL cover (Table 4). For ALI however, eight SVIs better predicted TOTAL cover than *L. maackii* cover, whereas only three SVIs showed the opposite pattern (Table 3). The difference in the ability for the two sensors to detect *L. maackii* cover vs. a combination *of L. maackii* and *R. multiflora* could be due to the later acquisition date of the ALI image or the difference in the information the sensors gather.

Limitations of this study include small sample size (20 woodlots) and the timing of the two satellite images. The ALI image, as noted above, was probably acquired too late in the season to capture most of the green *L. maackii* leaves. The timing of the Landsat TM image may also have been later than ideal to assess the cover of *L. maackii*. Most understory leaf drop occurred in the first half of November in the monitored sites, which were farther south than the area investigated with remote sensing. By the date the Landsat TM image was acquired, November 7, most of the *L. maackii* leaves may have already fallen. We note that *L. maackii* leaves remain green until they fall, and do not senesce and change color; thus before leaf drop is complete there is still a green leaf signal that can be perceived by remote sensing.

This research suggests that ALI is a good candidate to use for quantifying invasive shrubs in forest understory, as both *L. maackii*, and combined invasive shrub cover were significantly predicted by SVIs. However, SVIs from Landsat TM resulted in more significant regressions, which we hypothesize was due to the late date of the ALI image. This later image missed the "window" when *L. maackii* retained green leaves following canopy leaf drop.

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