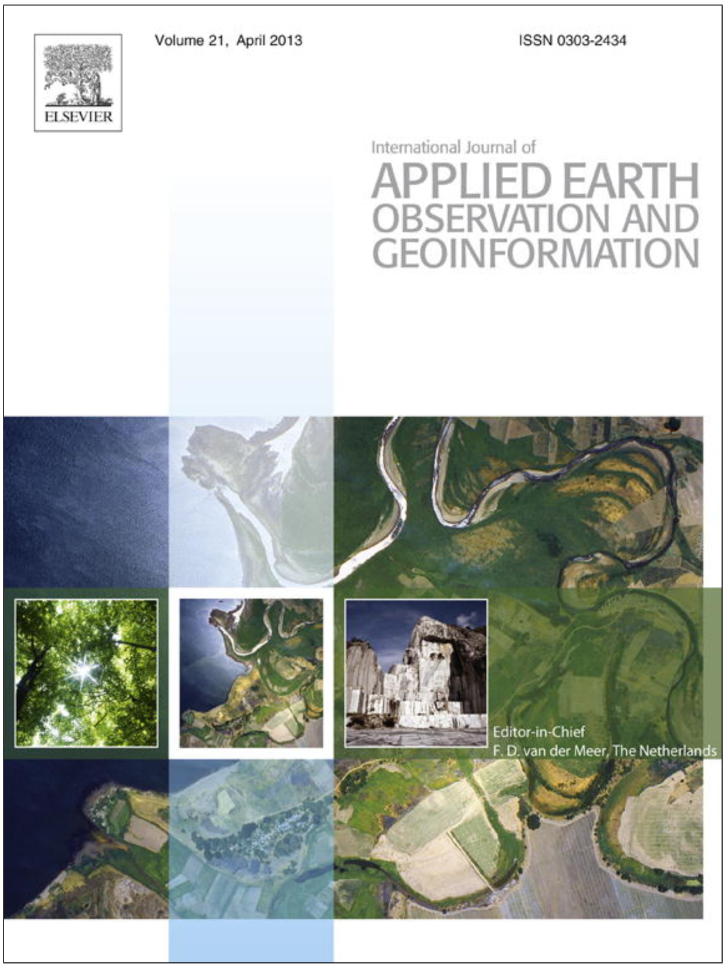
Volume 21, April 2013
ISSN 0303-2434
ELSEVIER
International Journal of
APPLIED EARTH
OBSERVATION AND
GEOINFORMATION
Editor-in-Chief
F. D. van der Meer, The Netherlands

International Journal of Applied Earth Observation and Geoinformation 21 (2013) 525–534

Contents lists available at SciVerse ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Identification of understory invasive exotic plants with remote sensing in urban forests

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ARTICLE INFO

Article history:
Received 23 February 2012
Accepted 11 July 2012

Keywords:
Invasive species
Remote sensing
Object based classification
Spatial resolution

ABSTRACT

Invasive exotic plants (IEP) pose a significant threat to many ecosystems. To effectively manage IEP, it is important to efficiently detect their presences and determine their distribution patterns. Remote sensing has been a useful tool to map IEP but its application is limited in urban forests, which are often the sources and sinks for IEP. In this study, we examined the feasibility and tradeoffs of species level IEP mapping using multiple remote sensing techniques in a highly complex urban forest setting. Bush honeysuckle (*Lonicera maackii*), a pervasive IEP in eastern North America, was used as our modeling species. Both medium spatial resolution (MSR) and high spatial resolution (HSR) imagery were employed in bush honeysuckle mapping. The importance of spatial scale was also examined using an up-scaling simulation from the HSR object based classification. Analysis using both MSR and HSR imagery provided viable results for IEP distribution mapping in urban forests. Overall mapping accuracy ranged from 89.8% to 94.9% for HSR techniques and from 74.6% to 79.7% for MSR techniques. As anticipated, classification accuracy reduces as pixel size increases. HSR based techniques produced the most desirable results, therefore is preferred for precise management of IEP in heterogeneous environment. However, the use of MSR techniques should not be ruled out given their wide availability and moderate accuracy.

1. Introduction

Invasion of exotic species has been recognized as a serious threat to various ecosystems, resulting in the reduction of native biodiversity and alteration of ecological structure, physiological condition, and ecosystem function and process (Adams and Engelhardt, 2009; Richardson et al., 2000). Invasive species also amount to substantial monetary loss through direct and indirect damages as well as control expenses (Cook et al., 2007; Pimentel et al., 2005). To minimize the impact caused by invasive species, strategic approaches for the control and treatment of invasiveness are desperately needed (Denslow, 2007). However, the development and implementation of treatment strategies have been slow, often due in part to the lack of knowledge regarding the detailed spatial pattern of invasive distribution at the landscape scale that entails successful management planning and implementation. Mapping of invasive species spatial distribution provides an important means in invasive management, which can assist natural resource managers in prioritizing current and projected invasive mitigation and prevention (Buckley, 2008; Byers et al., 2002).Due to a general lack of extensive ground survey, remote sensing has been widely used to detect and map the distribution of various invasive exotic plants (IEP) in different environments. Leaf structures of most plants interact with solar energy in essentially the same biophysical process: high absorption in visible (optimally red and blue) bands by leaf pigments (e.g., chlorophyll a, b and β-carotene), high reflectance in near-infrared band from the spongy mesophyll, and relatively high absorption in middle infrared bands by leaf water content. Hence, spectral reflectance patterns from plants are very similar in spite of species, making the separation of the invasive from natives a very challenging task using remote sensing. High spatial resolution (HSR, often <10 m in spatial resolution) and hyperspectral data are often required to discriminate subtle spectral differences among species (da Luz and Crowley, 2010; He et al., 2011; Kokaly et al., 2003). Studies specifically towards identifying invasive species of interest from the "background" vegetation were conducted using hyperspectral data such as those from Hyperion (Asner et al., 2008), AVIRIS (Asner et al., 2008), and other airborne sensors (Lass et al., 2005).Non-hyperspectral data, often combined with advanced image processing techniques or for relatively homogenous landscapes, have also been used for remote sensing of invasive species. For example, high spatial resolution aerial photos were used to identify Japanese Knotweed (*Fallopia japonica*) with an object-based classification approach (Jones et al., 2011). High resolution QuickBird imagery was used to identify invasive species in the wetland environment (Laba et al., 2008). Further,

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http://dx.doi.org/10.1016/j.jag.2012.07.010

utilizing phenological characteristics of the target species, medium spatial resolution (MSR ≥ 10 m spatial resolution) data can also be very useful (Joshi et al., 2006). Joshi et al. (2006) employed Landsat data to estimate canopy gaps to predict the infestation patterns of a shade-intolerant understory invasive species – *Chromolaena odorata*.Most of the studies using remote sensing to detect invasive species were conducted in a relatively homogeneous landscape that IEPs are either canopy species or free from canopy covers. Remote sensing of IEP in urban forests, defined in this study as the planted or remnant forests in a quick changing and interacting urban landscape (Wu, 2008), on the other hand, is particularly challenging. Hence, remote sensing of IEP conducted in the more complex urban setting has been lacking, despite a large body of evidence suggesting that urban forest ecosystems are a major source and sink of invasive exotic flora (Harris et al., 2009; Reichard and White, 2001).The first challenge in using remote sensing to detect IEP in urban forests is that urban landscapes are often highly fragmented, comprising diverse patches/corridors from multiple land-use/land-cover types. MSR imagery such as Landsat (30 m × 30 m) often does not have sufficient resolution to provide needed details for IEP identification/mapping and subsequent management practices in highly fragmented landscape such as urban forest. Hence, HSR imagery, which is usually more expensive to acquire, may be needed to detect IEP (Lass et al., 2005) in urban forests to allow finer resolution mapping and support management decisions. In addition, HSR imagery allows users to implement object-based classification technique to improve IEP mapping accuracy by considering the shape and size of landscape features in urban environments.An additional challenge of detecting IEP in urban forests is that IEP is often blocked by overstory trees. At occasions, this blocking effect of canopy trees can be overcome for certain understory IEP that have longer growing seasons (as reflected by earlier leaf budburst and/or later leaf retention) than native associates (Harrington et al., 1989). This phenological characteristic provides unique temporal windows for mapping the distribution of understory vegetation using remote sensing during the overstory leaf-off and understory leaf-on periods. For instance, Resasco et al. (2007) and Wilfong et al. (2009) demonstrated that the differential phenology of bush honeysuckle (*Lonicera maackii*) allowed for the detection of the species using MSR Landsat imagery in deciduous forest stands. Tuanmu et al. (2010) successfully mapped the distribution of two understory bamboo species by utilizing the phenological difference between overstory trees and understory bamboos with Landsat imagery. Therefore using satellite imagery from specific acquisition dates appears to be an effective means to differentiate some understory IEP from other vegetation covers.

In this study, we assessed the feasibility and reliability of multiple remote sensing techniques using both MSR and HSR imagery for IEP identification in an urban forest. Bush honeysuckle, a prevalent invasive species in the region, was used as our modeling species. Our objective is to provide an evaluation and cross-scale comparison of existing remote sensing techniques for detecting IEP, particularly in the critical but complex urban environment; and hence to promote a better use of remote sensing for acquiring necessary information for IEP control and management.

2. Materials and methods

2.1. Study area

This study was conducted in Cherokee Park (Fig. 1), located in a residential area on the east side of Louisville (38.30° N, 85.62° W), Kentucky, U.S. Cherokee Park is a 136 ha flagship park that was designed by Frederick Olmsted between 1891 and 1925. The park is characterized by a scenic driving/cycling loop of 3.9 km with many trails and roads branching out into local residential areas. Beargrass Creek runs through much of the east side of the park and is crossed by numerous pedestrian and automobile bridges. Cherokee Park is bounded by a golf course to the west and a major highway to the north. Prominent residential areas surround the park and possibly served as a source for IEP. In 1974, a tornado swept through this area and removed the majority of the forest overstory. This event, along with the use of bush honeysuckle as roadside vegetation along the highway corridor provided conditions for thirty years of unmanaged growth. Currently, the forest overstory is heavily dominated by red maple (*Acer rubrum*) and sugar maple (*A. saccharum*). The ground cover consists of a mixture of both native and invasive plants, primarily bush honeysuckle, for most of the year. There are very few grass species that regularly undergo late senescence besides bush honeysuckle, but their total coverage in the forest understory can be neglected in the study area.

2.2. Species studied

Bush honeysuckle, a tall deciduous shrub species native to eastern Asia, was introduced into North America in the late 1800s for use as ornamentals, wildlife cover, and soil erosion control (Luken, 1988). Bush honeysuckle is a fast expanding invasive plant that casts drastic ecological impact. In forest ecosystems infested by bush honeysuckle, the growth rate of overstory tree is reduced by more than 50% (Hartman and McCarthy, 2007) and regeneration of native tree and herbaceous species are prohibited (Miller and Gorchov, 2004; Hartman and McCarthy, 2004). It currently has various levels of distribution in 31 eastern and midwestern states in the U.S. and in Ontario, Canada (USDA, 2012). In particular, bush honeysuckle's spring leaf development is typically two to three weeks earlier, and for leaf coloration and abscission four to six weeks later than that of native shrubs, showing prolonged growing season extending from March to late November in the Ohio Valley (Resasco et al., 2007; Wilfong et al., 2009). Such differential leaf phenology allows bush honeysuckle to be separable from native vegetation using multi-temporal remotely sensed imagery (Trisel and Gorchov, 1994).

2.3. Remote sensing methodologies

We used both HSR and MSR imagery data for this project. A 0.3 m color aerial photo from the early spring of 2006,[1] along with ancillary planimetric data (buildings, roads, streams, water bodies, and boundaries) was obtained from the Louisville–Jefferson County Information Consortium. The aerial photo contained three bands (red, green, and blue) that can be utilized to derive spectral information for classification. It should be noted that at the time of observation (from both airplane and on the ground), native deciduous trees were in leaf-off conditions. Training data for this project was collected in June, 2009. This included locations for eight patches of bush honeysuckle and eight areas where bush honeysuckle was absent.

In addition, we obtained two 30 m Landsat 5 TM scenes (path 20, row 34, Level 1T) from U.S. Geological Survey (http://landsat.usgs.gov/) for a late-fall occasion (November 12, 2005) and a mid-winter occasion (January 2, 2007) near the time when the HSR aerial photo was captured. The level 1T Landsat product was systematically corrected for geometric, radiometric, and topographic accuracy. Both scenes selected had highest quality score (9: very good)) and were cloud free for our study site. The selection of scenes was intended to allow revealing bush

[1] Aerial photos for the city were captured during late March and early April in 2006, the exact acquisition date for the photo used in this study is not available.

Fig. 1. Aerial photo of the study area overlaid with a 30 m grid covering areas with predicted presence of bush honeysuckle (*Lonicera maackii*), used for percentage cover estimates (available in color online).

honeysuckle from its background vegetation given their phenological timing difference. The fall image, in particular, was to represent the time when bush honeysuckle was in its extended growing season when other species passed leaf senescence. To verify this, the fall image date (November 12, 2005) was found to be well after the "minimum greenness onset" (occurred in October, an indication of deciduous leaf senescence) for the study area from Moderate-resolution Imaging Spectroradiometer (MODIS) derived phenology estimate (http://daac.ornl.gov/MODIS/). The leaf-off date for bush honeysuckle in the region on average is around November 25. The winter image was used to indicate a condition in which all deciduous species already shed their foliages. Besides, with the red and near-infrared bands available, normalized difference vegetation index (NDVI) was calculated for both Landsat images.

In order to detect the distribution of bush honeysuckle, we first conducted a traditional pixel-based supervised classification on the late-fall Landsat TM image as well as the high resolution aerial photo. These two images both reflected vegetation conditions when bush honeysuckle was exposed to remote sensors through open canopies. Training sites for major cover types in the park (bush honeysuckle thickets, woods, grass, paved road, and building) were identified and manually digitized according to prior knowledge learned from ground visitations and visual assessments of the aerial photo. For both MSR and HSR images, the maximum likelihood method was specified to classify the entire study area based on spectral signatures defined by the training sites. For a dichotomous representation, predicted cover types other than bush honeysuckle were merged into a single class representing the absence of this species. This allowed for a dichotomous representation of bush honeysuckle distribution on which the subsequent accuracy assessment was based.

Given the expected leaf fall of bush honeysuckle in the winter, we further subtracted the mid-winter NDVI image from the late-fall NDVI image, akin to the method outlined in Wilfong et al. (2009). This approach was intended to better remove the background vegetation interference including those from coniferous species, thus to enhance capturing the fall foliage of bush honeysuckle during the forest canopy leaf-off period. However this approach did not provide a means to generate presence/absence information, instead the resultant NDVI difference image mainly indicates the probability of bush honeysuckle presence. Hence we evaluated the results from this classification using linear and quadratic regression models. The use of both linear and quadratic models was mainly to allow a more comprehensive comparison with the Wilfong et al. (2009) study. The models were built for ground estimated bush honeysuckle percentages in a 30 m grid (corresponding to Landsat pixels) as predicted by the November–January NDVI difference values or the November NDVI. However, in order to enable comparison with other techniques, we further applied a sequence of arbitrary thresholds (0, 0.05, 0.10, 0.15, and 0.20) for the NDVI difference values to generate binary presentations. The highest accuracy achieved was used for comparison purposes. So this was by no means to give the actual accuracy, but instead an approximation of potentially achievable accuracy. Image processing for this and prior tasks

Table 1
Accuracy matrices of bush honeysuckle (*Lonicera maackii*) classifications using high spatial resolution (HSR) and medium spatial resolution (MSR) data with selected techniques. "Invasive" indicates presence of the invasive species, and non-invasive indicates the absence of the species.

	Ground Invasive	Reference Non-invasive	Data Row total	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Kappa (%)	Predicted invasive area (ha)
HSR object based classification								
Invasive	21	2	23	91.3	95.5	94.9	89.2	22.5
Non-invasive	1	35	36	97.2	94.6			
Column total	22	37	59					
HSR supervised classification								
Invasive	20	3	23	87.0	87.0	89.8	78.6	30.3
Non-invasive	3	33	36	91.7	91.7			
Column total	23	36	59					
MSR supervised classification								
Invasive	12	11	23	52.2	75.0	74.6	43.5	28.1
Non-invasive	4	32	36	88.9	74.4			
Column total	16	43	59					
MSR NDVI differencing (threshold 0.1)								
Invasive	19	4	23	82.6	73.1	79.7	59.8	32.0
Non-invasive	7	28	35	80.0	87.5			
Column total	26	32	59					

was performed using ERDAS IMAGINE 9.3 software (ERDAS, 2009, Atlanta, Georgia).

A better utilization of the detailed information with high resolution imagery for classification purposes often lies in the more advanced object-based image processing technique, which takes account of feature properties (such as color, size, pattern, texture, and shape) in addition to reflectance (Addink et al., 2012; Navulur, 2006). The objects are defined as contiguous entities with resembled feature properties and contextual patterns on the imagery. In this study, we performed an object-based classification on the 0.3 m color aerial image using Feature Analyst 4.2 (VLS, 2009, Missoula, Montana) in ArcGIS. A supervised approach was employed, with training sites digitized for bush honeysuckle thickets according to field observation and visual assessment of the HSR image itself. Feature Analyst allowed using the digitized polygon training sites and their corresponding color, texture, and shape parameters to detect the presence of bush honeysuckle for the entire park. The initial classification result was post-processed for aggregating adjacent polygons and removing clutters with embedded feature analyst functions.

Accuracy assessments of these classification results were performed using field verification data. Point sampling unit (Stehman and Czaplewski, 1998) was used in our classification accuracy assessment because it allows the assessment of accuracy regardless of the pixel size of the classified map, avoiding the need to reconcile field assessment due to different pixel sizes. To guide the field work, we first generated a systematic 30 m × 30 m sampling grid for the study area. Based on HSR object-based classification result, we randomly selected 50 points with predicted bush honeysuckle presence and 50 points with predicted absence from the grid system. We then used a Trimble GeoXH handheld GPS unit navigating to each point where the presence or absence of living bush honeysuckle within a 2.5 m radius was determined. This radius was determined based on the accuracy of the GeoXH handheld GPS receiver. Due to an ongoing cut stump removal of bush honeysuckle that occurred between the times of aerial image capture and the field survey, the accuracy assessment excluded all sample points that contained bush honeysuckle debris (a possible result of bush honeysuckle removal at the exact location or deposit from nearby sites).

2.4. Up-scaling simulation

Further, we conducted an up-scaling experiment using the HSR object-based classification result, to evaluate how much information could potentially be lost when using medium spatial resolution satellite imagery for classifying IEP in a heterogeneous and fragmented urban landscape. For such a purpose, to demonstrate potential spatial scale effects on classification accuracy, we simulated medium spatial resolution representation for bush honeysuckle presence by aggregating the 0.3 m resolution classification map to 10 m, 15 m, and 30 m pixel sizes. These simulated grid sizes were meant to correspond with image resolutions of SPOT (10 m), ASTER (15 m), and Landsat (30 m) sensors. First, we masked out areas that were not wooded, including grass, water, roads, and buildings, leaving only two land cover classes: forest with bush honeysuckle and forest without bush honeysuckle. Next we overlaid the 0.3 m HSR object-based classification with 10 m, 15 m, and 30 m grids. In this dichotomy a single pixel must contain >50% bush honeysuckle in order to be classified as such. Using this criterion, the percentage of bush honeysuckle in each simulated pixel was calculated, based on the 0.3 m HSR object-based classification. With these calculations we compared the number of pixels that contained <25%, 25% to <50%, 50% to <75%, and >75% bush honeysuckle of each simulated scale size.

3. Results

3.1. Comparison of techniques

In this study we employed traditional pixel based classification, multi-temporal NDVI differencing, and object-based classification to identify understory bush honeysuckle in an urban forest across spatial scales. As expected, the classification results from the HSR image were significantly more accurate than the MSR-based (Table 1). The HSR object-based classification produced the most accurate classification in terms of producer's accuracy, user's accuracy, overall accuracy, and kappa value. HSR object-based classification of bush honeysuckle (as shown in Fig. 2) yielded highest overall accuracy (94.2%) and kappa (89.2%), which were 5.1% and 10.6% higher than those of the HSR classification from a pixel-based classification approach (Fig. 3). The producer's and user's accuracies were at the similar levels for each class for the HSR-based classifications. Supervised classification of MSR Landsat imagery (Fig. 4) yielded the lowest accuracy (74.6% for overall accuracy and 43.5% for Kappa), with disparately smaller producer's accuracy (52.2%) than the user's accuracy (75.0%) for bush honeysuckle prediction, suggesting larger omission errors pertained to this method.

NDVI-based identification of bush honeysuckle for MSR imagery was evaluated with regression analysis and an empirical binary

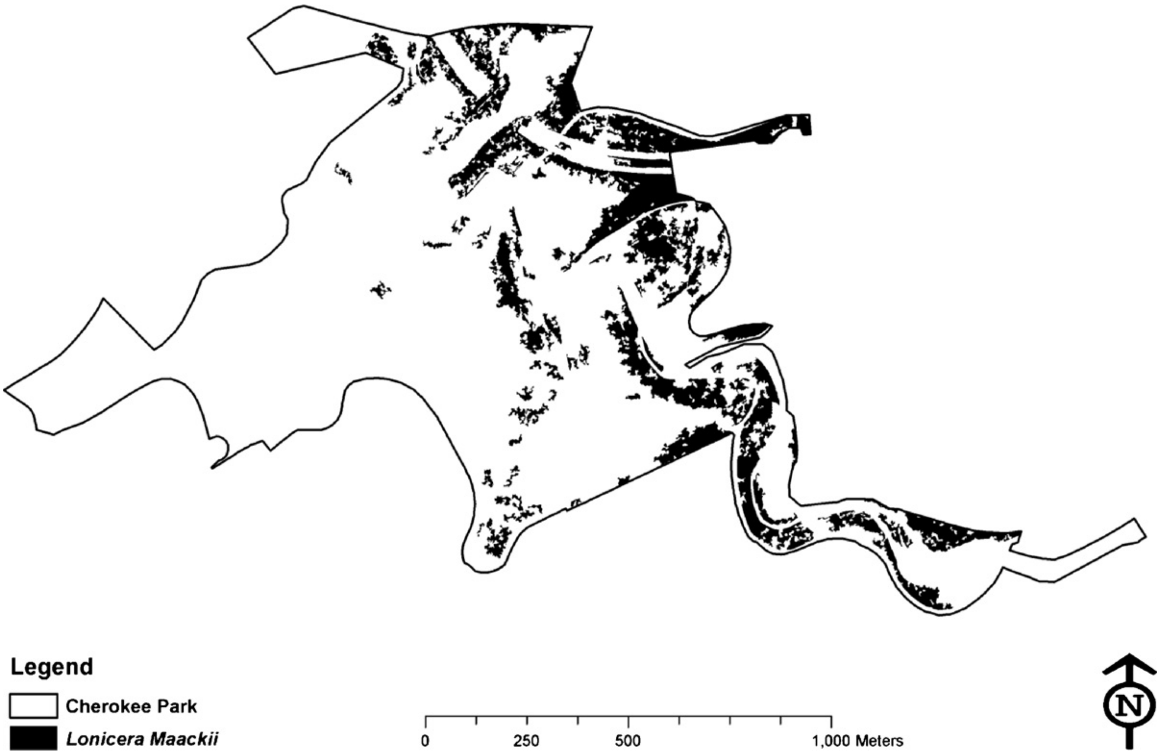

Fig. 2. Distribution of bush honeysuckle (*Lonicera maackii*) in an urban forest based on an object-based classification of a 0.3 m color aerial image.

classification. Akin to Wilfong et al. (2009), linear and quadratic regression models were fitted to predict the percentage of bush honeysuckle using November NDVI or November–January NDVI difference as the predictor (Table 2). Models with November NDVI as the explanatory variable predicted less than 4% of the ground variation, as indicated by their coefficients of determination (R^2). Models driven by November–January NDVI difference performed slightly better, explaining up to 13% of the ground variation. These R^2 values were significantly lower than those presented in Wilfong et al. (2009), which were above 60%. The prediction from November

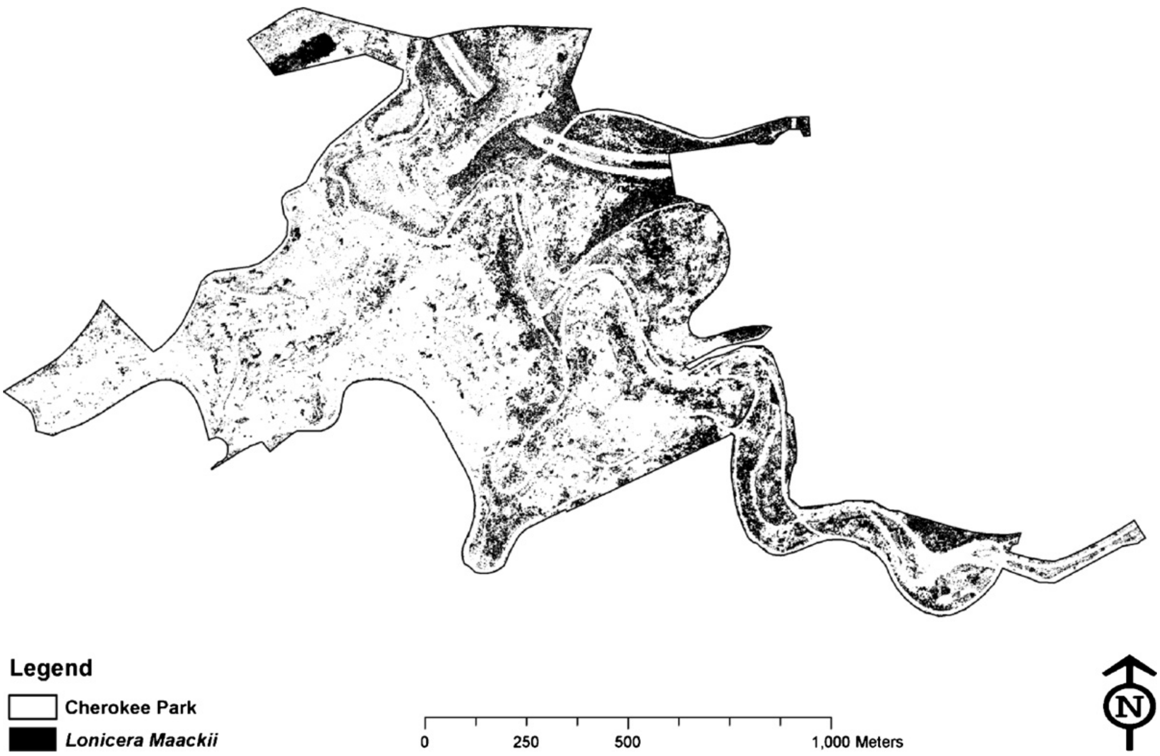

Fig. 3. Distribution of bush honeysuckle (*Lonicera maackii*) in an urban forest based on a pixel-based supervised classification of a 0.3 m color aerial image.

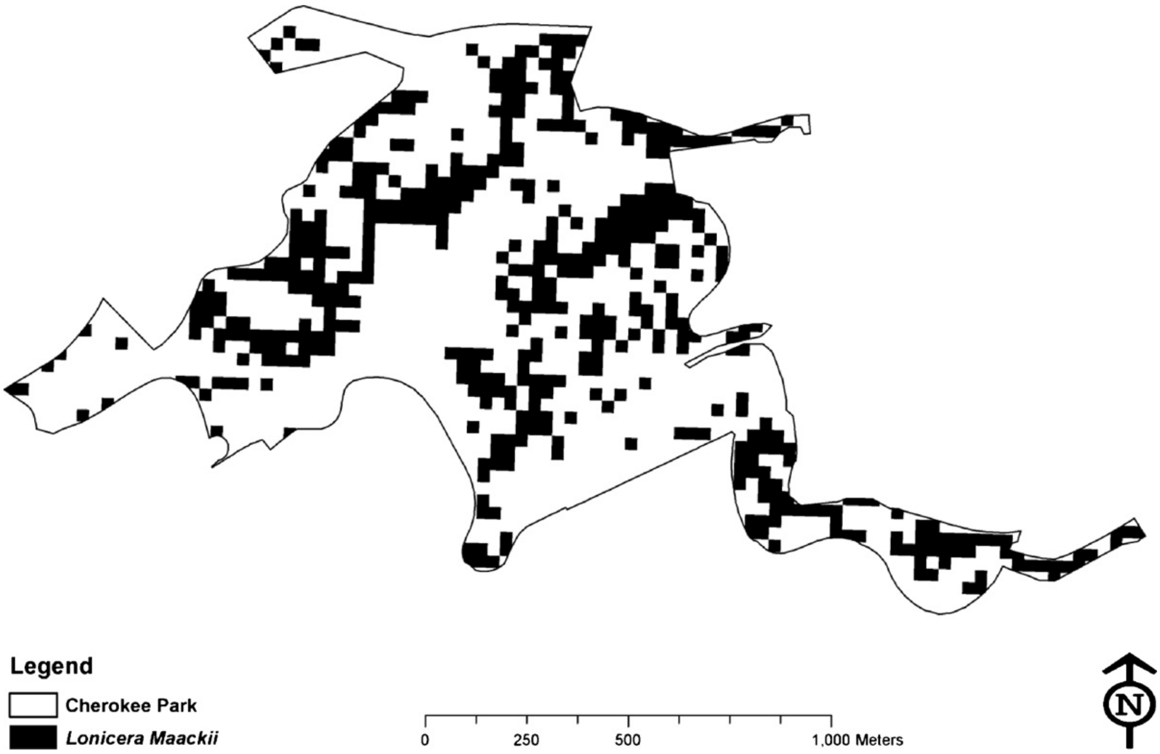

Fig. 4. Distribution of bush honeysuckle (*Lonicera maackii*) in an urban forest based on a supervised classification of a 30 m Landsat TM image.

to January NDVI difference (Fig. 5) appeared to provide an optimal accuracy when the arbitrary threshold of 0.1 was in use. This binary classification yielded an overall accuracy of 79.7% and kappa statistic of 59.8% for bush honeysuckle prediction (Table 1).

3.2. Simulated spatial scale effects

The total percentage of grids containing >50% bush honeysuckle decreased as anticipated when grid size increased (Table 3). For

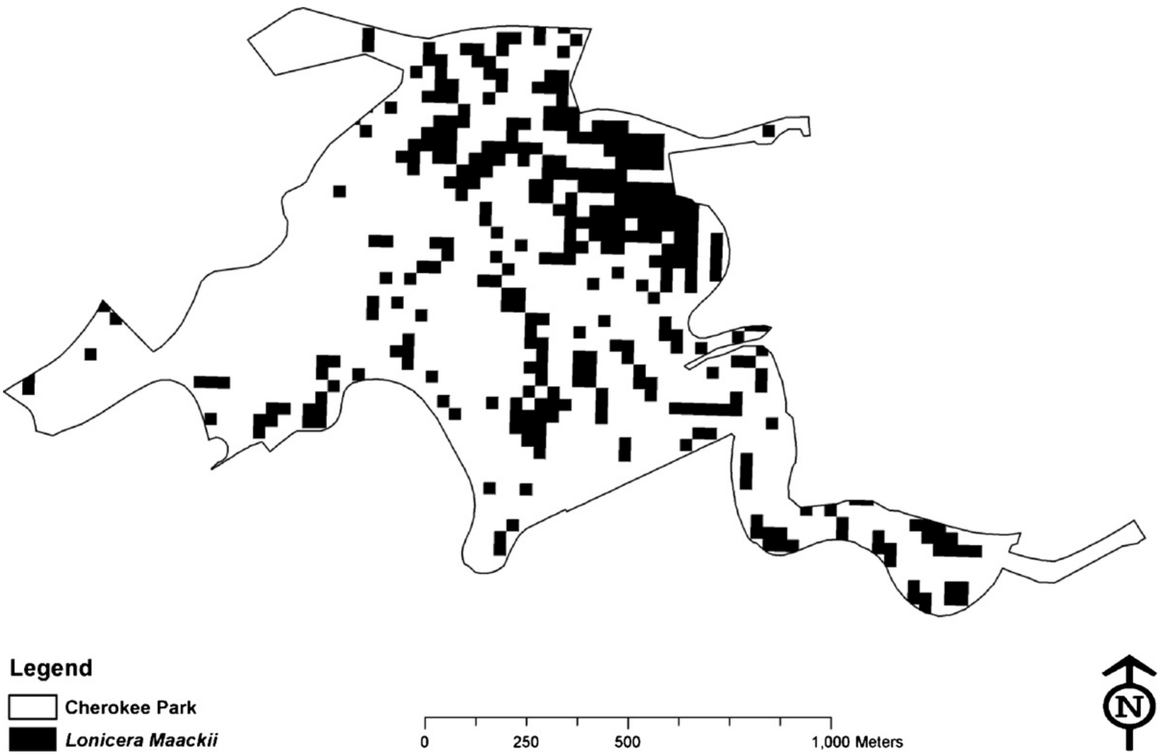

Fig. 5. Distribution of bush honeysuckle (*Lonicera maackii*) in an urban forest based on an NDVI difference classification (threshold 0.10) of a late fall and a winter 30 m TM image.

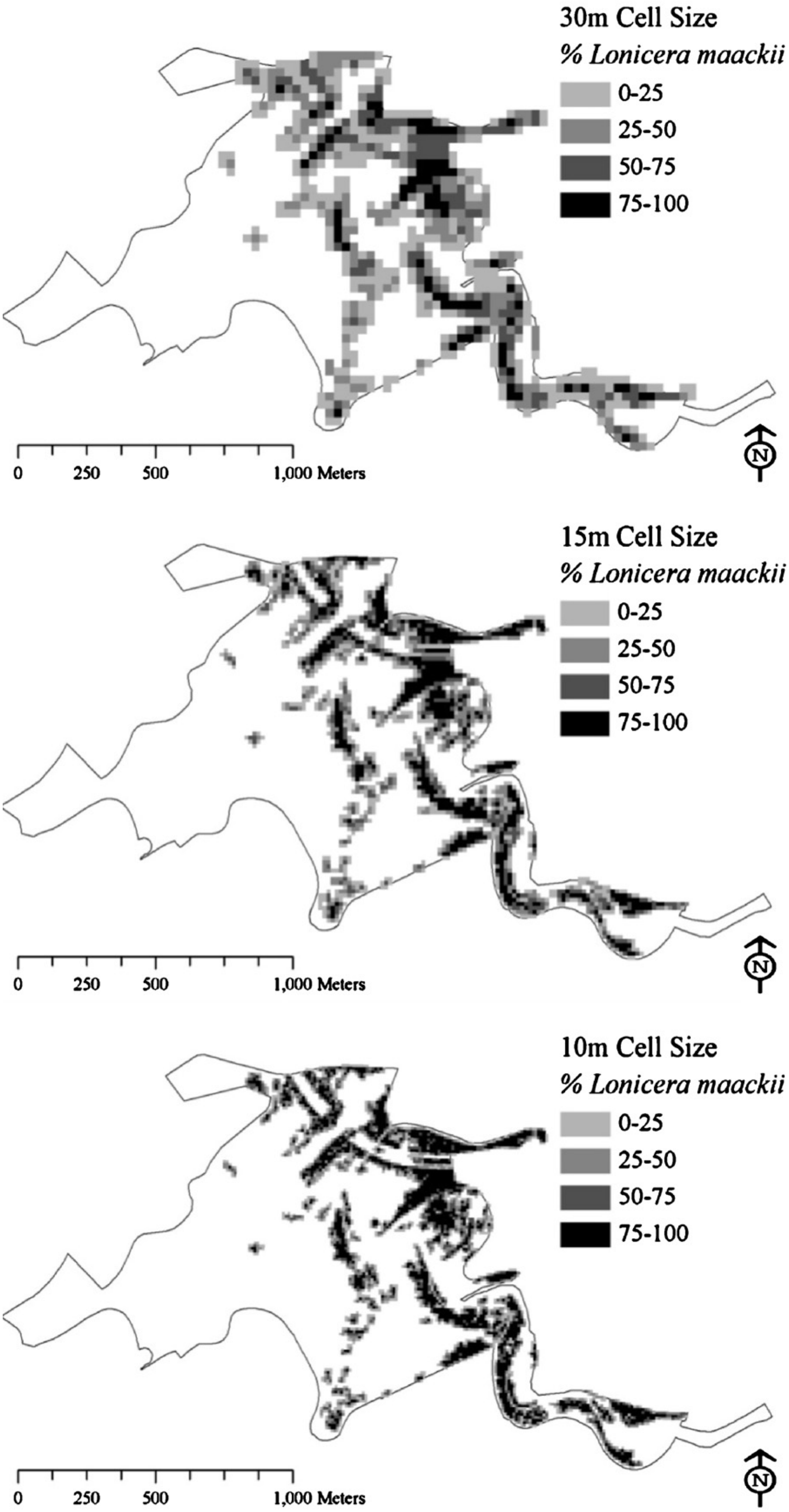

Fig. 6. Distribution of bush honeysuckle (*Lonicera maackii*) by percent of cover classes in a hypothetical up-scaling of a high resolution classification (Fig. 1) to 10 m, 15 m, and 30 m cell sizes.

Table 2
Linear and quadratic regression models of bush honeysuckle (*Lonicera maackii*) percentage on normalized difference vegetation index (NDVI) for the November 12, 2005 image and the November–January NDVI image difference.

Models	R^2	*p*-Value
% *L. maackii* = 73.1 × NDVI + 15.4	0.032	<0.001
% *L. maackii* = 209.1 × NDVI^2 − 37.5 × NDVI + 29	0.034	<0.001
% *L. maackii* = 177.2 × NDVIdiff[a] + 15.1	0.122	<0.001
% *L. maackii* = 538.4 × NDVIdiff^2 − 49.8 × NDVIdiff[a] + 21	0.130	<0.001

[a] NDVIdiff is difference between November and January NDVI classifications.

Table 3
Summary of 30 m, 15 m, and 10 m upscale classification pixel counts for bush honeysuckle (*Lonicera maackii*) percentage class based on a 0.3 m classification.

L. maackii class (%)	Pixels per class 30 m (%)	Pixels per class 15 m (%)	Pixels per class 10 m (%)
0–25	44.0	33.0	28.3
25–50	26.5	21.8	18.5
50–75	18.2	19.5	19.0
75–100	11.3	25.7	34.2

10 m, 15 m, and 30 m resolutions, the percentages of grids in the study area with over 50% bush honeysuckle presence were estimated to be 53.2%, 45.2%, and 29.5%, respectively. The 0–25% class contained the largest percentage of pixels in the 30 m class and 15 m class, and the second largest in the 10 m class. The 75–100% class placed in the top two for the 15 m and 10 m classes, but placed last in the 30 m class. The 10 m class had the highest percentage of its pixels classified in the 75–100% bush honeysuckle class. Comparisons of bush honeysuckle distributions between HSR object-based classification (Fig. 2) and up-scaling simulations (Fig. 6) indicated that the majority of the cells with less than 50% bush honeysuckle in simulated classifications are located near the edge of the distribution or areas with small bush honeysuckle population away from its core distribution. This trend intensifies as the simulated cell size increases (Fig. 6).

4. Discussion and conclusion

Remote sensing of bush honeysuckle in Cherokee Park using HSR imagery provided high accuracy from using both pixel-based and object-based classification techniques. The object-based classification did perform better in all aspects (overall accuracy, producer's accuracy, user's accuracy, and Kappa statistics) than the traditional pixel-based, suggesting the superiority in more fragmented urban environment. Although a near infrared band was not available in the visible color photo used, results suggested that the use of object-based approach on high resolution color imagery is effective. Further, an adequately executed supervised classification (pixel-based) appeared to provide relatively high accuracy (although less than that of object-based classification). This allows the flexibility for users to choose between the two classification methods according to respective applications and resource availabilities. The detailed information from HSR map could be used for the identification of small newly established populations of invasive plants which if removed could effectively limit further dispersal. The advantage of using high resolution data also includes a better representation of the actual spatial area of invasiveness, thus to facilitate precise management, such as more accurate cost estimation for removal projects. The combination of high accuracy and high resolution maps make HSR imagery ideal for the capture of IEP, especially for more complex landscapes.

Of course, the availability of high resolution remote sensing data is often limited. HSR imagery is usually expensive to acquire, discouraging wide utilization by natural resource managers. Besides, high resolution aerial images are only available for times when the relatively less frequent photo missions were conducted for designated regions, limiting its ability to conduct multi-temporal comparison, especially within an annual window. This could nullify its usefulness for cases when aerial photo acquisition dates do not match the time windows required for differential phenology based IEP detection. Nonetheless, if available, high resolution data provide opportunities for better mapping IEP in relatively small study areas of interest. In this study, HSR photos were provided to us from a local government agency at no cost, and covered the early spring period when bush honeysuckle stood out from background vegetation.

With lower accuracy than HSR mapping, medium resolution Landsat data also supported reasonably well predictions of bush honeysuckle distribution in Cherokee Park. Given the limited spatial resolution, the classification results unavoidably fell short of providing details for locating bush honeysuckle bushes in the Park, as also indicated by a relatively large omission error (47.8%). Although with limited accuracy, MSR data, such as Landsat, are useful for exploratory study and monitoring of IEP over extensive geographic regions because of their wide availability and often free of charge. However for more fragmented urban areas, HSR imagery may be more desirable when available, especially for landscape scale management purposes, such as the case for managing a state park. In addition, to better utilize medium resolution data, incorporation of the concept of differential phenology of invasive plants against native vegetation appeared to be pivotal, as evidenced by multi-temporal NDVI analysis in this and foregoing studies (Resasco et al., 2007; Wilfong et al., 2009). Besides, our NDVI driven regression models were largely unsuccessful compared to those by Wilfong et al. (2009), whom employed more precise field measurements of bush honeysuckle percentage cover in a rural setting. This may also implicate the increased impact of urban heterogeneity/fragmentation on medium resolution satellite signals in comparison to rural areas. Moreover, MSR data such as Landsat has a temporal limitation. Landsat data have a 16-day repeat cycle and often cloud contaminated, making it difficult to find useful scenes for a particular area that capture the phenologically differentiated periods between natives and IEPs.

Spatial scales, as expressed in different pixel/grid sizes of remotely sensed data, play a central role in affecting the precision/accuracy of IEP detection. In our study, we deliberately employed MSR and HSR imagery, and compared their ability to capture bush honeysuckle distribution in an urban forest. High resolution classification results were significantly more accurate than those of medium resolution. Further, in an up-scaling experiment, we simulated scale transitions towards coarser resolutions/larger grid sizes from fine resolution classification results. As anticipated, the loss of details was accompanied with accuracy reduction when spatial resolution enlarged. We believe this may also be the case when satellite data at different spatial resolutions (e.g. SPOT, ASTER, and Landsat) are in use. As mentioned before, finer spatial scale is better for discovering smaller IEP populations which often have greater expansion potential (Cousens and Mortimer, 1995; Henderson et al., 2006; Mack et al., 2000; Moody and Mack, 1988), therefore requiring more immediate treatment. Mapping IEP at the Landsat (30 m) resolution may be insufficient to provide needed details to guide management decisions, but would be useful for initial mapping over large regions. Therefore, the tradeoffs of different scales pertaining to selecting different remotely sensed data should be carefully considered in IEP distribution mapping projects.

Caution is needed when interpreting the results of different classification accuracy assessments. First, there is a limitation that field data collection date did not match that of the remote sensing data. All remote sensing data were taken 2–4 years prior field data collection, which could potentially influence the accuracy assessment. However, the influence could be minimal due to the fact that bush honeysuckle has been well established in the study area. The other factor that could affect our accuracy assessment is that we used point sampling unit to assess classification accuracy. This approach, as used in many other remote sensing studies (e.g., Watts et al., 2009; Kuemmerle et al., 2009), has an advantage in field data collection because it is independent of classification pixel size. However, the point sampling assessment has its limitation in a highly fragmented urban setting. Due to honeysuckle's monocultural patchy distribution, determining its pixel level presence/absence is straightforward when pixel size is relatively small. When pixel size increases as shown in the up-scaling simulation (Table 3), percentage of pixels with less than 50% honeysuckle cover also increases due to the highly fragmented nature of the urban landscape. This can result a higher probability of mismatch between the classification result and point-based field assessment at the pixel level, especially at the edge of honeysuckle distribution. Using aerial sampling unit that matches the pixel-size to conduct accuracy assessment could potentially alleviate the mismatch issue by assessing percent of honeysuckle coverage of a sampling pixel in the field. However, additional research is needed to determine the corresponding cutoff value (i.e., percentage of honeysuckle cover) that is needed for a pixel to be classified as honeysuckle presence.

In conclusion, we demonstrated in this study the feasibility and tradeoffs of applying both HSR and MSR remote sensing data to detect IEP in a complex urban forest setting. For more complex urban landscapes, higher resolution data with a more advanced object-based classification method is preferable as resource constraints allow. Being able to know the precise spatial locations (as suggested in this study by the exceptionally high classification accuracy) of understory IEP is promising for better treatment planning and more efficient resource allocation. But medium resolution data are advantageous for utilizing phenological differences between invasive/native species for detection purposes given their more frequent temporal coverage, in addition to its wide availability to large areas. Hence, the spatial scale effect and related issues shown in this study provides a useful reference to natural resource managers for selecting data/technique combinations appropriate to respective applications and study areas. Further, differential timing behaviors of invasive species and native species may be a key to allow separation of the two using appropriate temporal windows. Hence for invasive species showing closely resembled phenological patterns with those of native species, identification of IEP using remote sensing will be particularly challenging. Finally, accurate information on the spatial spread of invasive species is an indispensible basis for biological invasion research (Fei et al., 2008; Jules et al., 2002). We recommend continued exploration of the use of remote sensing, as enlightened by this study, for improving our ability to investigate/manage invasive species and conserve native vegetation and natural systems.

Acknowledgments

This study is supported by the USDA, Forest Service, National Urban and Community Forestry Advisory Council (Project No. 06-DG-11244225-246). We would like to thank Louisville Metro Parks, Olmsted Parks Conservancy, and Louisville-Jefferson County Information Consortium for allowing the use of their data and resources, and M. Walton and E. Thompson for project assistance.

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