ISSN 1946-7664. MCFNS 2018
Vol. 10, Issue 2, pp. 68–79
Mathematical and Computational Forestry & Natural-Resource Sciences

AVAILABLE ONLINE AT HTTP://MCFNS.COM

Submitted: May. 23, 2018
Accepted: Oct. 23, 2018
Published: Oct. 30, 2018
Last Correction: Oct. 23, 2018

COUNTY-SCALE MAPPING OF THE INVASION STAGE AND INVASIVENESS OF MAJOR NONNATIVE INVASIVE PLANTS IN THE UPPER MIDWEST FORESTLANDS, USA

Z. Fan [1,*], W.K. Moser [2], M.K. Crosby [3], W. Yu [4], Y. Zhang [5], M.H. Hansen [6], S.X. Fan [7]

[1] *School of Forestry and Wildlife Sciences, Auburn University, 602 Duncan Drive, Auburn, AL 36849 USA*
[2] *USDA Forest Service, Rocky Mountain Research Station, Flagstaff, AZ 86001 USA*
[3] *School of Agricultural Sciences and Forestry, Louisiana Tech University, Ruston, LA 71272 USA*
[4] *Department of Forestry, Mississippi State University, Mississippi State, MS 39762 USA*
[5] *School of Forestry and Wildlife Sciences, Auburn University, Auburn, AL 36849 USA*
[6] *USDA Forest Service, Northern Research Station, St. Paul, MN 55180 USA*
[7] *Statistical Consulting Center, Department of Mathematics and Statistics, Auburn University, Auburn, AL 36849 USA*
[*] *Corresponding Author: Ph.: +1(334)844-1014; Fax: +1(334)844-1084*

Abstract. The determination of invasion stages and the degree to which an invasive plant (non-native invasive plant, NNIP) has become established and spread in an ecosystem ("invasiveness") is essential for developing methods of mitigation and control. We mapped the invasion stages and quantified the invasiveness of four NNIPs of great concern, multiflora rose (*Rosa multiflora* Thunb), nonnative bush honeysuckles (including four species from the *Lonicera spp* family), common buckthorn (*Rhamnus cathartica* L.) and garlic mustard (*Alliaria petiolata* [M. Bieb.] Cavara & Grande) in the Upper Midwest forestlands. Specifically, we used the product of the estimated presence probability and mean cover rate of an NNIP from a group of Forest Inventory and Analysis (FIA) plots in a county to represent its severity or area occupied. We then calculated the empirical cumulative density function (ECDF) of the occupied area and used classification and regression tree (CART) to classify the ECDF into a number of disjoint segments to spatially represent invasion stages of an NNIP. The invasiveness of an NNIP in three major forest type groups was then investigated via regression analysis of the change in the estimated mean cover rate with the estimated presence probability across the mapped invasion stages (a proxy for invasion time). This study demonstrates the feasibility of using data from a single time period for determining invasion stages and invasiveness of NNIPs for the deployment of controlling or eradicating measures.

Keywords: empirical cumulative density function; CART; FIA; invasive plant.

1 Introduction

Mapping the invasion condition of nonnative invasive plants (NNIPs) in forested ecosystems has become a pressing concern in natural resource management. NNIPs can result in significant ecological and economic losses through competing with and displacing native species, changing the chemical properties of soil and the composition and structure of native ecosystems, altering natural disturbance regimes, and degrading ecosystem services including timber production, carbon sequestration, biodiversity, and recreation (e.g., Macdonald 1994, Pimentel et al. 2005, Moser et al. 2009, Eviner et al. 2012, Anderson and Crosby 2018). The degradation of ecosystem functions and services is directly related to the abundance and invasion stage as well as the "invasiveness" (degree to which an NNIP has become established and spread in an ecosystem) of NNIPs. There is extensive literature on the topic of invasion stages (Richardson et al. 2000) and invasion barriers (Williamson and Fitter 1996), largely reflecting the authors' orientation on plants or animals (Blackburn et al. 2011). Blackburn et al. (2011) proposed a more comprehensive model that integrates both stages and barriers in a quest to unify invasion biology. For the purposes of developing this elegant unified theory, such efforts are laudable. However, managers face situations with incomplete data and understanding of the site-specific dynamics of invasive plants. Occam's razor suggests that a simpler paradigm better reflects not only the situation on the ground but also the tools available to managers. Finally, similar to an industrial logistics model, managers measure "inventory" of invasive species or stages at a point in time, and infer flows or barriers between the stages. In that vein, we chose the four-stage model of Theoharides and Dukes (2007) They classified the invasion process of NNIPs into four stages: introduction, colonization, establishment, and spread. As Blackburn et al. (2011) observed, the barriers to progression from one stage to the next are implied. In the introduction stage, NNIPs are transported from their native regions to a new region via long-distance movements such as global commerce and travel, and their impact on local ecosystems is minimal or hardly detected. In the colonization stage, NNIPs survive and achieve positive net growth rates at low densities. In the establishment stage, NNIPs develop self-sustaining and expanding populations. In both the colonization and establishment stage, the impacts of NNIPs are confined to local ecosystems, so managers should take advantage of the relatively limited presence of NNIPs and promptly plan and conduct control measures. In the spread stage, NNIPs disperse within a region over long distances and the most efficient opportunity for controlling or eradicating NNIPs has already passed. Others have classified the invasion process into two stages (Davis 2009), three stages (Williamson and Fitter 1996 Radosevich 2007), or up to six stages (Henderson et al. 2006). All these classifications are primarily qualitative, providing a way to evaluate or characterize the impact of NNIPs on the bioecological processes of native ecosystems based on environmental factors or the life-history or genetic traits of the species.

Radosevich (2007) classifies the invasion process into three invasion stages— introduction, colonization, and naturalization—based on the logistic growth (i.e., occupied areas) of NNIPs with invasion time. In the introduction stage, the occupied area slowly increases with time; in the colonization stage, the occupied area quickly increases with time; and in the naturalization stage, the occupied area slowly increases and gradually reaches a stable limit or carrying capacity. Management strategies are different for each invasion stage. The cost of mitigation increases substantially as the populations of NNIPs become more established in the ecosystem (Hobbs and Humphries 1995). When the abundance of NNIPs is very low, the corresponding management strategies prioritize quarantine or eradication. When the abundance of NNIPs rapidly increases during the colonization stage, the management strategy, given limited resources, is to focus on limiting their spread (Webster et al. 2006). To prevent the spread of NNIPs, it is critical that managers detect them as early as possible and strategic inventories can help here (Moser et al. 2016). Finally, when the abundance of NNIPs is very high, in the naturalization stage, it is often extraordinarily expensive to remove NNIPs from an invaded area, particularly in forested ecosystems (Hobbs and Humphries 1995). Early detection of NNIPs is therefore an important step in cost-effective control of these species. Mapping the invasion stage (process) and quantifying the invasiveness of an NNIP in infested native ecosystems based on its occurrence, abundance, and spatial distribution will be of great value to the control and mitigation of NNIPs (Moser et al. 2016).

In order to quantify levels (or stages) of biological invasion, Catford et al. (2012) proposed and compared twelve potential indicators including presence/absence, abundance, cover and richness (absolute and relative) of NNIPs. They argued that an index of invasion level (stage) should not only facilitate the assessment of the extent or severity of NNIPs, reveal spatial and temporal trends and act as an early warning sign of ecological degradation, but also can be used to guide management efforts. Among the potential indices, Pearson at al. (2016) and Guo et al. (2015) used relative abundance (presence) and relative richness (cover rate) to quantify "apparent" impact of NNIPs and invisibility and degree of invasion for recipient communities and ecosystems. To date, we have not noted specific research or methodology that integrate these indices and spatial data of NNIPs for mapping invasion stages (delineating the boundary and/or spatial extent/range of invasion severity/level) and quantifying invasiveness of NNIPs at the regional scale.

Historical and contemporary land-use patterns have helped to shape the forests of the Upper Midwest region of the United States. Commercial timber harvesting in the 19th and early 20th century claimed extensive stands of eastern white pine (*Pinus strobus* L), shortleaf pine (*Pinus echinata* Mill.), and other species in northern Minnesota, Wisconsin, and Michigan and southern Missouri. At the same time, forest land in Iowa, Illinois, Indiana, and southern Wisconsin was cleared for agriculture as settlers took advantage of the productive soils. Savannas and prairies were also converted to farm land (Andersen et al. 1996, Soucy et al. 2005). Before settlement by Europeans, the periodic return of wildfires had maintained a mosaic of forest types and structures. Intensive timber harvesting, widespread land clearing, and management policies that suppressed wildfire contributed to a fragmented landscape. The resulting patchwork landscape and altered wildfire regime created conditions that NNIPs could exploit (Moser et al. 2009), often at the expense of understory development of native tree species.

The inventory data collected in 2005 and 2006 by the U.S. Department of Agriculture, Forest Service's Forest Inventory and Analysis (FIA) program recorded 25 commonly found invasive shrubs, vines, herbs, and grasses that may have adverse impacts on the forests in the Midwest (Fan et al. 2013). The primary factors known to affect the invasiveness of NNIPs are disturbances signified by county-level forest cover percent, distance to road, biodiversity, site quality, slope, and stocking level. As a continuation of our previous study in which the spatial distributional patterns of NNIPs were mapped using kernel smoothing (Fan et al. 2013), the objectives of this study are to 1) develop a methodology to map the invasion stage of four most dominant NNIPs, multiflora rose (*Rosa multiflora* Thunb), nonnative bush honeysuckles (including four species from the *Lonicera spp* family), common buckthorn (*Rhamnus cathartica* L.), and garlic mustard (*Alliaria petiolata* [M. Bieb.] Cavara & Grande) in the Upper Midwest counties based on the probability of presence and cover percentage data and 2) quantify the invasiveness of these four NNIPs in three major forest type groups (oak-hickory [*Quercus* spp.-*Carya* spp.], maple-beech-birch [northern hardwoods; *Acer* spp.-*Fagus* spp.-*Betula* spp.], and elm-ash-cottonwood [*Ulmus* spp.-*Fraxinus* spp.-*Populus* spp.]) in the Upper Midwest. The resultant maps of invasion stage and measures of invasiveness of selected NNIPs in major forest type groups will provide baseline information on current condition of NNIPs for management decision making about the control and mitigation of NNIPs in the Upper Midwest.

2 Materials and Methods

2.1 Study area

The Upper Midwest study area (Figure 1) consists of seven states: Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, and Wisconsin. Situated where several ecoregions come together, this area is characterized by diverse vegetation communities. The northern portions of the region are the most heavily forested areas (Minnesota - 29.3%, Wisconsin - 38.5%, Michigan - 31.2%, and Missouri - 32.8%, of total land area). The central portion of this area (Iowa, Illinois, and Indiana) is currently a patchwork of agricultural lands, urban areas, and some forest land; forests make up 8%, 12.2%, and 20.3%,of total land area in Iowa, Illinois, and Indiana, respectively [3,18]. A long history of human-caused disturbance and fertile soil provide favorable conditions for the establishment of NNIPs. In this study area, the primary forest-type groups infested by NNIPs are oak/hickory (37.7% of total forestland in the Midwest), maple/beech/birch (15.9% of forestland), and elm/ash/cottonwood (3.6 % of forestland) (Figure 1)

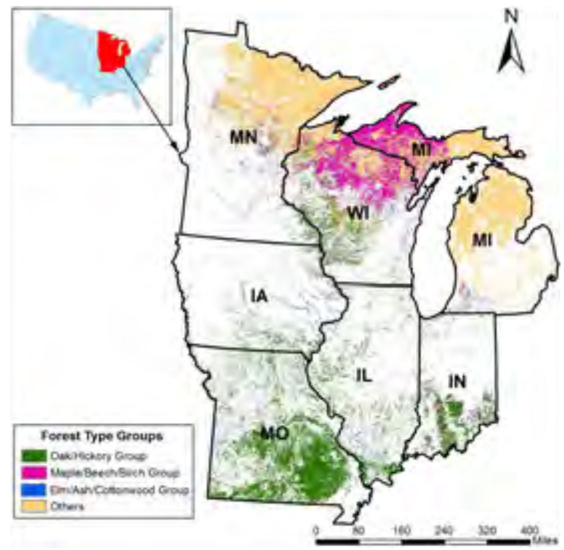

Figure 1: Distribution of three forest-type groups that have been infested by NNIPs in the Upper Midwest.

2.2 Data

We used FIA data from the 2005 and 2006 inventory years. Phase 2 (tree inventory) data are collected on the standard FIA plot grid (1 plot per 2400 ha) (https://www.fia.fs.fed.us/library/database-documentation/index.php). Each Phase 2 plot consists of four subplots with a radius of 7.3 m (McRoberts 1999, Woudenberg et al. 2010). In the Upper Midwest states, sampling of 25 NNIPs including shrubs, grasses, herbaceous species, and vines of interest was overlaid on these plots (Pearson et al. 2016). The presence and cover rate (%) were used to describe the presence and abundance of each NNIP in an FIA plot. For each NNIP, the value for presence is 1 if present or 0 if absent; the values for cover rate (%) are recorded as the middle value of the range of percent cover for each cover code (Table 1). In total, 8632 Phase 2 forested plots were assessed, and 594 counties out of 649 counties in the Upper Midwest had FIA plots (Moser et al. 2009) Four of the most abundant NNIPs (groups) in terms of presence probabilities (pp) in different life forms (shrubs and herbs) included in this study are multiflora rose (*Rosa multiflora* Thunb,pp = 15.3%), nonnative bush honeysuckles (including four species from the *Lonicera spp* family, pp = 9.2%), common buckthorn (*Rhamnus cathartica* L., pp = 4.8%) and garlic mustard (*Alliaria petiolata* [M. Bieb.] Cavara & Grande, pp= 3.1%) (Figure 2).

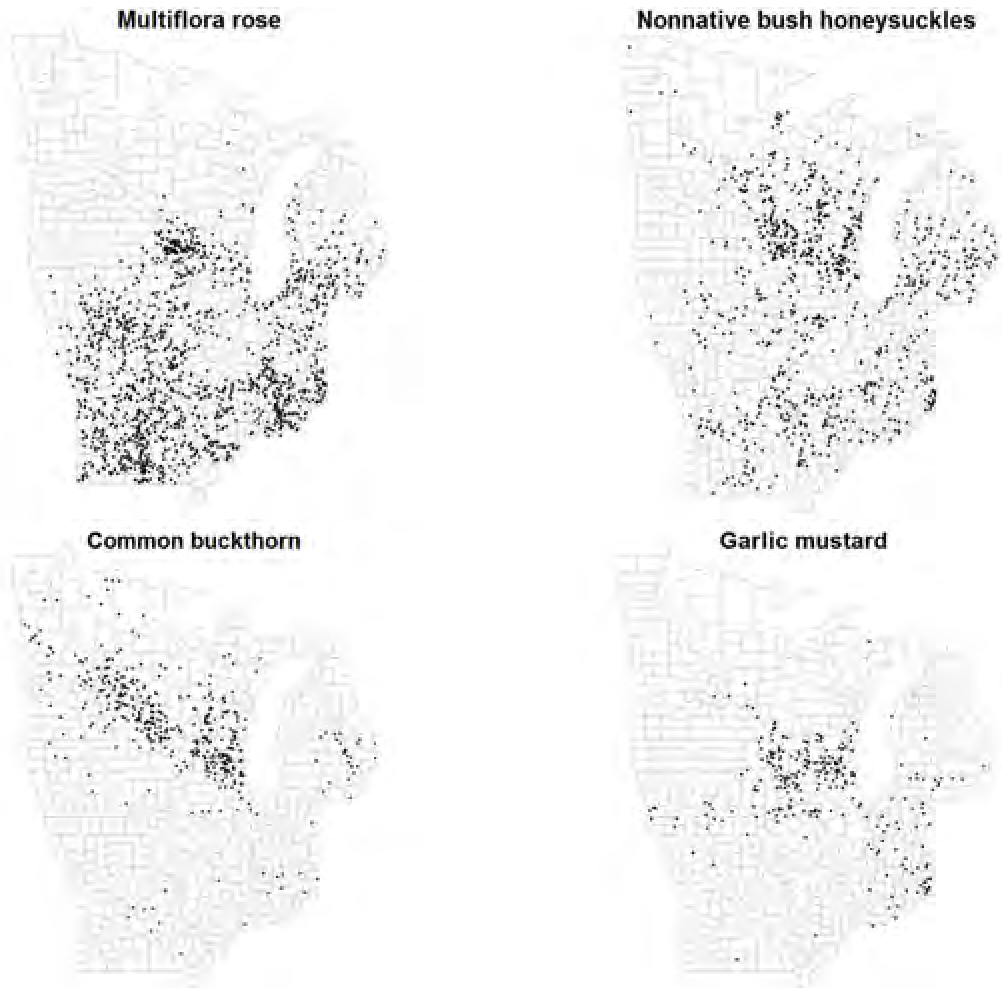

Figure 2: Spatial distribution of infested FIA plots by four major nonnative invasive plants in the Upper Midwest forestlands in the 2005-2006 inventory.

Table 1: Cover codes and ranges of percent cover of nonnative invasive plants (NNIPs) used in recording invasive species' presence, FIA plots, 2005-2006.

Cover Code	Range of % cover	Middle value (%)
1	< 1, trace	0.5
2	1 to 5	3.0
3	6 to 10	8.0
4	11 to 25	18.0
5	26 to 50	38.0
6	51 to 75	63.0
7	76 to 100	87.0

2.3 The presence probability and mean cover rate (%) of NNIPs at county level

In the dataset used for this study there are, on average, 15 plots in each county. Fifty-nine counties have only one FIA plot, whereas 65 counties have more than 30 FIA plots. In order to overcome this bias attributed to the sample size in calculating the presence probability and mean cover rate (%) of an NNIP for each county, we used the following formula (neighborhood smoothing) to define the presence probability for a county based on the positive spatial autocorrelation in NNIP data (Moser et al. 2016, Fan et al. 2013):

$$p_i = \frac{\sum_{i\in\eta_i} s_i}{\sum_{i\in\eta_i} n_i} \tag{1}$$

where s_i is the number of the presence plots (plots where at least one NNIP was recorded) in the county i, n_i is the total number of plots in the county i, and η_i is the set of counties that share a boundary with the county $i$based on the Rook's rule, including the county i. We define the presence probability as the ratio between the number of presence plots and the total number of FIA plots in the county. We calculated the mean cover rate of

NNIPs for a county using the same rule. The estimated presence probability and mean cover rate will be used to estimate the severity or occupied area of an NNIP in a county.

2.4 Classification of invasion stages through a proxy of the occupied area or invasion severity of NNIPs at county level

The presence probability (measuring abundance) and mean cover rate (measuring dominance) are two indicators of the invasion severity or occupied area of NNIPs in a county; values of these two variables are often positively correlated and increase with the invasion time (or stage). In our analysis, we used the product of the estimated presence probability and mean cover rate as a proxy to quantify the occupied area or invasion severity of NNIPs in a county, which considers both the abundance and the dominance of NNIPs in a group of FIA plots (Catford et al. 2012, Pearson et al. 2016). The empirical cumulative distribution function (ECDF) of the product shows the ranked (from low to high) distribution of the invasion condition or severity of NNIPs among the Upper Midwest counties. The ECDF often takes a sigmoid or exponential or spherical curve and can be viewed as a composite "space-for-time" version of the hypothetical, temporal invasion process (stage) on a particular site or area (Theoharides and Dukes 2007). Each point on the ECDF curve will represent one county with low invasion severity counties appearing on the left and high invasion severity counties on the right in a sequential order (from low cumulative probabilities to high cumulative probabilities).

In this study, classification and regression tree (CART) (Breiman et al. 1984) was used to segment the ECDF of the NNIP invasion proxy so that the 649 Upper Midwest counties were classified into different groups (invasion stages) using the cumulative probability of a county as the response and the invasion proxy (the product of the estimated presence probability and mean cover rate of NNIPs) as the predictor. Thus, counties are more homogenous in the invasion condition (similar ECDF values) within an invasion stage but significantly different between and among invasion stages. The R package *rpart* (R Development Core Team 2011) was used to construct the optimal regression tree model since it automatically performs cross-validation and calculates the cross-validation error rate, which estimates the expected error rate for use of the regression tree with new data. The cross-validation error rate gives an assessment of the performance of the resulting regression tree, that is, the change in prediction error with changing tree size. Therefore, the optimal regression tree model that minimizes the relative cross-validation error rate can be selected (Maindonald and Braun 2007) Taking multiflora rose as an example, the optimal regression tree size (the number of terminal nodes) with the minimal relative cross-validation error is four (Figure 3A). Figure 3B shows the optimal regression tree profile with four terminal nodes and figure 3C shows the corresponding four invasion stages (I, II, III, IV) displayed in the ECDF curve of the product of the estimated county-level presence probability and mean cover rate of multiflora rose.

2.5 Quantifying the invasiveness of NNIPs in an ecosystem

FIA plots were first grouped by forest type group and classified invasion stage. To assess the invasiveness of an NNIP in a forest type group, we calculated its presence probability and mean cover rate for each forest type group by classified invasion stages (time). The relationship between the mean cover rate (response variable, measuring the dominance or rate of the colonization and establishment of an NNIP) and the presence probability (independent variable, measuring the abundance or rate of spread of an NNIP) across different invasion stages was evaluated via regression analysis for each forest type group. The slope (increase of mean cover rate with presence probability) of the regression model was used to measure the invasiveness of an NNIP in a forest type group based on the assumption that the presence probabilities of NNIPs by invasion stage are an approximate measure of invasion time. A permutation test was conducted to test the statistical difference of the slope (invasiveness) of an NNIP between different forest type groups This study includes three major hardwood forest type groups, which account for 88.2% of the total forestland in the Upper Midwest and are increasingly threatened by NNIPs based on the FIA data (Moser et al. 2009, Moser et al. 2016, Fan et al. 2013)

All statistical computation and analysis were conducted under the R statistical environment (R Development Core Team 2011). The *rpart* package in R was used to implement CART analysis (Therneau and Atkinson 2012, John and John 2003). The *stats, maps* and *rpart.plot* and *ggplot2* packages were used to run linear regression and to draw graphics and map invasion stages.

3 Results

Approximately 15.3%, 9.2%, 4.8%, and 3.1% of FIA plots had been infested, respectively, by multiflora rose, nonnative bush honeysuckles, common buckthorn and garlic mustard based on the 2005-2006 inventory data (Table 2). Distribution of the four NNIPs varied across the landscape: multiflora rose predominantly occurred in central and southern counties, common buckthorn in

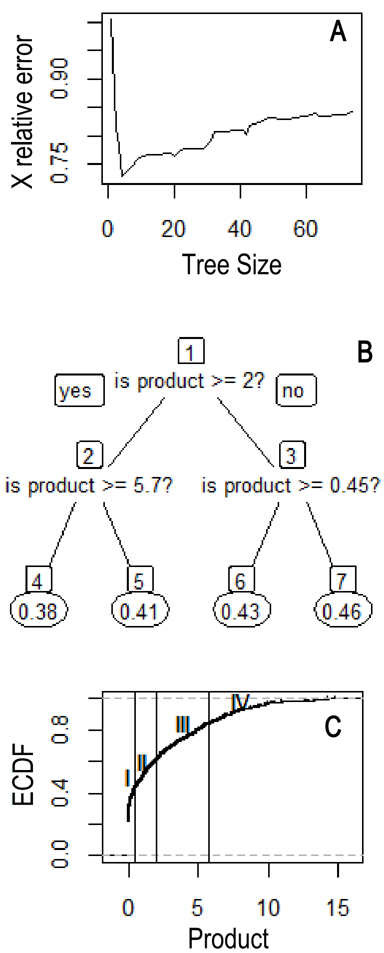

Figure 3: Classification of invasion stages of multiflora rose: (A) The plot of X relative error (relative cross-validation error) vs. the regression tree size (the number of terminal nodes) showing an optimal tree size of four corresponding to the minimal relative error. (B) The optimal regression tree model with four terminal nodes labelled as 4,5,6,7 (invasion stages I, II, III and IV) showing the cut-off values of the product of the estimated county-level presence probability and mean cover rate (%)). The numbers (0.38, 0.41, 0.43, 0.46) in the terminal nodes are the mean probability. (C) The ECDF of the product and four cut-off values to map multiflora rose into four invasion stages (labelled as I, II, III and IV) based on the CART model.

central and northern counties, and garlic mustard in central counties, while nonnative bush honeysuckles spread across the entire Upper Midwest (Figure 2). Figure 3 showed the mapping process of invasion stages for multiflora rose. Based on the relative cross-validation error change with regression tree size, the best regression tree with the minimum relative cross-validation error should have four terminal nodes (Figure 3A) as indicated by the resultant pruned regression tree (Figure 3B). The ECDF of the product of the estimated presence probability and mean cover rate (%), a proxy of the county-level invasion severity or occupied area of multiflora rose was then segmented into four sections representing the four invasion stages by using the breaks (cut-off values) of the pruned regression tree (Figure 3C). Same process was applied with the other three NNIP species. A graphic representation (Figure 4) displays the classified invasion stages on the plane of presence probability versus mean cover rate for all NNIPs. For multiflora rose, in invasion stages I and II, the estimated mean cover rate increases slowly and has relatively low variation with the presence probability, but in invasion stages III and IV the estimated mean cover rate increases rapidly and has greater variation. Except for 142 (22%) deep northern counties (Fig 5, shaded in white) where no multiflora rose was found in FIA plots, 138 (21%) and 111 (17%) counties (shaded in blue and green, respectively) belong to invasion stages I and II where multiflora rose has low cover class (<5%) and presence probability (<0.4). Multiflora rose was more prominent in the central counties and part of the southern counties, of which 153 (24%) and 105 (16%) counties belong to invasion stage III (shaded in brown) and IV (shaded in red) with moderate and higher cover classes (>5%) and presence probability (>0.4), respectively. For the other three NNIPs, all advanced invasion stages (III, IV) were spatially located in central counties. Nonnative bush honeysuckles spread over more (88%) counties than other species in four invasion stages with 36% of counties in advanced stages (III, IV). Common buckthorn spread over 56% counties in three stages with only 2% in advanced stage (III). Garlic mustard spread over 50% of counties in four stages with 3% of counties in advanced stages (III).

Regression analysis suggests that common buckthorn, garlic mustard, and nonnative bush honeysuckles were, overall, more invasive than multiflora rose in the Upper Midwest forest lands as shown by their significantly greater slope coefficients ($p < 0.0009$), but there were no significant differences among them (Figure 5). For each taxon that we studied, we did not find significant differences in regression slopes among the three forest-type groups at the significance level of $\alpha = 0.05$. This result suggests that the invasiveness of each genus or species is not statistically different by forest type group due to large standard errors (in parentheses in Figure 5.)

4 Discussion

4.1 4.1 Classification of invasion stages

The invasion stages presented in this study are quantitatively derived from data obtained over one measurement

Table 2: Proportion of FIA plots infested by NNIPs, number (proportion in parenthesis) of counties in different invasion stages based on the 2005-2006 survey data of nonnative invasive plants.

Species Name	FIA plots infested	Number of counties in stage I	II	III	IV	None
Multiflora rose (Rosa multiflora Thunb.)	15.3%	138 (21)	111 (17)	153 (24)	105 (16)	142 (22)
Nonnative bush honeysuckle (Lonicera spp.)	9.2%	161 (25)	238 (37)	100 (15)	72 (11)	78 (12)
Common buckthorn (Rhamnus cathartica L.)	4.8%	215 (33)	136 (21)	16 (2)		282 (44)
Garlic mustard (Alliaria petiolata (M. Bieb.) Cavara & Grande)	3.1%	197 (30)	105 (16)	21 (3)		326 (50)

period. Invasion stages are not labeled categorically as is done in other studies (Radosevich 2007) but can be thought of in terms of severity where greater numbers represent a greater degree of invasion (Guo et al. 2015). The product of the estimated county-level presence probability and mean cover rate (%) of NNIPs in a group of FIA plots as a measure of "invaded area" or invasion severity can be generated for individual species or all NNIPs (Table 2), making the analysis applicable to any spatial scale (Moser et al. 2016). Moody and Mack (1988) show that the area invaded is a non-linear function of time if there are multiple foci for invasion and the invaded area is a linear function of time if there is a single focus of the invasion. Here, if we treat the estimated cover rate as a proxy for the infested area and the estimated presence probability by invasion stage as a proxy for the infested time, then the non-linear relationship between the two variables (Figure 4 A and B) for multiflora rose and nonnative bush honeysuckles is consistent with the dispersal characteristics of most NNIPs: a mixture of long-distance dispersal (e.g., birds) and short-distance dispersal (e.g., through runoff, mammals). Evidently, both species had multiple (>3) foci for regional dispersion and spread (Figure 6). In contrast, the linear relationship between the estimated cover rate and presence probability for common buckthorn and garlic mustard (Figure 4 C and D) coincided with one focus for regional spread (Figure 6). Classification of invasion stage is an important component for the determination of any impacts invasions may have on native plants in an area. Presence and cover rate have been utilized to determine the effect of invasive plants on natives Pearson et al. 2016). The use of the product of presence probability and mean cover rate, compared to either of both, allows for a more accurate estimation of invasion severity of an area occupied by an NNIP (Yu 2011), which provides resource managers a method for prioritizing mitigation efforts based upon invasion stage. This would allow for both limiting foci for further invasion of NNIPs and minimize the local effects, or degree of invasion (Guo et al. 2015) on native species (Pearson et al. 2016).

The ECDF curve (Figure 3C) ranked the 649 Midwest counties based on the product of county-level presence probability and mean cover rate of an invasive plant species (the x-axis) and reported the cumulative probabilities (the y-axis) of a county corresponding to a value of this product. The counties that have low product values and cumulative probabilities are lightly invaded and are located in the left section (labelled as invasion stage I), followed by moderately invaded counties (labelled as II and III), and highly invaded counties (labelled as IV). Since the ECDF curve describes the change of the product of presence probability (abundance) and mean cover rate (dominance) of an invasive species, its shape is primarily related to the number of foci for invasion/spread, rate of spread and growth rate in focal environment. We found the shape of the ECDF curve is related to the invasiveness with less invasive species such as multiflora rose (having minimal slope, Figure 5) having a gentle slope of ECDF curve, while highly invasive species (large slope, Figure 5) have a steeply increased ECDF curves.

The CART integrated plot data at the county level provided an objective way to view the spread patterns of NNIPs and classify counties into invasion stages for regional-scale planning and management of NNIPs. The sole reason of using county as the unit to pool invasive data is to meet the need of local governments and land and resource management agencies in NNIPs management and planning although the spread of invasive species is intrinsically not related to the political boundaries. The classified invasion stages revealed, generally,

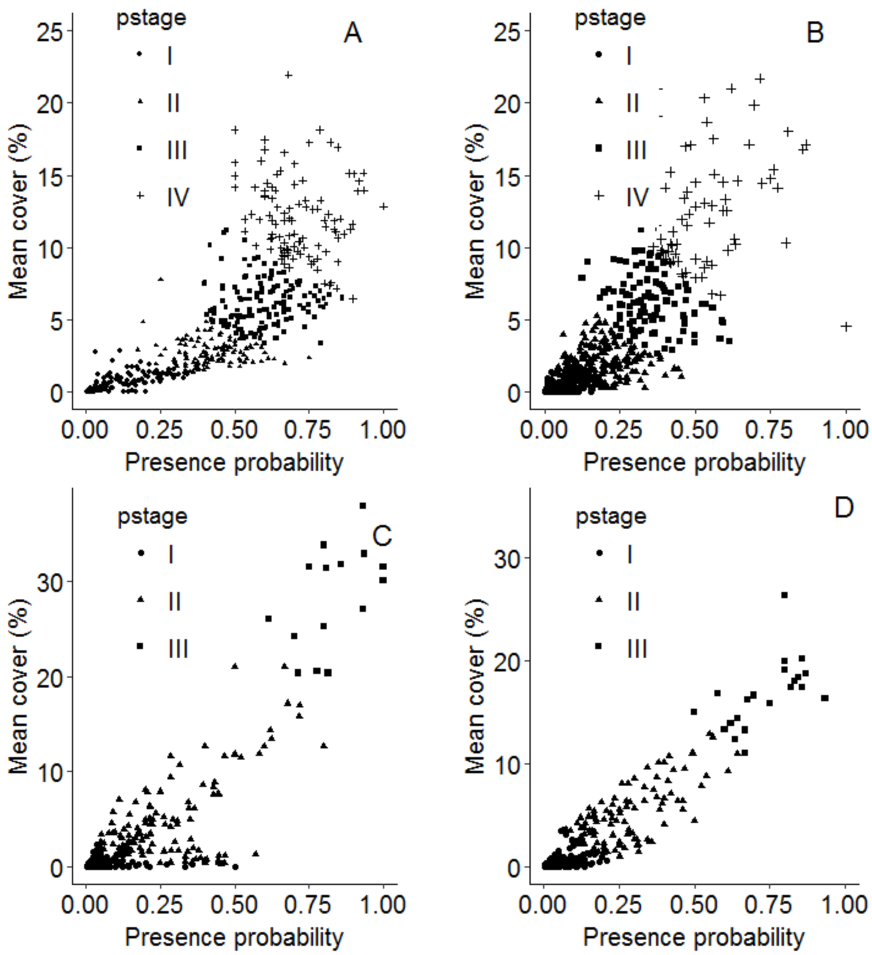

Figure 4: The relationship between the estimated county-level presence probability (pp) and mean cover rate (%) of (A) multiflora rose, (B) nonnative bush honeysuckles, (C) common buckthorn, and (D) garlic mustard by the invasion stage (pstage) classified by the CART model in the Upper Midwest counties.

that NNIPs were first introduced to the central counties and then gradually spread to surrounding counties; the highest category of invasion stage serves as a source region for the spread of NNIPs (Moser et al. 2009, Moser et al. 2016, Fan et al. 2013). The county maps of invasion stage give resource managers a tool to locate target counties and evaluate the severity of NNIPs to allocate resources for the control and mitigation of NNIPs. The use of single-measurement data provides objective criteria for determining areas of most-severe invasion by NNIPs and provides for the development of a more rapid response. The delineated invasion stage maps (Figure 6) provide more accurate information than separate smoothed maps of either presence probability or cover rate of NNIPs in previous studies (Moser et al. 2016, Fan et al. 2013), and can serve as baseline information for the NNIP's current condition and allow resource managers to develop timely plans for investigation, control, or eradication of threats posed by the plants. The data utilized in developing the invasion stage classifications was from the 2005-2006 inventory cycle. Further analysis will incorporate the subsequent inventory data and use to further refine models based on any newly detected presence or spread of these NNIPs in the region.

Future studies in this region should consider employing multi-temporal image analysis (after Becker et al. 2012). This level of analysis, incorporated with remotely-sensed data could enhance classification accuracy of NNIPs and allow for their tracking through time with a greater temporal and spatial resolution (e.g., 16 days for Landsat at 30 m). It also could provide invaluable data during non-inventory cycles and aid in tracking invasion stage.

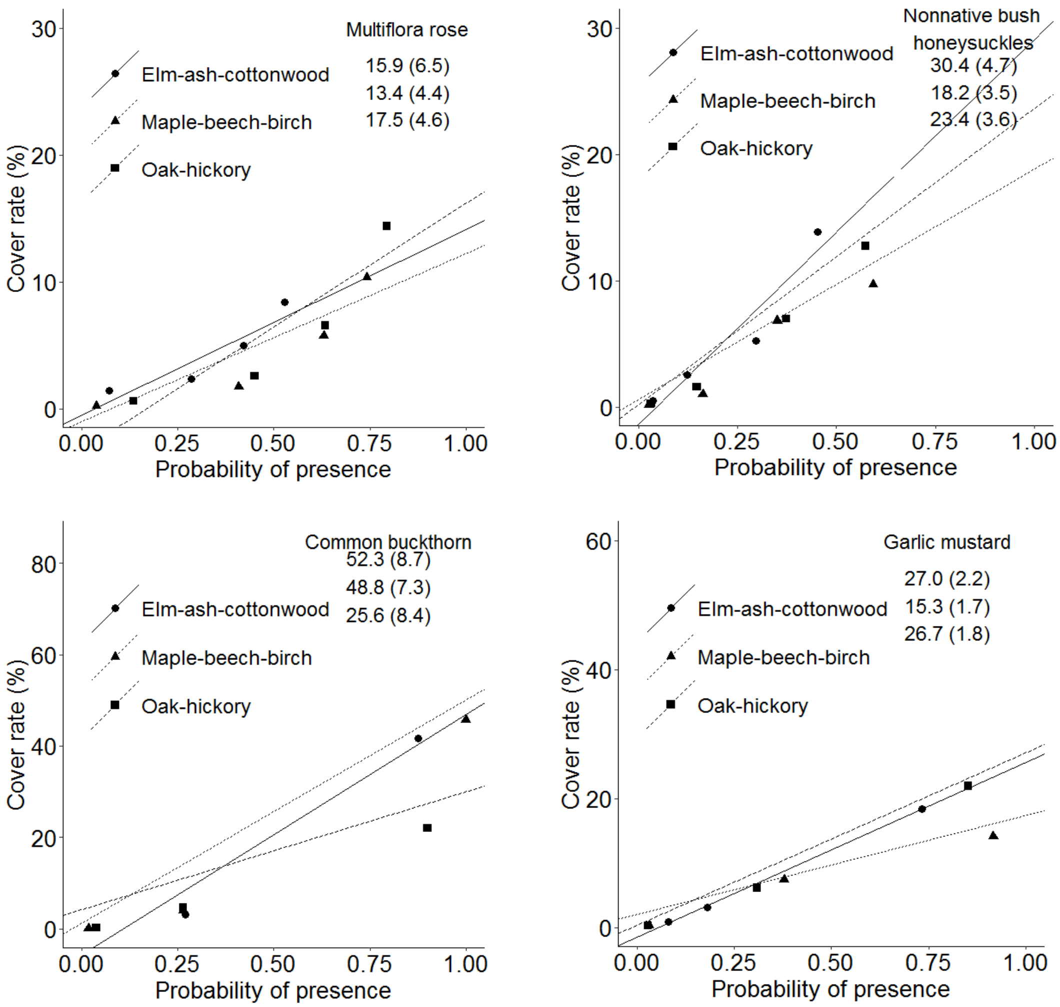

Figure 5: Regression lines showing the increase of the mean cover rate (%) with presence probability across classified invasion stages for four selected NNIPs. The numbers in the plot are the estimated regression coefficients and standard errors (in parentheses) for slope, a quantitative measure of the invasiveness of NNIPs for corresponding forest type groups.

4.2 Invasiveness of NNIPs

Invasiveness is illustrated by plotting the regression lines for the three assessed forest types (Figure 5). Two of the invasive shrubs, nonnative bush honeysuckles and common buckthorn, had a higher level of invasiveness in elm-ash-cottonwood forests than in maple-beech-birch forests and oak-hickory forests, as indicated by the slope of the regression line (steepest for elm-ash-cottonwood forests), but the difference was not statistically significant due to large variations in the data. Garlic mustard as an invasive herbaceous species had higher invasiveness in oak-hickory forests and elm-ash-cottonwood forests than in maple-beech-birch forests, but this difference was not statistically significant. Multiflora rose had nearly identical invasiveness levels in three forest-type groups (Figure 5). Generally, invasiveness decreases as the forest types progress toward later successional or at least more shade-tolerant species, although as Martin et al. (2008) point out, slow-invading shade-tolerant species can have dire negative consequences for late-successional forest systems. Following European settlement, anthropogenic influence has resulted in an increasingly fragmented landscape, leading to early- and mid-successional communities. In these communities, NNIPs can establish and spread, including communities of oak, birch, and aspen (*Populus* spp.) (Dieser and Ek 2016) While NNIPs may not readily invade mature, closed-canopy systems, disturbance may allow them to infiltrate an area where they outcompete native vegetation (Gilliam 2007).

Early- and mid-successional forests such as oak-hickory and elm-ash cottonwood (Sander and Clark 1971, Oliver 1996, Van Haverbeke 1990) have

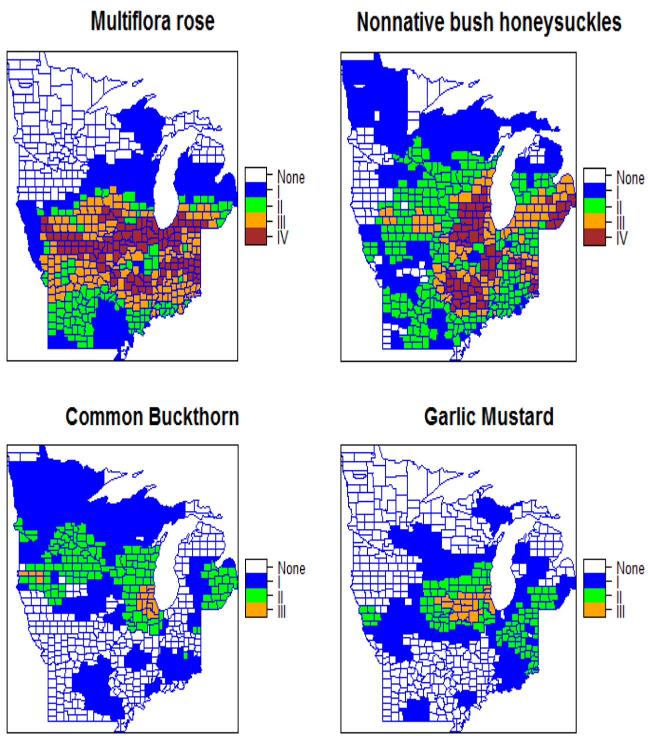

Figure 6: The spatial representation of invasion stages of selected NNIPs in the Upper Midwest counties.

growing space available for NNIPs. This is problematic for shade-intolerant species (i.e. cottonwood) that occupy growing space, particularly in open disturbed sites, into which NNIPs can establish (Van Haverbeke 1990). Late-successional forests, such as maple-beech-birch, forests, are generally comprised of shade-tolerant species (e.g., sugar maple [*Acer saccharum* Marsh] (Delcourt and Delcourt 2000); the niche space is occupied by these species and the greater leaf area reduces light availability and is not conducive to the establishment of NNIPs (Guo et al. 2015).

The balance of late-successional forests or the lack of NNIPs in early- and mid-successional forests can be influenced greatly by disturbance (e.g., wind-throw, harvest). Canopy reduction through wind-throw, etc. can disrupt species dominance (Oliver 1996) and create niche space for NNIPs, from which they can expand throughout the ecosystem (Frelich and Reich 1995). With new inventory data, the invasiveness of NNIPs and their impact on recipient ecosystems can be further evaluated using mapped invasion stages.

5 Conclusions

Procedures have been developed that can be used to classify the invasion stages of invasive plants based on estimated county-level presence probability and mean cover rate. This provides a method of classification without reliance on data collected over long intervals of time, allowing for a more timely deployment of monitoring and control measures for NNIPs. However, the coarse data of cover rate may influence the reliability and accuracy of the classification. We recommend that future research explore any potential impacts on the accuracy of maps that classify objective invasion stages. Only then might researchers and managers be able to evaluate the efficacy of a more detailed and comprehensive invasion stage and barrier model, such as that posited by Blackburn et al. (2011), in helping them achieve their resource management goals.

The results support the classification of the invasion process into various discrete stages. This practice is different from previous studies in that these classification procedures, based on information on occupancy (presence or absence) and abundance of NNIPs, do not require knowledge about the life-history and genetic traits of invasive plants and about environmental factors.

The invasion stage for a variety of NNIPs as well as the invasiveness (susceptibility to invasion) of major forest types has been shown. The invasiveness of four primary NNIPs that effect Midwestern forests have been mapped. The prevalence of multiflora rose led to it being the dominant NNIP. However, the results of this analysis show common buckthorn, honeysuckle, and garlic mustard to all be more invasive in Midwestern forests. If fragmentation and disturbance continue with no feasible control, these species will continue to spread throughout the region. Forested areas, particularly those with disturbed patches, should be monitored for the establishment of NNIPs. This is of greatest significance in those communities with earlier successional species. Where NNIPs are detected, steps should immediately be taken to remove them before they become established.

Acknowledgments

Dr. Mark D. Nelson, U.S. Forest Service, Northern Research Station, Forest Inventory and Analysis Program, provided valuable assistance with spatially joining FIA plots and other features. The authors gratefully acknowledge the input of anonymous reviewers on earlier versions of this manuscript for their valuable comments and suggestions.

Funding: The authors thank the United States Department of Agriculture, Forest Service, Forest Health Protection, Environmental Monitoring Program; the U.S. Forest Service, Northern Research Station, Forest Inventory and Analysis Program (Project #: 08JV11242305107); and the Department of Forestry, Mississippi State University for their support of this study.

Availability of Data and Materials: All data used in this study came from the Forest Inventory and Analysis National Program – United States Department of Agriculture, Forest Service (https://www.fia.fs.fed.us/), particularly the Northern Research Station FIA Program (https://www.nrs.fs.fed.us/fia/).

References

Anderson, M.P. & Crosby, M.K. 2018. An assessment of invasive plants on Shorter Universitys campus. Math. Comput. For. & Nat. Res. Sci. (MCFNS), 10(1): 24–29. Retrieved from: http://mcfns.net/index.php/-Journal/article/view/10.6/2018.

Andersen, O., Crow, T.R., Lietz, S.M., & Stearns, F. 1996. Transformation of a landscape in the upper midwest, USA: the history of the lower St. Croix river valley, 1830 to present. Landsc. Urban Plan. 35: 247–267.

Becker, R.H., Zmijewski, K.A., & Crail, T. 2012. Seeing the forest for the invasives: mapping buckthorn in oak openings. Biological Invasions 15(2): 315–326.

Blackburn, T.M., Pyšek, P., Bacher, S., Carlton, J.T., Duncan, R.P., Jarošík, V., Wilson, J.R.U., & Richardson, D.M. 2011. A proposed unified framework for biological invasions. Trends Ecol. & Evol. 26: 333–339.

Breiman, L., Friedman, J.H., Olshen, R.A., & Stone, C.J. 1984. Classification and regression trees. Wadsworth: Belmont, California.

Catford, J.A., Vesk, P.A., Richardson, D.M., & Pysek, P. 2012. Quantifying levels of biological invasion: towards the objective classification of invaded and invasible ecosystems. Global Change Biology. 18: 44–62.

Davis, M.A. 2009. Invasion biology. Oxford University Press: Oxford, UK.

Delcourt, H.R., & Delcourt, P.A. 2000. Eastern deciduous forests. In: Barbour MG, Billings WD (eds) North American terrestrial vegetation, Cambridge University Press: New York. pp. 357–395.

Dieser, P.J., & Ek, A.R. 2011. Cloquet Forestry enter continuous forest inventory for 2000: analysis and integration with the historical database. Department of Forest Resources, University of Minnesota, St. Paul, MN. Staff Paper Series No. 214.

Eviner, V.T., Garbach, K., Baty, J.H., & Hoskinson, S.A. 2012. Measuring the effects of invasive plants on ecosystem services: challenges and prospects. Invasive Plant Science and Management. 5: 125–136.

Fan, Z., Moser, W.K., Hansen, M.H., & Nelson, M.D. 2013. Regional patterns of major nonnative invasive plants and associated factors in upper Midwest forests. For. Sci. 59: 38–49.

Frelich, L.E., & Reich, P.B. 1995. Neighborhood effects, disturbance, and succession in forests of the Western Great Lakes region. Ecoscience. 2:148–158.

Gilliam, F.S. 2007. The ecological significance of the herbaceous layer in temperate forest ecosystems. BioScience. 57: 845–858.

Guo, Q., Fei, S., Duke, J.S., Oswalt, C.M., Iannone III, B.V., & Potter, K.M. 2015. A unified approach for quantifying invisibility and degree of invasion. Ecology. 96: 2613–2621.

Henderson, S., Dawson, T.P., & Whittaker, R.J. 2006. Progress in invasive plants research. Prog. Phys. Geog. 30: 25–46.

Hobbs, R. J., & Humphries, S.E. 1995. An integrated approach to the ecology and management of plant invasions. Conservation Biology. 9: 761–770.

John, M., & John, B. 2003. Data analysis and graphics using R: an example-based approach. Cambridge University Press, Cambridge, UK.

Macdonald, I.A.W. 1994. Global change and alien invasions: implications for biodiversity and protected area management, In: Solbrig OT, van Emden PG, van Oordt WJ (eds) Biodiversity and global change. CAB International, Wallingford-Oxon, UK. pp 197–207.

Maindonald, J., & Braun, J. 2007. Data analysis and graphics using R: an example-based approach, Cambridge University Press, Cambridge, UK.

Martin, P.H., Canham, C.D., & Marks, P.L. 2008. Why forests appear resistant to exotic plant invasions: intentional introductions, stand dynamics, and the role of shade tolerance. Front. Ecol. Environ. 7(3):142–149.

McRoberts, R.E. 1999. Joint annual forest inventory and monitoring system: the North Central perspective. J. For. 97:27–31.

Moody, M.E., & Mack, R.N. 1988. Controlling the spread of plant invasions: the importance of nascent foci. J. Appl. Ecol. 25:1009–1021.

Moser, W.K., Hansen, M.H., Nelson, M.D., & McWilliams, W.H. 2009. Relationship of invasive groundcover plant presence to evidence of disturbance in the forests of the upper midwest of the United States. In: Kohli RK, Jose S, Singh HP, Batish DR (eds) Invasive plants and forest ecosystems. CRC Press, Boca Raton, FL, pp 29–58.

Moser, W.K., Fan, Z., Hansen, M.H., Crosby, M.K., & Fan, S.X. 2016. Invasibility of three major nonnative shrubs and associated factors in Upper Midwest U.S. forest lands. For. Ecol. Manag. 379:195–205.

Oliver, C.D., & Larson, B.C. 1996. Forest stand dynamics, update edn. Wiley, New York.

Pearson, D. E., Ortega, Y.K., Eren, Q., & Hierro, J.L. 2016. Quantifying "apparent" impact and distinguishing impact from invasiveness in multispecies plant invasions. Ecological Applications. 26: 162–173.

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

R Development Core Team. 2011. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria: 2011, http://www.R-project.org/

Radosevich, S.R. 2007. Plant invasions and their management. Chapter 3 in: Center for Invasive Plant Management (ed.) Invasive plant management: CIPM online textbook. Center for Invasive Plant Management, Bozeman, MT. Available online: http://www.weedcenter.org/textbook/index.html Accessed 18 October 2008.

Richardson, D.M., Pyšek, P., Rejmanek, M., Barbour, M.G., Panetta, F.D., & West, C.J. 2000. Naturalization and invasion of alien plants: concepts and definitions. Diversity & Distrib. 6: 93–107.

Sander, I.L., & Clark, F.B. 1971. Reproduction of upland hardwood forests in the central states. Agric Handb 405. U.S. Department of Agriculture, Forest Service, Washington, DC.

Soucy, R.D., Heitzman, E., & Spetich, M.A. 2005. The establishment and development of oak forests in the Ozark Mountains of Arkansas. Can. J. For. Res. 35: 1790–1797.

Theoharides, K.A., & Dukes, J.S. 2007. Plant invasion across space and time: factors affecting nonindigenous species success during four stages of invasion. New Phytol. 176: 256–273.

Therneau, T.M., & Atkinson, E.J. 2012. An introduction to recursive partitioning using the rpart routine. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.304.3759&rep=rep1&type=pdf Accessed 14 May 2018.

Van Haverbeke, D.F. 1990. Populus deltoides var. occidentalis Rybd. Plains cottonwood. In: Burns RM, Honkala BH (tech coords) Silvics of North America, Volume 2, Hardwoods. Agric Handb 654. US Department of Agriculture, Forest Service, Washington DC. pp 537–543.

Webster, C.R., Jenkins, M.A., & Jose, S. 2006. Woody invaders and the challenges they pose to forest ecosystems in the eastern United States. J. For. 104: 366–374.

Williamson, M., & Fitter, A. 1996. The varying success of invaders. Ecology. 77: 1661–1666.

Woudenberg, S.W., Conkling, B.L., O'Connell, B.M., LaPoint, E.B., Turner, J.A., & Waddell, K.L. 2010. The Forest Inventory and Analysis database: Database description and users manual version 4.0 for Phase 2. Gen. Tech. Rep. RMRS-GTR-245. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO.

Yu, W. 2011. Constructing spatial weight matrix using local spatial statistics and its applications. Masters thesis, Mississippi State University, Mississippi State, MS.