Modeling the presence of exotic invasive shrubs in West Michigan forests based on habitat characteristics

Heather Taylor[1], and Sophie Bennett[1]

Dr. Alexandra Locher[2], Dr. Todd Aschenbach[2],

1 - Student Researcher, Grand Valley State University, Natural Resource Management

2 - Faculty Mentor, Grand Valley State University, Natural Resource Management

Abstract

The eradication of invasive species costs the U.S. government over 1 billion dollars annually. In order to more efficiently fight the spread of invasives, predictive models can be constructed to guide land managers to hot spots where they are likely to occur. Forest type, canopy cover, soil properties, past treatment, and the presence of other invasive species were investigated as possible predictors for the presence of autumn olive (Elaeagnus umbellatus), honeysuckle (Lonicera maakii, L. morrowii, and L. tatarica), and multiflora rose (Rosa multiflora) in West Michigan hardwood forests. Both a logistic regression and a classification and regression tree (CART) were used to evaluate the power of these possible predictors. Using geographic information systems (GIS), the results from the logistic regression were interpolated producing a predictive map that reflected current distributions of these species as well as the possibility of future spread. The reported predictive power of the models as well as the visual similarity between the predicted and observed distribution further supported the viability of predictive models. These types of models would help land managers concentrate efforts towards areas of highest concern saving time and money.

1. Introduction

Major ecological and economic issues have developed across many regions of the world due to the spread of invasive plant species (Pimentel, 2002). Invasive species tend to be strong competitors with few natural deterrents in the area they infest. As they outcompete local species, they may alter the composition, structure, and function of native ecosystems. Such alterations may negatively affect consumptive and nonconsumptive forest resources such as timber and wildlife habitat. The presence of invasive plant species often leads to reduced populations of native species and damaged crops, forage, and infrastructure (Haight and Polasky, 2010).

The US government spends more than one billion dollars annually on invasive species control efforts (US National Invasive Species Council, 2006). Because treatment is costly, there is value in knowing where these populations are likely to occur and spread. Monitoring populations of invasive plants allows researchers to gather invaluable information about the extent of the problem and how to best apply treatment (Haight and Polasky 2010). While on the ground monitoring is valuable, detection may not occur until populations are so vast that observable damages can be linked to them. Likewise, even if a population is detected it can be difficult to determine the extent of its infestation (Haight and Polasky 2010).

However, on the ground monitoring is not the only way to anticipate invasive hotspots. Recently, numerous predictive and habitat suitability models for invasive species have been constructed (McDonald et al. 2008; Andrew and Ustin 2009; Ibenez et. al 2009; David and Menges 2011). These models can be translated into GIS-based risk maps that allow natural resource managers to predict where source populations of invasive species are likely to occur (Moore et al. 2013). To create risk maps and target possible hot spots early, it is important to understand factors that lead to invasion (Iáñez et al. 2009, Brym et al. 2011). Many factors are easily assessed the in the field and subsequently may be incorporated into models to predict occurrence of invasive plants (Crall et al., 2013). Such factors include forest type, canopy cover, soil properties, and the presence of other invasive species. Past research illuminates possible relationships between habitat characteristics and invasive species presence. For example, Parks et al. (2005) found that the more intact a forest ecosystem, the less likely it was to support invasive species. Researchers have hypothesized that increased native plant diversity could limit the degree to which an invasive plant proliferates at a given site (Elton, 1958; Lodge, 1993; Lonsdale, 1999; Davies et al., 2007). This research highlights the importance of considering forest structure when constructing predictive models.

Another trait to consider is canopy cover. Numerous studies have found that the incidence of invasive species is often associated with canopy gaps and areas of recent disturbance, but are limited in closed canopy forests (Iáñez et al. 2009; Spence et al. 2011; Moore et al. 2013; Banasiak and Meiners 2009). Open areas often serve as source populations for invasive species, and surrounding forest gaps may be more likely to become subject to invasive infiltration (Pauchard and Alaback 2004, McDonald and Urban 2006).

Soil properties may also be important factors when determining the likelihood of invasive species establishment. Past research has illustrated that invasive species such as Japanese barberry (*Berberis thunbergii*), multiflora rose, and oriental bittersweet (*Celastrus orbiculata*) were significantly correlated with low C:N ratios (Greenberg et al. 1997; Lungren et al. 2004; Huebner and Tobin 2006; McDonald et al. 2008). Lower C:N ratios are often correlated with increases in plant available soil nitrogen (Brady and Weil 2002). Autumn olive is a known nitrogen fixer (Moore et al. 2013) and may affect the C:N ratio of the soil, thus impacting the suitability of an area to support other plants. In other words, autumn olive would have a competitive advantage in areas with low soil nitrogen levels, i.e. low C:N ratios.

The presence of other invasives may also be an important predictor. If more than one invasive species benefits from the same factors, then the performance and abundance of one invasive species likely may be related to the abundance and performance of others (Moore et al. 2013). This idea has been supported in past research. One study found that the average height and density of autumn olive in a managed forest landscape was positively related to that of other invasive plants on south- and east-facing aspects (Moore et al. 2013). Another study found that the presence of multiflora rose was positively correlated with Japanese barberry and round-leaved navel-wort (*Cotyledon orbiculata*) (McDonald et al. 2008).

The ultimate goal of this study was to understand environmental factors and past management practices that may affect presence of autumn olive (*Elangus umbellatus*), multiflora rose (*Rosa multiflora*), and invasive honeysuckle (*Lonicera maakii, L. morrowii, or L. tatarica*) in a hardwood forest in west Michigan. Our objectives were to 1) model the current distribution of the invasive plants in our study area, 2) develop predictive models to quantify the probability of presence based on environmental factors and management activities, and 3) create a risk map that illustrates which areas may be priorities for control or eradication.

2. Methods

This study was conducted at Pierce Cedar Creek Institute between May 5 and June 7, 2014. The Institute is located on 661 acres within Barry County, Michigan. The landscape includes young and old growth forests, prairies, wetlands, and Brewster Lake. We stratified the study area based on forest type and past treatment of invasive plants. The four forest types included old growth mixed hardwoods, old growth oak, young oak/hickory, and young mixed hardwoods. Three management types were explored: treated, burned, and untreated. Chemical treatment involved a cut stump technique with the application of 20% glyphosate. Chemical treatment occurred between the years of 2007 and 2013. Volunteers and the Institute staff performed a control burn in the Spring of 2010 as a form of invasive species treatment. Untreated areas received neither chemical treatment nor were burned. We collected 17 preliminary soil samples which were used to eliminate possible confounding variables and to develop a stratified sampling protocol. It was found that overall the soil textural class was homogeneous throughout the sampled areas, therefore we did not stratify based on soil type. For this study we stratified by both forest type and treatment type.

We used ArcGIS software v 10.1 (Environmental Systems Research Institute, Redlands, California, USA) to view shapefiles provided by the Institute that displayed all ecosystem types and treatment types on the property. We isolated areas of interest and established a systematic sampling grid (resolution = 100 feet) within each forest type (Figure 1).

We used a Thales Mobile Mapper to navigate to each point identified in the sampling grid. A 1/100th acre area (11.8 foot radius) surrounding each point was surveyed for the stem counts of autumn olive and invasive honeysuckle and the percent cover of multiflora rose. Using Nikon 16 megapixel digital camera, we took an image of the canopy by holding the camera parallel to the ground approximately one foot above the center of the plot. Soil samples were taken at every third point (figure from the center of the plot using a soil probe and stored at 40º F until all sampling was concluded to prevent any flux in nitrogen levels.

Once sampling was completed, soil samples were brought to Grand Valley State University for processing. First, we air dried the soil and passed it through #10 (2mm) sieves. Next, we measured soil pH by adding 10 g of soil to 10 ml of deionized water. This mixture was left to sit for approximately 10 minutes before measurement with an Oakton pocket pH tester. To assess organic matter, we ensured all moisture was removed from each soil sample by baking them at approximately 105 °C for 24 hours. We baked crucibles in a muffle furnace at 500 °C for two hours to remove all moisture and then weighed them. After drying, we processed the soils through a finer sieve (0.300mm) to remove large debris, added approximately 10–15 g of soil to a dry crucible, and determined a weight of the soil and crucible combined. We baked the combined crucible and soil samples in a muffle furnace at 500 °C for 5 hours. After this period, we assumed all organic matter had been burned away and the loss in weight represented the amount of organic matter originally present. We calculated the percent organic matter by dividing the weight of the processed sample by the weight of the sample before baking (minus the weight of the crucible). The remaining portion of the soil samples were sent to the Annis Water Resources Institute for nitrogen analysis.

Canopy cover was measured by analyzing the digital photos with ImageJ software. The program converts the photo into black trees against a white sky and reports the percent of the photo comprised of black pixels. Because sampling began early in the season, not all photos portrayed leaf-on canopy cover. We made the assumption that leaves would extend to the tips of the branches and added them to the photos using GIMP Photo Editor 2 (2014) prior to processing with ImageJ (Rasband, 2014).

To model the probability of invasive species presence based on the collected variables, we used logistic regression where invasive species presence was the dependent variable and soil pH, soil texture, percent organic matter, percent nitrogen, overstory canopy cover, forest type, treatment, and presence of other species were independent variables. Because soil samples were only collected at every third point, all soil-centric variables were interpolated in ArcGIS v 10.1 using inverse distance weighting (IDW) using a power of one and nearest neighbors of fifteen to provide a value for all sample points. We used SAS Enterprise Guide 4.3 (year 2012) to run the statistics. Backward stepwise selection was used to identify significant predictors and create the final model. The resulting model was spatially displayed within ArcGIS to better illustrate possible locations of each invasive species.

Because every model has limitations, an additional model was created to compare and contrast with the logistic regression. A classification and regression tree (CART) was constructed using the statistical package, R. Invasive species presence was the dependent variable and soil pH, soil texture, percent organic matter, percent nitrogen, overstory canopy cover, forest type, forest age, treatment, and presence of other species were used as independent variables.

3. Results

3.1 Summary of all Prospective Predictors

A chi-square test found a significant relationship between autumn olive present and forest type ($n = 452$, $p < 0.0001$). Autumn olive was present in 14% of sample points located in old forest mixed hardwood forests, 4% of sample points located in old forests oak, 50% of sample points in young forest mixed hardwoods and 30% of samples points in young forests oak (Figure 2). A chi-square test also found a significant relationship between honeysuckle presence and forest type ($n = 452$, $p < 0.0001$). Honeysuckle was absent from all points in old forest mixed hardwoods and old forest oak, but was present in 2% of sample points in young forest mixed hardwoods and 12% of sample points in young forest oak hickory. A significant relationship was also found between multiflora rose presence and forest type ($n = 452$, $p < 0.0001$). Multiflora rose was present in 62% of points in old forest mixed hardwoods, 32% of points in old forest oak, 80% of young forest mixed hardwoods and 65% of sample points in young forest oak hickory.

A chi-square test found a significant relationship between autumn olive presence and treatment type ($n = 453$, $p = 0.0011$). Autumn olive was present in 38% of sample points in burned areas, 58% of sample points where no treatment took place, and 30% or sample points in chemically treated areas (Figure 3). A chi-square test found a significant relationship between honeysuckle presence and treatment type ($n = 453$, $p = 0.0001$). Honeysuckle was present in 0.5% of sample points in burned areas, 4% of sample points in areas of no treatment, and 11% of areas that received chemical treatment. A chi-square test found a significant relationship between multiflora rose presence and treatment type ($n = 453$, $p = 0.0061$). Multiflora rose was present in 74% of burned areas, 82% or areas that received no treatment, and 63% or areas that were chemically treated.

Two sample t-tests were used to assess the differences in mean for quantitative variables where all conditions were met; wilcoxon ranked sum tests were used where t-tests were inappropriate and conditions for WRS were met (Table 1). It was found that pH was significantly lower in areas where autumn olive was present versus where autumn olive was absent ($n = 450$, $p=0.0005$). It was also found that pH was significantly higher where honey was present versus absent ($n =450$, $p=0.0196$). Canopy cover was found to be significantly lower where multiflora rose was present ($n =450$, $p=0.0986$). Due to abnormal distributions, a two sample t-test was not appropriate to test for significant differences of organic matter or canopy cover between areas where honeysuckle was present and absent. A wilcoxon ranked sum test was found to be appropriate to test organic matter, and found that the median percent organic matter was significantly lower where honeysuckle was found ($n = 450$, $p = 0.0236$). Wilcoxon signed rank was not appropriate to test canopy cover; this relationship remains untested.

3.2 Logistic Regression

A logistic regression model was fitted to each invasive species to predict the percent chance of seeing an invasive species occur based on gap size, soil pH, soil organic matter, treatment type, ecosystem type, and the presence of the other two invasive species (Table 2).

3.3 Autumn Olive

Ecosystem ($p < 0.0001$), multiflora rose presence ($p < 0.0001$), honeysuckle presence ($p = 0.0356$), treatment ($p = 0.0094$), and pH ($p < 0.0001$) were found to be significant predictors for autumn olive presence (n = 449) (Table 2). Autumn olive it was approximately 6 times more likely to be found in young forest mixed hardwoods than in young forest oak/hickory (Table 3). It was approximately one fifth as likely to occur in the absence of multiflora rose that in the presence of multiflora rose and approximately one third as likely to occur in the absence of honeysuckle than in the presence of honeysuckle. It was approximately one third as likely to be present in burned areas versus chemically treated areas. A negative relationship with pH was also found where every one unit increase of pH was associated with a decrease in odds of approximately two thirds. The usefulness of this model is good, with an estimated accuracy of 80% .

The resulting predictive map reflects current autumn density (Figure 4). The model seems to do particularly well in the northern section of the property. However, the area of high concentration in the eastern end of the southern portion is not mirrored in the prediction.

3.4 Invasive Honeysuckle

Treatment (p = 0.0007) and canopy cover (p = 0.0044) were found to be significant predictors for the presence of honeysuckle (n = 452) (Table 2). The odds of honeysuckle suckle occurring in burned areas were 4/125ths the odds of autumn olive occurring in chemically treated areas (Table 4). The odds of honeysuckle occurring in areas of no treatment were one fifth as great as the odds of honeysuckle suckle occurring in areas that received chemical treatment. A negative relationship with canopy cover was also found where every one percent increase in cover is associated with 3.6% decreased odds. It was also found that the odds of honeysuckle occurring in the absence of autumn olive was about one fifth as much as in the presence of autumn olive. The usefulness of this model is good, with an estimated accuracy of 86% (Table 2).

The predictive map constructed from this model mirrors well the observed population of honeysuckle in the northeastern section of the southern portion of the study area (Figure 5). The predictive map suggests a possible population in the northern most portion of the study area that is not yet observed.

3.5 Multiflora Rose

Ecosystem (p = .0041) and autumn olive presence (p < .0001) were found to be significant predictors for the presence of multiflora rose (Table 2). The odds of multiflora rose occurring in old growth was about one third the odds of multiflora rose occurring in young forest oak hickory (Table 5). The odds of of occurrence were 72% higher in young forest mixed hardwoods than in young forest oak/hickory. It was also found to be about one fifth as likely to occur in the absence of autumn olive than in the presence of autumn olive. The usefulness of this model is fair with an estimated accuracy of 71%.

The predictive map created from this model, like that of autumn olive, reflects well the population of multiflora rose in the northern section of the property (Figure 6). However, the southern section is not quite as defined.

3.6 Classification and Regression Tree

The classification and regression tree (CART) uses a recursive partitioning method to create a decision tree based on binary variables which can be used to make predictions about dichotomous outcomes; ie “Will autumn olive be present or absent?” The decision tree not only identifies the most influential variables by placing them near the top but also provides threshold conditions. The tree itself may be read as a flow chart. Begin at the top and follow the questions till a terminal node is reached and an outcome is identified.

CART identified multiflora rose presence, pH, organic matter, and ecosystem age as the most important predictors for autumn olive presence (Figure 7). The strength of this model is fair with a predictive power of 73%. For multiflora rose, autumn olive presence, canopy cover and percent organic matter were identified as important predictors (Figure 8). The strength of this model is fair with a predictive power of 76%. The total number of sample points containing honeysuckle was too small to properly construct a decision tree.

4. Discussion

Illuminating the relationships between environmental factors, past management practices, and invasive species presence was an important purpose of this study. Some of these relationships proved to be significant as predictors of the presence of autumn olive, multiflora rose, and invasive honeysuckle. Quantifying information such as this and investigating the trends that are illuminated can help land managers anticipate future invasive hot spots. Furthermore, incorporating these relationships into a risk map can help organize control efforts.

Models are very simplified versions of reality, and so all models have some limitations. In acknowledgement of this, we chose to build two models. By comparing them, we intended to highlight important relationships by identifying predictors that occur in both models and comparing the predictors that only occur in one of the two. We are able to do these comparisons for autumn olive and multiflora rose only, since we could not construct a CART model for honeysuckle.

For autumn olive, both models identified multiflora rose presence, ecosystem or ecosystem age, and pH as important predictors. Logistic regression also identified honeysuckle presence and treatment type as important predictors were CART did not. CART identified organic matter as an important predictor where logistic regression did not. The overlap here suggest that the shared variables are indeed important predictors. It is interesting to find percent organic matter chosen as an important predictor by CART because it was not shown to differ significantly between areas of autumn olive presence or absence by the two sample t-test.

For multiflora rose, autumn olive presence was identified as a significant predictor by both models. Ecosystem type was identified by logistic regression alone. Canopy cover and percent organic matter were identified as important predictors by CART alone. It is not surprising to see autumn olive presence identified by both models. The maps of observed occurrence of autumn olive and multiflora rose overlap to such a degree, that this association would be strongly suspected. However, it is very surprising to see organic matter identified by CART since the two sample t-test did not provide evidence for a significant difference in percent organic matter between areas with multiflora rose presence and absence.

CART has identified organic matter as an important variable even though it had no other signs of significance. This difference is likely due to the recursive partitioning process. Percent organic matter is not a significant predictor for autumn olive when looking at the entirety of the population of interest. But, if the population is narrowed down to include only only areas with a pH < 5.4 in old growth oak forests, it becomes significant. Likewise, percent organic matter was not a significant predictor for multiflora rose when considering the whole population, but it became significant when narrowed down to include only areas where percent canopy cover was greater than 70.74%. The different structure of the models has resulted in slightly different outcomes, but these differences improve our understanding of the relationships between environmental factors and invasive species growth.

The logistic regression identified forest type as a significant predictor for autumn olive and multiflora rose. In both cases, the model suggested that invasive presence was more likely in second growth forests. This finding was mirrored by CART, which found forest age to be a significant predictor for autumn olive. This result is in agreement with past studies (Parks et al., 2005; Davies et al., 2007; Elton, 1958; Lodge, 1993; Lonsdale, 1999). Additionally, it was more likely to find these invasives in young forest mixed hardwoods than in young forest oak/hickory. More research must be done to illuminate the reasons behind this relationship. Land managers should consider that second growth forests are more likely to contain autumn olive and multiflora rose than old growth forests when planning management activities.

Autumn olive presence was a significant predictor for both multiflora rose and honeysuckle presence. The tendency of the other invasives to be found near autumn olive may be due to similar habitat preferences (Moore et al. 2013), although there was no such relationship between multiflora rose and invasive honeysuckle. Perhaps autumn olive's ability to fix nitrogen (Schlesinger and Williams, 1984) encourages the growth of the other invasives near it by improving soil conditions. A previous study observed multiflora rose growing more rapidly than native species when there were experimental increases in the soil fertility (Gurevitch et al. 2008). In either case, land managers should consider that autumn olive is more likely to be found with multiflora rose and invasive honeysuckle nearby, than it is to be found by itself.

Treatment type was a significant predictor for autumn olive and invasive honeysuckle presence. Autumn olive presence was less likely in chemically treated areas than in burned and untreated areas. This suggests that the treatment has been working. However, our data cannot speak to the efficacy of the treatment since it only covers one season. Honeysuckle was most likely to be found in areas that received chemical treatment. This suggests that treatment is not working at all. However, because the area occupied by honeysuckle is relatively small, it is entirely possible that the treatment boundary completely enclosed the area that honeysuckle had established itself and set seeds in the seed bank, so the specimens we found grew in after treatment took place. Again, since only one year's worth of data was collected, we cannot speak to the efficacy of treatment.

Some studies do assert, however, that in the case of autumn olive, growth can be encouraged by practices such as burning, cutting, and girdling. Some researchers believe that burning is especially ineffective as it can stimulate vigorous production of new shoots within the plant (Kuhns 1986; Darlington 1994; Reed 1992; and Szafoni 1989). Staff at the the Institute may benefit by continued monitoring to make sure this trend does occur.

Soil pH was only a significant predictor for autumn olive. This invasive species was more likely to be seen in areas with low pH levels, which are indicative of poor soil fertility (Huebner et al. 2014). Past research has concluded that soil fertility was an adequate predictor of the establishment of invasive shrubs (Huebner et al. 2014). Perhaps autumn olive's ability to fix nitrogen gives it a competitive advantage in poor soils. Although soil pH is not as easily gauged as forest type, past treatment, and other invasive presence, testing pH may help managers gauge the possibility of autumn olive spreading to a certain area.

Canopy cover was a significant predictor for invasive honeysuckle. The shrub was more likely to be found in areas with less cover. Many other studies have found invasive species occurrence more likely in open areas (Iáñez et al. 2009; Spence et al. 2011; Moore et al. 2013; Banasiak and Meiners 2009), and we were expecting canopy cover to be significant for all three invasive species of interest. Perhaps honeysuckle is simply the least shade tolerant of the invasive species explored in this study. It has been noted that multiflora rose can persist under closed canopy conditions (Huebner 2003; Huebner and Tobin 2006). However, because our entire study occurred within a closed canopy forest with little variation in the canopy cover, and with many data points as estimations, we refrain from dismissing its importance as a predictor.

It must be mentioned that we cannot assign cause and effect based solely on this study. The observational nature and limited timescale of this study does not support such claims. For example, we cannot use our data to decide whether autumn olive was more likely to be found in areas with low pH because it prefers these areas or because its presence lowers pH; we can only say that the relationship between pH and autumn olive presence is a useful predictor in our study area and alert land managers to this pattern.

It is also important to note that the population on honeysuckle in our study was quite low compared to the other invasive species present, so this model may not accurately reflect the final spread of this invasive. Past studies have explored the spread of this shrub, and suggest that a lag phase may be a precursor to sudden, tremendous growth (Hobbs and Humphries, 1995). Ryan Deering and John Vankat also studied the establishment and development of invasive honeysuckle within a forest ecosystem. Their study indicated that during the first ten years, from when invasive species was detected, population growth was slow. This was surprising since invasive honeysuckle can begin reproduction by age 5. They posited that this was probably due to low population numbers where there was little opportunity for cross pollination to occur. Also, the seed production of the original colonizers may have been slow due to their position in the forest ecosystem. As determined by their observation, they found that interior forest colonizers produce far fewer seeds than edge colonizers (Deering and Vankat 2009). Their analysis suggests that this is most likely due to the fact that sunlight availability and canopy structure has a large influence on height and basal area, which are important factors in determining when a plant can begin seed production. Ultimately, due to the canopy limitations of a forested ecosystem, evidence such as this could explain why we found few individuals of invasive honeysuckle at Pierce Cedar Creek. It may also explain both its current and predictive spatial distribution (figure 6). It may be worthwhile to study this invasive further over time.

Conclusion

This study was conducted to determine if forest type, canopy cover, soil properties, the presence of other invasive species, and past treatment are significant predictors for the presence of autumn olive, honeysuckle, and multiflora rose in West Michigan forests. This information is sought after to aid management crews locate possible hot spots and improve the success of invasive treatment. Although not all possible predictors were found to be significant for all species of interest, the models created were reasonably strong and were successfully used to create predictive maps.

The final products of our study are these predictive maps. They reflect the observed distribution of invasive species and highlight areas of possible spread. When time, money, and manpower are scarce, delegating resources efficiently is vital to effectively treating the spread of invasive species. However, land managers are often required to use incomplete information. (Haight & Polaski, 2010) Predictive models in the form of spatial imagery may help alleviate this problem (Moore et al., 2013) and our research further validates the use of such models.

Table 1. Summary of quantitative variables. Significance tested with two sample t-test unless specified.

		Autumn Olive		Honeysuckle		Multiflora Rose	
		Present	Absent	Present	Absent	Present	Absent
Soil pH	Average	5.2692	5.4572	5.5506	5.3799	5.3883	5.3895
	Standard Dev	0.4515	0.5619	0.3569	0.5383	0.5155	0.5698
	Significance	**Pr < t = .0002**		**Pr > t = .0196**		Pr < t = 0.4916	
Organic Matter	Average	4.3281	4.2894	4.129**	4.25**	4.3432	4.2100
	Standard Dev	0.8624	0.9234	0.6639	0.9084	0.8902	0.9222
	Significance	Pr > t = 0.3281		**Pr < Z = 0.0236****		Pr > t = 0.7905	
Canopy Cover	Average	65.8744	66.4467	65.935	69.457	65.6438	67.6239
	Standard Dev	12.3595	15.5628	19.0909	14.1252	14.0829	15.2883
	Significance	Pr < t = 0.3335		NA		**Pr < t = 0.0986**	

** indicates that the measure of center is the median, significance tested with Wilcoxon ranked-sum.

Table 2. Analysis of the logistic regression for the predictive variables for the presence of autumn olive, invasive honeysuckle, and multiflora rose at Piece Cedar Creek Institute, June 2014.

Invasive Species Presence	Effect	Pr>ChiSq	ROC (Area Under Curve)
Autumn olive	Ecosystem	<.0001	0.8013
	Multiflora Rose Presence	<.0001	
	Invasive Honeysuckle Presence	0.0356	
	Autumn Olive Treatment	0.0094	
	Soil pH	<.0001	
Invasive honeysuckle	Autumn Olive Presence	0.0085	0.8597
	Honeysuckle Treatment	0.0007	
	Canopy Cover	0.0044	
Multiflora rose	Ecosystem	0.0041	.7158
	Autumn Olive Presence	<.0001	

Table 3. Odds ratio estimate for the presence of autumn olive at Pierce Cedar Creek Institute, June 2014

Effect	Point Estimate	95% Wald Confidence Limits	
Old Growth Mixed Hardwood vs Young Forest Oak/Hickory	0.727	0.178	2.963
Old Growth Oak vs Young Forest Oak/Hickory	0.138	0.017	1.089
**Young Forest Mixed Hardwoods vs Young Forest Oak/Hickory	6.098	2.145	18.180
**Multiflora Rose Absent vs Multiflora Rose Present	0.202	0.111	0.368
**Honeysuckle Absent vs Honeysuckle Present	0.362	0.141	0.934
**Burned vs Chemical Treatment	0.290	0.096	0.872
No Treatment vs Chemical Treatment	0.711	0.202	2.510
**pH	0.317	0.195	0.516

** indicates that the confidence interval does not contain one

Table 4. Odds ratio estimate for the presence of invasive honeysuckle at Pierce Cedar Creek Institute, June 2014

Effect	Point Estimate	95% Wald Confidence Limits	
**Autumn Olive Absent vs. Autumn Olive Present	0.285	0.112	0.726
**Burned vs. Chemical Treatment	0.032	0.004	0.245
**No Treatment vs. Chemical Treatment	0.186	0.041	0.854
**Canopy Cover	0.965	0.942	0.989

** indicates that the confidence interval does not contain one

Table 5. Odds ratio estimate for the presence of multiflora rose at Pierce Cedar Creek Institute, June 2014

Effect	Point Estimate	95% Wald Confidence Limits	
Old Growth Mixed Hardwood vs Young Forest Oak/Hickory	1.069	0.544	2.102
**Old Growth Oak vs Young Forest Oak/Hickory	0.341	0.136	0.853
**Young Forest Mixed Hardwoods vs Young Forest Oak/Hickory	1.722	1.055	2.810
**Autumn Olive Absent vs. Autumn Olive Present	0.205	0.116	0.362

** indicates that the confidence interval does not contain one

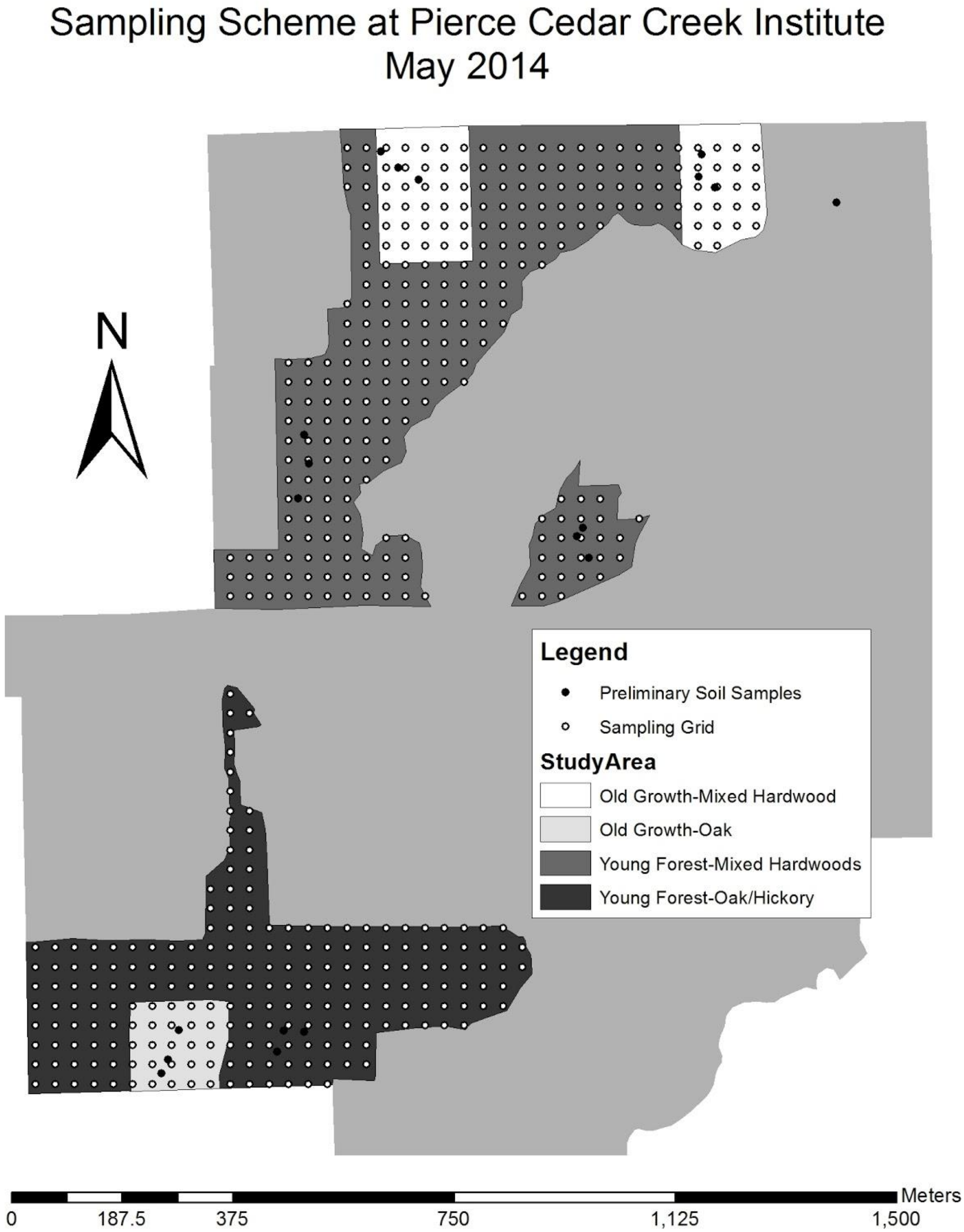

Figure 1. This map illustrates the systematic sampling plan, by forest type and treatment type.

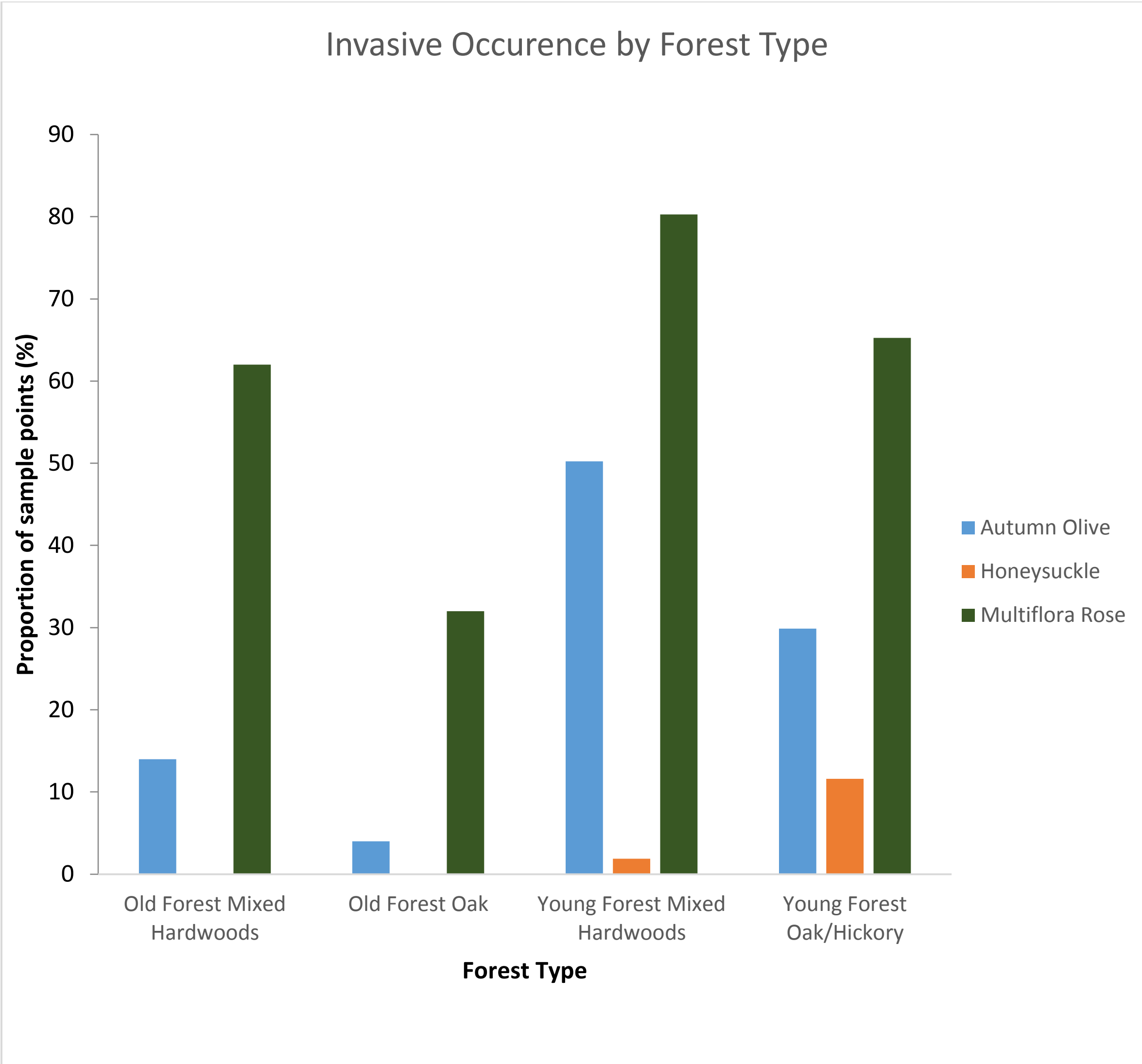

Figure 2. Autumn olive presence vs. absence by forest type, Pierce Cedar Creek institute, June 2014

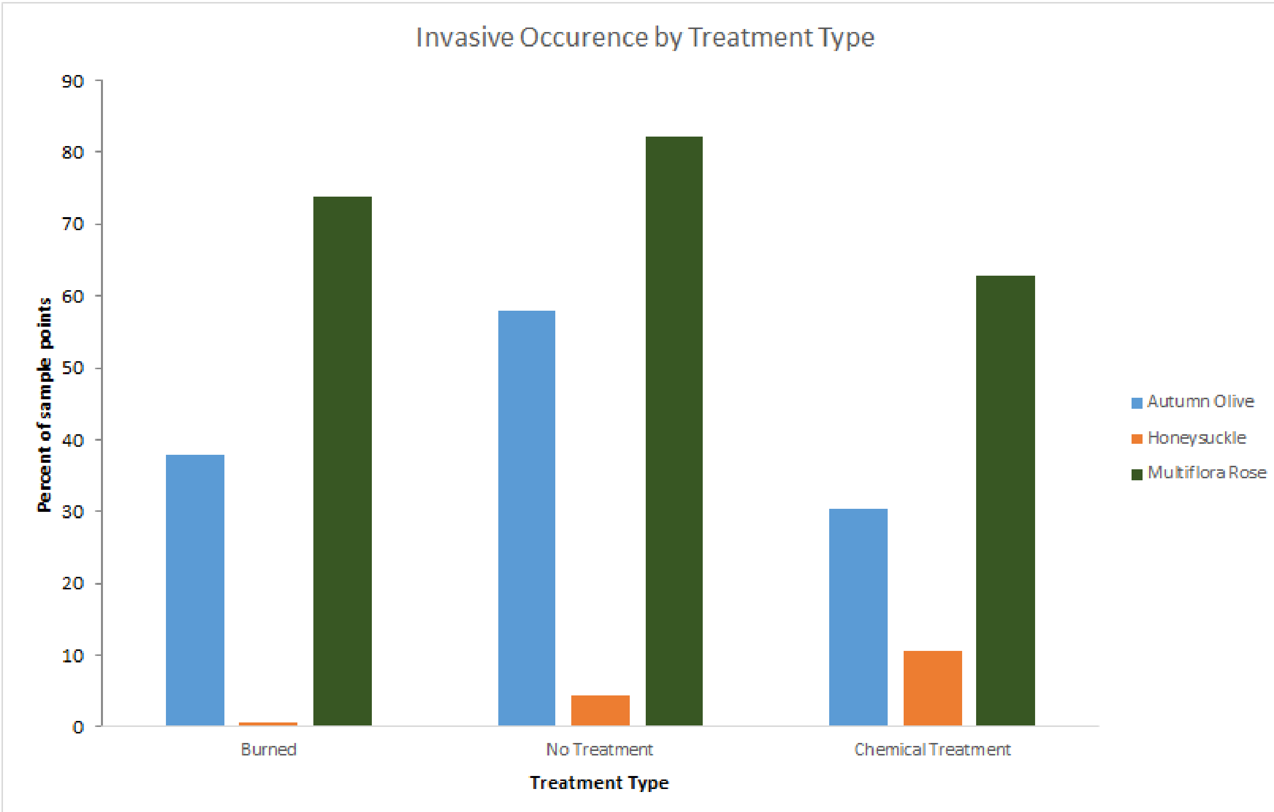

Figure 3. Observed density vs. predicted chance of occurrence of autumn olive occurrence, Pierce Cedar Creek Institute, 2014.

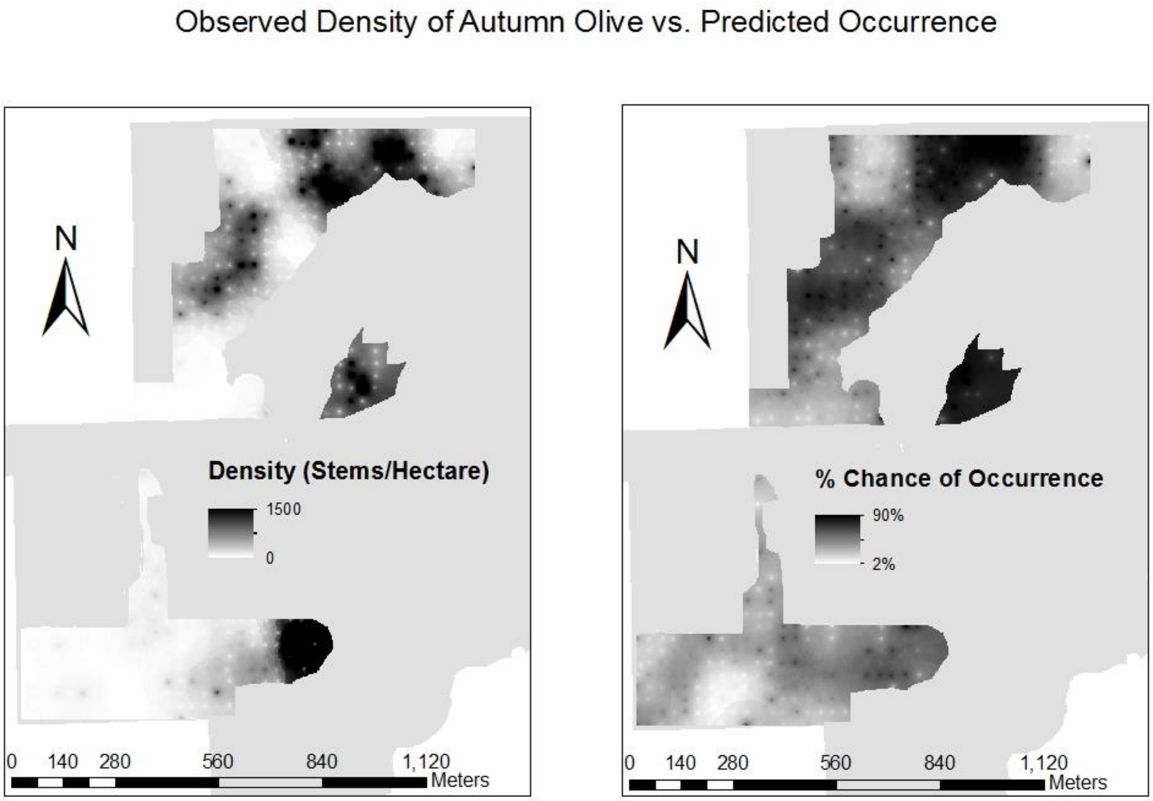

Figure 4. Observed density vs. predicted chance of occurrence of autumn olive, Pierce Cedar Creek Institute, 2014.

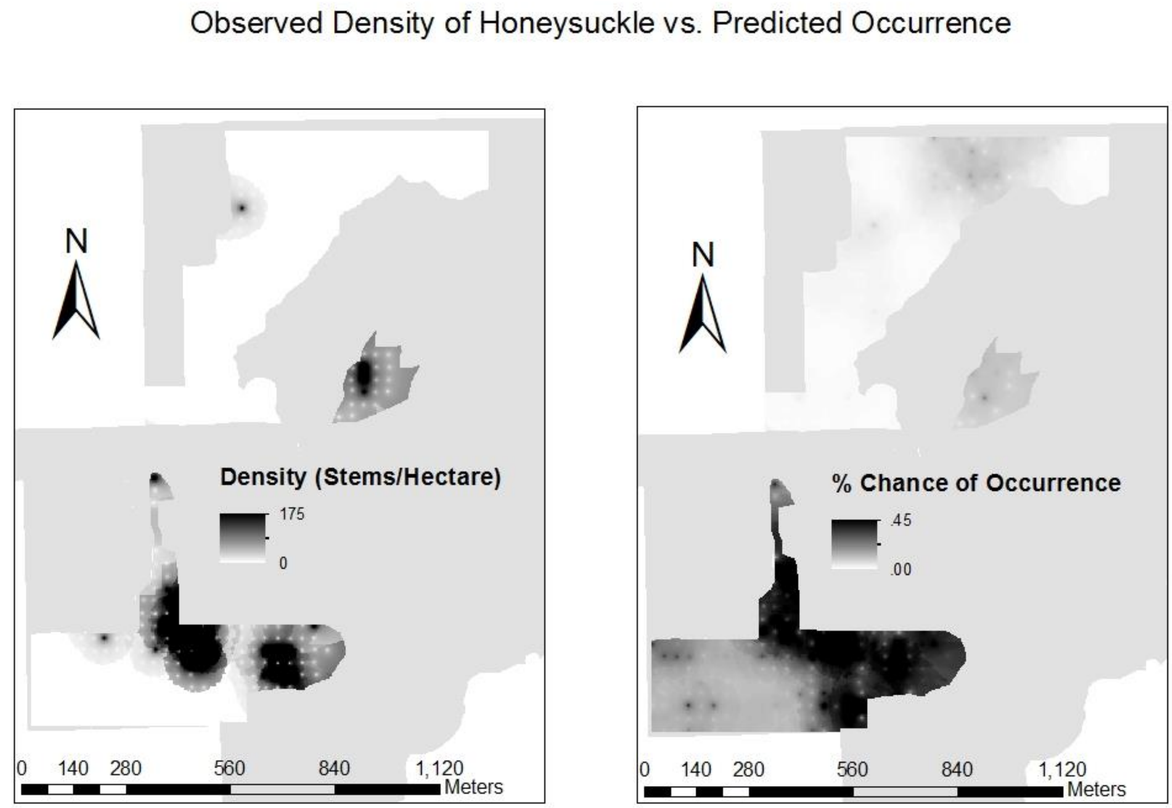

Figure 5. Observed density vs. predicted chance of occurrence of honeysuckle, Pierce Cedar Creek Institute, 2014.

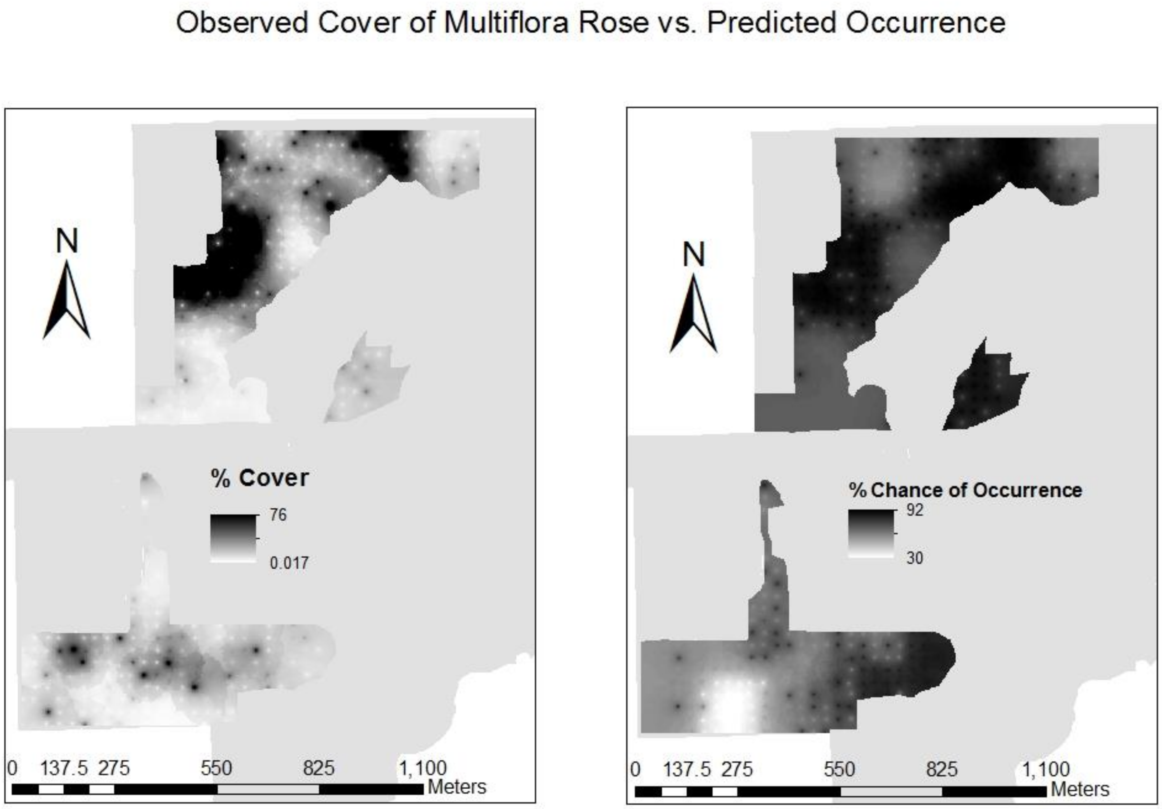

Figure 6. Observed density vs. predicted chance of occurrence of multiflora rose, Pierce Cedar Creek Institute, 2014.

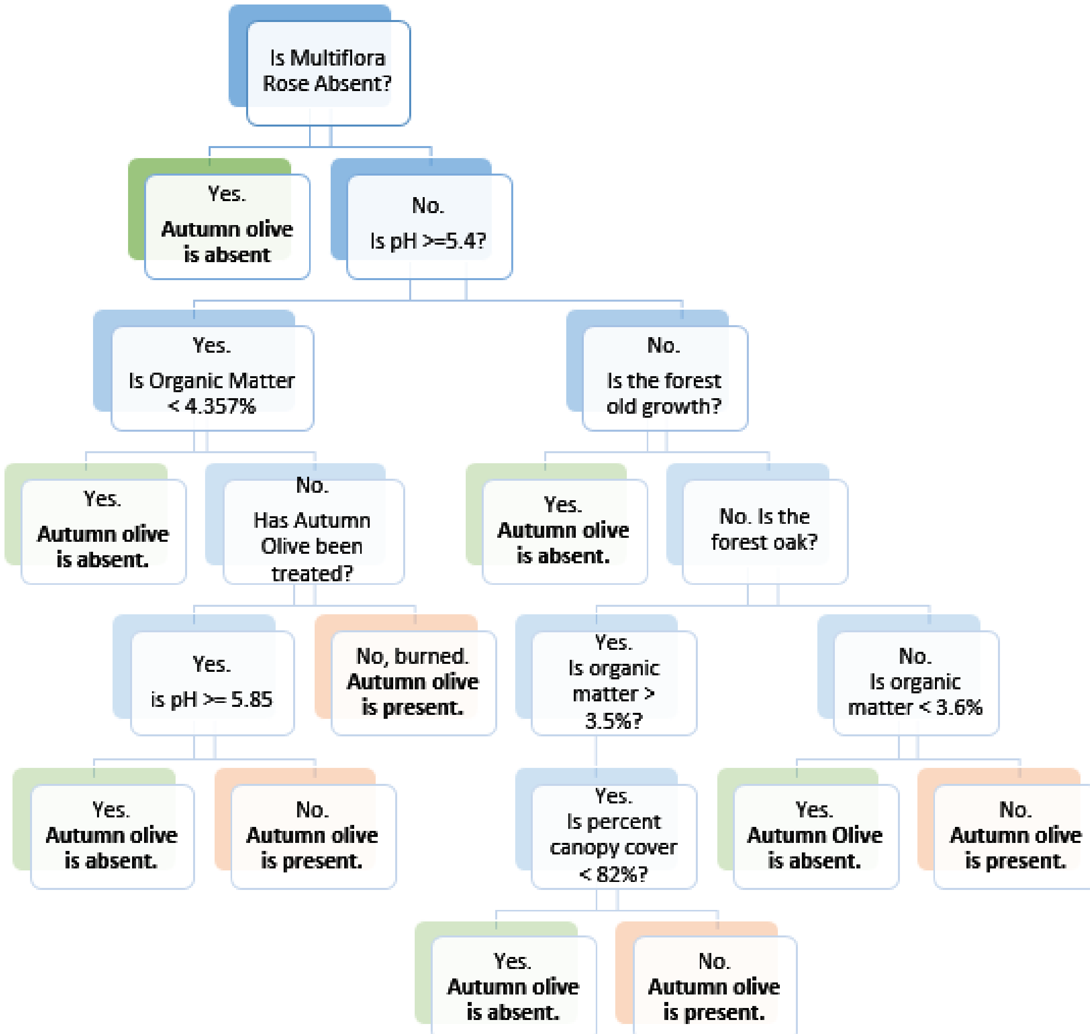

Figure 7. Classification and regression tree for predicting whether autumn olive will be present, Pierce Cedar Creek Institute, 2014.

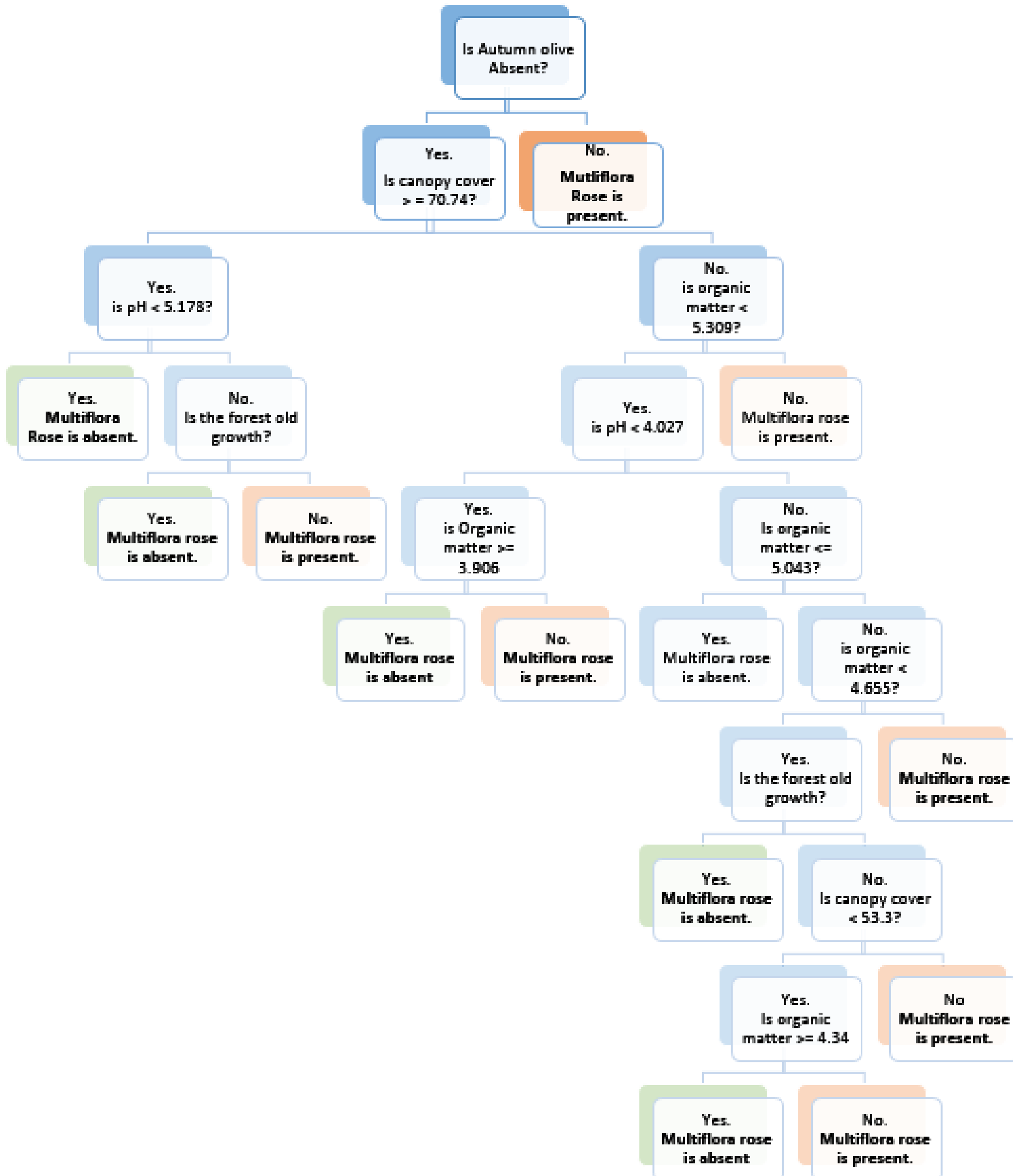

Figure 8. Classification and regression tree for predicting multiflora rose will be present, Pierce Cedar Creek Institute, 2014.

References

Andrew, M. E., and S. L. Ustin (2009) “Habitat suitability modeling of an invasive plant with advanced remote sensing data.” Diversity and Distributions 15: 627-40

Banasiak SE, Meiners SJ (2009) Long term dynamics of Rosa multiflora in a successional system. Biol Invasions 11:215–224

Brady, N. C., R. R. Weil (2002) The nature and properties of soil, 13th edition. Prentice Hall, Upper Saddle River, New Jersey, USA.

Brym, Z., J. K. Lake, D. Allen, and A. Osting (2011) Plant functional traits suggest novel ecological strategy for an invasive shrub in an understory woody plant community. Journal of Applied Ecology. 48(5): 1098-1106.

Crall, Alycia W., Catherine S. Jarnevich, Brendan Panke, Nick Young, Mark Renz, and Jeffrey Morisette (2013) “Using habitat suitability models to target invasive plant species surveys.” Ecological applications 23.1: 60-72

Darlington, J., Loyd, B.M., (1994) Control of autumn olive, multiflora rose, and tartarian honeysuckle. USDA Soil Conservation Service.

David, A. S., and E. S. Menges (2011) “Microhabitat preference constraints invasive spread of non-native natal grass (*Melinis repens*).” Biological Invasions 13: 2309-22

Davies, K.F., Harrison, S., Safford, H.D., Viers, J.H., (2007) Productivity alters the scale dependence of the diversity-invasibility relationship. Ecology 88 (8), 1940–1947.

Deering, Ryan H., and John L. Vankat (2009) "Forest colonization and developmental growth of the invasive shrub lonicera maackii." The American Midland Naturalist 141.1: 43-50.

Elton, C.S., (1958). The Ecology of Invasions by Animals and Plants. John Wiley & Sons Inc., New York, pp. 117.

Greenberg CH, Crownover SH, Gordon DR (1997) Roadside soils: a corridor for invasion of xeric scrub by nonindigenous plants. Nat Areas J 17(2):99–109

Gurevitch J, Howard TG, Ashton IW, Leger EA, Howe KM, Woo E, Lerdau M (2008) Effects of experimental manipulation of light and nutrients on establishment of seedlings of native and invasive woody species in Long Island, NY forests. Biol Invasions 10:821–831

Haight, Robert G., and Stephen Polasky (2010) "Optimal control of an invasive species with imperfect information about the level of infestation." Resource and energy economics 32.4 (2010): 519-33.

Hobbs, R. J. and S. E. Humphries. (1995) An integrated approach to the ecology and management of plant invasions. Conserv. Biol., 9:761-770.

Huebner CD (2003) Vulnerability of oak-dominated forests in West Virginia to invasive exotic plants: temporal and spatial patterns of nine exotic species using herbarium records and land classification data. Castanea 1–14

Huebner CD, Tobin PC (2006) Invasibility of mature and 15-year-old deciduous forests by exotic plants. Plant Ecol 186(1):57–68

Huebner, Cynthia D., et al. (2014) "The distribution of a non-native (rosa multiflora) and native (kalmia latifolia) shrub in mature closed-canopy forests across soil fertility gradients." Plant and Soil 377.1 (2014): 259-76.

Iáñez, I., J. A. Silander Jr., J. M. Allen, S. A. Treanor, and A. Wilson (2009) Identifying hotspots for plant invasions and forecasting focal points of further spread. Journal of Applied Ecology. 46(6): 1219-1228.

Ibañez, I., Silander Jr., J.A., Allen, J.M., Treanor, S.A., Wilson, A., (2009) Identifying hotspots for plant invasions and forecasting focal points of further spread. J. Appl. Ecol. 46, 1219–1228.

Kuhns L. J. (1986) Controlling autumn olive with herbicides. Proceedings, 40th annual meeting of the Northeast Weed Science Society, 289-294.

Lodge, D.M., (1993) Biological invasions: lessons for Ecology. Tree 8 (4), 133–137.

Lonsdale, W. (1999) Global patterns of plant invasions and the concept of invasibility. Ecology 80: 1522-1536.

Lungren MR, Small CJ, Dreyer GD (2004) Influence of land use and site characteristics on invasive plant abundance in the Quinebaug Highlands of Southern New England. Northeastern Nat 11(3):313–332

McDonald, R. I., G. Motzkin, and D. R. Foster (2008) Assessing the influence of historical factors, contemporary processes, and environmental conditions on the distribution of invasive species. The Journal of the Torrey Botanical Society. 135(2): 260-271.

McDonald, R. I, D. Urban (2006) Edge effects on species composition and exotic species abundance in the North Carolina piedmont. Biological Invasions. 8(5): 1049-1060.

Moore, M., D. S. Buckley, W. E. Klingeman III, and A. M. Saxton. (2013) Distribution and growth of autumn olive in a managed forest landscape. Forest Ecology and Management. 310: 589-599.

National Invasive Species Council (NISC) Fact Sheet Fiscal Year (2006). National Invasive Species Council Fiscal Year 2006 Interagency Invasive Species Performance-based Crosscut Budget. online source: Invasive Species: The National Invasive Species' Information System. (http://www.invasivespeciesinfo.gov/council/main.shtml).

Parks, C., S. R. Radosevich, B. A. Endress, B. J. Naylor, D. Ansinger, L. J. Rew, B. D. Maxwell, K. A. Dwire (2005) Natural and land-use history of the Northwest mountain ecoregions (USA) in relation to patterns of plant invasions. Perspectives in Plant Ecology, Evolution and Systematics. 7(3): 137-158.

Pauchard, A. and P. B. Alaback (2004) Influence of elevation, land use, and landscape context on patterns of alien plant invasion along roadsides in protected areas of south-central Chile. Conservation Biology 18: 238-248.

Pimentel, D., editor (2002) Biological Invasions: Economic and environmental costs of alien plant, animal, and microbe species. CRC Press, Boca Raton, Florida, USA.

Rasband, W.S., ImageJ, U. S. National Institutes of Health, Bethesda, Maryland, USA, http://imagej.nih.gov/ij/, 1997-2014.

Reed William R. (1992) *Elaeagnus umbellata* http://www.fs.fed.us/database/feis/plants/shrub/elaumb.html Accessed: 9/24/00

Schlesinger, R.C., Williams, R.D., (1984) Growth response of black walnut to interplanted trees. For. Ecol. Manage. 9, 235–243.

Spence, L. A., J. V. Ross., S. K. Allen, and D. A. Coomes (2011) Disturbance affects short-term facilitation, but not long-term saturation of exotic invasion in New Zealand forest. Proceedings of the Royal Society of B Sci. 1457-1466.

Szafoni B. (1989) Vegetation Management Guideline – Autumn Olive http://www.inhs.uiuc.edu/edu/VMG/autolive.html Accessed: 10/24/00

SAS Institute. 2012. The SAS system for Windows. Release 9.2. SAS Inst.., Cary, NC.

The GIMP team, GIMP (9.02.14). www.gimp.org, 1997-2014, retrieved on June 2014.