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Where's woolly? An integrative use of remote sensing to improve predictions of the spatial distribution of an invasive forest pest the Hemlock Woolly Adelgid

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ABSTRACT

Non-native pests and pathogens present serious challenges to the management of forested ecosystems around the world. Early detection of pest and pathogen invasions may allow timely control and prevention methods to be implemented. Species distribution models (SDMs) and remote sensing (RS) methods have both been used effectively to determine locations of pest and pathogen damage. However, previous work integrating these two methods has rarely used RS metrics that have biological meaning. We use RS difference indices that show changes in forest cover from defoliation in order to map Hemlock Woolly Adelgid (HWA), *Adelges tsugae*, locations using MaxEnt in the Delaware Water Gap National Recreation Area (DWGNRA). Brightness, greenness, wetness, and Normalized Difference Vegetation Index (NDVI) were calculated from Landsat Thematic Mapper (TM) images for December 1982 and 2010. A difference for each index was created by subtracting the 1982 value from the 2010 value. We compared two models, one using difference indices and the other using 2010 indices along with other ancillary data layers, to determine if the more complicated but more biologically relevant difference indices were necessary for improved model performance. Variables with low importance were removed from both models, leaving NDVI, Wetness, soil, and elevation in the two final models. The difference model had an improvement in accuracy of three percent, across a number of threshold values. Despite this small difference in accuracy, however, the infected area predicted by the difference model (5.1% of total area) was approximately ½ of that predicted by the single year model (9.6% of total area). These results suggest that using remote sensing difference indices improves model accuracy slightly in terms of errors of omission, but also decreases predicted area of forest infestation by about 50%, suggesting that errors of commission would be substantially reduced using the difference approach. This method can provide forest managers more accurate information on the best locations to sample and treat.

1. Introduction

Non-native pests and pathogens present serious challenges to the management of forested ecosystems around the world (Evans, 2008; Aukema et al., 2010). These challenges include predicting likely invasion locations, monitoring infested stands, maintaining key host species, and determining best treatment method (Byers et al., 2002). As of 2010, more than 450 non-native forest pests and 16 pathogens were discovered in the US (Aukema et al., 2010). These organisms have become an increasingly serious threat to forest productivity and diversity (Perles et al., 2010), and often lead to large economic losses and management costs (Aukema et al., 2011). For example, the emerald ash borer (*Agrilus planipennis*), Asian longhorned beetle (*Anoplophora glabripennis*), and sudden oak death (SOD) (*Phytophthora ramorum*) have caused damages estimated to be in the billions of dollars due to lost timber resources (GAO, 2006). Another study estimated approximately $1.7 billion in local government expenditures and $830 million in lost property value from wood and phloem-boring non-native insects in the United States (Aukema et al., 2011).

One particularly damaging phloem-boring non-native forest pest is *Adelges tsugae*, also known as the Hemlock Woolly Adelgid (HWA). HWA is a serious threat to the survival of eastern hemlock (*Tsuga canadensis*) forests. Since its introduction to the United States, in Virginia in 1951, HWA has killed 95% of *T. canadensis* trees in Virginia's Shenandoah National Park, and has spread to 50% of the total range of *T. canadensis* (Orwig et al., 2003; Morin

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et al., 2005). Improvements in mapping and predicting HWA outbreaks would benefit our understanding of HWA dispersal dynamics and impacts, and would support management relating to HWA interventions (Royle and Lathrop, 2002; Evans, 2009).

Species distribution models (SDMs) and remote sensing (RS) have previously been used as separate approaches to map areas of potential forest pest or pathogen infestation (Skakun et al., 2003; Cord et al., 2013). Like many disturbance events, forest pest or pathogen invasions often result in a measurable reduction in foliar biomass. When near anniversary images are cloud free this reduction can be indexed using a multi-temporal difference measure based on RS data, and infestation areas can be mapped in this way. This multi-temporal RS approach has been used to detect change in forest canopies due to growth or defoliation resulting from forest infestation by HWA (Royle and Lathrop, 2002), northern tamarisk beetle (*Diorhabda carinulata*) (Dennison et al., 2009), and SOD (Kelly and Meentemeyer, 2002; Kelly et al., 2004). The normalized difference vegetation index (NDVI) (Rouse, 1973) is the most commonly used measure to detect change in forest canopy due to its sensitivity to green foliar biomass.

SDMs have also been used to predict and map the distribution of invasive forest pests and pathogens such as HWA (Clark et al., 2012), cactus moth (*Cactoblastis cactorum*) (Brooks et al., 2012), and SOD (Václavík et al., 2010). There have also been a number of recent studies that integrate RS with SDMs (Cord et al., 2013, 2014). However, there is little explanation for how these RS metrics used in SDMs relate to the ecological processes of forest disturbance and succession (Cord et al., 2013).

Forest pest disturbances can vary in their impact on forest canopies, affecting site conditions in different ways, and initiating different rates and composition of biomass recovery (Holdenrieder et al., 2004; Cobb, 2010; Cobb et al., 2012). As a result, the relationships between RS metrics and disturbance may be contingent on the intensity or time since disturbance, as well as forest type (Royle and Lathrop, 2002; Chastain and Townsend, 2007). NDVI (or difference in NDVI) is most typically used as an indicator of forest pest disturbance because of its relation to green foliar biomass (Royle and Lathrop, 2002). Rapid succession in the sub-canopy and saturation at high levels could potentially confound the sensitivity of this index (Royle and Lathrop, 2002; Chastain and Townsend, 2007). This might occur, for example, where disturbance intensity is higher and succession may be initiated more rapidly due to higher light conditions. It is likely that other remote sensing indices that measure change in site conditions, such as difference in wetness or brightness, would be more reliable indicators of forest pathogen impacts at certain stages of the disturbance–recovery cycle, or under certain levels of disturbance impact. The wetness index has been found to be very sensitive to canopy health and structure (Cohen and Fiorella, 1998; Hansen et al., 2001).

In this study we combined RS difference indices, to capture pre- to post-infestation changes in foliar biomass as well as other site conditions (brightness and wetness), with a SDM in order to predict locations with HWA infestation. We also evaluated the relationship between the RS difference indices and the intensity of infestation to assess the relationship between remote sensing indices, disturbance intensity, and successional stage.

2. Materials and methods

2.1. Study system

T. canadensis, eastern hemlock, is a long-lived, shade tolerant conifer with a native range extending from northeast Minnesota across Wisconsin, and through New Brunswick and Nova Scotia (Fig. 1). It is commonly found in elevation ranges of 0–730 m in the northern portion of its range, from approximately 300–910 m in the Mid-Atlantic states, and from 610–1520 m in the southern Appalachians where it reaches the southern limit of its range (Brisbin, 1970; Godman and Lancaster, 1990). *T. canadensis* is found on most topographic positions in the northern portion of its range, but is restricted to coves and north and east facing slopes in the southern Appalachians (Brisbin, 1970; Ward et al., 2004). *T. canadensis* is one of the largest eastern US evergreen conifers and is integral for long-term ecosystem stability. Due to its dense evergreen canopy, light availability is limiting in the understory of *T. canadensis* stands creating moist, shady microclimates. Additionally, hemlock dominated stands have soils with low pH and high carbon to nitrogen ratios (Orwig and Foster, 1998; Jenkins et al., 1999; Yorks et al., 2003). These conditions, and the release from light-limitation following HWA infestation, partially govern the dynamics and signature of disturbance and post-disturbance succession in this system, and thus how they can be best assessed using remote sensing.

T. Canadensis forests benefit ecosystems in numerous ways. For example, streams draining *T. canadensis* watersheds have cooler summer temperatures and warmer winter temperatures, three times greater brook trout populations, and less eroded banks (Evans, 2002; Maloney and Rains, 2002; Ross et al., 2003). Many Neotropical migrant bird species prefer to nest in hemlock branches, for example, one study found that 84% of wood thrush nests were in *T. canadensis*, preferentially in young hemlocks (Farnsworth and Simons, 1999).

HWA is native to Asia, and was first reported in eastern Virginia in 1951. It has since spread throughout the eastern US along the Appalachians. It is now found in 17 eastern states from Georgia to Maine (Fig. 1) (Maloney and Rains, 2002; Orwig et al., 2003; Havill et al., 2006). The rate of HWA spread is 15.6 km/y south of Pennsylvania and 8.13 km/y north of Pennsylvania, and mortality is much faster in the southern portion of its range (Boer, 1968; Evans and Gregoire, 2007). HWA is the single greatest threat to *T. canadensis* survival in eastern North America because once introduced in a stand, HWA can increase rapidly due to the lack of resistance in *T. canadensis* and due to the absence of the natural predator of HWA, *Pseudoscymnus tsugae*, a type of lady beetle (Ward et al., 2004; Montgomery et al., 2009). Introductions of *P. tsugae* have had mixed success (McClure and Cheah, 1999; McClure et al., 2001). In Asia and Western North America, hemlock species are resistant to HWA impacts and the adelgid has natural predators (McClure, 1996; Orwig et al., 2003).

HWA damage to *T. canadensis* is characterized by a reduction in new shoot production in infested parts of the crown, followed by needle drop, branch tip dieback, thinning of foliage, dieback proceeds from the lower canopy to the upper canopy, and finally, tree mortality. Mortality usually occurs over a 2–20 year period (Souto and Shields, 1999; Ward et al., 2004; Cobb et al., 2006). This process of die-off affects successional processes by opening light gaps that allow other species to grow faster (Ellison et al., 2005; Ford et al., 2012; Orwig et al., 2013). In many *T. canadensis* stands, *Rhododendron maximum* makes up a large portion of the shrub understory in portions of its geographic range including our study area (Perles et al., 2007a, b; Evans, 2008; Ford et al., 2012). In studies of *T. canadensis* stands killed by HWA, *R. maximum* has been found to grow 2.6 times faster than other species and to lock up nitrogen making it difficult for other species to outcompete the *R. maximum* understory in growth (Ellison et al., 2005; Ford et al., 2012). Thus, *R. maximum*, which like hemlock is evergreen, often comes to dominate these ecosystems following disturbance by HWA. When *R. maximum* is not present in the understory black birch (*Betula lenta*) and red maple (*Acer rubrum*) commonly recruit into light gaps caused by hemlock mortality. These processes of disturbance and post-disturbance recovery have large impacts on

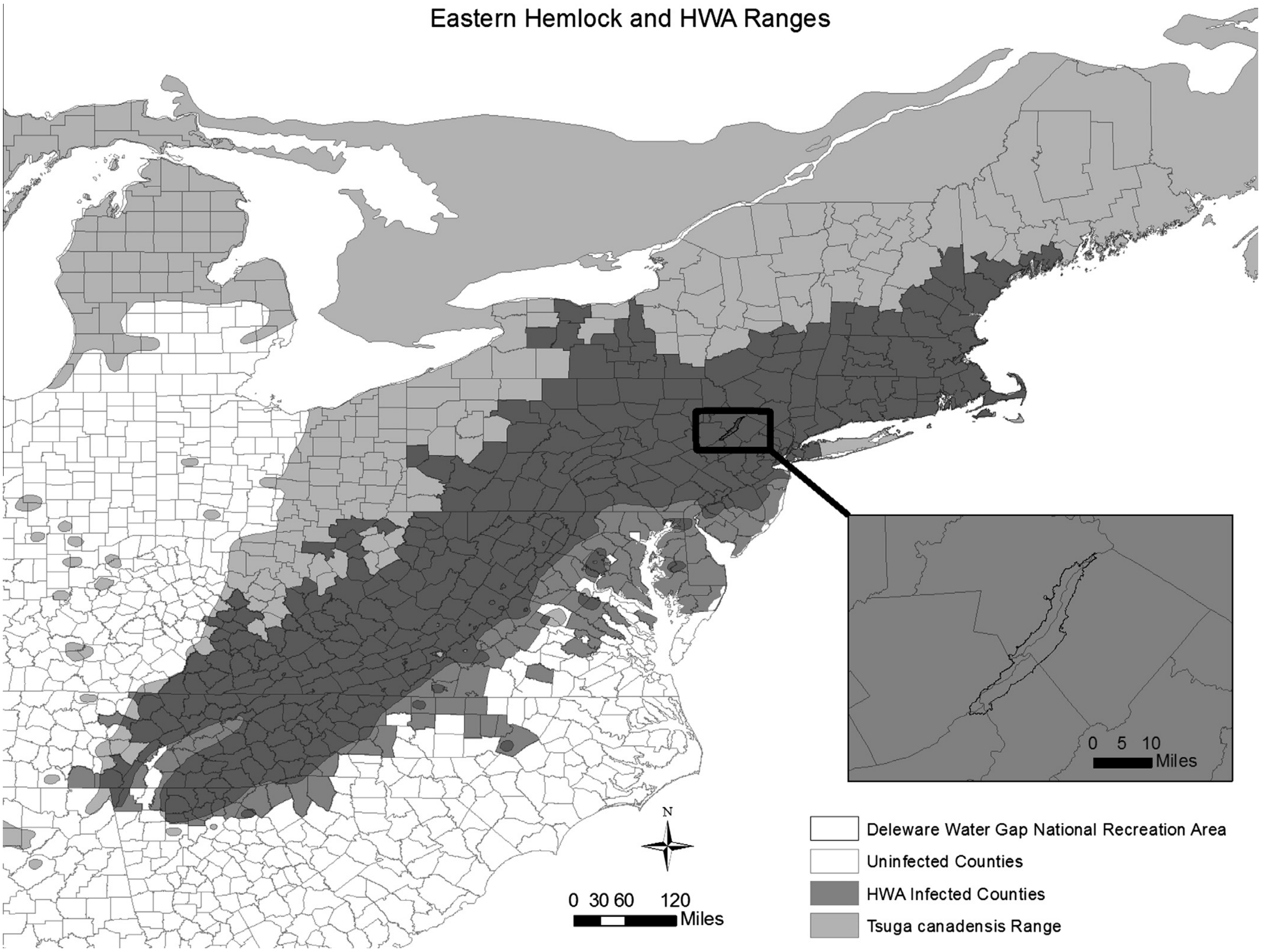

Fig. 1. *T. canadensis* range in light gray, HWA range in dark gray and the Delaware Water Gap National Recreation Area shown in the inset map.

ecosystems (Orwig and Foster, 1998; Ford et al., 2012; Orwig et al., 2013). Ecosystem effects of HWA infestation include reduced forest floor moisture, increased rates of nitrogen accumulation, nitrate leaching into streams, decrease in soil CO_2 efflux, and decreased stream flow in the summer (Boer, 1968; Jenkins et al., 1999; Ross et al., 2003; Yorks et al., 2003; Cobb et al., 2006; Orwig et al., 2008).

2.2. Study area

The Delaware Water Gap National Recreation Area (DWGNRA) covers 28,300 hectares along the Delaware River in northeastern Pennsylvania and northwestern New Jersey, and contains 2200 hectares of *T. canadensis* forest (Fig. 1). HWA was detected in 1989 in this region, and a monitoring program began in 1993 (Evans, 2008). The annual monitoring involves tracking of HWA infestations and *T. canadensis* tree health in 78 permanent plots. All plots are 6 m wide and as long as necessary to include 10 *T. canadensis* trees larger than 10 cm dbh. Plot lengths ranged from 11 to 73 m and vary in their spatial orientation. Tree health is assessed using the U.S. Forest Service visual crown rating methods (Evans, 2009). In 2000, the DWGNRA Park Service started using biological and chemical controls. Despite these measures, HWA has continued to increase (Evans, 2008; Perles et al., 2010). Survey and monitoring techniques are expensive and highly localized, which makes determining HWA infestation levels over large areas difficult using these approaches (Maloney and Rains, 2002).

There are 4 forest types where *T. canadensis* is codominant in the DWGNRA: eastern hemlock forest, dry eastern hemlock – oak forest, eastern hemlock – mixed hardwood palustrine forest, and eastern hemlock – northern hardwood forest (Perles et al., 2007a, b). It is important to note that in all of these forest types the foliar coverage of *T. canadensis* has been reduced due to HWA (Perles et al., 2007a, b). The eastern hemlock forest type in the park has 50–90% *T. canadensis* canopy cover with *Pinus strobus* being the most common codominant species and the most abundant shrub being *R. maximum*. The eastern hemlock – mixed hardwood palustrine forest type in the park contains at least 25% *T. canadensis*. Typical canopy codominant species are *A. rubrum*, *Betula alleghaniensis*, and *Nyssa sylvatica*. *R. maximum* thickets frequently make up 30–70% of the tall-shrub layer and is in the sparse short shrub layer as well. The eastern hemlock – northern hardwood forest type in the park typically has 50% *T. canadensis* dominant in the canopy but this can be as low as 25%. The other codominant canopy species are typically *B. lenta*, *A. rubrum*, and *Acer saccharum*. These species also make up the majority of the understory as well. The dry eastern hemlock – oak forest type in the park typically consists of greater than 25% *T. canadensis* in the canopy and subcanopy. Oaks are predominantly codominant with *Quercus prinus* being the most common. Subcanopy species include *A. rubrum*, *B. lenta*, and *T. canadensis* along with some oaks and hickories. Tall dense layers of *R. maximum* are frequently present (Perles et al., 2007a, b).

2.3. Data

Landsat Thematic Mapper (TM) images (path/row 14/31, spatial resolution 30 m) were obtained for December 13, 1982 and December 18, 2010. Winter images were chosen to reduce deciduous leaf interference with the canopy reflectance from coniferous *T. canadensis* stands. The 1982 image characterizes *T. canadensis* forests that had not experienced HWA damage, while the 2010 image represents 2010 conditions with HWA infestation in the DWGNRA. These images were atmospherically corrected using the dark object subtraction (DOS3) method (Song et al., 2001). This converts the raw digital numbers to surface reflectance which is necessary for the tasseled cap transformation (described below) (Song et al., 2001). Differences in phenology and atmospheric and solar illumination conditions are minimized by using images with near anniversary dates. For ratio based vegetation indices, such as NDVI, topographic effect is cancelled due to the primary topographic effect being the cosine factor which is the same and multiplicative to all bands. Additionally, among the Tasseled Cap indices, wetness is resistant to topography and atmospheric contamination (Song and Woodcock, 2003) and has been found to be sensitive to plant canopy changes (Cohen and Fiorella, 1998; Skakun et al., 2003). Visual inspection of the images indicates that snow was not present in either of our images. Additionally, snow cover maps reveal that for our study area snow was not present during the 2010 image, this further verification was not available for the 1982 image (SSEC, 2012).

After atmospheric correction, normalized difference vegetation index (NDVI) was calculated for both images as a proxy for photosynthetic biomass abundance, and tasseled cap transformations (Kauth and Thomas, 1976) were also calculated for each image to produce brightness, greenness, and wetness indices. The Tasseled Cap, or Kauth–Thomas transformation uses an ordination approach, or weighted linear combinations of the original spectral bands of surface reflectance data to derive approximately orthogonal indices that are strongly correlated to the brightness, greenness, and wetness of the scene. A difference image was created for each of the four indices by subtracting the 1982 values from the 2010 values. The NDVI, brightness, greenness, and wetness indices, and the differences, were then clipped to the extent of the study area. We used Pearson's correlation coefficient to analyze the relationship between NDVI, brightness, greenness, and wetness differences and the severity of *T. canadensis* damage for the complete set of plots to determine the effectiveness of each in detecting and estimating the level of HWA infestation.

We used several additional environmental inputs to the MaxEnt model for mapping HWA infestations. We used a Digital Elevation Model (DEM) (Osborn et al., 2007) (path/row 14/31; spatial resolution of 30 m), from which slope and aspect were calculated. Soil data for the study area was obtained from the Soil Survey Geographic (SSURGO) database (Soil Survey Staff, 2014) including four counties (Sussex and Warren counties in New Jersey, and Monroe and Pike counties in Pennsylvania); the soil datasets were merged together and resampled to 30 m resolution. Elevation, slope, aspect, and soils datasets were each clipped to the extent of the study area and aligned with the RS indices (Table 1). Soil type was treated as a categorical variable while all other variables were continuous.

For this study, each *T. canadensis* park monitored plot was assigned a damage index, ranging from 0.0 to 1.0, based on the condition of *T. canadensis* individuals within the plot. The park service assigns each tree with a damage value category. These categories are no damage, light damage, moderate damage, heavy damage, and mortality. The park service does not indicate whether the dead trees are standing or have fallen over (Evans, 2002, 2008). Within each plot, trees with no damage, light damage, moderate damage, heavy damage, and dead trees contributed values of 0, 0.025, 0.050, 0.075, and 0.1, respectively, to the weighted damage index of the plot as of 2010. Since each plot was designed to have exactly 10 hemlocks this damage index ranges from 0.0 to 1.0. To match the plot data with the spatial data, and to accommodate possible image geometric registration and GPS errors, a 3×3 pixel region of interest (ROI) was established for each plot with the center pixel containing the plot centroid. This ROI size was necessary to account for the size of the largest plots, 6 m $\times$ 73 m. The ROIs were then used as the units of analysis for the remote sensing and DEM data. While these ROIs are not perfect they are able to be used due to observations in the plots not being limited to the plots but the surrounding area as well. There were three separate plot pairs that shared an ROI. The damage index for these three pairs was averaged to have one value for the shared ROI, leaving 75 plots available for analysis.

2.4. MaxEnt

MaxEnt is a SDM that uses an environmental envelop approach to predict the potential distribution of a species of interest based only on conditions at locations where the species is known to occur (presence-only data) (Phillips et al., 2004, 2006). Maximum entropy modeling uses heterogeneous environmental variables to classify data. Only data from known occurrence locations are used to create the classification model. Each variable constrains the model, and the maximum entropy approach seeks to find the model with the greatest maximum entropy of all the models that satisfy the constraints (i.e. the model that retains the greatest amount of uncertainty). The result, in the case of MaxEnt, is a multidimensional environmental envelop that is mapped to create a potential geographic distribution (Manning and Schütze, 1999).

To determine whether the more complex procedure of assembling multi-temporal difference data is necessary, or whether a simpler single-date imagery approach is suitable, we compared the importance of the 2010 RS data and the 2010–1982 difference data for estimating *A. tsugae* distribution. This process is carried out using two model runs with different combinations of data (Table 1). Variables with low importance, as determined by MaxEnt jackknife analysis, were removed from both models, and the two final models were run 1000 times each. Each model run had the maximum number of iterations set at 2000 and a random 20% of the data chosen as test data. The MaxEnt predicted species probability of occurrence values (0.0–1.0) for all test pixels were analyzed for each run to determine the accuracy of the models. We tested a range of MaxEnt prediction thresholds from 0.0 to 1.0 and all showed improvement using the difference model. For example using a threshold of 0.10, a point with a MaxEnt predicted value of 0.10 (meaning a 10% probability of being infested with HWA) was counted as having HWA. For discussion of model accuracy we will only discuss the prediction threshold values of 0.6 and 0.12. The threshold value 0.12 represents the threshold value that results in the highest accuracy (correct predictions) with minimal over prediction. At threshold values above 0.6, the predicted area is reduced significantly to the point of limiting the models usefulness for management decisions. Any prediction greater or equal to these thresholds was a correct prediction for the test data, and values below the threshold indicated a prediction of absence, or an error for the test data. The accuracy of each run was calculated as the number of accurate test pixels divided by the total number of test pixels. Accuracy for single year models and the difference models was calculated as the average of the accuracy for the 1000 runs.

Table 1
Environmental variables used to build MaxEnt models. Initial runs of each model had 8 variables. Variables that did not improve performance were eliminated and the final models each contained four variables (* 2010 model only, ** Difference model only, *** both models, $^{\varphi}$ did not improve model performance so were not used in final models).

USGS DEM
Elevation***
Slope$^{\varphi}$
Aspect$^{\varphi}$
Soil Survey Geographic Database
Soil type***
Landsat TM (2010 and 1982)
2010 NDVI*
2010 Wetness*
2010 Brightness$^{\varphi}$
2010 Greenness$^{\varphi}$
NDVI difference (2010–1982)**
Wetness difference (2010–1982)**
Brightness difference (2010–1982)$^{\varphi}$
Greenness difference (2010–1982)$^{\varphi}$

3. Results

The Pearson's correlations analysis for all four of the remote sensing difference indices were statistically significant, but varied greatly in explaining the variance in observed hemlock damage for the 75 plots (Table 2). The NDVI difference and the wetness difference were positively correlated with HWA damage severity, and were the best predictors of hemlock damage with R^2 values of 0.538 and 0.538, respectively (Figs. 2 and 3). The Greenness difference had the lowest correlation with hemlock damage and was negatively correlated with hemlock damage. The Brightness difference was intermediate and was negatively correlated with hemlock damage. The indices from individual years explained a smaller portion of the variance. Out of these, brightness 2010 and wetness 2010 index were significant and brightness 2010 explained more variance than brightness difference, but still explained little of the variance in observed hemlock damage compared to the Wetness difference and NDVI difference (Table 2). The correlation for the individual year indices with hemlock damage are the opposite sign of those for the difference indices (Table 2). The mean and variance for the difference indices for the plot ROIs were significantly different from those of the areas outside of the plots, meaning that the phenomenon demonstrated here is not just a climatological signal for the entire area, but is most likely due to HWA damage in the plots and consequent changes in reflectance characteristics (Table 3).

The initial run of both MaxEnt models (single-year indices and difference indices) show that the only important variables for prediction were NDVI, wetness, elevation, and soil. In both models, soil was the most significant predictor. NDVI and wetness were both equally influential in both models and removing either decreased model performance. This is consistent with the linear regression analysis, which showed change in NDVI and change in Wetness to be the best single remote sensing predictors of hemlock damage.

The area under the curve (AUC) statistics for the single-year model and the difference model were 0.973 and 0.986, respectively. The difference model had increased accuracy compared to the 2010 model at all threshold values. At the 0.12 threshold average model accuracy for the difference and 2010 models was 0.94 ± 0.07 and 0.91 ± 0.07, respectively. At the 0.6 threshold average model accuracy for the difference and 2010 models was 0.55 ± 0.14 and 0.52 ± 0.14, respectively (Fig. 4). Despite this small difference in accuracy, however, the infected area predicted by the difference model (5.1% of the total area within the park) was approximately ½ of that predicted by the single year model (9.6% of total area within the park) when the model is applied to the entire study area (Fig. 5). We compared the two model outputs

Table 2
Linear regression coefficients R^2 values, and p-values for hemlock damage on each index ($^{*}p$-value $\leqslant 0.05$, $^{**}p$-value $\leqslant 0.01$, $^{***}p$-value $\leqslant 0.001$).

Model	Coefficients	*R*-squared
ΔNDVI	4.145	0.538***
ΔBrightness	−45.914	0.309***
ΔGreenness	−25.676	0.14**
ΔWetness	77.5613	0.538***
NDVI 2010	−0.164	0.107
Brightness 2010	2.416	0.369***
Greenness 2010	1.073	0.054
Wetness 2010	−5.992	0.247***

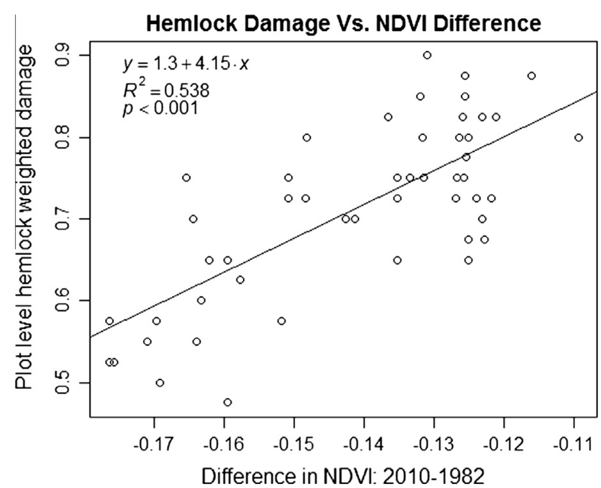

Fig. 2. Plot level hemlock damage compared to the NDVI difference index, black circles represents plot data and the black line is the linear regression fit. Note that this represents a relationship in which NDVI difference decreases with increasing hemlock damage. This is counter intuitive but could be explained by evergreen understory response. We also tested for a density affect by adjusting the NDVI difference using the 1982 NDVI values and it did not change the relationship which supports understory recovery.

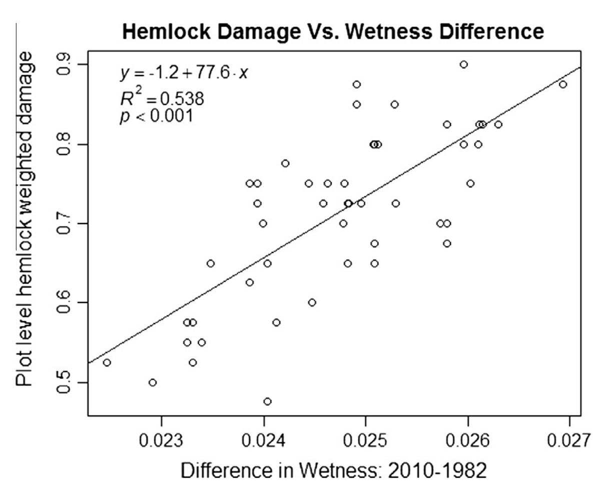

Fig. 3. Plot level hemlock damage compared to the wetness difference index, black circles represents plot data and the black line is the linear regression fit. The wetness index is generally negative for conifer forests. A healthier conifer has a more negative wetness value (Song et al., 2007). A positive wetness difference indicates more damage by HWA as expected.

Table 3
To ensure that the phenomenon we see within our plots was not the result of climate on the entire study area we compared the mean and standard deviation for our plot ROIs compared to areas outside of our plots. Areas outside of the plot ROIs show opposite difference in the indices meaning that the vegetation was healthier in these areas.

Index	Mean	SD	Plot Y/N
NDVI difference	−0.14	0.01897	Y
Wetness difference	0.025	0.00100	Y
Brightness difference	0.041	0.00126	Y
Greenness difference	−0.0027	0.00155	Y
NDVI difference	0.085	0.06708	N
Wetness difference	−0.031	0.07616	N
Brightness difference	−0.038	0.07141	N
Greenness difference	0.0026	0.05831	N

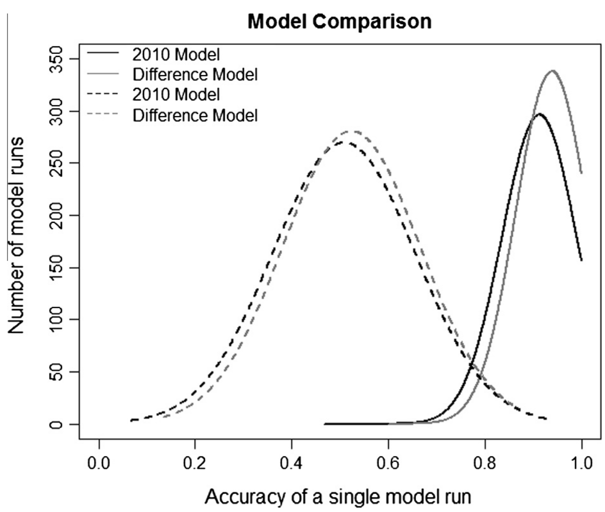

Fig. 4. Count of model runs at a given accuracy for the chosen threshold. Solid lines represent a threshold value of 0.12 and dashed lines represent a threshold value of 0.6. Black lines represent the 2010 model and gray lines represent the difference model. Model runs differ because each run reserves a 20% subset of the data for validation. This shows that accuracy is improved with the difference model.

to the previously mapped hemlock forest types by the USDA NPS discussed previously (Perles et al., 2007a, b). We grouped the 4 hemlock forest types together to determine what percentage of our predicted area fell within these predefined hemlock forests. For the difference model and the 2010 model 89.06% and 60.80% of the area predicted as having HWA fell within the hemlock forests, respectively. The models preformed best in the eastern hemlock and dry eastern hemlock – oak forest types, which combined account for ~66% of the total hemlock forests in the park. While the accuracy assessment for the plots shows only a small improvement, the errors of commission are greatly reduced.

4. Discussion and conclusions

For the 75 affected stands, the brightness index increased from 1982 to 2010, presumably due to greater background soil reflectance through the canopies of unhealthy and dead trees. However, the brightness difference index was negatively correlated with hemlock damage (Table 2). As discussed previously, *R. maximum* grows more rapidly following hemlock loss than other understory species and is a dominate component in the understory in 3 of the 4 hemlock forest types. This leads us to believe that this rapid growth of *R. maximum* is dampening the soil brightness signal in plots that have higher damage, which are predominately in the eastern hemlock forest type (Todd and Hoffer, 1998; Ford et al., 2012). The greenness difference for all 75 plots was negative (i.e. greenness decreased), and this index was negatively correlated with hemlock damage.

The NDVI difference was likewise negative across all 75 plots due to HWA caused defoliation, this agrees with the previous research when taking into account that they subtracted the newest from the oldest image (Royle and Lathrop, 2002). However, it was positively correlated with hemlock damage which differs from Royle and Lathrop (2002), most likely due to the time since HWA in the park being 5 years for their study and 20 years for our study. NDVI difference became less negative with increasing hemlock damage likely due to the high damage stands having greater light availability to the understory, potentially allowing the *R. maximum* understory in these forest types to grow rapidly (Fig. 2) (Ford et al., 2012). In contrast, the wetness differential was positive for all 75 plots, indicating less canopy moisture following disturbance, and was positively correlated with hemlock damage (Fig. 3). This is due to the fact the health undamaged conifer stands have a more negative wetness index (Song et al., 2007). Thus positive wetness difference corresponds to more severe HWA damage. Although rhododendron is evergreen, retaining high levels of leaf biomass through the winter (thus increasing NDVI values), the leaves do not open their stoma when temperatures are below freezing, as was likely the case in these winter images, and thus appear to have a lower wetness index than other evergreen vegetation (Chastain and Townsend, 2007). This is a possible explanation for why even though NDVI difference declined with increasing hemlock damage, the wetness difference increases with increasing hemlock damage, because *R. maximum* increases NDVI values in the winter as it is evergreen but has little effect on wetness. In the future, a study of this nature looking at the temporal aspects HWA spread to see at what time step this method would be most useful would be extremely valuable.

The results found in the analysis of the MaxEnt model support previous research on *T. canadensis* which shows that in the northern portion of the its range aspect and slope have little to no correlation with presence of *T. canadensis* (Brisbin, 1970; Ward et al., 2004). There has been little field research done to test the effects of aspect and slope on HWA infestations. However, our analysis suggests that there is little effect of these variables in this portion of the range. There may be slope and aspect effects in hotter or drier portions of the *T. canadensis* range.

The results from the MaxEnt jackknife analysis corresponded with the remote sensing linear regression analysis, indicating that the most useful indices for determining HWA distribution are wetness and NDVI differentials. This finding is to be expected given that unhealthy hemlock vegetation has substantial changes in both wetness and NDVI, while brightness and greenness have been unable to accurately predict changes in conifer forests and have been unable to separate old growth from mature conifer (Fiorella and Ripple, 1993; Collins and Woodcock, 1996; Franklin et al., 2000; Wilson and Sader, 2002). Soil types that were strongly correlated with HWA locations included cobbly fine sandy loams, stony loams, very cobbly sandy loams, and complex; all soil types were in areas classified as extremely stony, very rocky, or rubbly and very acid. These findings correspond with literature suggesting that *T. canadensis* prefers moist, loamy soils that are well-drained and highly acidic (Rogers, 1980; Godman and Lancaster, 1990; Ward et al., 2004). The results of the MaxEnt models suggest that using remote sensing difference indices improves model performance slightly in terms of errors of omission, but also decreased predicted area of forest infestation by about 50%, and decreased amount of area predicted outside of hemlock forest substantially from 39.2% for the 2010 model to 10.94% for the difference model of the total area predicted by the models. Both of our models that include

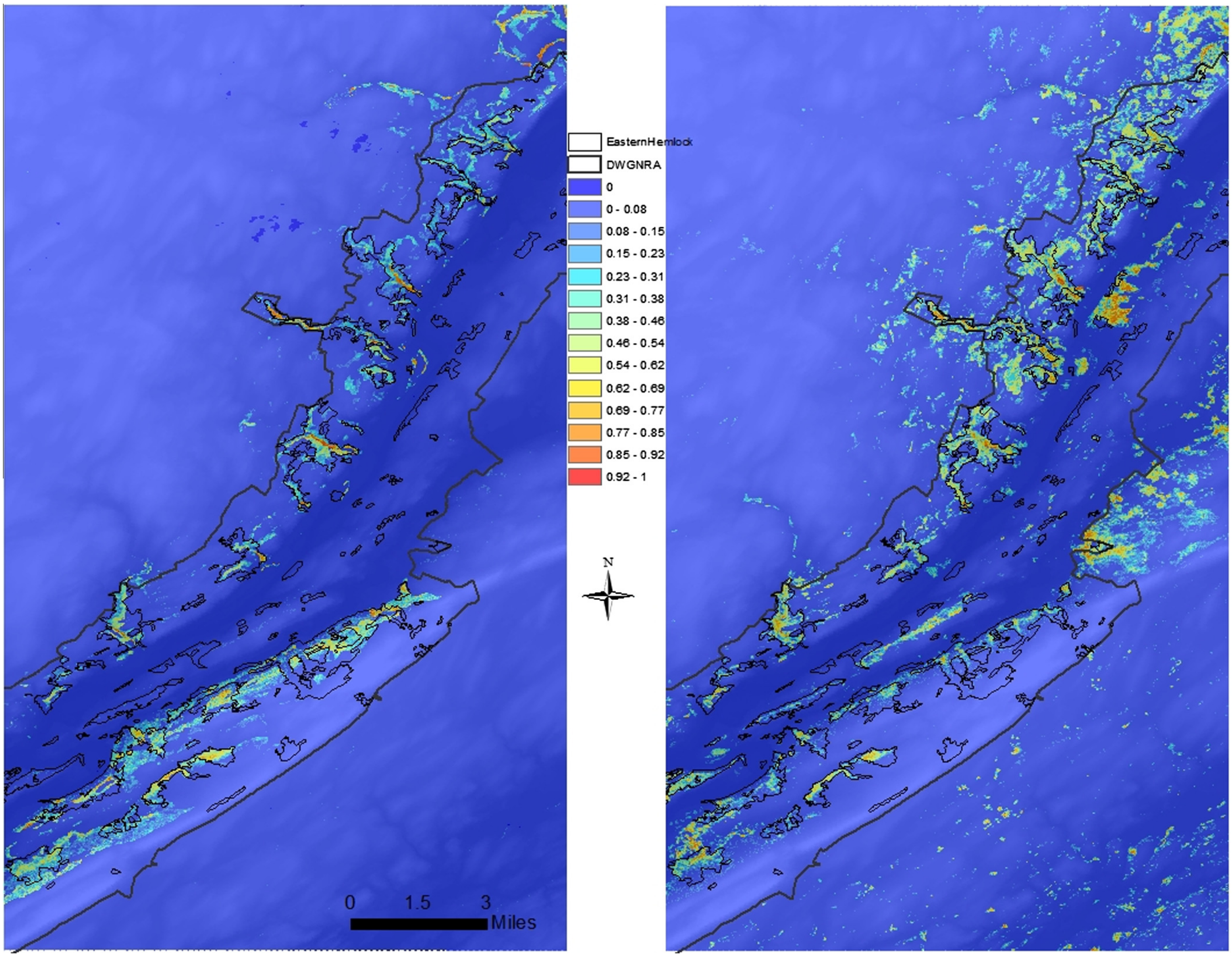

Fig. 5. From left to right: predicted HWA map using the difference model, predicted HWA map using 2010 model. Values represent the predicted likelihood of HWA presence. As can be seen the predicted area of the difference model within the park approximately half that of the single year model potentially increasing commission errors. Also a much higher percentage of the predicted area falls outside of the hemlock forest types.

remotely sensed indices (0.973–0.986 AUC) showed improvement in terms of AUC when compared to models without remotely sensed indices in Kentucky (AUC of 0.88–0.94) by (Liang et al., 2014). This is the only accuracy assessment provided for their model so we cannot make further comparisons. The methods used here can be applied to a variety of forest pest and pathogen infestations to obtain more accurate predictions of infestation areas, and thus help inform management activities. However the value of remote sensing difference indices as a proxy for level of disturbance should be informed by and appropriately capture the changes in site and canopy conditions specific to the particular disturbance and recovery regime, which would inevitably vary by ecosystem type. In the future, this method could be applied over a larger area to determine if it is robust at larger spatial extents.

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