Environ Monit Assess (2015) 187:87
DOI 10.1007/s10661-015-4332-x

Mortality rates associated with crown health for eastern forest tree species

Randall S. Morin · KaDonna C. Randolph · Jim Steinman

Received: 30 July 2014 / Accepted: 26 January 2015

Abstract The condition of tree crowns is an important indicator of tree and forest health. Crown conditions have been evaluated during inventories of the US Forest Service Forest Inventory and Analysis (FIA) program since 1999. In this study, remeasured data from 55,013 trees on 2616 FIA plots in the eastern USA were used to assess the probability of survival among various tree species using the suite of FIA crown condition variables. Logistic regression procedures were employed to develop models for predicting tree survival. Results of the regression analyses indicated that crown dieback was the most important crown condition variable for predicting tree survival for all species combined and for many of the 15 individual species in the study. The logistic models were generally successful in representing recent tree mortality responses to multiyear infestations of beech bark disease and hemlock woolly adelgid. Although our models are only applicable to trees growing in a forest setting, the utility of models that predict impending tree mortality goes beyond forest inventory or traditional forestry growth and yield models and includes any application where managers need to assess tree health or predict tree mortality including urban forest, recreation, wildlife, and pest management.

Keywords Tree crown health · Tree mortality · Forest inventory · *Adelges tsugae* · Beech bark disease · Forest health

Introduction

An important indicator of the health of a tree is the condition of its crown. The US Forest Service Forest Inventory and Analysis (FIA) program uses visual assessments of tree crown condition to monitor trends in forest health. Trees with vigorous, healthy crowns tend to have higher growth rates. By contrast, trees with damaged or degraded crowns have a reduced capacity for photosynthesis and slower growth rates. Many stressors have been correlated with crown degradation including insects, disease, weather events, senescence, competition (Kenk 1993), and atmospheric deposition (Duarte et al. 2013). Additionally, trees with unhealthy crowns are more susceptible to mortality (Kulman 1971; Lawrence et al. 2002).

Assessments of tree crown conditions have been conducted by the US Forest Service Forest Health Monitoring (FHM) program since 1990 and as a part of FIA since 1999 (Riitters and Tkacz 2004).

R. S. Morin (✉)
USDA Forest Service, Northern Research Station, 11 Campus Blvd., Suite 200, Newtown Square, PA 19073, USA
e-mail: rsmorin@fs.fed.us

K. C. Randolph
USDA Forest Service, Southern Research Station, 4700 Old Kingston Pike, Knoxville, TN 37919, USA

J. Steinman
USDA Forest Service, Northeastern Area State and Private Forestry, 11 Campus Blvd., Suite 200, Newtown Square, PA 19073, USA

Published online: 06 February 2015

Preliminary analyses of crown condition data through the FHM program demonstrated the data's utility in classifying tree health and likelihood of survivorship, with crown dieback as the best indicator of crown condition (Steinman 2000), but this study was limited in geographic scope and volume of remeasurement data. Since 2001, the following crown health indicators have been consistently assessed for live overstory trees (DBH ≥12.7 cm) within the US network of FIA plots: uncompacted live crown ratio (UNCR), crown light exposure (CL), crown density (CDEN), crown dieback (CDBK), and foliage transparency (TRANS) (Schomaker et al. 2007). Results from crown condition data have been presented as frequency statistics for individual crown indicators (e.g., Randolph et al. 2010), quantification of crown health based on composite crown indicators (Zarnoch et al. 2004), summaries of tree health by species in FIA 5-year reports (e.g., Widmann et al. 2012), and more specific analyses investigating changes in forest health (e.g., Morin et al. 2004; Will-Wolf and Jovan 2009).

A model that predicts impending tree mortality would have utility beyond forest inventory or traditional forestry growth and yield models. Other uses could include early detection of pest presence, prediction of pest impacts, assessment of the impacts of atmospheric deposition or climate change, urban tree management, recreation management, and wildlife management. Such a model could be used anywhere managers need to assess tree health or predict tree mortality. The objective of this study is to develop probability models of tree survival for common tree species in the eastern USA using crown health measurements. Application of the models is demonstrated by comparing the observed and model-predicted mortality rates for American beech (*Fagus grandifolia*) and eastern hemlock (*Tsuga canadensis*) in areas affected by beech bark disease (BBD) and the hemlock woolly adelgid (HWA) (*Adelges tsugae* Annand), respectively.

BBD is an insect-fungus complex involving the non-native beech scale insect, *Cryptococcus fagisuga*, which feeds on bark fluids from stems of American beech, providing an opportunity for the native canker fungi *Neonectria faginata* and *Neonectria ditissima* (Castlebury et al. 2006) to invade the inner living bark and cambium leading to dieback and mortality (Mize and Lea 1979; Houston 1994). The beech scale insect was accidentally introduced with live plants imported to Halifax, Nova Scotia from Europe, in the 1890s (Houston 1994). The scale insect has since slowly spread (~15 km/year) into the New England states, New York, Pennsylvania, and West Virginia, and several discontinuous "jumps" have transported it into North Carolina, Tennessee, and Michigan (Fig. 1a) (Morin et al. 2007; Wieferich et al. 2013). Three phases of BBD are generally recognized: (1) the "advancing front," which corresponds to areas recently invaded by scale populations, (2) the "killing front," which represents areas where fungal invasion has occurred (typically 3–5 years after the scale insects appear, but sometimes as long as 20 years) and tree mortality begins, and (3) the "aftermath forest," which are areas where the disease is endemic (Shigo 1972; Houston 1994).

HWA, native to East Asia, may have been introduced to the eastern USA as early as 1911; however, the first report of its presence was in Richmond, VA, in 1951 (Havill and Montgomery 2008). Since then, it has slowly expanded its range at 8–30 km/year (Fig. 1b) (Evans and Gregoire 2007; Morin et al. 2009). In areas where the species has established, populations often reach high densities, causing widespread defoliation and sometimes mortality of hemlock (McClure et al. 2001; Orwig et al. 2002).

Models could have been adjusted for specific geographic areas (e.g., the different duration classes for BBD and HWA), but that is beyond the scope of this paper. Our intention was to develop a general model for the entire eastern USA as well as provide a technique that could be employed for specific species, geographic areas, or other applications.

Methods

FIA data

FIA inventory plots are permanently located across the USA and consist of a cluster of four 7.2-m fixed radius subplots with subplot centers located 36.6 m apart. Plots on which tree crown conditions are assessed are spatially distributed so that the sampling intensity is one plot per approximately 38,850 ha (Bechtold and Patterson 2005). Crown conditions are assessed on all live trees ≥12.7 cm DBH on each subplot. The five crown condition variables included in this summary are (1) UNCR—the length of a tree that supports live foliage relative to the actual tree length; (2) CL—the amount of direct sunlight that a tree receives when the sun is

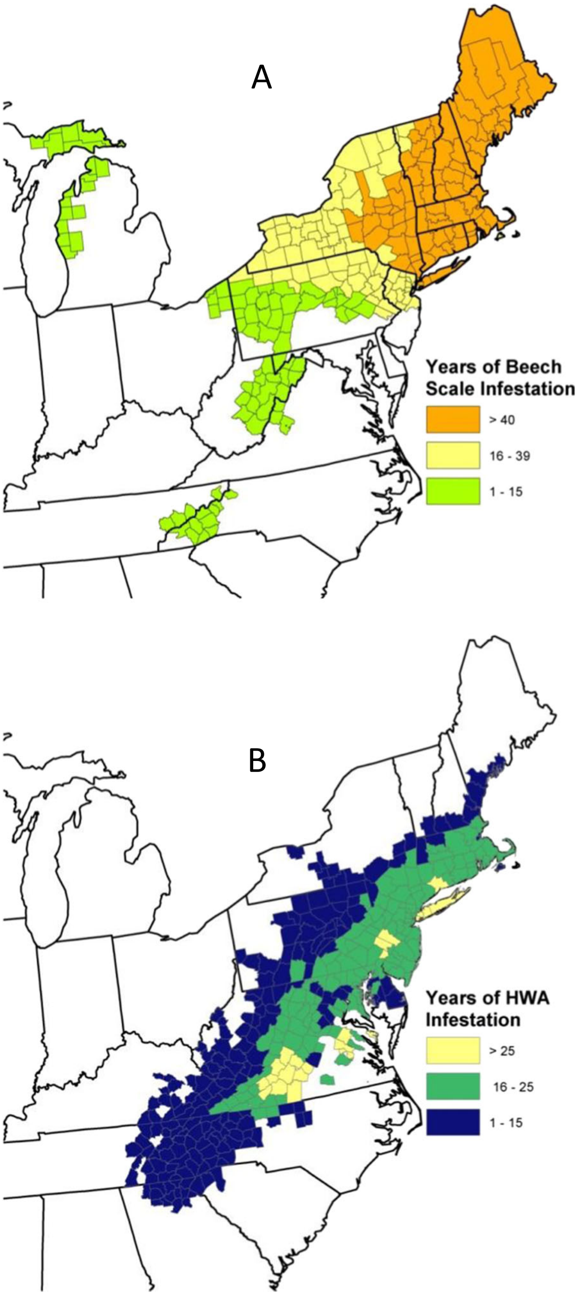

Fig. 1 **a** Map of the historical spread of the beech scale insect in the eastern USA. **b** Map of the historical spread of hemlock woolly adelgid in the eastern USA

directly overhead; (3) CDEN—the amount of crown branches, foliage, and reproductive structures that blocks light visibility through the projected crown outline; (4) CDBK—the recent mortality of branches with fine twigs, which begins at the terminal portion of a branch and proceeds inward toward the trunk; and (5) TRANS—the amount of skylight visible through the live, normally foliated portion of the crown, excluding dieback, dead branches, and large gaps in the crown (Schomaker et al. 2007).

All five variables were visually assessed during the full leaf-on season (typically June through August). UNCR, CDEN, CDBK, and TRANS were measured in 5 % increments and recorded as a two-digit code: 00, 05, 10 … 99, where the code represents the upper limit of the class; e.g., 1 to 5 % is code 05 and 96 to 100 % is code 99. When assessing CL, field crews visually divided the crown into five sections—four equal vertical quarters, i.e., faces or "sides," and the top—and rated the crown with a value ranging from zero to five depending on the number of sections exposed to direct sunlight. Within a species, higher crown density values, lower foliage transparency values, and lower crown dieback values typically are associated with better tree health. More detailed descriptions of the crown condition indicator data collection protocol and data analysis procedures are available in Schomaker et al. (2007).

Tree species and crown conditions for all live trees (DBH ≥12.7 cm) measured between 2001 and 2005 (time t_1), along with matching crown condition and tree status (live or dead) data from 2006 to 2010 (time t_2), were obtained from the FIA database (Woudenberg et al. 2010). All plots were remeasured at a 5-year interval. Inventory data from all states east of, and including, North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, and Texas were included in the study. Trees that were cut and removed between times t_1 and t_2 were not included. The data were divided into two sets, 75 % for model building and 25 % for model cross-validation. The cross-validation dataset was selected randomly from the complete dataset. The final model was built using the full dataset.

BBD and HWA infestation data

To assess the usefulness of the models for detecting or predicting mortality induced by invasive pest activity, historical county-level records of the year of initial beech scale insect (*C. fagisuga*) and HWA establishment were obtained for all counties with these infestations (Fig. 1). Infestation records were made by the US Forest Service, Northeastern Area State and Private Forestry work unit in Morgantown, WV, and are available online (BBD, http://na.fs.fed.us/fhp/bbd/infestations/infestations.shtm; HWA, http://na.fs.fed.us/

fhp/hwa/infestations/infestations.shtm). These data were not based upon systematic surveys, and therefore, slight inconsistencies may exist among years and states in how HWA and beech scale populations were detected. Although these records are based on establishment of the beech scale insect that transmits the canker fungi that cause BBD, we generally refer to BBD throughout the remainder of the paper. Based on county location, all American beech and eastern hemlock trees from the FIA database were assigned a duration of infestation based on the number of years between the initial BBD or HWA infestation and the year 2000.

Data analysis

Logistic regression

Tree status from times t_1 and t_2 was used to classify each tree as either a survivor or mortality tree, and the probability of survival was modeled using the logistic equation:

$$\mathrm{P(survival)} = \frac{exp(b0 + b1X1 + b2X2 + b3X3 + b4X4 + b5X5)}{1 + exp(b0 + b1X1 + b2X2 + b3X3 + b4X4 + b5X5)}$$

where X_1 through X_5 are distinct independent variables and b_0 through b_5 are the regression coefficients. The crown variables—UNCR, CDEN, CDBK, CL, and TRANS—were the only independent variables included in the model. Regular linear regression including tolerance and variance inflation diagnostics were used to test for multicollinearity. None was observed because tolerance was above 0.4 in all cases (Allison 1999). Several other tree-level and stand-level attributes (DBH, relative density, stand age, and stand basal area) were included initially, but none was found to be statistically significant predictors (α=0.05), so they were dropped from the models. A standard logistic regression procedure would not account for correlation among trees of the same species within a plot. Therefore, the PROC SURVEYLOGISTIC procedure (SAS Institute 2009) was used to address this lack of independence among trees sampled on the same plot.

Model goodness-of-fit was evaluated with the area under the receiver operating characteristic (ROC) curve, max-rescaled R^2, and percent accuracy of survivor classification. The usual application of logistic regression probabilities for classification is to assign each tree as live or dead based on the one with the higher predicted probability (i.e., the one with a probability above 0.5). However, this method did not work well for these data, where it was found that mortality was underpredicted based on the 0.5 probability threshold. This is likely to be due to the rarity of mortality occurring. Consequently, decision thresholds (another term for these are probability cut points) were applied to perform the classification based on the predicted values from the logistic regression models. Several methods for selecting cut points have been proposed when using logistic regression as a dichotomous classifier (Greiner et al. 1995; Swets et al. 1979; Yarnold et al. 1994), but the most appealing method depends on criteria specific to a given study (e.g., the tolerance for misclassified observations). For this analysis, cut points were needed to differentiate between the two categories. Cut points were selected based on the probabilities associated with the observed proportion of trees that died between times t_1 and t_2. These cut points were then used to determine which trees died when the models were applied to the t_2 surviving trees to predict mortality at t_3. The difference between the observed past mortality (t_1 to t_2) and predicted future mortality (t_2 to t_3) is referred to as the change in mortality (Δ_m). Although it cannot be tested, our assumption is that mortality rates between t_3 and t_2 will be similar to those observed between t_2 and t_1 based on the crown measurements. The purpose of examining Δ_m is to look for differences in the trajectory of crown health between species and between pest infestation categories for beech and hemlock.

Example applications (BBD and HWA)

The American beech and eastern hemlock trees were stratified into groups based on duration of infestation by BBD and HWA, respectively. For BBD, these groups were 0, 1 to 15, 16 to 39, and ≥40 years and, for HWA, 0, 1 to 15, 16 to 25, and >25 years. The BBD classes were selected to correspond to the recognized phases of BBD invasion: (1) the advancing front, (2) the killing front, and (3) the aftermath forest (Shigo 1972; Houston 1994). We chose similar classes for HWA to determine if mortality progression would be comparable to BBD, but the largest class is of a shorter duration due to HWA's more recent invasion. Our expectation was that mortality over the next 5 years would be greater in groups with longer infestations. Thus, the logistic models with cut points were applied to the crown measurements to see if this was indeed the case. In addition to the BBD and HWA application, the logistic models with cut points also were applied to crown measurements of the t_2 surviving trees.

Results

A total of 55,013 trees were measured on 2616 FIA plots between 2001 and 2005 and remeasured between 2006 and 2010. The number of plots in each state ranged from 2 in Rhode Island to 202 in Minnesota. Parameter estimates based on the validation dataset were within 10 % of the estimates based on the model-fitting dataset, and the confidence intervals associated with the parameters overlapped in all cases. Therefore, the validation and model-building datasets were pooled, and the final model was built with the full dataset. Additionally, accuracy statistics were nearly identical for the full and validation datasets, but in both cases, the poor accuracy in predicting mortality highlights the need for using the cut point method (Table 1). Fifteen species had more than 1000 observations before the 25 % cross-validation dataset was removed (Table 2).

Logistic regression

For all species combined, we found all crown variables to be significant ($P<0.05$) for predicting survival; for each species individually, we found CDBK to be significant ($P<0.05$) for all species except loblolly pine, yellow poplar, and eastern white pine (Table 3). TRANS was significant for only two species, American beech and northern red oak. CDEN was the only variable significant for the yellow poplar model. The area under the ROC curve is provided for the classification models

Table 1 Accuracy statistics (% correct) for full and validation datasets

Dataset	Observed status (t_2)	Predicted dead	Predicted alive	Accuracy	Overall accuracy
Full	Dead	330	3982	7.7	92.5
	Alive	138	50,563	99.7	
Validation	Dead	85	984	8.0	92.6
	Alive	42	12,837	99.7	

as an indicator of classification accuracy (Table 3). An ROC value of 0.5 occurs when the classification is no better than random prediction; a value of 1.0 indicates perfect classification accuracy. A rough guide to interpretation is given by Fischer et al. (2003): ROC area greater than 0.9≈high accuracy, 0.7–0.9≈moderate accuracy, and 0.5–0.7≈low accuracy. To judge the relative importance of the variables, chi-square values are given in Table 3. ROC values for all but two species indicated "moderate classification accuracy" (Table 3).

Parameter estimates conform to expectations in nearly all cases. The coefficient of CDBK is negative in all cases (Table 2), indicating decreasing survival with increasing CDBK. Similarly, the coefficient of TRANS is negative in all significant cases, indicating decreasing survival with increasing TRANS. Except for CL in the models for balsam fir and eastern hemlock, the coefficients of the other significant variables are all positive, which indicates increasing survival with increases in that crown variable (Table 2).

The chi-square statistics in Table 3 reveal that the most important variable for all species combined and about half the species individually is CDBK. The second most important variable for all species combined is CDEN, and it is also the most important for sugar maple, sweetgum, and yellow poplar. Beyond CDBK, there is no consistency in the variable rankings in terms of importance among the species.

The models underpredicted mortality for all species, but there were some differences in the magnitude of the underprediction (Table 4). The differences do not appear to be related to observed proportions of mortality or silvical characteristics of the species. For example, the models with the highest accuracy based on the proportion of trees that died were northern red oak, balsam fir, red maple, and quaking aspen. Two of these, balsam fir and quaking aspen, had the highest percentage of trees that died in the observed data. However, the other two, northern red oak and red maple, had low mortality proportions in the observed data relative to the other species.

Cut points

To apply a mortality proportion that matched the observed data, probability cut points were implemented to perform the classification (Table 5). The underrepresentation of mortality prediction (t_1 to t_2) in our models required us to reduce probability cut points from the

Table 2 Estimated parameters for logistic regression survival models

Species	Sample size (*n*)	Variable					
		Intercept	CDBK	UNCR	CDEN	CL	TRANS
All species	55,013	*0.7365 (0.1382)*	*−0.0373 (0.00234)*	*0.0138 (0.00147)*	*0.0293 (0.00213)*	*0.1198 (0.0201)*	*−0.0117 (0.00306)*
Red maple (*Acer rubrum*)	5324	−0.4548 (0.3931)	*−0.0481 (0.00677)*	*0.0245 (0.00559)*	*0.0373 (0.00586)*	*0.3989 (0.0902)*	0.0162 (0.0119)
Loblolly pine (*Pinus taeda*)	4554	0.2102 (0.6031)	−0.0623 (0.0452)	0.0123 (0.00917)	*0.0338 (0.0131)*	*0.2441 (0.0638)*	0.00934 (0.0110)
Sugar maple (*Acer saccharum*)	3205	−1.319 (0.6962)	*−0.0385 (0.00945)*	*0.0269 (0.00799)*	*0.056 (0.0103)*	*0.4263 (0.1426)*	0.0296 (0.0159)
White oak (*Quercus alba*)	2119	*2.9183 (0.917)*	*−0.0679 (0.0139)*	−0.00043 (0.00984)	0.0162 (0.0154)	0.3224 (0.1829)	−0.00819 (0.0186)
Northern white-cedar (*Thuja occidentalis*)	1962	*1.8116 (0.8929)*	*−0.0342 (0.00883)*	0.00635 (0.00957)	0.0195 (0.0174)	*0.2752 (0.1358)*	0.00993 (0.0222)
Balsam fir (*Abies balsamea*)	1603	−0.2903 (0.5387)	*−0.1134 (0.0233)*	*0.0264 (0.00429)*	*0.0233 (0.00773)*	*−0.201 (0.0672)*	−0.0189 (0.0137)
Quaking aspen (*Populus tremuloides*)	1536	−0.418 (0.5399)	*−0.0619 (0.0144)*	*0.0205 (0.00908)*	*0.031 (0.00821)*	0.0637 (0.0932)	−0.00075 (0.00776)
Sweetgum (*Liquidambar styracifula*)	1329	0.4619 (0.6283)	*−0.0308 (0.0145)*	0.0130 (0.00793)	*0.0365 (0.0103)*	0.1387 (0.1043)	−0.00684 (0.0116)
Northern red oak (*Quercus rubra*)	1284	2.2781 (1.4805)	*−0.0631 (0.0155)*	0.00937 (0.0146)	0.0222 (0.0201)	*0.3691 (0.1594)*	*−0.0398 (0.00905)*
Paper birch (*Betula papyrifera*)	1290	0.6707 (0.7081)	*−0.0267 (0.0108)*	−0.00242 (0.00806)	*0.0195 (0.00906)*	*0.3156 (0.0967)*	−0.0106 (0.0113)
Yellow poplar (*Liriodendron tulipifera*)	1147	−0.6775 (0.6311)	−0.00214 (0.0139)	0.00340 (0.00804)	*0.0726 (0.0133)*	0.1107 (0.1303)	−0.00500 (0.0185)
Black cherry (*Prunus serotina*)	1116	1.1884 (0.6985)	*−0.0465 (0.00912)*	0.00412 (0.00809)	*0.0302 (0.00954)*	0.1156 (0.261)	−0.00245 (0.0171)
Eastern white pine (*Pinus strobus*)	1089	0.8847 (1.2581)	−0.0693 (0.0369)	*0.0295 (0.0114)*	0.0111 (0.0249)	0.2537 (0.2049)	−0.011 (0.0255)
American beech (*Fagus grandifolia*)	1041	0.9952 (0.665)	*−0.0233 (0.00916)*	*0.0260 (0.0085)*	0.0176 (0.0112)	0.0390 (0.1289)	*−0.0332 (0.0161)*
Eastern hemlock (*Tsuga canadensis*)	1032	2.358 (1.8261)	*−0.0714 (0.0184)*	0.0238 (0.0144)	0.0313 (0.0187)	*−0.3383 (0.1549)*	−0.0484 (0.0415)

Standard errors are given in parentheses. Italicized entries indicate significance ($P<0.05$)

CDBK crown dieback, *UNCR* uncompacted live crown ratio, *CDEN* crown density, *CL* crown light exposure, *TRANS* foliage transparency

Table 3 Performance of the logistic regression model of tree survival by species based on receiver operating characteristic (ROC) curve area, max-rescale R^2 value, and chi-square values for the parameter estimates in Table 2

Species	ROC curve area	Max-rescaled R^2	Chi-square statistic					
			Variable					
			Intercept	CDBK	UNCR	CDEN	CL	TRANS
All species	0.702	0.1276	28	253	88	188	36	15
Red maple	0.772	0.2180		50	19	40	20	
Loblolly pine	0.661	0.0609				7	10	
Sugar maple	0.804	0.2073		17	11	30	9	
White oak	0.739	0.1858	10	24				
Northern white-cedar	0.724	0.1207	4	15			4	
Balsam fir	0.758	0.2090		23	38	9	9	
Quaking aspen	0.708	0.1706		19	5	14		
Sweetgum	0.688	0.1224		9	7	17		
Northern red oak	0.780	0.2652		17			5	19
Paper birch	0.715	0.1380		6		5	11	
Yellow poplar	0.743	0.1433				30		
Black cherry	0.705	0.1380		26		10		
Eastern white pine	0.769	0.1618			7			
American beech	0.753	0.1627		6	9			4
Eastern hemlock	0.825	0.1914		15			5	

CDBK crown dieback, *UNCR* uncompacted live crown ratio, *CDEN* crown density, *CL* crown light exposure, *TRANS* foliage transparency

usual application of logistic regression probabilities where dichotomous classification is selected as the one with a probability above 50 %. Probability cut points ranged from 0.0655 for white oak to 0.2676 for balsam fir (Table 4). The difference (Δ_m) between predicted mortality proportions of surviving trees (t_2 to t_3) from the applied logistic models with selected cut points was within 4 % of the observed mortality proportions (t_1 to t_2) in all cases (Table 5). Balsam fir and loblolly pine had the largest Δ_m; conversely, quaking aspen had the smallest Δ_m.

BBD and HWA

Although the predicted level of mortality (t_2 to t_3) across the range of American beech and eastern hemlock was similar to the observed proportion (t_1 to t_2), there was variation between the groups of trees in duration of BBD and HWA categories (Table 5). Interestingly, Δ_m was 4 % in areas that have not been uninfested with BBD for less than 15 years and −2 % where BBD has been present for more than 15 years (Table 5). By contrast, Δ_m for eastern hemlock was approximately −1 % in areas that were uninfested with HWA or infested for less than 15 years and slightly higher than observed in areas where HWA has been present for more than 15 years. The predicted mortality rate generally increased with the increasing duration of infestation by BBD and HWA.

Discussion

The results of this study highlight the usefulness of FIA crown measurements to predict survival with logistic regression. Parameter estimates conform to expectations in nearly all cases. The coefficient of CDBK is negative in all cases (Table 2), indicating decreasing survival with increasing CDBK. CDBK was the most important crown condition variable for predicting tree survival for all species combined and for many of the 15 individual species in the study. CDBK is defined as recent

Table 4 Proportion of mortality, classification accuracy, and cut point probabilities for all species combined and individually for species with at least 1000 observations

Species	*N* live trees (t_1)	% Mortality observed (t_1 to t_2)	% Mortality predicted without cut points (t_1 to t_2)	% Classification accuracy (without cut points)	Cut point probability	% Mortality predicted with cut points (t_1 to t_2)
All species	55,013	7.87	0.84	10.71	0.1360	7.74
Red maple	5324	5.90	1.01	17.09	0.1416	4.53
Loblolly pine	4554	5.67	0.09	1.52	0.1121	8.69
Sugar maple	3205	3.48	0.46	13.16	0.1192	3.03
White oak	2119	3.04	0.47	15.38	0.0655	3.13
Northern white-cedar	1962	3.52	0.31	8.70	0.0789	3.46
Balsam fir	1603	17.72	3.56	20.07	0.2676	21.55
Quaking aspen	1536	17.45	3.06	17.54	0.2331	14.41
Sweetgum	1329	6.40	0.51	8.05	0.1176	7.19
Northern red oak	1284	5.04	1.47	29.23	0.1016	3.37
Paper birch	1290	16.20	2.33	14.35	0.2263	14.76
Yellow poplar	1147	6.83	0.58	8.54	0.1507	8.31
Black cherry	1116	8.07	1.24	15.38	0.1293	8.98
Eastern white pine	1089	6.89	0.64	9.33	0.1485	6.33
American beech	1041	7.92	1.13	14.29	0.1518	7.22
Eastern hemlock	1032	2.42	0.39	16.00	0.0767	3.62

t_1 includes years 2001 to 2005. t_2 includes years 2006 to 2010

mortality of branches, and it generally increases with severe stresses including damage to roots, stem damage that interferes with moisture and nutrient transport, direct crown injury, severe defoliation, or leaf scorch (Schomaker et al. 2007). A previous study by Steinman (2000) also identified crown dieback as the best predictor of tree mortality. However, the measurement period in that study was 1 year, and the geographic scope was limited to 15 states. Crown dieback has previously been positively correlated with tree stressors including wood borers (Fan et al. 2008), insect defoliators (Morin et al. 2004), water stress (Randolph et al. 2012), drought (Hogg et al. 2008), and atmospheric deposition (Duarte et al. 2013).

Similarly, the coefficient of TRANS is negative in the most significant cases, indicating decreasing survival with increasing TRANS. However, TRANS was only significant in three models (Table 2). This lack of predictive capability of mortality is not surprising given that the TRANS variable has most often been correlated with insect defoliation (Korb et al. 1992; Kulman 1971). Additionally, Allen et al. (1992) reported that following a single year of pear thrips (*Taeniothrips inconsequens* Uzel) defoliation, TRANS of sugar maple in Vermont and Massachusetts actually decreased by 75 % or more in the following year. Thus, a flush of foliage following a severe defoliation event may show up as improved crown condition when measured by the TRANS assessment.

By contrast, the coefficients of the other significant variables are all positive, which indicates increasing survival with increases in the crown variable, except for CL in the models for balsam fir and eastern hemlock (Table 2). Because balsam fir and eastern hemlock are the only two conifers included in the study that are classified as very shade tolerant (Burns and Honkala 1990), the negative relationship between survival and CL is not surprising. The decrease in survivability could be a function of increased competition from other less tolerant species (Klooster et al. 2007; Kobe et al. 1995; Luo and Chen 2011).

Balsam fir and loblolly pine were the only two species with Δ_m of 3 %t or greater. The predicted increase in balsam fir mortality could reflect declining crown health related to balsam woolly adelgid (*Adelges piceae* Ratzeburg) impacts in Maine and New Hampshire in the mid-2000s as well as intraspecific competition or competition from shade-tolerant hardwoods (Burns and

Table 5 Proportion of mortality for predictions from logistic models applied to surviving trees using the selected cut points

Species	N live trees (t_2)	% Mortality predicted (t_2 to t_3)	% Mortality observed (t_1 to t_2)	Δ_m (t_2 to t_3)-(t_1 to t_2)
All species	50,593	7.74	7.87	−0.1
Red maple	4996	4.53	5.90	−1.4
Loblolly pine	4293	8.69	5.67	3.0
Sugar maple	3086	3.03	3.48	−0.5
White oak	2047	3.13	3.04	0.1
Northern white cedar	1893	3.46	3.52	−0.1
Balsam fir	1319	21.55	17.72	3.8
Quaking aspen	1268	14.41	17.45	−3.0
Sweetgum	1244	7.19	6.40	0.8
Northern red oak	1216	3.37	5.04	−1.7
Paper birch	1081	14.76	16.20	−1.4
Yellow poplar	1069	8.31	6.83	1.5
Black cherry	1016	8.98	8.07	0.9
Eastern white pine	1014	6.33	6.89	−0.6
American beech	956	7.22	7.92	−0.7
BBD—uninfested	204	3.21	3.03	0.2
BBD—1–15 years	124	6.45	2.36	4.1
BBD—16–39 years	252	9.13	11.23	−2.1
BBD—≥40 years	376	8.51	10.05	−1.5
Eastern hemlock	1010	3.62	2.42	1.2
HWA—uninfested	750	1.47	2.34	−0.9
HWA—1–15 years	225	1.33	2.17	−0.8
HWA—>15 years	35	5.71	5.41	0.3

American beech and eastern hemlock data are also presented in beech bark disease (BBD) and hemlock woolly adelgid (HWA) duration of infestation categories. t_2 includes years 2006 to 2010. t_3 includes years 2011 to 2015. Δ_m is the difference between the predicted future mortality and the observed past mortality

Honkala 1990). Loblolly pine decline, which typically causes declining crowns (Eckhardt et al. 2007) and has been reported in plantations throughout the southeastern USA (Eckhardt et al. 2010), may be associated with the predicted increase in loblolly pine mortality. The variation in Δ_m among the American beech infestation categories corresponds with the recognized phases of BBD. In our study, the 1–15-year infested category may reflect the killing front where mortality is still increasing. Conversely, the 16–39- and ≥40-year categories represent the aftermath forest where mortality has actually begun to decrease after the advancing and killing front phases.

The accuracy of the models may have been affected by the frequency with which the tree crowns were assessed. All of the crown condition variables were developed by the FHM program that, before 1999, conducted surveys on an annual basis. Since 1999, however, the FIA program has conducted the surveys on a cycle of 5 years across most of the eastern USA (Riitters and Tkacz 2004). The 5-year remeasurement interval should be adequate for detecting forest health problems that cause slow crown deterioration, but it may be too long for detecting rapid declines. Thus, the poor predictive power of the models before implementing the cut points may be due, in part, to trees that at t_1 had healthy crowns but rapidly declined and succumbed to mortality before t_2.

Conclusion

The utility of models that predict impending tree mortality goes beyond forest inventory or traditional forestry growth and yield models. Invasive insects and diseases, atmospheric deposition, drought, and other biotic and abiotic disturbances have important implications for forest management and policy due to the often severe impacts that they have on growth and mortality of host trees. Understanding the relationship between the health of host tree crowns and biological invasions may allow for early detection of pest presence and activity or prediction of future mortality levels. Although our models are only applicable to trees growing in a forest setting, mortality models that are based upon crown health indicators could be used anywhere managers need to assess tree health or predict tree mortality. For example, to project urban tree population effects, mortality rates must be known (Nowak et al. 2004) in order to prepare for future removals and replacements. Likewise, recreation management depends on managing trees in parks, campgrounds, and along trails where identifying hazard trees and maintaining aesthetic quality are important. Finally, wildlife managers may be interested in identifying potential snag trees that provide more cavities than live trees (Fan et al. 2003). The BBD and HWA examples reported here demonstrate this potential. In both cases, the correspondence between proportion of mortality increases (Δ_m) and duration of infestation categories is similar to increases in mortality associated with BBD and HWA estimated from regional forest inventory data (Morin and Liebhold 2015). Once the third cycle of remeasurement has been completed in 2017, further analysis can be performed to quantify the differences between mortality rates over two remeasurement cycles.

Acknowledgments We would like to thank Christopher Oswalt, Stan Zarnoch, and two anonymous reviewers for their constructive reviews of earlier versions of this manuscript.

References

Allen, D. C., Barnett, C. J., Millers, I., & Lachance, D. (1992). Temporal change (1988-1990) in sugar maple health, and factors associated with crown condition. *Canadian Journal of Forest Research, 22*(11), 1776–1784.

Allison, P. D. (1999). *Logistic regression using the SAS system: theory and application*. Cary: SAS Institute Inc.

Bechtold, W. A. & Patterson, P. L. (eds.) (2005). *The enhanced Forest Inventory and Analysis program—national sampling design and estimation procedures*. Gen. Tech. Rep. SRS-80. Asheville, NC.

Burns, R. M. & Honkala, B. H. (tech. coords.) (1990). *Silvics of North America: 1. Conifers; 2. Hardwoods*. Agriculture Handbook 654. Washington, DC.

Castlebury, L. A., Rossman, A. Y., & Hyten, A. S. (2006). Phylogentic relationships of *Neonectria*/*Cylindrocarpon* on *Fagus* in North America. *Canadian Journal of Botany, 84*, 1417-1433.

Duarte, N., Pardo, L. H., & Robin-Abbott, M. J. (2013). Susceptibility of forests in the northeastern USA to nitrogen and sulfur deposition: critical load exceedance and forest health. *Water, Air, & Soil Pollution, 224*, 1355.

Eckhardt, L. G., Weber, A. M., Menard, R. G., Jones, J. P., & Hess, N. J. (2007). Insect-fungal complex associated with loblolly pine decline in central Alabama. *Forest Science, 53*(1), 84–92.

Eckhardt, L. G., Sayer, M. A. S., & Imm, D. (2010). State of pine decline in the southeastern United States. *Southern Journal of Applied Forestry, 34*, 138–141.

Evans, A. M., & Gregoire, T. G. (2007). A geographically variable model of hemlock woolly adelgid spread. *Biological Invasions, 9*, 1387–3547.

Fan, Z., Shifley, S. R., Spetich, M. A., Thompson, F. R., III, & Larsen, D. R. (2003). Distribution of cavity trees in midwestern old-growth and second-growth forests. *Canadian Journal of Forest Research, 33*, 1481–1494.

Fan, Z., Kabrick, J. M., Spetich, M. A., Shifley, S. R., & Jensen, R. G. (2008). Oak mortality associated with crown dieback and oak borer attack in the Ozark Highlands. *Forest Ecology and Management, 255*(7), 2297–2305.

Fischer, J. E., Bachman, L. M., & Jaeschke, R. (2003). A readers' guide to the interpretation of diagnostic test properties: clinical example of sepsis. *Intensive Care Medicine, 29*, 1043–1051.

Greiner, M., Sohr, D., & Göbel, P. (1995). A modified ROC analysis for the selection of cut-off values and the definition of intermediate results of serodiagnostic tests. *Journal of Immunological Methods, 185*(1), 123–132.

Havill, N. P., & Montgomery, M. E. (2008). The role of arboreta in studying the evolution of host resistance to the hemlock woolly adelgid. *Arnoldia, 65*(3), 1–9.

Hogg, E. H., Brandt, J. P., & Michaelian, M. (2008). Impacts of a regional drought on the productivity, dieback, and biomass of western Canadian aspen forests. *Canadian Journal of Forest Research, 38*, 1373–1384.

Houston, D. R. (1994). Major new tree disease epidemics: beech bark disease. *Annual Review of Phytopathology, 32*, 75–87.

Kenk, G. (1993). Growth in "declining" forests of Baden-Wurttemberg (southwestern Germany). In R. F. Huettl & D. Mueller-Dombois (Eds.), *Forest decline in the Atlantic and Pacific region* (pp. 202–215). New York: Springer-Verlag.

Klooster, S. H. J., Thomas, E. J. P., & Sterck, F. J. (2007). Explaining interspecific differences in sapling growth and shade tolerance in temperate forests. *Journal of Ecology, 95*, 1250–1260.

Kobe, R. K., Pacala, S. W., Silander, J. A., Jr., & Canham, C. D. (1995). Juvenile tree survivorship as a component of shade tolerance. *Ecological Applications, 5*, 517–532.

Korb, T. E., McCormick, L. H., Simons, E. E., & Jeffery, D. J. (1992). Impacts of pear thrips damage on root carbohydrate, sap, and crown characteristics of sugar maples in a Pennsylvania sugarbush. *Forest Science, 38*, 381–392.

Kulman, H. M. (1971). Effects of insect defoliation on growth and mortality of trees. *Annual Review of Entomology, 16*, 289–324.

Lawrence, R., Moltzan, B., & Moser, W. K. (2002). Oak decline and the future of Missouri's forests. *Missouri Conservationist, 63*(7), 11–18.

Luo, Y., & Chen, H. Y. H. (2011). Competition, species interaction and ageing control tree mortality in boreal forests. *Journal of Ecology, 99*, 1470–1480.

McClure, M. S., Salom, S. M., & Shields, K. S. (2001). Hemlock wooly adelgid. USDA For. Serv. FHTET-2001-03.14 p.

Mize, C. W., & Lea, R. V. (1979). The effect of beech bark disease on the growth and survival of beech in northern hardwoods. *European Journal of Forest Pathology, 9*, 243–248.

Morin, R. S. & Liebhold, A.M. (2015). Two invaders collide: a pair of invasive insects intersect and alter the trajectory of eastern forest composition. *Forest Ecology and Management*.

Morin, R. S., Jr., Liebhold, A. M., & Gottschalk, K. W. (2004). Area-wide analysis of hardwood defoliator effects on tree conditions in the Allegheny Plateau. *Northern Journal of Applied Forestry, 21*(1), 31–39.

Morin, R. S., Liebhold, A. M., Tobin, P. C., Gottschalk, K. W., & Luzader, E. (2007). Spread of beech bark disease in the eastern United States and its relationship to regional forest composition. *Canadian Journal of Forest Research, 37*, 726–736.

Morin, R. S., Liebhold, A. M., & Gottschalk, K. W. (2009). Anisotropic spread of hemlock woolly adelgid in the eastern United States. *Biological Invasions, 11*, 2341–2350.

Nowak, D. J., Kuroda, M., & Crane, D. E. (2004). Tree mortality rates and tree population projections in Baltimore, Maryland, USA. *Urban Forestry & Urban Greening, 2*, 139–147.

Orwig, D. A., Foster, D. R., & Mausel, D. L. (2002). Landscape patterns of hemlock decline in New England due to the introduced hemlock woolly adelgid. *Journal of Biogeography, 29*, 1475–1487.

Randolph, K. C., Morin, R. S., & Steinman, J. (2010). *Descriptive statistics of tree crown condition in the northeastern United States*. Gen. Tech. Rep. SRS–124. Asheville, NC.

Randolph, K., Bechtold, W. A., Morin, R. S., & Zarnoch, S. J. (2012). Evaluating elevated levels of crown dieback among northern white-cedar (*Thuja occidentalis* L.) trees in Maine and Michigan: a summary of evaluation monitoring. In: Potter, K. M., & Conkling, B. L. (Eds.), *Forest health monitoring: 2009 national technical report*. Gen. Tech. Rep. SRS-167. Asheville, NC: pp. 219-223.

Riitters, K., & Tkacz, B. (2004). The U.S. forest health monitoring program. In B. Wiersma (Ed.), *Environmental monitoring* (pp. 669–683). Boca Raton: CRC Press.

SAS Institute Inc. (2009). *SAS OnlineDoc® 9.2*. Cary: SAS Institute Inc.

Schomaker, M.E., Zarnock, S.J., Bechtold, W.A., Latelle, D.J., Burkman, W.G., & Cox, S.M. (2007). *Crown-condition classification: a guide to data collection and analysis*. Gen. Tech. Rep. SRS-102. Asheville, NC.

Shigo, A. L. (1972). The beech bark disease today in the northeastern U.S. *Journal of Forestry, 54*, 286–289.

Steinman, J. R. (2000). Tracking the health of trees over time on Forest Health Monitoring plots. In: Hansen, M., & Burk, T. (Eds.), *Integrated tools for natural resources inventories in the 21st century: an international conference on the inventory and monitoring of forested ecosystems*. Gen. Tech. Rep. NCRS-212. St. Paul, MN: pp. 334-339.

Swets, J. A., Pickett, R. M., Whitehead, S. F., Getty, D. J., Schnur, J. A., Swets, J. B., et al. (1979). Assessment of diagnostic technologies. *Science, 205*, 753–759.

Widmann, R. H., Cook, G. W., Barnett, C. J., Butler, B. J., Griffith, D. M., Hatfield, M. A., et al. (2012). *West Virginia's forests 2008*. Resour. Bull. NRS-61. Newtown Square, PA: 64 p.

Wieferich, D. J., McCullough, D. G., Hayes, D. B., & Schwam, N. (2013). Distribution of American beech (Fagus grandifolia) and beech scale (Cryptococcus fagisuga Lind.) in Michigan. 2005-2009. *Northern Journal of Applied Forestry, 28*, 173–179.

Will-Wolf, S., & Jovan, S. (2009). Lichens, ozone, and forest health—exploring cross-indicator analyses with FIA data. In: McWilliams, W., Moisen, G., Czaplewski, R., (Comps.), *Forest Inventory and Analysis* (*FIA*) *symposium 2008*. Proc. RMRS-P-56CD:18 p.

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. RMRSGTR-245. Fort Collins, CO.

Yarnold, P. R., Hart, L. A., & Soltysik, R. C. (1994). Optimizing the classification performance of logistic regression and Fisher's discriminant analyses. *Education and Psychological Measurement, 54*(1), 73–85.

Zarnoch, S. J., Bechtold, W. A., & Stolte, K. W. (2004). Using crown condition variables as indicators of forest health. *Canadian Journal of Forest Research, 34*, 1057–1070.