EVALUATION OF LANDSAT IMAGERY FOR DETECTING ICE STORM DAMAGE IN UPLAND FORESTS OF EASTERN KENTUCKY

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Abstract—Two categories of forest canopy damage (none to light vs. moderate to heavy) resulting from a 2003 ice storm in eastern Kentucky could be identified on readily available Landsat Thematic Mapper imagery using change detection techniques to evaluate the ratio of spectral bands 4 and 5. Regression analysis was used to evaluate several model formulations based on the spectral ratio and topographic variables for detecting the two categories of damage, which could be applied with a geographic information system. Results of this study suggest that moderate to heavy forest canopy damage caused by ice storms can be detected on sample plots from satellite imagery. Additional work is needed, however, to determine if these results can be used to produce an accurate landscape-scale map of canopy damage beyond the study area.

INTRODUCTION

Ice storms are a major, recurring type of disturbance in deciduous forests of the Eastern United States, with annual probability of occurrence ranging from 0.11 to 0.22 (U.S. Department of Agriculture Forest Service 1969, Hauer and others 1994). Mapping and assessing the extent and severity of storm damage in managed forests is necessary to estimate economic loss, salvage products, and plan recovery activities. Aerial photography is typically used for such assessment following a disturbance event (Lewis 2004), but results in unanticipated costs for its procurement and interpretation. Conventional Landsat Thematic Mapper (TM) satellite imagery has been shown to be useful for detecting forest damage to tree canopies resulting from insects (Vogelmann and Rock 1989) and ice (Burnett 2003). Because Landsat TM imagery is economical, readily available, and generally well suited to detect changes in vegetation (U.S. Department of Agriculture Forest Service 1995), methods for using it to detect and assess forest damage resulting from ice storms could be of significant practical value to managers.

A major ice storm occurred on February 15, 2003, in a large area of northeastern Kentucky and southeastern Ohio that included parts of the Daniel Boone and Wayne National Forests. Up to 2 inches of ice accumulated on exposed surfaces, causing breakage of limbs and stems, and uprooting (fig. 1). A report for the Wayne National Forest indicated that damage “...appeared to be light to moderate over the entire district, with many trees having some crown damage. In smaller pockets, ranging up to hundreds of acres in size, damage ranged from heavy to severe ...” (U.S. Department of Agriculture Forest Service 2003). Initial effects of forest damage resulting from this storm were assessed from conventional aerial photography (Lewis 2004). The success of other workers in using satellite imagery to assess levels of ice damage in mesophytic forests of Vermont (Burnett 2003) has encouraged us to test those methods in predominately upland oak forests of eastern Kentucky. The scope of our study was limited by available resources to a rudimentary application of well-developed methodology used to detect change in forest conditions from Landsat imagery (Heikkonen and Varjo 2004).

PROCEDURES

Study Site and Data Collection

An area representative of common forest types and typical ice damage was selected near Morehead, KY, in the Morehead District of the Daniel Boone National Forest (38.1° N, 83.5° W). Forest composition consists of over 40 commercial species that are distributed primarily in relation to moisture regime. On mesic sites of coves and northerly slopes are northern red oak (Quercus rubra L.), American basswood...
(Tilia americana L.), American beech (Fagus grandifolia Ehrh.), yellow-poplar (Liriodendron tulipifera L.), sugar maple (Acer saccharum Marsh.), black birch (Betula lenta L.), red maple (Acer rubrum L.), and Canadian hemlock (Tsuga canadensis [L.] Carr.). Westerly slopes are occupied by yellow-poplar, northern red oak, white oak (Q. alba L.), and hickories (Carya spp. Nuttall.). On xeric southerly slopes and ridges are chestnut oak (Q. prinus L.), white oak, Virginia pine (Pinus virginiana Mill.), and shortleaf pine (P. echinata Mill.). Understory tree species include flowering dogwood (Cornus florida L.), sourwood (Oxydendrum arboreum [L.] DC.), and blackgum (Nyssa sylvatica L.). Two shrubs are widespread: rosebay rhododendron (Rhododendron maximum L.) on moist slopes and mountain laurel (Kalmia latifolia L.) on drier sites. Stand basal areas ranged from 70 to 120 square feet per acre.

Aerial photography was obtained soon after the storm for mapping the extent of the disturbance and assessing the severity of damage to forest resources. A study area of approximately 3,400 acres was selected on the basis of ground reconnaissance and aerial photography to include the range of disturbance, which varied from undisturbed patches of trees to canopy gaps associated with almost complete uprooting and crown breakage. The 1:10,000 scale, leaf-off, panchromatic photography was electronically scanned at 800 dpi, orthorectified to establish a coordinate system and remove image distortions resulting from camera and terrain sources, and displayed on a computer monitor at a scale of approximately 1:24,000. Plot locations were selected from a computer-generated grid overlaid randomly on the image; the grid intersects defined the center of potential plot locations. Intersects were randomly selected and a standard density grid was used to assign canopy damage to four categories:
Category | Range of canopy damage
---|---
None | No apparent damage to forest canopy
Light | < 25 percent of canopy damaged
Moderate | From 25 to 65 percent of canopy damaged
Heavy | More than 65 percent of canopy damaged

The categories were defined prior to classification of the sample plots on the digital image and had been used by the third author in an unreported trial of forest damage resulting from a windstorm. Selection of grid intersections continued until approximately 30 plots were chosen in each category of canopy damage. Coordinates of the location of each plot were recorded from the scanned photographic images using geographic information system (GIS) software. The GIS was also used to derive aspect (degrees azimuth) and gradient (percent) at each plot location from a digital elevation dataset. Elevation varied relatively little in the study area, from 800 to 1,250 feet, and was not tested for significance.

Each plot selected from the aerial photographs was located in the field during the following summer using a geographic positioning system to navigate to the recorded map coordinates. The plotless inventory method (Grosenbaugh 1952) was employed, and each sample tree identified by a 10-factor prism was classified as damaged or not damaged. Forest type on each plot was subjectively classified to provide supplemental information on variability of ice damage by species composition.

We obtained a cloud-free Landsat TM image of the study area for June 2002 and July 2003. A Landsat image represents an area about 106 by 115 miles in extent and consists of a grid of picture elements, or pixels. Each square pixel represents a ground area of approximately 0.22 acre. Data associated with each pixel consists of values for seven spectral bands, and the magnitude of these values varies depending on characteristics of objects or vegetation on the ground that reflects light to sensors on the satellite.

We used the moisture stress index (MSI) as the response variable to quantify forest damage (Hunt and Rock 1989). MSI is the ratio of mid-infrared band 5 (1.55–1.75 microns) to near-infrared band 4 (0.76–0.90 microns) and has been found useful for detecting the moisture content of vegetation because of differences in reflectance by the two bands. MSI is not without problems, however, because it may be influenced by factors unrelated to the disturbance event, such as soil moisture beneath vegetation or defoliation by insects. We used MSI as the response variable because we hypothesized that less photosynthesizing biomass would be present after the event than before it as a consequence of canopy gaps resulting from crown breakage and uprooted trees. MSI was calculated for each pixel in the study area satellite image scenes before (MSIb) and after (MSIa) the ice storm and extracted to a database for pixels containing a field plot. Data were not normalized for differences in atmospheric conditions between the two image dates.

**Data Analysis**

The kappa statistic (Cohen 1960) was used to test for agreement between categories of forest damage on the sample plots estimated from aerial photography and determination of damage in the field. We used chi-square to test for independence of damage category with aspect and gradient classes. Analysis of variance (ANOVA) was used to test the hypothesis that damage category had no significant effect on MSI at the 0.05 percent level of probability. The difference (MSId) between pre- and post-disturbance MSI was used as the ANOVA response variable, which follows methodology typically used in studies of vegetation change detection based on satellite imagery (Burnett 2003). Treatments consisted of the four categories of canopy damage determined by means of ground examination at each plot location. Significant differences among damage categories were separated by the Bonferroni test at the 0.05 level of probability.
We used logistic regression to evaluate formulations of prediction models that could be useful in automated detection of forest damage on satellite imagery obtained before and after an ice storm:

\[ \text{logit (DC)} = \text{function of (MSI}_b, \text{ MSI}_a, \text{ MSI}_d, \text{ aspect, gradient)} \quad (1) \]

The dependent variable, DC, is a binary damage category (i.e., None or Light vs. Moderate or Heavy). Two model formulations were evaluated that included either MSI\(_d\) alone or a combination of MSI\(_a\) and MSI\(_b\). Aspect was transformed from a circular to a continuous measure by taking the sine and cosine of the direction in which each plot faced. A probability level of \( p = 0.05 \) was used to retain independent variables in the model. The two model formulations were tested with data for three groups of forest type (see table 1): (1) all types, (2) the two predominant types of mesic oak and mixed mesophytic, and (3) the majority type of mesic oak. Unlike the ANOVA, which tested for the effect of damage categories on the change of MSI before and after the ice storm, these regression analyses provided an evaluation of two methods of expressing MSI and the value of topographic variables for detecting and mapping ice storm damage using a GIS.

RESULTS AND DISCUSSION

Damage Assessment

A total of 117 plots representing 4 categories of forest canopy damage were selected for study using aerial photography (table 2). The required number of plots selected for two categories, None and Moderate, was less than desired. Agreement was high, > 90 percent (kappa = 0.87), between the classification of damage estimated from aerial photography compared to damage assessed in the field. Six plots were discarded as a result of missing field data or outlier values of MSI\(_b\) and MSI\(_a\), leaving 111 plots for subsequent analysis.

Sample plots were generally distributed uniformly among quadrants of azimuth, although fewer plots (17) were situated on northerly aspects. Chi-square tests indicated that category of canopy damage varied by aspect class \( p < 0.000 \); plots with westerly and northerly aspects tended to receive None to Light damage while plots with easterly aspects received Heavy damage. Slope gradient of the sample plots ranged from

<table>
<thead>
<tr>
<th>Forest type</th>
<th>Plots</th>
<th>MSI(_b)</th>
<th>MSI(_a)</th>
<th>MSI(_d) ± SE (_c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mesic oak</td>
<td>55</td>
<td>0.756</td>
<td>0.815</td>
<td>0.069 ± 0.014</td>
</tr>
<tr>
<td>Mixed mesophytic</td>
<td>32</td>
<td>0.766</td>
<td>0.819</td>
<td>0.043 ± 0.018</td>
</tr>
<tr>
<td>Mixed oak-pine</td>
<td>5</td>
<td>0.744</td>
<td>0.722</td>
<td>-0.022 ± 0.043</td>
</tr>
<tr>
<td>Mixed oak-yellow pine</td>
<td>8</td>
<td>0.784</td>
<td>0.785</td>
<td>0.001 ± 0.026</td>
</tr>
<tr>
<td>Yellow pine</td>
<td>2</td>
<td>0.804</td>
<td>0.681</td>
<td>-0.123 ± 0.028</td>
</tr>
<tr>
<td>Xeric oak</td>
<td>9</td>
<td>0.792</td>
<td>0.818</td>
<td>0.025 ± 0.040</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>111</strong></td>
<td><strong>0.764</strong></td>
<td><strong>0.810</strong></td>
<td><strong>0.045 ± 0.010</strong></td>
</tr>
</tbody>
</table>

MSI = moisture stress index; SE = standard error.

\(^a\)MSI is the ratio of Landsat spectral band 5 to band 4; MSI\(_b\) was determined from June 2002 imagery (before the ice storm); MSI\(_a\) was determined from July 2003 imagery (after the storm); MSI\(_d\) is the difference between MSI\(_a\) and MSI\(_b\).

\(^b\)Six of the 117 total plots (see table 1) were omitted from the analysis because of missing data or values of MSI considered as outliers.

\(^c\)There were no significant differences of MSI\(_b\), MSI\(_a\), or MSI\(_d\) among forest types at alpha = 0.05.
6 to 74 percent. Chi-square analysis indicated that damage category did not vary by class of slope gradient \( (p = 0.064) \), although plots with Heavy canopy damage tended to occur on steeper (> 40 percent) slopes.

Six forest types were identified on the 111 sample plots (table 1). The predominant forest types were mesic oak and mixed mesophytic, which together accounted for 78 percent of the plots. Mean MSId increased by 0.045 in July 2003, indicating that less photosynthesizing vegetation was present after the ice storm compared to before. MSId did not differ among forest types (table 1), which allowed pooling of data from all plots for the change detection analysis. ANOVA of the MSId data indicated that category of damage had a significant \( (p = 0.001) \) effect on MSId. Separation of significant damage category means using the Bonferroni test indicated that there were real differences between the Light and Medium categories \( (p = 0.01) \) and between the Light and Heavy categories \( (p = 0.01) \); there was no real difference between the None and Light categories or between the Medium and Heavy categories. Therefore, two new damage classes were formed for further analysis by combining None and Light, and Medium and Heavy. Analysis of these two new damage classes revealed significant \( (p<0.01) \) differences of MSId. Results of a supplementary analysis not described in detail here indicate that simple unsupervised and supervised classifications of the two damage classes based on MSId produced accuracy levels of about 60 percent.

Our findings agree with those reported by Burnett (2003), who found that damage to hardwood forest canopies can be detected by low-resolution Landsat TM imagery. Our results differed from those of Burnett, however, in that we were unable to detect levels of damage. A difference between our study and that of Burnett (2003) is forest type, which was mixed mesophytic in Vermont and predominantly oak in Kentucky. How these forest types differ in response to the ratio is unknown, but such a difference may contribute to the discrepancy between Burnett’s findings and our own. Our results agree with those of Lewis (2004), who reported difficulty in separating medium and heavy levels of storm damage using conventional aerial photography.

### Damage Modeling

We developed six predictive models for evaluating two expressions of MSI and three groupings of forest type (table 3). Accuracy in detecting canopy damage increased slightly as variation in forest type decreased, from an average of 75 percent for all six types (models 1 and 2 in table 3) to 83.5 percent for the single forest type (models 5 and 6). Likewise, the optimum expression of MSI changed from MSId and MSId, for the analysis including all forest types, to MSId alone for the single type. In formulations based on MSId and MSId (models 2, 4, and 6), the two variables probably accounted for variation associated with different forest types, somewhat as if a covariate had been included in the ANOVA used for the damage category analysis.
Topographic variables varied in their importance in the prediction models. Aspect and gradient generally were not important for predicting canopy damage for all forest types combined. Their value increased, however, with increased uniformity of species composition. Including topographic variables in a model involves additional work because digital elevation data must be obtained for the image area, followed by derivation of the variables and assignment of a value to each pixel of the Landsat image. Finally, however, a relationship must be established between canopy damage and the important topographic variables to provide coefficients for the prediction model.

Our analysis suggests a likely increase in overall accuracy of damage assessment by developing a model for each individual forest type. Application of a system of models using a GIS would be problematic, however, because an accurate determination of forest type would be required for each pixel of a Landsat image. Model 2 is appealing for general application because it utilizes only MSIb and MSIa, and has high relative accuracy (77 percent). The classification error matrix (table 4) based on model 2 resulted in about equal levels of false negative (10.5 percent) and false positive (12.5 percent) predictions.

The predictive models indicated that pre- and post-disturbance MSI and topographic variables accounted for much of the variation in forest damage resulting from the February 2003 ice storm in eastern Kentucky. Our results agree largely with those of Millward and Kraft (2004), who found that aspect, species composition, and weather conditions during an ice storm event were important factors in determining the pattern and extent of forest damage. Although we could detect differences in MSI based only on two canopy damage classes (None and Light vs. Medium and Heavy), this degree of discrimination will likely be adequate for most assessments because it will allow identification of areas of potential salvage and regeneration needs. We can not speculate on how our results would have changed if

Table 3—Comparison of two regression model formulations that utilized three forest type groupings for relating moisture stress index and topographic variables to forest canopy damage caused by an ice storm in February 2003 on the Morehead District of the Daniel Boone National Forest

<table>
<thead>
<tr>
<th>Dependent variables or statistic</th>
<th>All (n = 111)</th>
<th>MO + MM (n = 87)</th>
<th>MO (n = 55)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MF1</td>
<td>MF2</td>
<td>MF1</td>
</tr>
<tr>
<td>MSIa</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>MSIb</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>MSIa</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Aspect (degrees)</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Gradient (percent)</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>ROC (percent)</td>
<td>80</td>
<td>86</td>
<td>87</td>
</tr>
<tr>
<td>Accuracy (percent)</td>
<td>73</td>
<td>77</td>
<td>78</td>
</tr>
<tr>
<td>Model number</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

Note:
- a Forest type (see table 1) groupings: (1) all sampled, (2) the two predominant types of mesic oak and mixed mesophytic, and (3) mesic oak.
- b Damage categories: none and little vs. moderate and heavy.
- c MSIa = moisture stress index (MSI) after the storm, MSIb = MSI before the ice storm, MSIa = difference between MSIa and MSIb. MSI was determined from pre- and post- Landsat imagery as the ratio of spectral band 5 to band 4.
- d ROC = receiver operator curve; Accuracy = percent of plots classified correctly.
- e Model formulation (MF) 1 tests MSIa with aspect and gradient; MF2 tests MSIa and MSIb with aspect and gradient.
- f 0 = variable tested in the model but omitted from the final formulation because it was not significant at the $p \leq 0.05$ level of probability; 1 = variable tested in the model and retained because it was significant at the $p \leq 0.05$ level of probability; — indicates variable not tested in the model.
we had used values of MSI that had been corrected for image differences occurring between the two years of observation, although making such corrections is clearly recommended (Vogelmann and Rock 1989).

In summary, we demonstrated that moderate to heavy ice damage in forests of eastern Kentucky could be detected on Landsat TM imagery using an index of moisture stress. The degree of canopy damage resolution that we attained with satellite imagery was slightly lower than the level achieved by conventional methods using aerial photography; better results would likely be achieved with satellite imagery of higher resolution. A possible limitation of the satellite imagery method, however, is that ground verification of damage will probably be required unless the manager assumes that changes in pre- and post-disturbance MSI values were caused by a known weather event, such as an ice storm, and not, for example, from recent unknown insect defoliation. We consider this technique of using Landsat TM imagery to detect canopy damage resulting from ice storms to be promising. Additional refinement and testing with independent data is needed, however, before the technique can be considered an operational tool for producing accurate maps of canopy damage resulting from ice storms.

ACKNOWLEDGMENTS
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LITERATURE CITED


Table 4—Error matrix for a regression model of crown damage in all forest types resulting from a February 2003 ice storm on the Morehead District of the Daniel Boone National Forest

<table>
<thead>
<tr>
<th>Classified by regression model 2&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Classified by field examination (sample plots)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Not damaged</td>
<td>Not damaged</td>
<td>Damaged</td>
<td>Total</td>
<td></td>
</tr>
<tr>
<td>39</td>
<td>12</td>
<td>51</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>46</td>
<td>60</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>53</td>
<td>58</td>
<td>111</td>
<td></td>
</tr>
</tbody>
</table>

<sup>a</sup> Provided in table 3.


