Detecting wind disturbance severity and canopy heterogeneity in boreal forest by coupling high-spatial resolution satellite imagery and field data

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A B S T R A C T

Wind disturbance events can impact spatially heterogeneous patterns in vegetation structure and disturbance severity in forested landscapes. Characterizing these patterns in forested ecosystems with remote sensing data has been a persistent challenge as variation in severity may be heterogeneous at fine spatial scales. Yet the degree and pattern of disturbance severity are an important influence on successional dynamics. This study explored how spectral and textural characteristics of high-spatial resolution IKONOS imagery reflected patterns of disturbance severity across a windstorm damaged, 121-km² area of the Boundary Waters Canoe Area Wilderness (BWCAW) in northeastern Minnesota, USA. In this study, spectral and spatial features of high-spatial resolution (1-m panchromatic and 4-m multispectral) IKONOS satellite imagery from a single post-disturbance date are coupled with field observations of disturbance within 0.045-ha field plots to access the potential for empirically modeling disturbance severity across this heterogeneous landscape within the BWCAW. Combining textural and spectral features led to a multiple regression model that explained 68% of the variance, and predicted disturbance severity equally well for ground data not included in the model development. The results suggest the utility of combining spatial and spectral data for detecting differences in forest structure caused by ecological processes such as disturbance.

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1. Introduction

Spatial heterogeneity is an observable characteristic of forests that corresponds to functionally important aspects of ecological patterns and processes at a variety of scales (Legendre and Fortin, 1989; Kolasa and Rollo, 1991; Pickett and Cadenasso, 1995). On a landscape scale, spatial heterogeneity in forests can represent shifts in physiographic, climatic, or disturbance regimes. At finer scales, it may reflect various ecological drivers; for instance, microclimatic changes, fertility gradients, forest development and successional patterns, or local variation in disturbance susceptibility. At any scale, spatial heterogeneity represents a mosaic of biotic and environmental diversity (Heinselman, 1973, 1996; Kolasa and Rollo, 1991; Pickett and Cadenasso, 1995; Frelich and Reich, 1995).

The fields of remote sensing and ecology have approached the analysis of spatial heterogeneity in forest ecosystems from gradually converging perspectives and spatial dimensions. Remote sensing has described and detected spatial heterogeneity at progressively finer scales, exploring the linkages between object size and image spatial resolution as sensing technologies and analysis tools have improved (Atkinson and Aplin, 2004; Gergel, 2007). Ecology has approached the characterization of heterogeneity by increasing the spatial extent or multiple scale approaches in field studies to assess the scale-dependence of various processes (Wiens, 1988). Increases in the spatial extent of ground-based ecological studies are limited by myriad practical considerations such as financial cost or the rigor of data collection. Assessing ecologically relevant forest landscape characteristics accurately in spatially heterogeneous areas remains a challenge (Strahler et al., 1986; Treitz and Howarth, 2000). Characterizing wind disturbance events exemplifies this challenge because the patterns created are large in extent but heterogeneous at the scale of individual trees or small patches.

On July 4, 1999, a supercell derecho with winds estimated at up to 190 km/h produced a 64-km long by 6 to 20-km wide swath of damage affecting approximately 200,000-ha of southern boreal forest in and around the Boundary Waters Canoe Area Wilderness (BWCAW) in northeastern Minnesota, USA (Fig. 1). This paper analyzes the match between high-spatial resolution satellite imagery and ground-based ecological data regarding disturbance severity in this heterogeneous landscape.

Remote sensing of wind disturbance severity patterns, such as within the BWCAW, would prove informative since large-scale disturbances can restructure ecosystem functions depending on the distribution and severity of disturbance (Foster, 1988; Paine et al., 1998; Turner and Dale, 1998). Such information would also enable management and monitoring efforts to focus on high disturbance severity areas where heavy fuel loads pose a fire danger (USDA Forest Service, 2001). In this study, spectral and spatial features of high-spatial

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resolution (1-m panchromatic and 4-m multispectral) IKONOS satellite imagery (Dial et al., 2003) from a single post-disturbance date are coupled with field observations of disturbance within 0.045-ha field plots to access the potential for empirically modeling disturbance severity across this heterogeneous 121-km² landscape within the BWCAW.

More importantly, this approach explores the utility of direct linkages between the spatial and spectral components of high-spatial resolution imagery and field measured data. High-spatial resolution satellite imagery enables the juxtaposition of detailed field measurements with satellite remote sensing (Curran, 2001). Digital imagery such as IKONOS with its 1-m panchromatic and 4-m multispectral resolution approaches the scale of individual forest components such as tree crowns and forest canopy gaps (St-Onge and Cavayas, 1997). Therefore, a more explicit linkage between remotely sensed spectral and spatial characteristics and field measured ecological phenomena is potentially feasible at a landscape level (Collins and Woodcock, 1996; Cohen et al., 1995, 2001).

In this study, we expect the spectral and spatial domains to have value in detecting wind severity since increased disturbance severity reflects the exchange of standing canopy for dead tree boles and stems, understory vegetation, and forest soils, changing both the amount and pattern of reflectance. The high-spatial resolution of the IKONOS imagery will allow detection of low levels of disturbance severity since the imagery will discriminate fine-scale patches of forest, ground cover, and shadow.

It is increasingly common to classify and discriminate forest structure with empirical models combining spectral and spatial characteristics (Wulder, 1998; Franklin et al., 2001; Wunderle et al., 2007; Song et al., 2008). Still, the spatial domain is an underutilized aspect of remote sensing data (Curran, 2001). Past studies suggest the value of assessing changes within the spatial domain with respect to wind disturbance severity. Measures of spatial variance or texture have been used in forest cover analysis to distinguish age classes or classify forest stands (Hay et al., 1996; Franklin et al., 2001; Coburn and Roberts, 2004; Wunderle et al., 2007; Gergel, 2007), characterize woody plant invasion (Hudak and Wessman, 1998), and identify spatial patterns present with forest succession (Song and Woodcock, 2002). The use of texture and the spatial domain in analyzing forest development and dynamics is an emerging method in remote sensing but remains limited because it necessitates congruence between image spatial resolution, window size, and scale of objects (Strahler et al., 1986; Wulder et al., 2004).

The spatial pattern of forest canopy reflectance has been described with semivariograms and other measures of variance over various size moving windows (St-Onge and Cavayas, 1995, 1997; Coops and Culvenor, 2000). Generally, the distances at which reflectance changes become greater as forests develop. Texture observations are influenced by spatial resolution, where higher resolution allows heterogeneity to be observed at finer scales (Hay et al., 1996; Hudak and Wessman, 1998; Franklin et al., 2000). The high-spatial resolution of IKONOS imagery provides the potential to assess fine-scale canopy heterogeneity or spatial variance at typical forest plot scales such as our 12-m radius (0.045 ha) circular plots. Although studies have been
done to match forest canopy spatial patterns with the appropriate scale of spatial variance measurement with various size moving windows (St-Onge and Cavayas, 1995, 1996; Coops and Culvenor, 2000), this study is limited to using window sizes that are no larger than the scale of field plots in order to preserve the linkage between ecological data and the imagery. This is an area equivalent to an 11 × 11 pixel window using the 1-m IKONOS panchromatic band.

First order texture measures measure the variability among neighboring pixels within a defined area or moving window where higher values indicate a rougher surface within that area (Curran, 2001). In landscapes with continuous forest canopy cover, we expect that undisturbed forests will have lower variation in values at the small patch scale (e.g., 0.045-ha) using the high-spatial resolution 1-m IKONOS panchromatic band. In continuous landscapes, first order texture values should increase with increasing windstorm disturbance severity, because disturbance opens up an otherwise homogeneous surface. In contrast, in landscapes with discontinuous forest canopy cover, we expect that undisturbed forests will have higher initial variation in texture at the same spatial scale or moving window size. First order values should decrease with increasing windstorm disturbance severity because disturbance increases the proportion of canopy-free surface in effect smoothing the surface. In boreal forests, canopy cover is intermediate in continuity, and thus whether image texture or variance values decrease with increasing windstorm disturbance severity will depend on the degree of cover continuity prior to disturbance. Mechanistically, a decrease in spatial variance could result from the reduction of within-canopy and ground-to-canopy shadows in proportion to the number of windthrown trees.

Spectral reflectance characteristics also will contribute to the characterization of disturbance severity given that wind severity changes the proportion of disturbed versus undisturbed cover. The 4-m spatial resolution of the IKONOS multispectral bands is intermediate in scale, finer in comparison to Landsat or SPOT 10-m imagery but coarser compared to aerial imagery or the 1-m IKONOS panchromatic band. Although the spatial detail of IKONOS multispectral bands is not sufficient to distinguish individual forest components, the mix of elements within each pixel (such as living or dead tree crowns, boles and overturned root masses, bare patches of soil, and canopy shadow) should vary enough among pixels to distinguish disturbed and undisturbed forest. Thus, the 4-m spatial resolution of the spectral bands may still discriminate finer-scale patches of disturbed versus undisturbed forest than previous studies have shown. In boreal forest thinning, a disturbance that resembles windthrow, increases in reflectance were observed for Landsat TM bands 1–3, 5, and 7 across gradients of thinning (but not below 50% basal area removal) (Olsson, 1994). Removal of trees and incidental damage to forest canopies from forest thinning result in increased visible reflectance due to: decreases in foliage absorption, browning of foliage, and increased reflectance from ground surfaces (Olsson, 1994; Franklin, 2001). These results suggest that higher-resolution IKONOS imagery should be useful in detecting similar attributes from wind damage.

Across the visible IKONOS bands, spectral responses (digital number values) will be greater on plots in areas where wind disturbance severity is greater because of decreased shadow component. Alternatively, if the reflectance pattern observed is similar to ice damage and insect defoliation disturbances, then we expect that there will be only minor increases in red (MS-3) responses and decreases in green (MS-2) responses with increasing disturbance severity because of decreases in green leaf area along with a decline in chlorophyll due to physiological stress (Murtha, 1978; Reid, 1987; Gholz et al., 1996; Franklin, 2001).

It is unclear how the near infrared (MS-4) response will change with increased wind disturbance severity as variability in the near infrared following disturbance may be associated with various potential contrasting reflectance sources such as remaining trees, soils, understory vegetation cover, and cutting debris (Olsson, 1994; Franklin, 2001; Nilson et al., 2001). Near infrared reflectance decreases in response to incipient foliage damage (Murtha, 1978; Reid, 1987; Gholz et al., 1996), but may increase with time since disturbance because of shifts in foliage composition or understory exposure (Franklin, 2001; Radeloff et al., 1999). Lower spatial resolution studies of thinning disturbances have observed near infrared reflectance to either be unchanged (Olsson, 1994) or to increase (Nilson et al., 2001) with increased thinning severity. Reduction of within-canopy and canopy-to-ground shadow as disturbance severity increases may lead to less variability in this band.

Derived from MS-3 and MS-4, the normalized difference vegetation index (NDVI) is another potential indicator of disturbance severity. NDVI is a good indicator of vegetation biomass and condition (Bannari et al., 1995), and thus the absence of healthy vegetation from a forested area should decrease NDVI values, and therefore indicate a landscape of downed stems or bare soil.

2. Methods

2.1. Study area

The study area (≈121-km²) is centered on 90°56’ W longitude and 48°0’8’’ N latitude within the Boundary Waters Canoe Area Wilderness, a 400,000-ha federally designated wilderness area within the Superior National Forest in northeastern Minnesota, USA (Fig. 1). The wilderness area affected is the largest tract of uncut fire-origin forest in eastern United States and has a well-documented disturbance history (Ohmann and Ream, 1971; Heinselman, 1973, 1996; Grigal and Ohmann, 1975; Freilich and Reich, 1995, 1999).

The area has low relief with gently rolling hills and frequent exposed rock outcrops; elevations range from 400 to 580-m above sea level. The climate is cold-temperate continental with a frost-free season of 100 days and mean temperatures of 17 °C and −8 in July and January respectively. Mean annual precipitation is 64-cm, but ranges from 38 to 100-cm (Heinselman, 1996).

The landscape is a mosaic of southern boreal forests underlain by granitic bedrock interlated by a network of glacier-formed lakes and wetlands. Forest communities include early successional, primarily fire-adapted species, such as jack pine (Pinus banksiana), red pine (Pinus resinosa), and aspen (Populus tremuloides); late successional species such as white cedar (Thuja occidentalis), balsam fir (Abies balsamifera), and black spruce (Picea mariana), which are able to regenerate continuously in older stands; and paper birch (Betula papyrifera), which occupies both early and late successional positions in boreal forests (Freilich and Reich, 1995). Over the last century, fire exclusion has interrupted the fire-adapted forest dynamics in the BWCAW; fire rotation periods have extended from 50 to 100 years in pre-settlement to >1000 years from ≈1920 onward (Grigal and Ohmann, 1975; Freilich and Reich, 1995). Prior to the 1999 derecho, the BWCAW forests were becoming more heterogeneous in composition and spatial configuration as larger monodominant stands of early successional species were replaced by mixed stands of late successional species with some patches as small as individual trees (Freilich and Reich, 1995). The 1999 storm accelerated this process, especially as stands previously dominated by early successional species were highly susceptible to wind (Rich et al., 2007).

The specific study area was selected because the existing field data had been collected in a uniform manner after the wind disturbance during the same time frame as the IKONOS image, and the field data represents a wide range in windstorm severity from zero to complete canopy mortality. No pre-disturbance IKONOS imagery existed for this area prior to the disturbance.

2.2. Field sampling

To quantify disturbance severity, the status of each tree before and after the windstorm was assessed on 780 upland plots on 56 transects
during the summers of 2000 and 2001. Trees had not been salvaged or burned at the time of fieldwork, so it was possible to assess which trees had died during the windstorm on each plot. Individual field plots were distributed along transects to increase sampling efficiency because site access required traveling by canoe and then traversing wind-damaged forests. Each transect began 5-m from a lakeshore at an azimuth perpendicular to the lake edge and extended 250 to 400-m. These transects ran orthogonal to the natural gradient and community distribution within the landscape. The exact locations were determined before sampling began by picking shoreline locations (from an unlabelled USGS 7-minute map). Although their exact locations were random, transects were distributed throughout the landscape with respect to forest stand age (years since major fire) by using BWCAW stand origin maps to ensure comprehensive coverage of upland forest types (Heinselman, 1973, 1996). This sampling approach is logical for this area because a large proportion of the land area is very close to lakes. Almost 80% of the land area is within 500-m of a lake when all lakes are considered. Almost 50% of the land area is still within 500-m of a lake when only lakes greater than 40-ha are considered (Rich et al., 2007).

12-m radius plots were located every 25-m along each transect. The center point of each plot was geo-referenced and later differentially corrected using GPS base station information from Thunder Bay, Canada, 120-km from the study area. Revisiting plots and error estimates indicate that the GPS positions are accurate to ±2-m. The number of usable plots for this study was 301 of the original 780 12-m radius field plots. This reduction was due primarily to the high proportion of clouds cover and cloud shadows present in the IKONOS imagery (Fig. 2). Other plots were eliminated during image processing because of their close proximity to lakes or wetlands, which were masked out of the imagery. The usable field plots were subdivided into 245 (~80%) model fitting plots and 56 (~20%) accuracy assessment plots; we had a large data set and wanted to maximize the capacity to assess the potential for detecting disturbance severity and thus favored having more plots used for initial model fitting. Accuracy plots were chosen by a random number generator with a uniform distribution.

Since fewer plots were used for this study than the original data collection, the distance to adjacent plots was greater than 25-m for 119 of 245 model plots and no plots were closer than 30-m to a lake shore edge as a precaution against including water pixels.

On each 12-m radius plot, species, size class, and damage class were recorded for all trees greater than 5-cm in diameter at 1.4-m dbh (diameter at breast height) whose stem center was rooted within the pre-disturbance plot. There were two size classes: “pole” trees (5–15-cm dbh) and “large” trees (over 15-cm dbh). Almost all trees were less than 35-cm dbh due to poor site conditions and climatic constraints. Trees were classified as dead, severely damaged, or living depending on their condition with respect to their potential contribution to the forest canopy (Rich et al., 2007). The data set for the 301 usable plots had more than 14,000 trees of 15 species.

4-m radius subplots were nested within the 12-m radius plots and shared a plot center. To census at least 15 individual trees, these subplots had a radii of 3, 4, or 5-m. Detailed information that was not logistically possible to collect at the 12-m radius plot was collected at the 4-m radius plot, including: dbh, canopy position, and damage type of all trees greater than 2.5-cm dbh that were rooted in the plot. These 4-m radius data were used to assign basal area estimates to trees in the 12-m radius plot by species and size class.

We defined disturbance severity as the degree of mortality or physical damage that occurs among tree populations in a given stand (Frelich, 2002). Disturbance severity was quantified as the proportion of the pre-windstorm live basal area at each 12-m radius plot that was classified as dead after the windstorm: (Basal area sum of individual trees on a given 12-m plot dead)/(Basal area sum of individual trees on a given 12-m plot alive pre-disturbance). The resulting severity coefficient is a continuous number ranging from 0 to 1; a plot with a severity equal to 1 would have complete mortality of trees greater than 5-cm dbh. The plots had a wide range of disturbance severity from no damage to complete mortality of all canopy trees. This severity coefficient is similar to those commonly used when considering changes in forest composition (Everham, 1995).

2.3. Image processing

A single IKONOS image acquired August 15, 2000, approximately 13 months after the storm, was used for this study (Fig. 1), under the following conditions: nominal collection azimuth, 104.90°; nominal collection elevation, 83.62°; sun angle azimuth, 148.08°; and sun angle elevation, 52.27°. The 1-m panchromatic and 4-m multispectral bands, MS-1 (blue), MS-2 (green), MS-3 (red), and MS-4 (near infrared), were used in the analysis.

An “upland forest only” image was created for analysis, where image areas that were clouds, cloud shadows, and non-upland areas such as lakes and non-forested wetlands were removed. The image was geometrically rectified in ERDAS Imagine 8.7 then clustered into 10 classes using the ISODATA algorithm and the classes identified as water and wetland were masked out. Cloud cover and cloud shadow covered nearly 40% of the image; these were delineated and removed. Additionally, a 12-m buffer surrounding masked cover types was added to ensure that the image for this analysis was limited to upland forest only.

2.4. Coupling field data to imagery

Spectral information for each plot was extracted from the IKONOS imagery by placing 12-m radius buffers around geo-referenced plot centers to create a polygon coverage that geographically corresponded to the 12-m radius field plots. Then the digital number (DN) values were extracted for pixels within this coverage for the four multispectral bands (MS-1-4) and the panchromatic band. We derived the mean DN value and the standard deviation for all IKONOS bands. Additionally, the normalized difference vegetation index (NDVI) was calculated. Texture features were derived by applying textural algorithms to the panchromatic band using ERDAS Imagine texture functions. The algorithms used were both first order measures: mean Euclidian distance and variance (Table 1). Textural algorithms used a moving window to compute the texture value for the center pixel of a given size window. We derived texture information using 5 × 5, 11 × 11, and 15 × 15 pixel windows for the panchromatic band (1-m spatial resolution). To link the texture parameters with the field plots, texture values were summarized as a mean for all pixels within each of the field plot polygons. Initially, 17 potential model terms were calculated (Table 2).

Regression analysis in Arc v.1.0 (Cook and Weisberg, 1999) was used to determine the relationship between satellite-derived features and wind disturbance severity. Initial linear ordinary least squares regression analyses indicated that several spectral and textural features were potential predictors of disturbance severity and also correlated with one another. Multiple linear regression was then used to distinguish the best combination of features to predict wind disturbance severity. Several candidate models were obtained by using backwards selection from a function containing all terms shown in Table 2 (Cook and Weisberg, 1999).
The disturbance severity response was transformed because it was bounded between 0 and 1, making residual analysis difficult to interpret. To achieve a multivariate normal distribution, the natural log function, \( \ln(\text{Severity}/1 - \text{Severity}) \), was used to transform the values range from (0, 1) to \((-\infty, \infty)\). In practice, the transformed range of values was between -4 and 4, and a severity value of 0.5 equals 0.0 using the transforming function. This transformation was used for all analyses.

Backwards selection procedures in Arc serve to delete terms based on Mallows’s \( C_p \) statistic. Model selection was further refined by manually testing hierarchically nested models against one another in S-Plus and evaluating them with Akaike’s information criterion (AIC) criterion (S-Plus 2000, 2000). All two-way interactions were included as an initial full model and then each term was systematically dropped or retained based on an ANOVA and an \( F \)-statistic. AIC was used as an evaluation tool where the lowest value of AIC was sought for a given number of terms. Each successive model also was visually tested for lack of fit against a mean function and LOWESS smoothing of the data (Cook and Weisberg, 1999). Multicollinearity was also tested by determining tolerance values for each predictor. Terms with multicollinearity were removed from the model based on the AIC criterion.

A successful model would match the mean function throughout the range of response and have no patterning among the residual plots for all terms within the model. A model with fewer terms was rejected if there was a significant difference between the new model and the previous model (\( F \)-statistic, \( p < 0.05 \)) (Cook and Weisberg, 1999).

### 2.5. Model accuracy and application to image

The 56 plots reserved for accuracy assessment were used to: 1) statistically evaluate model accuracy, and 2) assess accuracy in an application of the model across the upland only extent. These 56 plots were spatially distributed over the entire study area and spanned the entire range of disturbance severity. The multiple regression model was used to model a response surface on a per pixel basis using ERDAS Imagine (Fig. 2). The model was applied based on the 1-m spatial resolution. For MS-1–4, the DN value was used to determine by value of the 4-m pixel spatially corresponding to each 1-m panchromatic band pixel. The standard deviation of mean DN values for MS channels were derived from a 5×5 pixel moving window (20×20-m), an area equivalent to the original field plots but applicable across the entire image. Response surface accuracy was evaluated at the scale of the field plots by calculating the mean severity response for pixels within each of the 56 accuracy plots.

### 3. Results

#### 3.1. Correlations and regression model

Mean DN values of MS 1–3 were correlated and all increased with disturbance severity (Fig. 3). The coefficient of determination (\( r^2 \)) between MS 1–3 and disturbance severity (ln(Severity/(1 – Severity))) ranged from 0.38–0.43 with \( p < 0.0001 \) for MS 1–3 (Table 2, Fig. 3). These correlations and the ability to detect changes in response were consistent across the entire range of severity from no damage to complete canopy mortality. No significant correlation was observed between mean DN of MS-4 (near infrared) and disturbance severity (Fig. 3). However, the standard deviation of DN in MS-4 and MS-2 decreased significantly with disturbance severity, \( r^2 = 0.34 \) and 0.18 respectively (Fig. 3), indicating that the disturbed forest plots were more homogeneous in the near infrared and green spectral bands than the undisturbed forest. As a result, the near infrared band still contributed significant information to the overall multiple regression model (Table 3). There was no significant correlation between the standard deviation of DN values from MS-1 or MS-3 and disturbance severity but a pattern of increased heteroscedasticity in mid-range of severity was present. NDVI decreased significantly with disturbance severity but was not a strong term in the multiple regression model selection (\( r^2 = 0.21 \)).

Texture features derived from the panchromatic band were significantly correlated with disturbance severity. Mean Euclidian distance and variance were linearly correlated to disturbance severity, with \( r^2 \) values of 0.52 and 0.54 respectively at the 5×5 window size (Fig. 3 and Table 2). There was little difference in correlation or significance level among the different window sizes used for analysis (Table 2). Texture values decreased with increased disturbance severity, indicating that the disturbed forest plots were more homogeneous in panchromatic band values than the undisturbed forest plots.

Texture and spectral features were combined to develop a multiple regression model with four terms: MS-3, MS-4, standard deviation of MS-1, and the texture feature, mean Euclidian distance, derived from the panchromatic band using a 5×5 pixel moving window (Table 3). The AIC criterion model selected models that retained MS 1–3; but given their collinearity with each other, only MS-3 was retained in the final model as it was the best of the three potential models fitting MS-1, MS-2, or MS-3. This model was significantly better than models with fewer coefficients and was not significantly different from models with additional coefficients correcting for multicollinearity. The \( r^2 \) for the overall model is 0.65 with 240 degrees of freedom and a standard error of regression of 0.85 (~0.16 when severity ranges from 0 to 1).
0 to 1). All terms in the model were significant (Table 3). Fig. 4 shows the fitted values against the field observed values. Neither the residual plots for the overall model nor individual terms had meaningful curvature or showed any evidence of lack of fit. Using power analysis, we computed the least significant plot number for each term in the multiple linear regression model to give an indication of how many plots would be necessary to achieve a 0.05 significance level (JMP software 5.01a; Quinn and Keogh, 2002). Least significant number estimates range from 15 to 40 plots for all but MS-4, which needed 159 plots.

### 3.2. Model accuracy assessment

Model accuracy was assessed by comparing field observations of severity from 56 plots kept out of the model development process to the IKONOS-derived estimates. The regression model showed significant agreement between field severity values and model predicted severity values ($r^2 = 0.65$, $p < 0.0001$; Fig. 5).

### 3.3. Checking for spatial autocorrelation

Given the opportunistic nature of this study and the limitations of the sampling design, considerations were made to allay concerns that spatial autocorrelation was influencing model fit. Some degree of spatial correlation is to be expected because adjacent areas receive similar levels of wind disturbance intensity. Empirical correlograms (S-plus 2000, 2000) of disturbance severity and the model response, showed strongly significant correlation (Morans I = 0.77, $p < 0.001$) for the closest neighboring plots, but also repeat oscillation of weak and high correlation (~0.3) throughout all distance lags. This observation indicates that the severity pattern observed is an actual gradient in the landscape (Legendre and Legendre, 1998). Thus, it was not surprising that model residuals weakly echo the pattern seen in disturbance severity with significant correlation (Morans I = 0.40, $p < 0.001$) for the closest neighbors and low-level oscillations (~0.2) across the whole correlogram. A Mantel test examining spatial correlation of model residuals at all plot distances found no correlation (Mantel statistic $r = -0.011$, $p = 0.3199$). In comparison, disturbance severity for all plot distances has a higher and significant correlation (Mantel statistic = 0.214, $p = 0.001$). Lastly, to test the robustness of our model, we tested several randomly subsetted models that had a minimum of 60-m between plots against the full model. F-tests show no significant difference between any distance-subsetted model and the full model. When plotted, all distance-subsetted models were within a 95% confidence interval of the reported model. For all these reasons, we do not believe that spatial autocorrelation should detract from overall utility of the model or the degree to which texture may be a useful feature for detecting disturbance patterns.

### 4. Discussion

In this study, high-spatial resolution IKONOS satellite imagery was coupled with field-measured data to characterize windthrow disturbance severity across a southern boreal forest landscape. The results indicate that IKONOS imagery contains substantial information to describe variation in forest structure and disturbance processes in the spectral and textural features. DN values in MS 1–3 increased 10 to 25% along the gradient of disturbance severity. The largest change in response occurred in MS-3 (red). The observed increase in MS-2 (green) with increased disturbance differs from the decrease seen in

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**Table 3**

Coefficients for multiple linear regression model predicting disturbance severity ($\ln (\text{severity}/(1 \text{− severity}))$).

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>Std. error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
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<tr>
<td>Intercept</td>
<td>−0.9969</td>
<td>0.7671</td>
<td>−1.3000</td>
<td>0.1950</td>
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<tr>
<td>MB-1 standard deviation DN</td>
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<td>0.0220</td>
<td>−5.7480</td>
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<tr>
<td>MB-3 mean DN</td>
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<td>0.0042</td>
<td>8.8710</td>
<td>0.0000</td>
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<tr>
<td>MB-4 mean DN</td>
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<td>0.0009</td>
<td>−2.6880</td>
<td>0.0077</td>
</tr>
<tr>
<td>Mean Euclidean distance of PAN band</td>
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<td>0.0127</td>
<td>−4.9620</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
response to foliage damage. Altogether, the spectral response of the IKONOS imagery was dominated by forest components aside from canopy foliage and canopy foliage damage. In the visible bands, our results are similar to those from imagery along a gradient of forest thinning (Olsson, 1994). Unlike previous studies with Landsat TM imagery, differences in response levels among sites with low levels of disturbance severity were detected. This is most likely due to the higher spatial resolution of the imagery, enabling detection of smaller patches of disturbance.

In this study, MS-4, the near infrared band, did not increase or decrease significantly along the severity gradient. However, in conjunction with other bands, MS-4 reduced variability of the model response, indicating that at some sites, the near infrared band was informative. Near infrared response is often a useful indicator of vegetation condition and has value in discriminating defoliation events. It may have been of reduced value in this study because image acquisition was during August, a sub-optimum time for data collection since infrared response peaks immediately after leaf-green-up (Peterson, 1992). The infrared bands are often most valuable for examining incipient damage to forest canopies (Murtha, 1978; Franklin, 2001; Dupigny-Giroux et al., 2003), and our imagery was acquired a year after the initial damage occurred.

Evaluating the relative utility of the spectral parameters versus the spatial parameter is difficult as the spatial resolution differs. Some observations suggest that the spectral bands hold similar information. For example, MS 1–3 DN values all increased with disturbance, indicating that they also were detecting canopy shadow reduction and increases in ground and stem elements, albeit in a mixed pixel presentation. Although not useful as a model term, the significant decreases in DN standard deviation in MS-2 and MS-4 (Fig. 3) show that the variability of the near infrared and green bands decreases with wind disturbance severity similar to the texture parameters. The heteroscedasticity of DN standard deviation values in MS-1 and MS-3 and the relatively low correlation of NDVI with severity indicate that the variation in the spectral data may be better represented through a tasseled cap transformation (Horne, 2003; Coops et al., 2007; Healey et al., 2005). The utility of the spectral bands also may be offset by the contrasting spectral responses of forest structure, shadow, and ground components within individual pixels. For example, moderately disturbed sites with dense understory vegetation and some residual canopy may have a similar near infrared response to a site with a closed canopy.

Texture features derived from the panchromatic band had the highest individual correlations with wind disturbance severity among the features we examined. Our results for individual correlations for 1st and 2nd order texture functions with boreal forest canopy are similar to other studies in boreal forest (Wunderle et al., 2007). The mean Euclidean distance function is an effective measure of spatial heterogeneity within areas of 0.03–0.05 ha scale. At this scale, our results indicate that undisturbed forest canopy in the study area was more heterogeneous (had rougher texture) than moderately wind disturbed forest, which in turn was more heterogeneous than heavily disturbed areas (Fig. 6).

This relationship must be discussed within the context of image and field observation scales and the canopy-landscape dynamics of the boreal forest. Boreal forests, especially on rocky landscapes such as the one observed, are more spatially heterogeneous than many denser, temperate broad-leaved forests, (Kotz et al., 2004; Wulder et al., 2007). Additionally, the undisturbed sites in our study region were relatively heterogeneous (pre- windstorm) due to the breakup of post-fire, pine-dominated stands that were undergoing transition to more diverse uneven-aged stands (Freligh and Reich, 1995). The texture values for each moving window size (from 5 × 5 to 15 × 15) were almost identical in $\hat{r}^2$ and interchangeable in their contribution to candidate models. This interchangeability indicates that the patterns in image texture did not change from 25 to 225-m$^2$ scale.

As has been found in other studies (Woodcock and Strahler, 1987; Song and Woodcock, 2002; Wunderle et al., 2007; Johansen et al., 2007), the potential utility of texture features for assessing canopy

![Fig. 4. Multiple regression model coupling field plot severity with data derived from IKONOS imagery. A) Model fit of fitted values versus field disturbance severity ($\ln (\text{severity}/1−\text{severity})$). Dashed line is confidence interval and dotted line is prediction intervals ($r^2 = 0.65$, $p < 0.0001$). B) Residual plot.](image)

![Fig. 5. Model accuracy assessment was analyzed by examining field disturbance severity ($\ln (\text{severity}/(1−\text{severity}))$ versus multiple regression model predicted disturbance severity ($\ln (\text{severity}/(1−\text{severity}))$) for 56 plots, $r^2 = 0.65$.](image)
structure was demonstrated. However, there is still a need for a general framework that links texture properties with forest disturbance dynamics in a spatial domain independent manner. Currently, there is no such framework that fully relates spatial variance observations with variables such as forest canopy development, tree crown size variation, sensor spatial resolution, and differing scales of the variance measurement (moving window size). The degree of correlation between texture observations and forest characteristics is dependent on how the above variables are appropriately combined to answer a particular question (St-Onge and Cavayas, 1995, 1996; Hay et al., 1996; Hudak and Wessman, 1998; Franklin et al., 2000; Coops and Culvenor, 2000; Song et al., 2007). Figure 6 proposes how texture observations may fit into a framework where wind disturbance severity may lead to increases or decreases in heterogeneity depending on both the initial canopy condition and the degree of disturbance severity. This figure assumes that the scale at which heterogeneity measurements can detect variation is correlated with forest structural components. Thus, the window size used in image analysis may have to be scaled up or down to match the canopy components, provided that the imagery spatial resolution is sufficient to correlate with canopy structure. This figure illustrates how texture parameters would be most useful when going either from closed canopy to some canopy openness, such as under moderate wind disturbance regimes in temperate forests, or from moderate canopy openness to very open, such as was the case in this study of boreal forest. Gradients in heterogeneity allow for gradients in wind disturbance severity to be observed in either case.

This study approach was able to overcome some of the limitations of a typical low spatial resolution image model where imagery resolution obscures and aggregates individual components on the landscape (Strahler et al., 1986). However, in our approach we were not able to explicitly link pixels with specific forest structures. The methods employed compared aggregated field data (% trees wind-thrown) with image features at a congruent scale. Crucial to this approach were multiple observations in both image and field data at a plot scale (0.045 ha). The spatial resolution of the satellite imagery (~452 pixels in the 1.0-m resolution panchromatic band) was greater than the number of individual field observations (~45 individual trees per plot).

Although the desire to develop relationships with remote sensing data was present from the initiation of field plot sampling, the field sampling design was primarily for standalone ecological research. Hence, the success of the model development suggests that post hoc development of ecological modeling and assessment from the combination of ground data and satellite imagery is possible, albeit undesirable from an efficiency perspective. Improvements in sampling could be made by positioning plots with respect to the large scale variations in landscape patterns that may alter DN response within an image such as slope or aspect direction. Also, a priori knowledge of imagery geometry and spatial resolution might be of great benefit in determining the size and shape of field plots. For example, rectangular field plots would have been a better match with the moving window used for texture calculations.

The model fit would likely be better with additional predictors such as species composition data or digital elevation models. We observed a nearly 7% increase in $r^2$ value for models with composition data from our field plots (data not shown), suggesting that it may be worthwhile to collect such data if corresponding data were available for the study area.

Our approach in this study is free of the limits imposed by pre-existing imagery such as in change detection analysis where the spatial and spectral resolution is limited to that of the imagery available prior to the disturbance (Dupigny-Giroux et al., 2003). The tradeoff is the challenge of simultaneously coordinating imagery resolution and field observation scale to a spatial domain relevant to forest canopy structure.

5. Conclusions

In this study differences in disturbance severity were detected and modeled using data from MS 1–4 and the texture of the panchromatic band of IKONOS imagery. Texture features, measured by mean Euclidean distance, proved particularly useful in predicting disturbance severity in the near-boreal landscape. The results indicate that textural analysis was useful for detecting differences in forest structure caused by ecological processes such as disturbance. Although texture variables may be comparable only within a given spatial resolution, we observed that texture values increased with disturbance severity, but the range and functional shape of texture parameters, specifically spatial variance, across forest ecosystems have not yet been generally formulated. DN values in MS 1–3 increased 10 to 25% along the gradient of disturbance severity. The spectral response of the IKONOS imagery was dominated by forest components other than canopy foliage and canopy foliage damage. These results suggest that wind disturbance is spectrally similar to forest thinning and that foliage-based detection and using near infrared or NDVI may not be an effective approach for structurally complex disturbances. Our multiple regression model using both spectral and textural data explained 68% of the variation in disturbance severity using the features from the IKONOS imagery. We are optimistic that integrated use of field-based measures and high-spatial resolution satellite imagery will be effective and efficient tools for future analyses. Nevertheless, considerable questions exist as to how spectral and textural models may be combined to detect a range of ecological processes along with patterns in forest development.

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