Using Remotely Sensed Data and Elementary Analytical Techniques in Post-Katrina Mississippi to Examine Storm Damage Modeling

Curtis A. Collins, David L. Evans, Keith L. Belli, and Patrick A. Glass

Curtis A. Collins, research associate II, and **David L. Evans**, professor, Department of Forestry, Mississippi State University, Mississippi State, MS 39762; **Keith L. Belli**, Head, Department of Forestry, Wildlife and Fisheries, University of Tennessee, Knoxville, TN 37996; and **Patrick A. Glass**, Director of Operations, Mississippi Institute for Forest Inventory, Mississippi Forestry Commission, Jackson, MS 39201.

Abstract

Hurricane Katrina's passage through south Mississippi on August 29, 2005, which damaged or destroyed thousands of hectares of forest land, was followed by massive salvage, cleanup, and assessment efforts. An initial assessment by the Mississippi Forestry Commission estimated that over $1 billion in raw wood material was downed by the storm, with county-level damage percentages ranging from 50 percent to 60 percent across Mississippi's three coastal counties. Remotely sensed data were used to provide a more complete picture of the damage inflicted by Katrina. Moderate (56- to 29-m) and high (1- to 0.3-m)-resolution data were acquired from spaceborne and airborne platforms in natural color and MultiSpectral (MS) formats. Transformed data such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI), along with damage estimates obtained by interpreting aerial photography, were also used as variables in a linear modeling process. This continuous damage prediction process demonstrated the effect of incorporating forest condition thematic information, prestorm moderate-resolution imagery with transforms, and poststorm moderate-resolution imagery with transforms. The resulting models, all of which used a large number of regressors, had overall fit values of R^2_{adj} = 0.708 and RMSE = 0.130 with all variable types used, R^2_{adj} = 0.492 and RMSE = 0.172 with all variables except the forest condition data, and R^2_{adj} = 0.599 and RMSE = 0.153 with all variables except the poststorm imagery data.

Keywords: AWiFS, damage modeling, forest damage, hurricane damage, Katrina damage, timber damage.

Introduction

Overview

Hurricane Katrina made landfall in Mississippi near the outlet of the Pearl River on August 29, 2005, as a category 3 storm on the Saffir-Simpson scale (Knabb and others 2005). Loss of life and damage to property were catastrophic, as New Orleans was flooded, and many towns and cities along the Louisiana and Mississippi Gulf Coasts were destroyed or severely affected. Rural areas whose economy depends on agriculture and forest industry were devastated also. Accordingly, preliminary damage estimates obtained through aerial surveys of the affected region by the Mississippi Forestry Commission (MFC) exceeded $1 billion in damaged wood and timber stumpage. These estimates underscore the need for more continuous damage estimates that can be developed when remotely sensed, storm, and pre-existing thematic data are employed in the modeling process.

Moderate-resolution remotely sensed data, from sources such as Landsat, have been used in modeling various forest parameters related to timber harvesting (Healey and others 2005), canopy closure (Butera, 1986, Cohen and others 2001, Larsson 1993), and other forest attributes (Cohen and others 2001, 2003). Cohen and others (2001) modeled percentage green canopy cover in a predominantly evergreen softwood region of the Pacific Northwest, similar to south Mississippi, with a coefficient of determination (R^2) of 0.74 and a root mean squared error (RMSE) of 12 percent. Similarly, Healey and others (2005) used a series of transformations on independent variables as well as a natural logarithm transformation on percentage cover, the dependent variable, in a series of simple linear regressions to determine adequate univariate models. The results of their work were promising with regard to using single Short Wave InfraRed (SWIR) bands, as well as the Normalized

Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI) transformations described in the methods section of this work.

Damage assessments of past catastrophic tropical storms in the Southeast United States were not able to use the large number of image sources and processing techniques that are presently available. The use of geographic information systems (GISs) and remote sensing techniques in these assessment activities were, for the most part, restricted to a minor role in the wake of Hurricane Hugo in South Carolina (Nix and others 1996) with an expanded role noted for Hurricane Andrew (Jacobs and Eggen-McIntosh 1993, Ramsey and others 1997, 2001). With these two storms and the studies mentioned, a progression of technology and techniques can be noted. In Nix and others (1996), remote Hugo forest damage assessments were made in a GIS through aerial photointerpretation and digitization. Jacobs and Eggen-McIntosh (1993) also used visual image interpretation to perform assessments of Hurricane Andrew-induced damage with the imagery taking the form of airborne digital video frames. The two works led by Ramsey (Ramsey and others 1997, 2001) show a final evolution to satellite acquired moderate (Landsat)- and coarse (Advanced Very High Resolution Radiometer or AVHRR)-resolution imagery, along with storm data, in identifying Andrew's damage in a largely hardwood area in south Louisiana.

Objectives

Because the MFC assessment was performed rapidly through aerial viewing using expert approximation, a more definitive and continuous damage assessment model was sought. In our work here, we studied the viability and possible methods needed to develop predictive storm damage assessment models. The acquisition and analysis of remotely sensed data acquired before and after hurricane Katrina, along with various storm data and pre-existing thematic data created for the Mississippi Institute for Forest Inventory (MIFI), were used to determine the feasibility of mapping storm impacts in a more accurate and continuous form.

Beyond characterization of Katrina-induced forest resource damage, we explored model development to predict the likely scope and severity of damage from future hurricanes. This procedure involved use of MIFI forest thematic data, storm data, prestorm imagery (which can be simulated to note the effects from different size and intensity storms), and poststorm imagery to determine their relative importance in producing predictive damage models. The implications here involve two aspects: (1) model performance without poststorm data so that predictive equations can be used to forecast future hurricane damage, and (2) level of predictive model improvement afforded by use of forest type and age thematic layers that accompany inventory protocol employed by MIFI.

Methodology

Remotely Sensed Data

Acquiring Remotely Sensed Data—

Moderate-Resolution Data

Indian Remote Sensing (IRS) Advanced Wide Field Sensor (AWiFS) data were acquired for use in pre- versus post-storm damage assessment as a moderate spatial resolution (56 m at nadir) data source. These data were selected for several reasons:

- Relatively high visibility, although minor cloud coverage was noted in both pre- and poststorm images.
- Compatibility of spatial resolution with Landsat Thematic Mapper (TM) data, which were used in the creation of thematic data also used in this study.
- Acquisition dates of June 19 (prestorm) and September 4 (poststorm), less than one week after Katrina's landfall in Mississippi.

Spectral attributes associated with the AWiFS sensor included four bands representing the following reflected energy wavelengths, respectively: green (520-590 nm), red (620-680 nm), near-infrared (NIR) (770-860 nm), and shortwave infrared (SWIR) (1550-1700 nm).

High-Resolution Data

We used prestorm digital imagery taken throughout the summer of 2004 (before Katrina's landfall) that was acquired through the United States Department of Agriculture's (USDA) National Agriculture Inventory Program (NAIP) and made available via the internet by the Mississippi Automated Resource Information System (MARIS). These data were acquired in natural color, sampled at a spatial resolution of 1 m, and presented as mosaiced county-level images. Within 2 months of Katrina's landfall, a private contractor using a Leica ADS40 sensor provided post-Katrina digital imagery for the U.S. Army Corps of Engineers (USACE) over south Mississippi from 31° N to the Gulf Coast. These poststorm data were made available by the United States Geological Survey (USGS) via a disaster-support Web site. They were acquired in natural color with an approximate 0.3-m spatial resolution.

Preprocessing Remotely Sensed Data—
Using the existing thematic MIFI data as a georegistration base, the AWiFS data were georegistered in Leica's ERDAS Imagine 8.7 using first- or second-order polynomial models (ERDAS 2003) in order to achieve subpixel spatial root mean squared (RMS) values. The resulting products were thus projected into the Mississippi Transverse Mercator (MSTM) (MARIS 2005), as this was the native projection of the MIFI base data. This procedure, as recommended by Lillesand and Kiefer (2000) and Lu and others (2004) to analyze multidate imagery, ensured highly aligned overlapping pixel registration so that data extraction for later modeling purposes would use correctly sampled reflectance and thematic values. In contrast to AWiFS data, visual inspection of the spatial orientation of high-resolution data sets appeared to match the MIFI base data, so no georegistration was required.

Cloud cover and corresponding shade, although minimal, was present in the AWiFS data sets and required removal to reduce the possibility of sampling erroneous reflectance data. To achieve this removal, both pre- and poststorm rectified AWiFS imagery was clustered using the Iterative Self-Organizing Data Analysis Techniques (ISODATA) algorithm in Imagine (ERDAS 2003) with 250 clusters, 12 maximum iterations, and a convergence threshold of 0.95. The resulting two thematic layers were next interpreted, in a heads-up fashion, coded, and recoded in order to create two cloud and cloud shadow (code = 1) versus noncloud (code = 0) masks. These masks were then used to remove all cloud-tainted spectral information from the rectified AWiFS images by recoding the eight image layers to zero (four per pre- and poststorm imagery) in these problem areas.

Transforming Remotely Sensed Data—
In exploring various simple band differences, general trends were noted to be unique but subtle for the green and red, NIR, and SWIR bands across the anticipated storm-damaged region. Visually, the red and green bands appeared highly correlated with each other. Because the red appeared more contrasting moving orthogonally from the anticipated center of damage just east of the eye's track (Boose and others 1994), it was chosen for further examination along with NIR and SWIR bands.

Previous studies confirmed the choice in directly using the red, NIR, and SWIR bands (Hame 1991), along with their use in two transformations. These transformations employed two band ratios proven to work in forest change detection: Normalized Difference Vegetation Index (NDVI) (Healey and others 2005; Jin and Sader 2005; Mukai and Hasegawa 2000; Ramsey and others 1997, 2001; Sader and others 2003) and Normalized Difference Moisture Index (NDMI) (Healey and others 2005, Jin and Sader 2005, Sader and others 2003). These indices not only use the visible and infrared bands of interest through proven functions, they also serve to reduce the dimensionality of the data to be analyzed. The formulae for NDVI and NDMI are:

$$NDVI = \frac{NIR\ band - Red\ band}{NIR\ band + Red\ band} \tag{1}$$

and

$$NDVI = \frac{NIR\ band - SWIR\ band}{NIR\ band + SWIR\ band} \tag{2}$$

Land Cover and Type Thematic Data

In Collins and others (2005), the creation of thematic data for use by MIFI in a statewide forest inventory, per the inventory's procedural pilot study (Parker and others 2005), was outlined and resulted in forest age and type thematic layers. The forest-age layer used an approximate 5-year temporal resolution back to the genesis of the Landsat program in the early 1970s and covered the entire State. In other words, this data set attempted to identify the year of regeneration for areas harvested between 1972 and 2003 in 5-year increments. The data were created using Landsat Multi-Spectral Scanner (MSS) and TM data with the finished products' resolution taking on the finer TM resolution (29 m). The forest-type layer mapped the entire State into water, other nonforest, regenerating forest, softwood, mixed softwood-hardwood, and hardwood classes using 2002–03 TM imagery. Data were georegistered to USGS Digital Ortho Quarter Quadrangles (DOQQs) county-level mosaics, making this the base resolution and orientation for all subsequent analyses involved in this study.

Ancillary Storm Data

Four data set types were obtained from the Internet for use in this study as storm attribute layers. The first two types were acquired from the Atlantic Oceanographic and Meteorological Laboratory (AOML), a subunit of the National Oceanic and Atmospheric Administration's (NOAA's) Hurricane Research Division (HRD), in 14, 3-hour-interval gridded surface wind data sets depicting conditions from 21:00 CDT, August 28, 2005, to 12:00 CDT, August 30, 2005. The grid spacing of these data as the storm passed through south Mississippi was approximately 0.054 degrees in latitude and longitude resulting in a linear distance of approximately 5.25 km in easting and 6 km in northing near the city of Bay St. Louis, Mississippi. These data included sustained surface windspeed (mph) and direction (azimuth degrees), both of which are believed to be influential in structural (Powell and Houston 1996) and forest damage (Ramsey and others 2001) over time. The third data type also came from the AOML and was another gridded surface wind product demonstrating the maximum sustained windspeeds (mph) inflicted by Katrina as it moved through the entire State. The fourth and final storm attribute data obtained for this project included a storm surge extent vector layer acquired from Federal Emergency Management Agency's (FEMA's) Katrina recovery GIS Web site (http://www.fema.gov/hazard/flood/recoverydata/katrina/katrina_ms_gis.shtm).

Model Creation

Independent Variable Assignment—

Remotely Sensed Data

Using the two described band transforms, NDVI and NDMI, and the four original bands from both pre- and poststorm imagery, 18 remotely sensed variables were defined. These variables were created using bands one through four for both pre- and poststorm data sets as well as a delta variable whereby the six prestorm layers, comprising bands and transforms, were subtracted by their poststorm counterparts.

Land Cover and Type Thematic Data

The MIFI thematic data demonstrating statewide age and forest types were used as continuous variables and model strata, respectively. In this construct, age, which could at best be determined back to 1972, was used as a continuous variable with detected year of regeneration being reduced by 2, to account for nearly half the temporal resolution of the age-creation process, and then subtracted from 2005, the year of Katrina's landfall. If the year of regeneration was not found for a forested area, we assumed it was older than the timeframe afforded by the Landsat program, and it was coded with age 40 (2005 minus 1965). This represented a reduction of one temporal resolution interval of 5 minus the interval midpoint correction of 2 years for 1972, the last year of detection. Our assumption was that within the three forest types beyond this age, stand-stocking levels and size were probably more alike than not. As a discriminant, the types could or could not be used as classes for stratifying three different models for softwood, mixed, and hardwood areas.

Ancillary Storm Data

Among the four data set types downloaded for use in this study as storm attributes, one was removed from consideration, one was left alone, and two were compressed into a series of time- and location-dependent storm variables. The surge variable was removed owing to low sampling intensity because the data set indicated that 21 hardwood, 4 mixed, and 0 softwood plots were located within the area of mapped surge inundation. Unlike the 3-hour intervals of

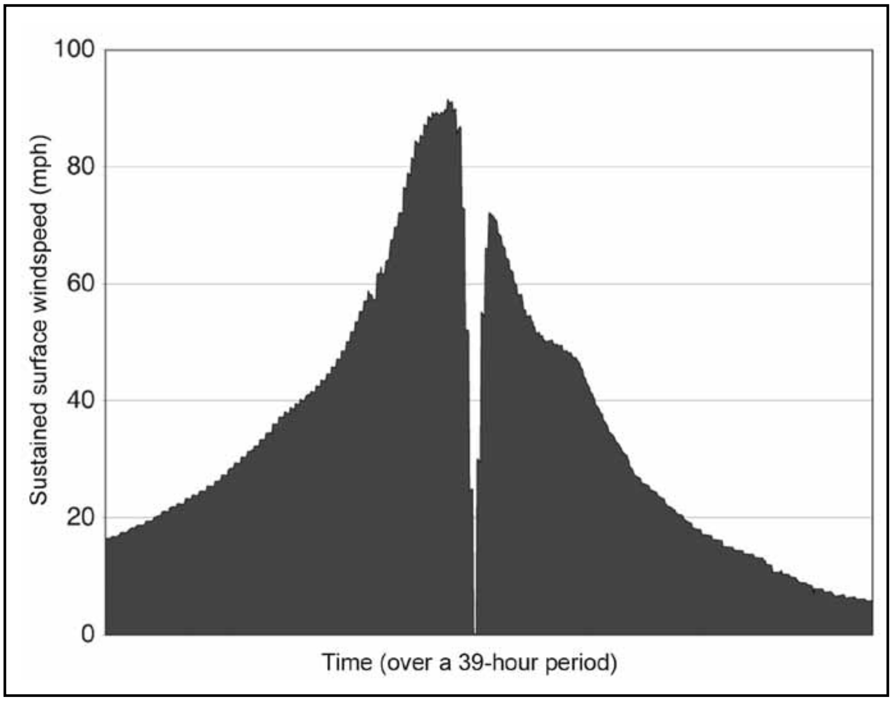

Figure 1—This is a plot-level graph of the resulting 3-minute-interval continuous windspeeds over a 39-hour period from 21:00 CDT, August 28, 2005, to 12:00 CDT August 30, 2005, for a plot located along Katrina's eye track (note the drop to near zero in the graph's middle), illustrating the converted data used in determining wind duration and stability variables.

windspeed and direction data, the maximum sustained wind variable required no manipulation for use in the model, but it did require interpolation. Using Imagine 8.7, these gridded data were surfaced to the same resolution and orientation as the MIFI base data by using a linear rubber sheeting method (ERDAS 2003).

The first step in transforming the direction and speed attributes from the gridded 3-hour-interval surface wind field data into more usable variables was to create a Microsoft Excel spreadsheet. This helped interpolate the wind data at each plot into more continuous values with regard to speed; direction, as azimuth drastically steps between 360° and 0°; and time, which, in this case, was interpreted into 3-minute (0.05-hour) intervals. Azimuth values were converted to sine and cosine trigonometric function values, and the plot nearest a respective grid point at that point's designated time was allowed to assign its sine, cosine, and windspeed values to that plot at that time. Time intervals located between fixed 3-hour periods were next assigned weighted x- and y-coordinate locations away from a weighted location of the storm's eye. Weighting was defined so that proximity to the upper or lower 3-hour time bound for an interpolation time was used to create proportional weights, with the two weights summing to one, for calculating the location and variable weighted averages at an interpolation point. These weights were next used in weighted variable averaging by taking an interpolation time point's weighted location, with respect to storm eye, and calculating windspeed and directional values from the corresponding above and below bounding time points at the same relative weighted location. In Figure 1, a graph of the resulting 3-minute windspeeds for a plot located near Katrina's eye track, illustrates an example of this process's result.

The resulting 3-minute windspeed, sine, and cosine values were next used to create wind duration and stability variables per the anticipated applicability (Powell and Houston 1996, Ramsey and others 2001) of these variables in hurricane damage modeling. The duration variables were calculated over given windspeed thresholds in 10 mph intervals from 30 to 100 mph. For example, the variable for wind duration at or above 40 mph at a specific plot would count the number of 3-minute time intervals attributed to that plot that were at or above 40 mph and multiply that count by 0.05 hours to get duration in hours. The stability values were also calculated over given windspeed thresholds in 10 mph intervals from 30 to 100 mph. They were done such that the sine and cosine values, isolated for interpolated time points that met the windspeed threshold criteria, were used to calculate two variances, one each for sine and cosine, and then combined into a pooled variance.

Dependent Variable Assignment—

To replace the lack of field data due to ongoing storm damage field sampling, we performed interpretations of high-resolution imagery, pre- and poststorm, with the expectation that aerial-viewed canopy damages were highly correlated with field-measured forest damage. The sample area included Mississippi's six southernmost counties, corresponding to that portion of south Mississippi from 31° N to the Gulf Coast. The USACE imagery was acquired and stratified into 54 interaction classes based on combined forest type, maximum sustained wind (max mph windspeed of >93.5, 93.5-76.5, and <76.5), and age (year constraints of >1993, 1993-88, 1987-83, 1982-78, 1977-70, and <1970). Then we randomly allocated 5 plots into each interaction class, yielding 270 total plots.

Crown closure interpretations and resulting pre- and poststorm differences began with the creation of GIS-generated 0.084-ha rectangular plots (29 by 29 m). Interpretation of these plots involved use of GIS-generated plot boundaries and regular dot grids to employ a systematic method for determining green canopy coverage. The grids were created in a 5 by 5 construct, allowing each dot to represent 4 percent of plot canopy, with outer rows and columns being spaced 2.9 m from their immediate plot bounds and inner rows being spaced 5.8 m in sequence from each other (Figure 2). Using this grid, interpretation was reduced from estimating plot-level green canopy percentages to counting the dots in each plot that fell on interpreted green canopy pixels. The purpose in creating this data set was to develop a bank of prestorm, poststorm, delta (i.e., pre- minus poststorm), or all, canopy data for use in model construction.

Resulting interpretation data were next edited to remove plots that fell within the cloud-classified areas in the AWiFS-derived cloud mask. This masking reduced the plot count from 270 to 252 with an additional 7 plots being removed in the photointerpretation phase owing to lack of forest canopy (this either indicated error in the MIFI forest type layer or canopy removal since acquisition of the 2003 imagery used to generate the MIFI product). The resulting 245 plots were situated across the mapped softwood, mixed, and hardwood forest types in counts of 82, 83, and 80, respectively.

Upon reviewing these edited prestorm, poststorm, and delta canopy measures, the intuitive dependent variable choice appeared to be the delta canopy variable (defined as pre- minus poststorm green canopy cover percentage). However, because these data were largely dependent on prestorm canopy data, this variable was added to the list of independent variables and incorporated into the list of prestorm variables. Also, we believe that prestorm canopy can be created for the study area with moderate to good success (Cohen and others 2001).

Model Definition and Fitting—

The model creation stage of this study was focused on creating multiple linear regression models using ordinary least squares. The sought-after final models were hoped to be parsimonious with optimistic fit values, which, in this case, were high adjusted coefficient of determination or R^2_{adj} values and low RMSE values, for the variable types of interest in the study's objectives. Initial attempts to use the 37 previously described variables (Table 1) in single linear terms produced unsatisfactory fit values. Immediate improvements, however, were noted with the introduction of interaction and quadratic terms (Rawlings and others 1998). The result of creating all these new variables from the above single variables increased the number of possible variables from 37 to 740.

With 740 possible variables available for use in this modeling exercise, a two-step process was organized to reduce the possible number of variables to 40 or fewer, which represented about half (or fewer) the number of plots in each forest type. The first reduction took place

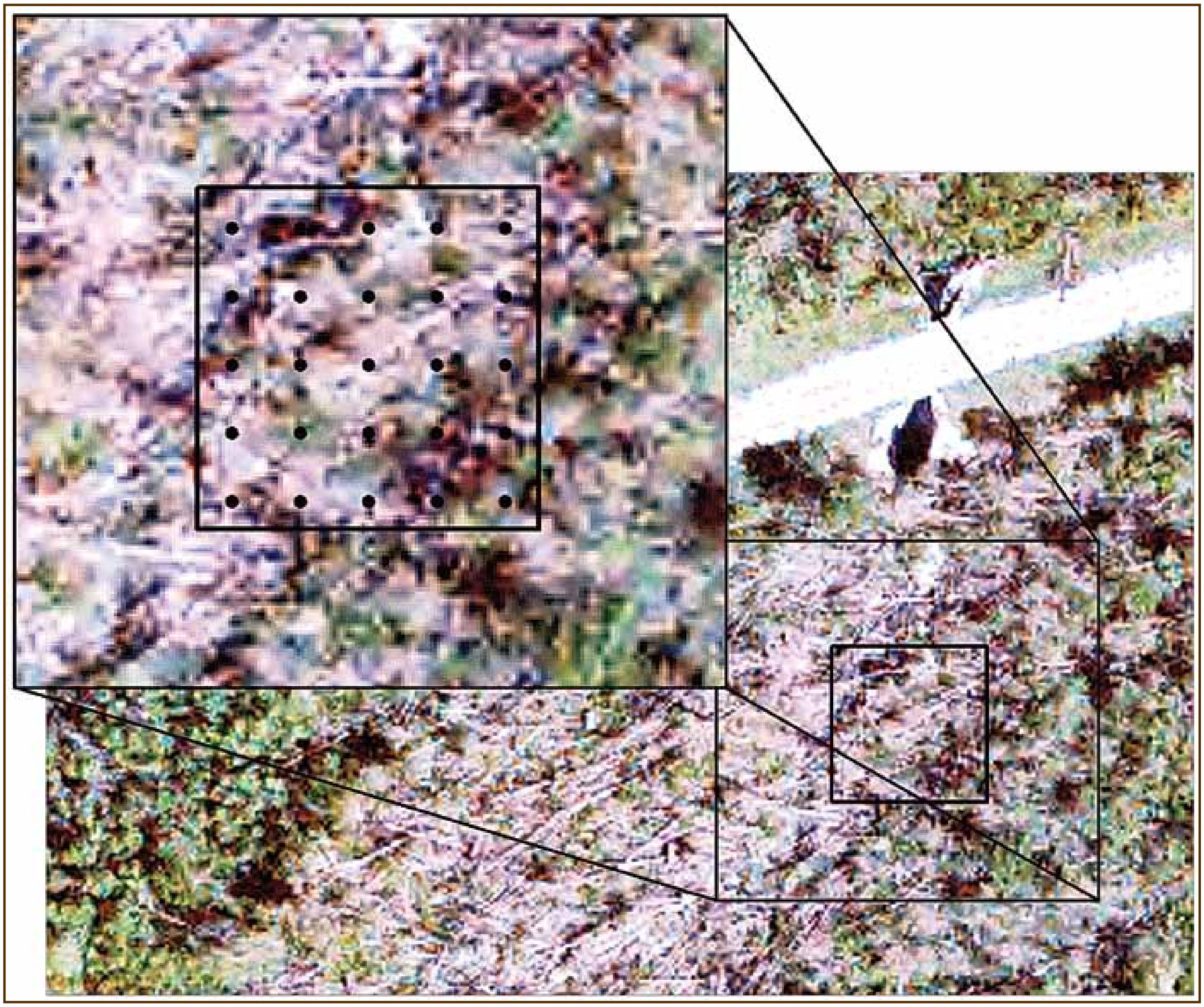

Figure 2—A plot-level view of a photointerpretation plot bound and grid. This image illustrates a highly storm-damaged plot from Pearl River County, Mississippi (note the southeast to northwest oriented downed stems). In the inset, the 5- by 5-point grid used in determining green canopy percentages along with the plot's boundary can be seen.

using stepwise regression methods in SAS's PROC REG procedure (SAS 1999). Using this method, eight model types were reduced using some or all available variables: an overall (regardless of forest type) pre- (including ancillary storm variables) and poststorm data model; an overall prestorm data model; three (for each forest type) prestorm, poststorm, and MIFI variable (forest age) models; and three prestorm and MIFI variable models. In order to regulate that the output stepwise models identify 40 or fewer independent variables for phase two reduction, the significance entry level (SLENTRY in SAS) was set at 0.5, whereas the significance stay level (SLSTAY in SAS) was accordingly and incrementally adjusted up or down from an initial setting of 0.25 in 0.01 increments until 40 or fewer variables were isolated in the final step.

After isolating eight reduced but still cumbersome models, the leaps-and-bounds algorithm (Furnival and Wilson 1974) in PROC REG (SAS 1999) was employed to hone in on the eight best remaining variables from the field of 40 or fewer with respect to R^2_{adj} and RMSE. The use of R^2_{adj} was deemed advantageous at this point because this value tends to be more comparable than R^2 over models

Table 1—Individual (main effects) model variables and their types

Variable	MIFI	Pre-storm	Post-storm	Variable	MIFI	Pre-storm	Post-storm
Forest age	X			Delta AWiFS NDVI			X
Prestorm green canopy		X		Delta AWiFS NDMI			X
Max sustained wind		X		Wind duration > 30 mph		X	
Prestorm AWiFS band 1		X		Wind duration > 40 mph		X	
Prestorm AWiFS band 2		X		Wind duration > 50 mph		X	
Prestorm AWiFS band 3		X		Wind duration > 60 mph		X	
Prestorm AWiFS band 4		X		Wind duration > 70 mph		X	
Prestorm AWiFS NDVI		X		Wind duration > 80 mph		X	
Prestorm AWiFS NDMI		X		Wind duration > 90 mph		X	
Poststorm AWiFS band 1			X	Wind duration > 100 mph		X	
Poststorm AWiFS band 2			X	Wind stability > 30 mph		X	
Poststorm AWiFS band 3			X	Wind stability > 40 mph		X	
Poststorm AWiFS band 4			X	Wind stability > 50 mph		X	
Poststorm AWiFS NDVI			X	Wind stability > 60 mph		X	
Poststorm AWiFS NDMI			X	Wind stability > 70 mph		X	
Delta AWiFS band 1			X	Wind stability > 80 mph		X	
Delta AWiFS band 2			X	Wind stability > 90 mph		X	
Delta AWiFS band 3			X	Wind stability > 100 mph		X	
Delta AWiFS band 4			X				

Note: A listing of all 37 single variable or main effects used in the study's modeling exercise along with pertinent variable type classifications used in model comparisons. Even though MIFI forest type data were used, they were employed defining strata, not as a model variable.

involving different numbers of parameters (Rawlings and others 1998). This best-eight rule followed the rule of thumb to have 10 observations for each variable while being mindful that the hardwood strata had only 80 observations. To make a more theoretically sound set of model decisions, we also used Hocking's (1976) prediction criteria of using the smallest model, with regard to variable count, that had a Mallow's C_p (Rawlings and others 1998) value of less than or equal to 1 plus the particular model's variable count.

Results

In Table 2, the best eight variable models illustrate moderate fits with RMSE values below 0.15 in only one model and R^2_{adj} values above 0.55 in two models. Between the no MIFI variables pre- and poststorm models, there was a dramatic increase in R^2_{adj} from 0.176 in the prestorm model to 0.439 in the pre- and poststorm situation along with a matching magnitude reduction in RMSE from 0.219 to 0.181, respectively. In order to compare these no MIFI models to MIFI models, which were created in multiples of three matching the three MIFI forest type designations, a set of pooled RMSE and R^2_{adj} values were created. This creation occurred by combining the three models' error sum of squares, in the case of RMSE values, and by combining the three error and total corrected mean sum of squares considering all three models' degrees of freedom, in the case of the R^2_{adj} values. Comparing these fit values for the eight variable models again demonstrated the drastic improvement in model fit. With the use of poststorm imagery, we observed R^2_{adj} values increasing from 0.381 to 0.506 and RMSE decreasing from 0.190 to 0.170. Additional gains were made in using the MIFI data in models by increasing prestorm no MIFI versus pooled R^2_{adj} values from 0.176 to 0.381 and reducing RMSE from 0.219 to

Table 2—Model fit results by variable types and variable selection criteria

Variables type(s) used	Forest type(s)	Best eight variable models R^2_{adj}	Best eight variable models RMSE	Hocking's criteria models No. of var.	Hocking's criteria models R^2_{adj}	Hocking's criteria models RMSE	Other models of interest No. of var.	Other models of interest R^2_{adj}	Other models of interest RMSE
Prestorm, poststorm[a]	All	0.4392	0.1805	23	0.4923	0.1717			
Prestorm, poststorm, MIFI	Softwood	0.6796	0.1168	24	0.7893	0.0947			
Prestorm, poststorm, MIFI	Mixed	0.5701	0.1800	25	0.8588	0.0860			
Prestorm, poststorm, MIFI	Hardwood	0.4897	0.2009	15	0.5881	0.1805			
Prestorm, poststorm, MIFI[a]	Pooled	0.5058	0.1694		0.7081	0.1302			
Prestorm[a]	All	0.1758	0.2188	21	0.2765	0.2050			
Prestorm, MIFI	Softwood	0.3366	0.1680	26	0.6405	0.1237			
Prestorm, MIFI	Mixed	0.4300	0.1727	37	0.7735	0.1088	25	0.7142	0.1223
Prestorm, MIFI	Hardwood	0.3647	0.2242	37	0.7542	0.1394	15	0.5258	0.1937
Prestorm, MIFI[a]	Pooled	0.3812	0.1896		0.7345	0.1242		0.5994	0.1525

Note: The modeling exercise results indicating variable types used and MIFI forest type usage along with fit values (adjusted R^2 or R^2_{adj} and RMSE) and number of variables used, when not fixed by the variable selection method.

[a] All types or pooled model rows used in numerical data type comparisons.

0.190. Similarly, by incorporating MIFI thematic data, poststorm models were affected with an R^2_{adj} increase from 0.439 to 0.506 and an RMSE reduction from 0.181 to 0.170.

The models derived using Hocking's (1976) method (Table 2) illustrate the same general trend as the eight variable models. Again, improvements with the addition of MIFI and poststorm data were noted in overall (with no MIFI data) and pooled (with MIFI data) R^2_{adj} and RMSE values, except in cases where the application of Hocking's method yielded models with very large variable counts (2 instances used 37 variables). In an attempt to rectify this problem, the other models in Table 2 were created for models that still used a large number of variables. These further reduced models corresponded to the Hocking's identified MIFI, prestorm, and poststorm variable models in the number of employed variables for mixed and hardwood, MIFI, and prestorm models. Examination of these modified models indicates one difference from the eight variable comparisons. The pooled fit values for the prestorm and MIFI models (R^2_{adj} = 0.599 and RMSE = 0.153), in tandem with the prestorm, poststorm, and MIFI models (R^2_{adj} = 0.708 and RMSE = 0.130), when compared to the pre- and poststorm model (R^2_{adj} = 0.492 and RMSE = 0.172) and prestorm model (R^2_{adj} = 0.277 and RMSE = 0.205) indicate an increased advantage from the eight variable models with regard to using MIFI data as opposed to poststorm image data.

Discussion

Model and Variable Characteristics

The prediction-minded evaluation of data/variable types reported in the previous section states the obvious—that more independent variables tend to improve model predictability of dependent variables. This situation says nothing about the direct applicability of all the work involved with this study and the possible creation of predicted damage values across or outside of the study area, or both, with the various models produced. What is of importance in this work, however, is where, with respect to the variables and variable types used, the gains in model fit occur, although no statistical inference can be associated with these gains. We expect that similar models can yield predicted canopy changes with RMSE values at or near 0.13 (13 percent) for situations like the passage of a strong hurricane over a mostly undisturbed Southern forested area, such as south Mississippi before Katrina. These estimates can be improved from the forest industry perspective. Industry is often focused on the softwood resource in the South, which is where the best of the stratified models we developed demonstrated a RMSE 0.09 (9 percent). Model fit was comparable in mixed and softwood stands but was poor in hardwoods. This could be the result of a variety of issues from some unknown data bias that was unintentionally introduced into the modeling process or some natural occurrence unknown and unaccounted for in these analyses. These poor results could also illustrate the inherent difficulty and complexity in modeling conditions in hardwood areas.

Potential model flexibility to create comparable predictive models, regardless of the use of poststorm imagery, was a much sought-after finding in this study with mixed results. The reason for this exploration was to display the applicability of modeling anticipated storm damage prior to a weather event. This focus was best explored in comparing the other models (or adjusted) pooled fit values for the MIFI and prestorm variables models and Hocking method pooled MIFI, prestorm, and poststorm variables models where RMSE values were 0.153 versus 0.130, respectively. This comparison is somewhat indecisive as MIFI, prestorm, poststorm variables models outperformed the MIFI and prestorm variables models but only by a small amount (difference in RMSE of < 0.03). Similarly, in the corresponding eight variable models, there was a difference of 0.02 with respect to RMSE. This difference is of a smaller magnitude, however, than the lack of MIFI data comparisons of overall pre- and poststorm variables (R^2_{adj} = 0.492 and RMSE = 0.172) versus prestorm only variables (R^2_{adj} = 0.277 and RMSE = 0.205). In comparing the Hocking pre- and poststorm model (RMSE = 0.172) versus the adjusted pooled MIFI and prestorm model (RMSE = 0.153) and the corresponding eight variable models (RMSE = 0.181 versus RMSE = 0.190), it does appear that use of the MIFI data in model development at least offsets, maybe even improves, model performance in using prestorm data with the absence of poststorm data.

Possible Model/Variable Improvements

Actual field damage values are being collected in MIFI's Southeast region, which includes Jefferson Davis, Covington, Jones, Wayne, Marion, Lamar, Forrest, Perry, Greene, Pearl River, Stone, George, Hancock, Harrison, and Jackson Counties. These data are the direct metric of interest in this series of work, as opposed to the photointerpreted canopy metric used here. Incorporation of these data is expected to improve development, although model fits may worsen, of any hurricane damage assessment model subsequently created owing to the dependent variable's added meaning. The data could also help address a noted problem of hardwood defoliation versus damage. Poststorm high-resolution imagery indicated that many hardwood areas, particularly in the Pearl River bottom, were defoliated with only minor damage to tree crowns and boles. Differences in this defoliation versus damage aspect of hardwood areas may also be more sensitive to individual hardwood species, which is one of the field metrics, as opposed to the whole hardwood type.

Along with the analysis of field data, future work will also incorporate statistically inferential results, such as variable significance, as opposed to the simple fit comparisons made in this work. These analyses will provide more meaningful results with potential adaptations for collinearity and validation of model assumptions. Model development for repeated application may also be achieved in order to create a more robust and possibly automated product.

Conclusions

Clutter and others (1983) defined risk in the statement: "the inability to estimate future cash flows with certainty is the basic cause of risk in an investment." At play in this analysis are other issues that effect the probability of acquiring an expected return. Examples include rotation lengths (with which MIFI type information may be of further use), intermediate weather conditions (i.e., droughts, floods, etc.), and market fluctuations. Whereas this study is not a risk assessment in totality, it does place a foundation, albeit not a large one, for development in this direction.

The implications developed in this work with regard to variable creation and the data types utilized are promising for future meaningful region-level continuous damage assessment model creation. The thrust will continue to locate additional ancillary data that may serve to further supplant the advantages of poststorm imagery incorporation in the development of these models. Field data will soon replace the photointerpreted data so heavily relied upon here, and with it a new set of obstacles are expected. In all, however, it does appear possible to create a meaningful damage model that will aid in both economic recovery and assessment of risk associated with storms similar to Hurricane Katrina, possibly before said storms occur.

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