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Predicting ground-based damage states from windstorms using remote-sensing imagery

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Abstract. Researchers have recently begun using high spatial resolution remote-sensing data, which are automatically captured and georeferenced, to assess damage following natural and man-made disasters, in addition to, or instead of employing the older methods of walking house-to-house for surveys, or photographing individual buildings from an airplane. This research establishes quantitative relationships between the damage states observed at ground-level, and those observed from space using high spatial resolution remote-sensing data, for windstorms, for individual site-built one- or two-family residences (FR12). "Degrees of Damage" (DOD) from the Enhanced Fujita (EF) Scale were determined for ground-based damage states; damage states were also assigned for remote-sensing imagery, using a modified version of Womble's Remote-Sensing (RS) Damage Scale. The preliminary developed model can be used to predict the ground-level damage state using remote-sensing imagery, which could significantly lessen the time and expense required to assess the damage following a windstorm.

Keywords: damage; remote-sensing; Enhanced Fujita Scale; tornadoes; hurricanes; Katrina; satellite; Super Tuesday

1. Introduction

1.1 Ground-based damage surveys

Ground-based studies of windstorm damage have been completed for numerous events spanning more than four decades and became common practice in the 1970's when engineering and atmospheric science researchers at Texas Tech University surveyed the damage caused by the F-5 (Fujita 1971) Lubbock tornado in May 1970 (Thomson *et al.* 1970, Mehta *et al.* 1971). Following a major tornado, damage documentation teams are often deployed to the damaged area within a few days following the event to collect perishable damage data to allow for an understanding of the structural failure mechanisms and with the hopes that the information gleaned can assist in making future buildings stronger and better able to survive a similar disaster (Minor 2005). Ground surveys

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collect data by photographs, maps, and written or oral notations, and are generally focused on mapping the overall path of the tornado(es), delineating the gradation of damage and associated wind speeds across the path, and assessing the performance of particular building systems, and have been completed for numerous historic events including the Palm Sunday tornadoes in 1965 (Fujita *et al.* 1970), the "Super Outbreak" in April, 1974 (Mehta *et al.* 1976), and the Central Oklahoma tornadoes of May 3, 1999 (Marshall 2002, Speheger *et al.* 2002), among others. Ground surveys are time-consuming and labor intensive and resources are often limited following a major tornado outbreak (Speheger *et al.* 2002, Yuan *et al*. 2002). In addition, obtaining access to the damaged areas is often difficult immediately after the event. However, detailed inspection of select individual structures and components can be afforded, making ground surveys quite valuable.

1.2 Remote-sensing damage surveys

Researchers have long used airplanes to survey large areas of tornado damage, primarily to determine the path-length, width, severity, gradation of damage, and wind flow patterns (Fujita *et al*. 1970, Fujita and Smith 1993). In many cases, a combination of ground surveys and aerial surveys have been used to assess damage (Marshall and McDonald 1982, Wurman and Alexander 2005). In addition to aerial photography, newer remote-sensing technologies allow for satellite and LIDAR imagery to be used to capture damage data following a tornado or other natural disaster. Satellites are automated and are able to collect perishable data rapidly which is a significant advantage over ground-based surveys, as clean-up after a disaster usually begins as soon as possible, resulting in the loss of valuable information (Visser and Dawood 2004). The imagery can cover a large area with little restraint on access. The main limitation of remote-sensing technology is that frequently only roofs or small sections of the walls of buildings are imaged, making the conditions of other key components such as windows, doors, and connections unknown. High-resolution oblique aerial imagery is rapidly becoming widespread, allowing for the viewing of walls. In addition, cloud cover can occasionally obscure the view, especially in the case of hurricanes, where cloud cover may remain for several days following an event. Furthermore, the effort required for extracting useful information from images manually can grow exponentially as the coverage area becomes larger. Automated damage detection techniques are being explored and developed (Yuan *et al*. 2002, Womble 2005) and rely heavily on change detection (Singh 1989), where changes in the pixels of the imagery before and after the event are determined.

1.3 Advances in data collection

While traditional ground surveys remain valuable for understanding windstorm damage, new methods of surveying are being developed and utilized with each new windstorm event. The traditional method of walking surveys is being replaced by technology such as ImageCat's VIEWS^{TM} (Visualizing Impacts of Earthquakes with Satellites) system which allows for rapid collection of ground-based damage states via high-definition video (Adams *et al*. 2004, McMillan *et al*. 2008), or the use of handheld computers to systematically capture prescribed data and compile it into a database (He *et al*. 2005). In addition to advances in ground survey methods, the technology of remote-sensing is growing rapidly, with new platforms and better spatial resolution available, increasing its value as a tool for collecting and analyzing damage data (Yuan *et al*. 2002, Womble *et al*. 2005). The technology has advanced significantly since the beginning of the Landsat program in the 1970's, when the image spatial resolution was 80 m (Adams 2005). Current high-resolution satellite imagery includes the WorldView 2 satellite with 46 cm panchromatic and 1.84 m multispectral images, IKONOS imagery with 82 cm panchromatic and 4 m multispectral images, QuickBird imagery with 61 cm panchromatic and 2.44 m multispectral bands, and the GeoEye-1 satellite with a spatial resolution of 41 cm for panchromatic and 1.65 m for multispectral imagery.

While significant improvements in the spatial resolution of remote-sensing imagery have been made, full automation of damage detection has not yet been achieved. Damage analysis requires at least some human interpretation of imagery. Overhead remote-sensing imagery cannot fully facilitate damage detection at this time, as it displays only a portion of the true damage state. Oblique imagery, such as Pictometry imagery can give a view of the roof of a structure, as well as portions of the wall sections, which aids in damage assessment, but does not give a full view of the damage. Ground surveys still provide the highest level of detail. Using remote-sensing imagery to predict the extent of damage at ground-level would significantly lessen the time and expense required to assess the damage, and could be especially valuable in outbreak events when resources are limited. Verification of the true ground-level damage state and a comparison with the remotely-sensed damage state is needed to achieve automated damage detection.

2. Objective and scope

This study seeks to develop statistical relationships between remote-sensing damage states and ground-level damage states for windstorm events. The relationships were developed by assessing the damage observed in both data sources for each FR12 structure. The developed regression models were fitted using datasets which include ground-based digital images from the "Super Tuesday" tornado outbreak in February 2008, as well as high-resolution imagery from two satellite platforms obtained a few days after the outbreak. Only site-built homes (FR12) from the Enhanced Fujita (EF) Scale (WISE 2006), were used to parameterize the models; the dataset could later be expanded to include other types of structures. The developed regression models were validated using ground-based digital images and high-resolution imagery from two aerial platforms following Hurricane Katrina. Ideally, this study will pilot the initiative to process remote-sensing imagery following a windstorm, and use it with developed regression models to determine ground-level damage states.

3. Damage assessment methodology

To parameterize the regression models, a ground-based damage state and remotely-sensed damage state were both required for a given set of structures from the "Super Tuesday" dataset. To determine the damage state at ground level, a "Degree of Damage" (DOD) from the EF Scale was assigned for each structure in the ground survey, and recorded in a database. There are ten DODs for FR12 structures which are provided in Table 1, along with an expected (Exp), lower bound (LB), and upper bound (UB) of wind speeds that would likely cause that level of damage (WISE, 2006). The pictures and descriptions of the various DODs in the EF Scale were used to assess the most severe damage to each structure.

To determine the damage state from remote-sensing imagery, each structure which was rated from the ground survey was also assigned a remote-sensing damage state according to Womble's RS

Table 1 Degree of Damage (DOD) states and wind speed parameters for FR12 structures from the Enhanced Fujita (EF) Scale (WISE 2006)

DOD	Damage description	Exp*	LB*	UB*
1	Threshold of visible damage	65	53	80
2	Loss of roof covering material (<20%), gutters and/or awning; loss of vinyl or metal siding	79	63	97
3	Broken glass in windows and doors	96	79	114
4	Uplift of roof deck and loss of significant roof covering material (>20%); collapse of chimney; garage doors collapse inward or outward; failure of porch or carport	97	81	116
5	Entire house shifts of foundation	121	103	141
6	Large sections of roof structure removed; most walls remain standing	122	104	142
7	Exterior walls collapse	132	113	153
8	Most walls collapsed in bottom floor, except small interior rooms	152	127	178
9	All walls collapsed	170	142	198
10	Destruction of engineered and/or well-constructed residence; slab swept clean	200	165	220

*3-sec gust wind speed values in mph

Table 2 Womble's Remote Sensing (RS) Damage Scale for Residential Construction (2005)

Damage rating	Most severe physical damage
RS-A	No apparent damage.
RS-B	Shingles/tiles removed, leaving decking exposed.
RS-C	Decking removed, leaving roof structure exposed.
RS-D	Roof structure collapsed or removed. Walls may have collapsed. (Oblique imagery may be needed to determine wall condition.)

Scale, which utilizes letters ranging from A-D (2005), and is provided in Table 2. Like the EF Scale, a structure was rated according to the most severe damage observed. While Womble applied his scale to each individual facet of a roof to aid in automated damage assessments, this research assigned a RS Scale rating to the structure's roof as a whole. In addition, a new parameter was included in the remote-sensing rating, indicating the percentage area of a certain damage state. Categories of percent damage are as follows: 0%, 1-25%, 26-50%, 51-75%, and >75%. For example, a home with a RS Scale rating of B 26-50% means that 26-50% of the roof's shingles or tiles were removed leaving the decking exposed. This additional parameter was included to allow for a finer categorization of damage levels.

4. Tornado damage datasets

The 2008 "Super Tuesday" tornado outbreak began the afternoon of February 5, 2008 and continued until early the next morning. The outbreak left widespread damage in Arkansas, Mississippi, Alabama, Tennessee, and Kentucky. Two weeks after the outbreak, researchers from

Texas Tech University's Wind Science and Engineering (WISE) Research Center partnered with ImageCat Inc., to deploy the VIEWS^{TM} system to capture high-definition ground-based photographs of the damaged areas (McMillan *et al*. 2008). The VIEWS^{TM} system for this deployment was comprised of two high-definition video cameras mounted on either side of a moving vehicle, which could capture imagery and GPS data as the vehicle drove by damaged structures, enabling georeferencing of each frame of video captured. From this ground survey, 32 hours of high-definition video were obtained and segments were processed to extract individual still digital images. The extracted images included photographs from Macon and Madison Counties in Tennessee. Examples are shown in Fig. 1; the clarity and level of detail in these high-definition images is remarkable, and damage to components, such as window breakage can be readily evaluated. Shortly after these images were obtained, WISE researchers rated the DOD for FR12 structures in the more than 4,000 photographs using the EF Scale.

In addition to ground-based data, WISE and ImageCat purchased DigitalGlobe satellite imagery for an area covering the center of Madison County. Imagery was obtained on February 8, 2008 from the QuickBird satellite; this imagery features both panchromatic and multi-spectral bands and has been pan sharpened to a spatial resolution of 61 cm. Imagery was also obtained on February 10,

Fig. 1 Examples of still images extracted from the VIEWS^{TM} survey in Madison County, Tennessee

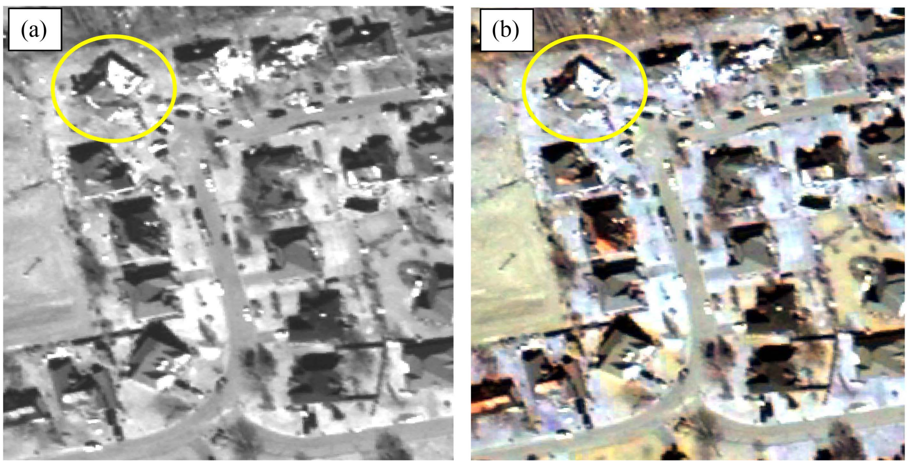

Fig. 2 (a) QuickBird panchromatic imagery from February 8th, 2008 in Madison County, TN. and (b) same image, but pan sharpened. Spatial resolution is 61 cm for both. The yellow circles provide a point of reference by indicating the same structures in both images. Credit: DigitalGlobe, Inc. <www.digitalglobe.com>

Fig. 3 WorldView 1 panchromatic imagery from February 10th, 2008 in Madison County, TN, shows the same location as depicted in Fig. 2. Spatial resolution is 50 cm. The yellow circles indicate the same structures highlighted in Fig. 2. Credit: DigitalGlobe, Inc. <www.digitalglobe.com>

2008 from the WorldView 1 satellite; this imagery is panchromatic and offers a 50 cm spatial resolution. Samples of the imagery are provided in Figs 2(a), (b) and 3. For reference, the home circled in yellow in these figs is the same structure in Fig. 1(b). It can be noted that the WorldView 1 image in Fig. 3 is sharper and clearer than the QuickBird images in Fig. 2. For the purposes of parameterizing the regression models, 271 structures in Madison County were selected for damage evaluations, which represented all of the FR12 structures which were visible in both the ground-based and remote-sensing surveys. Each of these structures was assigned a RS Scale rating according to Womble (2005).

5. Hurricane KATRINA datasets

Hurricane Katrina made its second U.S. landfall near the Louisiana-Mississippi state line on August 29, 2005 as a Category 3 hurricane. Just one day before landfall, Katrina was a Category 5 storm and still carried the size and surge levels common to a Category 5 storm when it made landfall, despite the weakened winds. Katrina wreaked havoc along the coasts of Louisiana, Mississippi, and Alabama, with storm surge estimates of 24-28 ft above sea level and became the most deadly natural disaster in the United States since the 1920's (Knabb *et al*. 2006). Following Katrina's landfall, researchers from ImageCat Inc. partnered with researchers from Louisiana State University (LSU) Hurricane Center and TTU WISE to deploy VIEWS™ to collect perishable damage data in numerous communities in coastal Mississippi. The VIEWS™ system for this deployment was comprised of a single high-definition camera with GPS data. The imagery is similar to that collected for the "Super Tuesday" tornado reconnaissance, shown in Fig. 1 above. VIEWS™ imagery utilized in this study was obtained from the cities of Waveland, Bay St. Louis, Gulfport, Biloxi, Ocean Springs, Gautier, and Pascagoula.

Two sets of aerial images were obtained for use in evaluating damage states with the parameterized regression models. Vertical aerial images were obtained by Pictometry in September

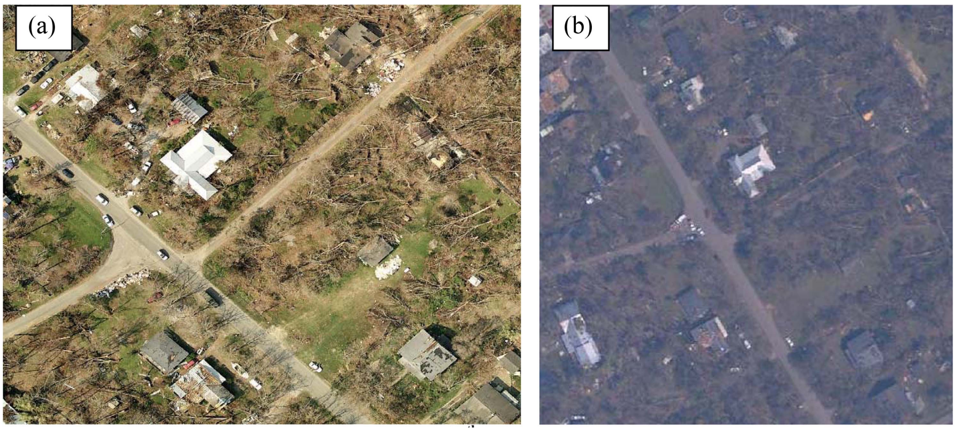

Fig. 4 (a) Pictometry imagery from September 10th, 2005 in Waveland, MS. Spatial resolution is 15 cm. Credit: Pictometry Internation Corp. <www.pictometry.com> and (b) NOAA aerial imagery from September 2nd, 2005 in Waveland, MS. Spatial resolution is 37 cm. Credit: NOAA

and October, 2005, in all of the ground survey cities, with the exception of Pascagoula. These images have a spatial resolution of 15 cm. NOAA aerial photos were also obtained in August and September, 2005, in all of the ground survey cities. These images have a spatial resolution of 37 cm. Samples of both types of imagery are provided in Figs 5(a) and (b). Both figs depict the same location within a neighborhood. The color, brightness, and level of detail provided by the Pictometry vertical images are highly desirable, and are among the best aerial imagery currently available on a wide-spread basis. Although Pictometry also has oblique imagery available, these images are not easily orthorectified and georeferenced and were therefore not used in this study.

To test and refine the developed regression models, the RS Scale ratings were determined from both remote-sensing platforms for the Hurricane Katrina datasets. The developed regression models were then used to estimate the ground-level damage states for those structures, and these data were then compared to the actual DOD ratings completed by a trained professional utilizing a ground-based damage dataset.

Table 3 Numerical representation scheme for DOD used in the regression models

DOD Category	Representative numerical value
<1	0
1	1
2	2
3	3
4	4
5	5
6	6
7	7
8	8
9	9
10	10

Table 4 Numerical representation scheme for the RS Scale used in the regression models

RS Category	Representative numerical value
A 0%	0
B 1-25%	1.125
B 26-50%	1.375
B 51-75%	1.625
B >75%	1.875
C 1-25%	2.125
C 26-50%	2.375
C 51-75%	2.625
C >75%	2.875
D 1-25%	3.125
D 26-50%	3.375
D 51-75%	3.625
D >75%	3.875

6. Development of the regression models

Before beginning the regression modeling, a representation scheme was developed to define a numerical value for each DOD and for each alphanumeric RS Scale category, for ease in plotting and developing the regression models, as the statistical analysis requires numeric values. The representation schemes are presented in Tables 3 and 4, for DOD and the RS Scale, respectively. The scheme developed for DOD is simple, where the numerical value used in the regression analyses is equal to the DOD rating. The representation scheme for the RS Scale essentially assigned a value of 0 to 3 for the RS Scale ratings of A to D respectively. Because the RS Scale was modified by the addition of a percent damage level to delineate a finer gradation of damage states, the representation scheme used for the regression models features a decimal value, which is equivalent to the center point of the percentage rating. For example, a structure rated with a RS Scale rating of B 26-50% would be assigned a representative value of 1.375, where the value "1" indicates that it is a "B" rating, while the decimal value "0.375" indicates that the percentage of that damage state that was observed was in the range of 26-50% (where 37.5% is the center point of that percentage range). As technology improves and spatial resolutions become finer, it may soon be possible to assign an exact percentage of RS Scale damage to a structure, rather than an estimated range.

Six linear, six exponential, and six quadratic regression models were parameterized (described later in this section) using these data. The regression models developed using these data resulted in R^2 values ranging from 0.47 to 0.62, depending upon the dataset and regression technique utilized. After these 18 models were parameterized, concerns were raised regarding the spread of data at the lower end of the DOD damage ratings. Homes that were rated with the no-damage state from the remote-sensing survey were rated with DOD values as high as 4 from the ground-based survey. Further examination of the data led to the conclusion that there was a source of bias introduced into the fitted models that resulted from the categorization of damage in the EF Scale. In the EF Scale, the description for FR12 structures suffering DOD 2 damage is "loss of roof covering material

(<20%), gutters and/or awning; loss of vinyl or metal siding," while the description for DOD 4 damage is "uplift of roof deck and loss of significant roof covering material (>20%); collapse of chimney; garage doors collapse inward or outward; failure of porch or carport." Each of these categorizations was common in the "Super Tuesday" tornado dataset and each addressed roof covering loss. Many structures exhibited roof covering loss greater than 20% and were therefore rated DOD 4 to match the highest damage level, but did not experience the required decking loss, collapse of chimney, garage doors, or porches and carports. It was hypothesized that these structures were likely overrated, and that the true DOD for these structures was somewhere between DOD 2 and DOD 4.

Dr. Kishor Mehta, one of the developers of the EF Scale, was consulted on this problem. He stated that it takes a great deal more force to cause decking uplift or collapse of chimney, garage doors, or porches and carport, as opposed to just roof covering loss. He agreed that the language provided in the descriptions of DOD 2 and DOD 4 damage states were unclear as to how to rate homes with more than 20% roof covering loss, but meeting none of the other criteria of DOD 4. The intermediate value of DOD 3 was not appropriate, as it already had a definition pertaining to glass breakage, and its expected wind speed was only 1 mph less than that of DOD 4. After much examination, it was decided that homes with more than 20% roof covering loss, but that did not meet any of the other criteria in DOD 3 or DOD 4 should be rated as DOD 2.5, to acknowledge that the damage was more severe than DOD 2, but less severe than DOD 3 or DOD 4 (Mehta 2009). This deficiency was conveyed to a group of meteorologists and engineers at the inaugural EF Scale Stakeholders Forum in Norman, OK in March 2010, and it is believed that future versions of the EF Scale will be modified to account for this issue, among others (Brown *et al*. 2010). Similar issues were also discovered for other "Damage Indicators" (DIs).

The "Super Tuesday" tornado damage database was queried, resulting in 40 homes with a rating of DOD 4. Each of these 40 homes was reevaluated from the ground-based survey and re-rated according to Mehta's recommendations. Of these 40 homes, only four still qualified for a DOD 4 rating, while 19 were changed to the new DOD 2.5 category, and the remaining 17 were rated DOD 3 because glass breakage was evident. The dataset including these re-rated DOD values was used to re-parameterize the original 18 regression models, along with many others.

The first model developed was a simple linear regression relating the ground-based damage state incurred from the "Super Tuesday" tornadoes to the remotely-sensed damage state observed with the QuickBird imagery. The second model utilized the same ground-based damage states and related them to ratings obtained from the WorldView 1 imagery. The third model employed a linear regression to relate the ground-based damage state to an "average" remote-sensing damage state, obtained by numerically averaging the values obtained from the QuickBird and WorldView 1 surveys. For each simple linear regression model developed, there were two corresponding non-linear regression models developed from the same datasets—an exponential model and a quadratic model. For each dataset (QuickBird, WorldView 1, and averaged) and each regression type (linear, exponential, and quadratic), statistical transformations were also completed and models were fitted to the transformed data as well. Logarithmic, exponential, square root, and squared transformations of the input variable, the output variable, and both input and output variables were performed, resulting in a total of 144 fitted regression models. The correlation coefficient, R^2, indicates the strength of the regression models, where a value of 1 indicated a perfect correlation. The R^2 values for these models ranged from 0.3374 to 0.8496; however, those models with R^2 values greater than 0.7 did not have random, normally distributed residuals, and were therefore not considered. The models parameterized with the re-rated DOD value per Mehta's recommendation had R^2 values

Table 5 Results from the top five performing regression fitted to the “Super Tuesday” tornado dataset.

Model	Satellite platform	Regression type	Statistical transformation	Regression equation	R^2 value	Sample size
1	averaged	quadratic	square root (input)	DOD = 2.256 * RS – 1.143 * RS +0.3565	0.6863	271
2	averaged	quadratic	logarithmic (input)	DOD = 2.737 * $(\ln(RS + 1))^2$ – 0.2846 * ln(RS + 1) +0.3465	0.6859	271
3	averaged	quadratic	none	DOD = 0.1656 * RS^2 + 1.070 * RS + 0.2654	0.6795	271
4	averaged	exponential	logarithmic (input)	DOD = 0.4224 * exp(1.772 * ln(RS + 1))	0.6767	271
5	averaged	quadratic	squared (input)	DOD = –0.03206 * RS^4 + 0.8830 * RS^2 + 0.4650	0.6740	271

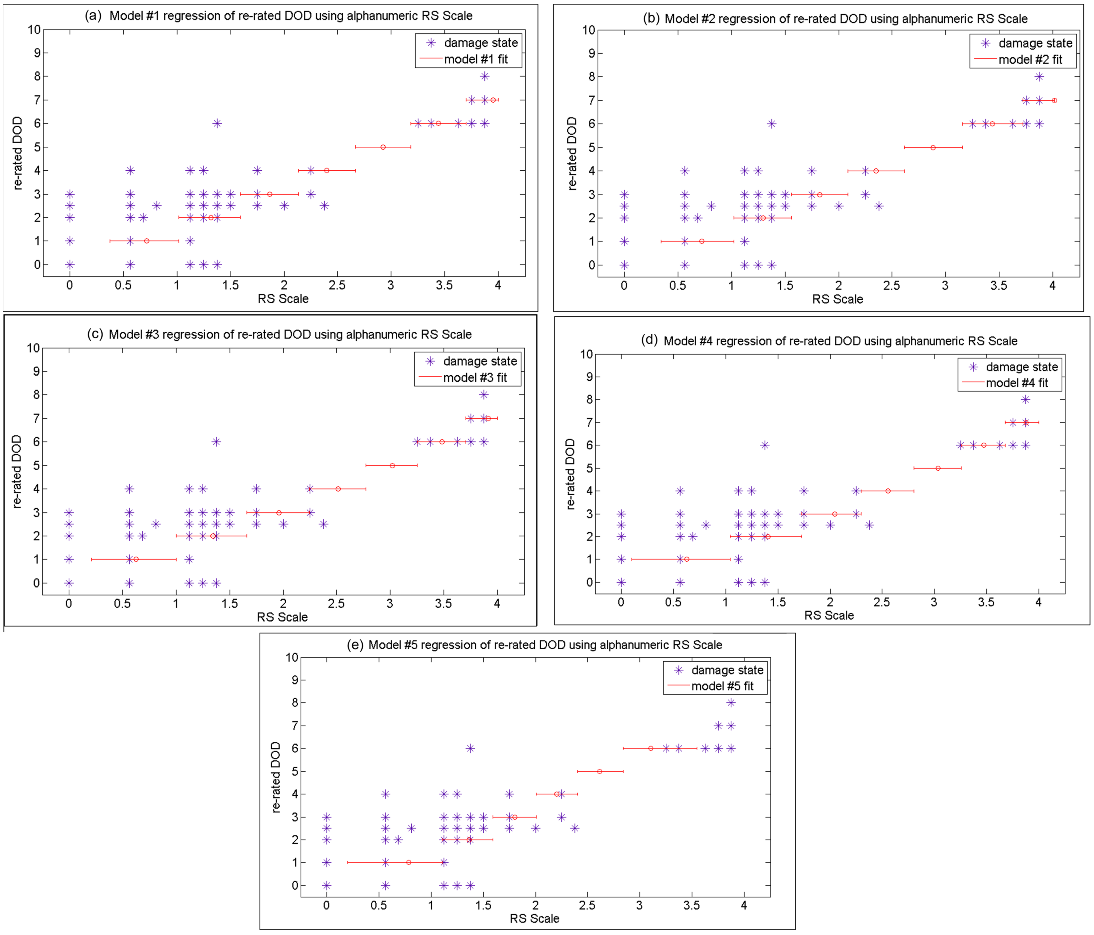

Fig. 5 Regression models selected for validation. All models utilized the averaged satellite damage state and the re-rated DOD values. Model specifics are provided in Table 5. (a) Model 1, (b) Model 2, (c) Model 3, (d) Model 4 and (e) Model 5

improved by as much as 17%.

Several general statements can be made about the fitted models and the datasets utilized to parameterize them. First, the models fitted with the averaged QuickBird and WorldView 1 damage rating data were superior to either platform used alone. The use of an averaged damage state helps to eliminate the effects of any erroneous ratings that may be present in each individual dataset. Second, the quadratic regression models nearly always outperformed their linear and exponential regression model counterparts. Last, statistical transformations of the input variable often resulted in better model fits than the untransformed datasets, or the transformations of the output variable, and both the input and output variables. The five best models with the highest R^2 values, which also had random, normally distributed residuals, were selected for validation with the Hurricane Katrina dataset. The results of the selected models are provided in Table 5, and in Figs 4(a)-(e). As the figure indicates, with each model, there are a range of RS Scale ratings that would result in rounding to a particular DOD value.

7. Model performances

For the purposes of validating the developed regression models, 505 homes which were visible in both the Pictometry and NOAA aerial surveys following Hurricane Katrina were rated using the alphanumeric RS Scale, and the damage states were then averaged. These averaged damage states were used with Models 1-5 in Table 5 to "predict" the ground level damage state. The predicted values were then compared to the actual ground level damage state, as determined by a trained professional who assigned a DOD to the structures based on the VIEWS^{TM} data collected. The comparison is provided in Fig. 6. In each figure, the line indicated a perfect correlation between the actual DOD determined from the ground-based survey and the predicted DOD from the regression

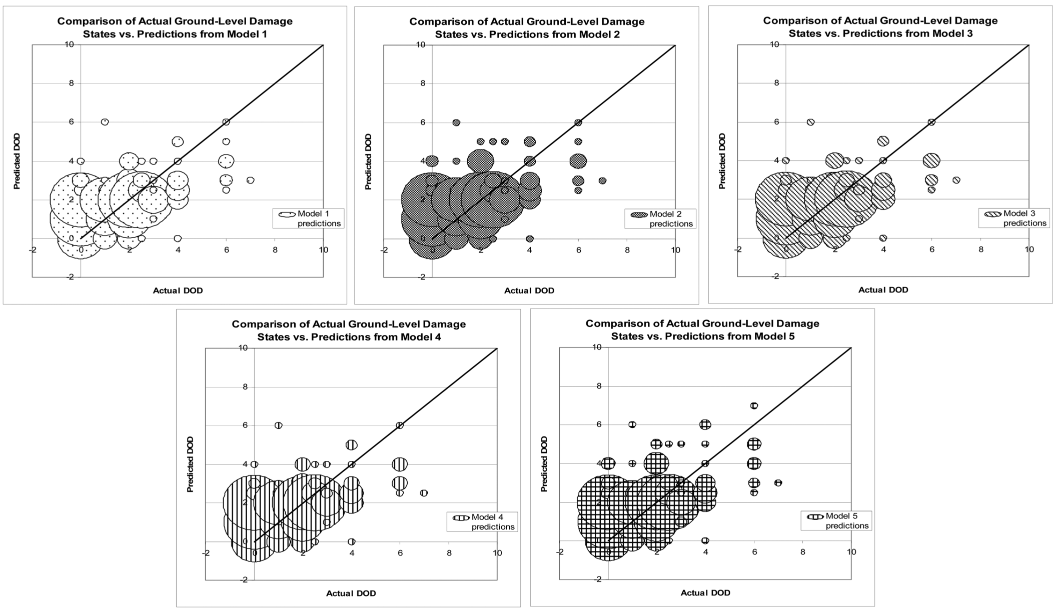

Fig. 6 Model predicted damage states vs. actual damage states obtained from the ground survey

Table 6. Frequency analysis comparing the actual DOD values to those predicted by Models 1-5. Value indicates the frequency (percentage of time) that the damage state predicted by the model matches a particular actual ground-based damage state.

		Actual DOD								
		<1	1	2	2.5	3	4	5	6	7
Predicted DOD Using Model 1	<1	.21	.12	.08	.01	.00	.04	.00	.00	.00
	1	.37	.30	.26	.03	.05	.00	.00	.00	.00
	2	.37	.52	.52	.75	.79	.26	.00	.00	.00
	2.5	.02	.04	.02	.14	.05	.33	.00	.10	.00
	3	.03	.01	.08	.06	.05	.26	.00	.30	1.0
	4	.01	.00	.05	.01	.05	.04	.00	.40	.00
	5	.00	.00	.00	.00	.00	.07	.00	.10	.00
	6	.00	.01	.00	.00	.00	.00	.00	.10	.00
	7	.00	.00	.00	.00	.00	.00	.00	.00	.00
Predicted DOD Using Model 2	<1	.21	.12	.08	.01	.00	.04	.00	.00	.00
	1	.37	.30	.26	.03	.05	.00	.00	.00	.00
	2	.37	.52	.52	.75	.79	.26	.00	.00	.00
	2.5	.02	.04	.02	.14	.05	.33	.00	.10	.00
	3	.02	.00	.03	.06	.05	.23	.00	.20	1.0
	4	.02	.01	.09	.00	.00	.07	.00	.50	.00
	5	.00	.00	.01	.01	.05	.07	.00	.10	.00
	6	.00	.01	.00	.00	.00	.00	.00	.10	.00
	7	.00	.00	.00	.00	.00	.00	.00	.00	.00
Predicted DOD Using Model 3	<1	.21	.12	.08	.01	.00	.04	.00	.00	.00
	1	.37	.30	.26	.03	.05	.00	.00	.00	.00
	2	.38	.53	.52	.77	.79	.33	.00	.00	.00
	2.5	.02	.03	.05	.13	.11	.33	.00	.10	.00
	3	.01	.01	.05	.06	.00	.19	.00	.30	1.0
	4	.01	.00	.05	.01	.05	.04	.00	.50	.00
	5	.00	.00	.00	.00	.00	.07	.00	.00	.00
	6	.00	.01	.00	.00	.00	.00	.00	.10	.00
	7	.00	.00	.00	.00	.00	.00	.00	.00	.00
Predicted DOD Using Model 4	<1	.21	.12	.08	.01	.00	.04	.00	.00	.00
	1	.37	.30	.26	.03	.05	.00	.00	.00	.00
	2	.38	.52	.52	.77	.79	.33	.00	.00	.00
	2.5	.02	.03	.05	.14	.11	.37	.00	.10	1.0
	3	.01	.01	.07	.03	.00	.15	.00	.40	.00
	4	.01	.00	.03	.01	.05	.04	.00	.40	.00
	5	.00	.00	.00	.00	.00	.07	.00	.00	.00
	6	.00	.01	.00	.00	.00	.00	.00	.10	.00
	7	.00	.00	.00	.00	.00	.00	.00	.00	.00
Predicted DOD Using Model 5	<1	.21	.12	.08	.01	.00	.04	.00	.00	.00
	1	.37	.30	.26	.03	.11	.00	.00	.00	.00
	2	.37	.52	.52	.75	.74	.26	.00	.00	.00
	2.5	.02	.04	.02	.14	.05	.33	.00	.10	.00
	3	.02	.00	.03	.06	.05	.23	.00	.20	1.0
	4	.02	.01	.08	.00	.00	.04	.00	.30	.00
	5	.00	.00	.02	.01	.05	.04	.00	.30	.00
	6	.00	.01	.00	.00	.00	.07	.00	.00	.00
	7	.00	.00	.00	.00	.00	.00	.00	.10	.00

models. The circles indicate the density or frequency of each comparison of ratings, where larger circles indicate a high density/frequency, and smaller circles indicate a low density/frequency.

A frequency analysis of the model regressions was also generated to evaluate the models' performances. This frequency analysis is provided in Table 6. Within the table, those entries highlighted in light gray indicate the frequency at which the model predicted the exact observed damage state. Those entries highlighted in medium gray indicate the frequency at which the model predicted the damage state to be within one DOD category of the actual damage state. Those entries highlighted in dark gray indicate the frequency at which the model predicted the damage state to be within two DOD categories of the actual damage state. The regressions from Model 1-5 were within two DOD categories of the actual damage rating at the lower end of the damage scale (DOD <1 through DOD 3) at least 90% of the time; for an actual rating of DOD 4, the models' regressions were correct at least 60% of the time; for DOD 6 and DOD 7, the models' regression was not as accurate. It is important to note that there were no actual damage ratings of DOD 5, nor were there any ratings greater than DOD 7. It is also important to note that the majority of the damage samples were of lower damage ratings; less than 8% of the entire Hurricane Katrina dataset had a true ground level damage state higher than DOD 3.

After reviewing the frequency analysis, it can be seen that each of the five models selected for validation produce nearly the same prediction accuracy. The data in Table 5 indicate that the R^2 values for the five models are also nearly identical. Based on this, the author recommends utilizing model 3, which is a quadratic regression, because it requires the least manipulation of the input or output data since it does not call for a statistical transformation. Its ease of use comes without sacrificing regression accuracy, and the R^2 value is less than 1% lower than model 1.

8. Conclusions

A series of 144 statistical regression models relating ground-based damage states to remotely-sensed damage states were parameterized utilizing damage ratings from 271 FR12 structures obtained from imagery following the "Super Tuesday" tornado outbreak of February 2008. The five best-performing models were selected for validation with the Hurricane Katrina dataset, which included 505 FR12 structures, whose damage ratings were determined from remote-sensing imagery. The selected regression models were used to "predict" the ground level damage states based upon the remotely-sensed damage states. The model regressions were compared to actual damage ratings obtained from a ground-based survey of the Katrina damage area. Frequency analysis showed that the developed regression models were accurate to within two DOD categories at least 90% of the time for damage ratings of DOD <1 through DOD 3. The models were accurate to within two DOD categories at least 60% of the time for a damage rating of DOD 4. The models' performances were less accurate for damage ratings of DOD 6 and DOD 7. However, less than 8% of the data used for calibrating and validating the models included damage rated in the higher damage range to recalibrate and improve the developed models. With more data and recalibrated models, it is hoped that the model regressions will be accurate for all levels of damage with 90% accuracy. Until ground-based and remotely-sensed damage states for higher levels of damage can be incorporated into the database and the models are recalibrated, the author recommends utilizing model 3, as it requires the least manipulation of the datasets without sacrificing accuracy, with the caveat that the results are reasonably accurate up to a ground-based damage state of DOD 4.

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