Development of a Statistical Relationship between Ground-Based and Remotely-Sensed Damage in Windstorms

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ABSTRACT

With rapid growth in technology, new methods of wind engineering research are being explored, and new tools are being utilized. In the past, ground-based surveys of windstorm damage were frequently performed with the aid of aerial photographs in some cases. Researchers have recently begun using remote-sensing data such as digitized satellite, aerial, and LIDAR imagery, to assess damage following natural and man-made disasters, in addition to, or instead of employing the older method of walking house-to-house for surveys. This research explores the relationship between the damage states observed at ground-level, and those observed from space using remote-sensing data, for both tornadoes and hurricanes, and for site-built one- or two-family residences (FR12). From the Enhanced Fujita (EF) scale, “Degrees of Damage” (DOD) can be determined for ground-based observations. Damage states can also be assigned for remote-sensing imagery, using a modified version of Womble’s Remote-Sensing (RS) Damage Scale. The completion of both types of assessments for a given dataset is necessary to develop the statistical relationship between the damage states, which will be based upon a simple linear regression. Several methods were utilized to fit a regression model to the data. Using both an alphabetic and alphanumeric RS damage state, models were fit to relate the ground-based and remotely-sensed damage. The model fitted with the alphabetic RS scale has the best fit. Models were also fitted using RS damage states identified by imagery from different satellite platforms, with different resolutions. The results indicate that the model fitted utilizing QuickBird imagery has a better fit to the data. Several additional methods and/or combinations of datasets will be utilized in future work to refine the models. In addition, the developed models will be tested against other datasets, such as Hurricanes Katrina and Ivan to verify their performance. We anticipate that, once fully developed, the relationship can be used to predict the ground-level damages state using remote-sensing imagery.

INTRODUCTION

Ground-based studies of windstorm damage have been completed for numerous events, and became common practice at Texas Tech University in the 1970’s, when researchers documented the damage caused by the F-5 Lubbock tornado in May 1970. In order to understand building failures following a natural or man-made disaster, damage documentation teams are often deployed to the damaged area within a few days following the event. Teams are tasked with collecting the perishable damage data to allow for an understanding of the failure mechanisms and with the hopes that some of the information gleaned can assist in making future buildings stronger and better able to survive a similar disaster [1][2][3]. In the past these kinds of investigations required several people to travel to the affected area and complete building-to-
Building assessments, which result in a costly and time-consuming investigation. While these types of assessments are still valuable and necessary, there is a new emerging technology which allows for rapid assessment of a much larger area. Remotely-sensed data, including aerial photography, satellite imagery, and LIDAR imagery, can capture the damage states in a large area much faster than conventional ground surveys. The ability to collect information rapidly is a big advantage of remote-sensing, as clean-up after a disaster usually begins as soon as possible.

Each type of damage survey has its advantages and disadvantages. Ground surveys are time-consuming, costly, and obtaining access to the damaged areas is often difficult immediately after the event; however, ground-based surveys provide much better detail than any other type of observations, and allow for detailed inspection of individual structures and components. Remote-sensing surveys can collect the data rapidly, covering a large area, and can generally visit the area quicker than a ground team might be able to gain access, but remote-sensing surveys lack the same level of detail that a ground-based survey might achieve. In addition, depending on the type of imagery, only the roof or small sections of the walls may be visible, making it difficult to determine the conditions of other building components, such as windows, doors, and connections. Although remote-sensing imagery may seem costly, when considering the amount of time it would take a ground team to cover a similar-sized area, it is much more reasonably priced. In order to obtain the best information regarding damage states, a combination of both methods would be beneficial, but because of the high cost of completing both types of surveys, it may be unreasonable to use both types for every significant storm case. Instead, it would be quicker and more cost-effective to gather the damage data via remote-sensing methods, and relate it to expected damage states at ground level. In order to do this, a probabilistic relationship between the remote-sensing damage states and the ground-level damage states will be developed using existing data sets at Texas Tech University. Once the relationship is formulated, future researchers will be able to process remote-sensing imagery and assign a probabilistic damage state at ground level.

Datasets to be used in this research include ground-based digital images captured from the “Super Tuesday” tornado outbreak in February 2008, as well as high-resolution satellite imagery obtained a few days after the outbreak. Only site-built homes (FR12) from the Enhanced Fujita Scale [4], will be used for the development of the regression model; the dataset could later be expanded to include other types of structures. Once developed, the regression model can be tested using other event datasets, including Hurricanes Katrina, Ivan, and others.

**Advances in Data Collection**

While traditional ground surveys are still valuable in understanding windstorm damage, new methods of surveying are being developed and utilized with each new windstorm event. The traditional method of walking surveys, which collect data by photographs, maps, and written or oral notations, is being replaced by technology such as ImageCat’s VIEWS (Visualizing Impacts of Earthquakes with Satellites) [5][6] system which allows for rapid collection of ground-based damage states via high-definition video, or the use of personal data assistants to systematically capture prescribed data and compile it into a database. In addition to advances in ground survey methods, the technology of remote-sensing is growing rapidly, with new platforms and better resolution available, increasing its value as a tool for collecting and analyzing damage data. The technology has advanced significantly since the beginning of the Landsat program in the 1970’s, when the image spatial resolution was 80 m. Current high-resolution satellite imagery includes the IKONOS imagery with 82 cm panchromatic and 4 m multispectral images [7], and the QuickBird imagery with 61 cm panchromatic and 2.44 m multispectral bands [8]. With the
launch of DigitalGlobe’s Worldview 1 satellite in September 2007, the commercially-available imagery resolution increased to 50 cm [9]. GeoEye’s launch of the GeoEye-1 in September 2008 further increased that resolution to 41 cm for panchromatic and 1.65 m for multispectral imagery [7].

While significant improvements in the 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 [10]. Ground surveys still provide the highest level of detail but, as previously discussed, are costly and time-consuming. Using remote-sensing imagery to predict the level of damage at ground-level would significantly lessen the time and expense required to assess the damage. A quicker evaluation of damage would lessen the emergency response time and would mean that resources (goods, funds, and personnel) could be distributed to the most devastated areas more quickly following an event. Processing time for insurance claims could also be reduced, as adjusters and claims representatives could focus their efforts on the most adversely affected areas and companies could potentially provide partial payments to many claimants until more-thorough investigations could be completed.

**Damage Assessment Methodology**

In order to develop the regression model, a ground-based damage state and a remotely-sensed damage state are both required for a given set of structures. To determine the damage state at ground level, a trained professional will assign a “Degree of Damage” (DOD), based on photographs and descriptions provided in the EF scale, to the VIEWS still images. There are 10 DODs for FR12 structures where DOD 1 is the least damage, and DOD 10 represents total destruction. The DODs are provided in Table 1, along with an expected wind speed (Exp), a lower bound (LB), and an upper bound (UB) of wind speeds that would likely cause that level of damage [4]. The EF scale rating could be determined from these expected wind speeds if desired. To determine the damage state from remote-sensing imagery, a trained professional will first categorize the damage according to Womble’s RS scale [11]. Womble’s RS scale utilizes letters ranging from A-D, and is provided in Table 2. Like the EF scale, a structure will be 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 will assign a RS scale rating to the structure’s roof as a whole. In addition, a new parameter will be included in the remote-sensing rating, which indicates the percentage area of a certain damage state. Categories of percent damage are as follow: 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.
Table 1: Degree of Damage (DOD) states and wind speed parameters for FR12 structures from the Enhanced Fujita (EF) Scale [4]

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

*3-sec gust wind speed values in mph


<table>
<thead>
<tr>
<th>Damage Rating</th>
<th>Most Severe Physical Damage</th>
</tr>
</thead>
<tbody>
<tr>
<td>RS-A</td>
<td>No apparent damage.</td>
</tr>
<tr>
<td>RS-B</td>
<td>Shingles/tiles removed, leaving decking exposed.</td>
</tr>
<tr>
<td>RS-C</td>
<td>Decking removed, leaving roof structure exposed.</td>
</tr>
<tr>
<td>RS-D</td>
<td>Roof structure collapsed or removed. Walls may have collapsed. (Oblique imagery may be needed to determine wall condition.)</td>
</tr>
</tbody>
</table>

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 system to capture high-definition ground-based photographs of the damaged areas [6]. The VIEWS system for this deployment was comprised of two high-definition video cameras mounted on either side of a moving vehicle, which could capture imagery as the vehicle drove by damaged structures. GPS data were also collected, enabling the georeferencing of each frame of video captured. From this ground survey, 32 hours of high-definition video were obtained from the affected areas. Segments of these video tapes were processed to extract individual still digital images, which were georeferenced via their GPS coordinates, and displayed in Google Earth. The extracted images include photographs from Macon and Madison Counties in Tennessee. Examples are shown in Figure 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 structures in the more than 4,000 photographs using the EF scale. All structures, including many “Damage Indicators” (DI), such as residences, buildings, trees, signs, etc., were assigned a DOD and a corresponding EF scale value. For the purposes of this research in developing the statistical relationship, only FR12 DIs will be used. The distribution of damage to FR12 structures in Madison County is given in Figure 2. Figure 3 depicts the tornado’s footprint determined from the DOD ratings of damage to FR12 structures.
Figure 1: Examples of still images captured by VIEWS in Madison County, Tennessee.

Figure 2: Distribution of DOD to FR12 structures in Madison County, Tennessee following the Super Tuesday Tornado Outbreak of February 2008.
In addition to ground-based data collected by VIEWS, WISE and ImageCat purchased DigitalGlobe satellite imagery for an area covering nearly 26 square kilometers in Madison County, for three dates and from two different platforms. Imagery was obtained on February 8 and March 2, 2008 from the QuickBird satellite; this imagery is panchromatic and multi-spectral, with 61 cm resolution, and has been pan sharpened. Imagery was also obtained on February 10, 2008 from the WorldView 1 satellite; this imagery is panchromatic and offers a 50 cm resolution. Samples of the imagery are provided in Figures 4a, 4b, and 5. It can be noted that the WorldView 1 image is sharper and clearer than the QuickBird images.
Each of the FR12 structures evaluated from the VIEWS survey was assigned a RS scale rating according to Womble [11], as well as a categorical percentage of damage, for each of the three satellite images. The differences in resolution of the images may have an impact on the developed regression model. Although outside the scope of this paper, the progress of recovery could also be studied by the amount of debris cleanup and rebuilding evident in the second QuickBird image in March. Figures 6 and 7 illustrate the distribution of RS-scale damage depicted from the QuickBird imagery on February 8th, and the WorldView 1 imagery on February 10th, respectively. Comparing Figures 6 and 7, the evaluations from the lower resolution imagery appear to overestimate the number of damaged structures and the severity of the damage. The higher-resolution imagery generally has a smaller number of homes in each of the damage categories, and more homes rated with the no-damage case of A 0%. With these observations in mind, it is important to note that the type of imagery selected for a remote-sensing assessment can affect the predicted ground-level damage states. Figures 8 and 9 illustrate the tornado’s footprint evaluated from the February 8th QuickBird imagery, and the February 10th WorldView 1 imagery, respectively. Comparing Figures 8 and 9, one can see that the overall area of damage is reduced in the higher resolution imagery. There are also additional areas of RS-D damage in the higher-resolution footprint. In general, the shape and pattern of the tornado footprint is similar. Comparing the tornado footprint constructed from the ground survey (Figure 3) to the footprints constructed from the remote-sensing surveys (Figures 8 and 9), the general shape and pattern is the same. The areas of high, moderate, and low levels of damage are similar for each of the surveys. The gradation provided by the ground survey is finer, due to the larger number of categories of damage. The similarity between these figures indicates the strong relationship between the ground-level and remotely-sensed damage states.
Figure 6: Distribution of RS scale damage depicted in QuickBird imagery from February 8th in Madison County, TN.

Figure 7: Distribution of RS scale damage depicted in WorldView 1 imagery from February 10th in Madison County, TN.
REGRESSION MODEL

The models relating ground-based damage to remotely-sensed damage are based upon a simple linear regression. Before beginning the regression modeling, a representation scheme was developed to define a numerical value to each alphabetic or alphanumeric RS scale category, for ease in plotting the scales and developing the regression models. The representation scheme is presented in Table 3.
To develop the model, several methods and combinations of datasets were utilized. First, a regression model relating the DOD to the alphabetic categories of the RS-scale was developed, for both the QuickBird and WorldView 1 datasets. Second, a regression model relating the DOD to the modified alphanumeric categories of the RS scale was developed for both platform datasets. Table 4 presents the results of the regression model for each combination of datasets and each method. Figures 10-13 illustrate the results for the February 8th QuickBird and the WorldView 1 imagery. There are several patterns to note from the regression modeling. The models fitted with QuickBird data have a better fit than the models fitted with the WorldView 1 data, contrary to the expected results; one would expect the regression fitted to the higher-resolution data to exhibit a better match. The models utilizing the alphabetic RS scale fit better than the alphanumeric values. Some of the model agreements were quite good, with R² values of 0.7 or more. There is still much room for improvement. By examining the weighted scatter plots provided in Figures 10a-13a, it is apparent that the largest portions of the samples exist in the lowest damage state and the highest damage state. The lack of data in the moderate damage states will have an effect on the fitted regression. 

Table 4: Results from the various regression models

<table>
<thead>
<tr>
<th>Satellite Platform</th>
<th>RS Comparison Type</th>
<th>Regression Equation</th>
<th>R² value</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>QuickBird</td>
<td>alphabetic</td>
<td>DOD = 1.3367 * RS - 0.0345</td>
<td>.9529</td>
<td>271</td>
</tr>
<tr>
<td>QuickBird</td>
<td>alphanumeric</td>
<td>DOD = 0.8635 * RS - 0.0261</td>
<td>.7468</td>
<td>271</td>
</tr>
<tr>
<td>WorldView 1</td>
<td>alphabetic</td>
<td>DOD = 1.9835 * RS - 0.0433</td>
<td>.8822</td>
<td>271</td>
</tr>
<tr>
<td>WorldView 1</td>
<td>alphanumeric</td>
<td>DOD = 1.4494 * RS - 0.0343</td>
<td>.4143</td>
<td>271</td>
</tr>
</tbody>
</table>
Comparison of DOD to alphabetic RS scale for QuickBird 02-08

DOD rating vs. RS scale rating

Figure 10a: Weighted scatter plot comparing DOD to the alphabetic RS scale for QuickBird imagery on February 8th, 2008. Figure 10b: Same dataset, with the weighted linear regression line plotted.

Comparison of DOD to alphanumeric RS scale for QuickBird 02-08

DOD rating vs. RS scale rating

Figure 11a: Weighted scatter plot comparing DOD to the alphanumeric RS scale for QuickBird imagery on February 8th, 2008. Figure 11b: Same dataset, with the weighted linear regression line plotted.

Comparison of DOD to alphabetic RS scale for WorldView 1

DOD rating vs. RS scale rating

Figure 12a: Weighted scatter plot comparing DOD to the alphabetic RS scale for WorldView 1 imagery on February 10th, 2008. Figure 12b: Same dataset, with the weighted linear regression line plotted.
Comparison of DOD to alphanumeric RS scale for WorldView 1 imagery on February 8th, 2008.

Figure 13a: Weighted scatter plot comparing DOD to the alphanumeric RS scale for WorldView 1 imagery on February 8th, 2008. Figure 13b: Same dataset, with the weighted linear regression line plotted.

FUTURE WORK
The results presented in this paper represent the first attempt at fitting a linear regression model to relate ground-based and remotely-sensed damage states. In some cases the model fitted is good, while in others a low $R^2$ value indicates that additional methods or data may need to be included. Additional variables, such as proximity of debris and the condition of adjacent structures could be included. Switching to a non-linear model, such as an exponential or logarithmic model may be necessary to improve the fit. The addition of variables and the application of non-linear models will be explored in the next phase of this research. In addition, datasets involving higher levels of damage would be useful for fitting the regression models. The highest level of ground-based damage observed in the “Super Tuesday” case was EF-3 (corresponding to DOD 8), so there are no data points at the extreme end of the ground-based damage scale. There were however, data points at the extreme of the RS scale which indicates the possibility that a non-linear modeling technique might fit the data better, where the RS value reaches a peak but the DOD and corresponding EF scale value continue to increase. The data and models will also need to be tested for other storm cases. Data from Hurricanes Katrina and Ivan, and perhaps some others can be used to evaluate the relevance of this study to other windstorms.

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REFERENCES


