Satellite Remote Sensing of Forest Disturbances Caused by Hurricanes and Wildland fires

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at George Mason University

By

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DEDICATION

To my parents, Fu Zhou and Rujing Wang, and my husband, Brian D. Fleeger with gratitude and love.
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<td>ABBA</td>
<td>Automated Biomass Burning Algorithm</td>
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<td>ABI</td>
<td>Advanced Baseline Imager</td>
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<tr>
<td>ASTER</td>
<td>Advanced Spaceborne Thermal Emission and Reflection Radiometer</td>
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<td>ATSR</td>
<td>Along Track Scanning Radiometer</td>
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<td>AVHRR</td>
<td>Advanced Very High Resolution Radiometer</td>
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<td>BIRD</td>
<td>Experimental Bi-Spectral IR Detection Mission</td>
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<td>BRDF</td>
<td>Bidirectional Reflectance Distribution Function</td>
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<td>CIMSS</td>
<td>Cooperative Institute for Meteorological Satellite Studies</td>
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<td>DAAC</td>
<td>Distributed Active Archive Center</td>
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<td>DBH</td>
<td>Diameter at Brest Height</td>
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<td>De Soto NF</td>
<td>De Soto National Forest</td>
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<td>DFT</td>
<td>Discrete Fourier Transform</td>
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<td>DMSP-OLS</td>
<td>Defense Meteorological Satellite Program Operational Linescan System</td>
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<td>DR</td>
<td>Direct Readout</td>
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<td>DTED</td>
<td>Digital Terrain Elevation Data</td>
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<td>EDC</td>
<td>Earth Resources Observation Systems Data Center</td>
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<td>EDG</td>
<td>EOS Data Gateway</td>
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<td>EROS</td>
<td>Earth Resources Observation Systems</td>
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<td>ERS</td>
<td>Earth Resource Satellite</td>
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<td>ESA</td>
<td>European Space Agency</td>
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<td>ETM</td>
<td>Enhanced Thematic Mapper</td>
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<td>ETM+</td>
<td>Enhanced Thematic Mapper Plus</td>
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<td>EVI</td>
<td>Enhanced Vegetation Index</td>
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<td>EXPOS</td>
<td>Topographic Exposure Model</td>
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<td>FIA</td>
<td>Forest Inventory and Analysis</td>
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<td>FIMMA</td>
<td>Fire Identification, Mapping and Monitoring Algorithm</td>
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<td>Fpar</td>
<td>Fractional Photosynthetically Active Radiation</td>
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<td>FRP</td>
<td>Fire Radiative Power</td>
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<td>GMT</td>
<td>Greenwich Mean Time</td>
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<td>GOES</td>
<td>Geostationary Operational Environmental Satellite</td>
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<td>GV</td>
<td>Green Vegetation</td>
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<td>HRG</td>
<td>High Resolution Geometric</td>
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<tr>
<td>Acronym</td>
<td>Term</td>
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<td>IGBP</td>
<td>International Geosphere Biosphere Program</td>
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<td>InSAR</td>
<td>Interferometric SAR</td>
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<td>IQR</td>
<td>Interquartile of Range</td>
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<td>LAI</td>
<td>Leaf Area Index</td>
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<td>Lidar</td>
<td>Light Detection and Ranging</td>
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<td>MISR</td>
<td>Multi-angle Imaging Spectroradiometer</td>
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<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
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<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
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<td>NBAR</td>
<td>Nadir BRDF-Adjusted Reflectance</td>
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<td>NDII</td>
<td>Normalized Difference Infrared Index</td>
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<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
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<td>NFDRS</td>
<td>National Fire Danger Rating System</td>
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<td>NIR</td>
<td>Near-Infrared</td>
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<tr>
<td>NOAA</td>
<td>National Oceanic and Atmospheric Administration</td>
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<tr>
<td>NPOESS</td>
<td>National Polar-orbiting Operational Environmental Satellite System</td>
</tr>
<tr>
<td>NPP</td>
<td>NPOESS Preparatory Project</td>
</tr>
<tr>
<td>NPV</td>
<td>Nonphotosynthetic Vegetation</td>
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<td>PCA</td>
<td>Principle Component Analysis</td>
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<td>POES</td>
<td>Polar Orbiting Environmental Satellites</td>
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<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
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<td>SD</td>
<td>Standard Deviation</td>
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<tr>
<td>SLICER</td>
<td>Scanning Lidar Imager of Canopies by Echo Recovery</td>
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<td>SPOT</td>
<td>Satellite Pour l’Observation de la Terre</td>
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<td>SSD</td>
<td>Satellite Services Division</td>
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<td>SWIR</td>
<td>Shortwave Infrared</td>
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<td>TCW</td>
<td>Tasseled Cap Wetness</td>
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<tr>
<td>TIR</td>
<td>Thermal Infrared</td>
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<td>TM</td>
<td>Thematic Mapper</td>
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<td>TRMM</td>
<td>Tropical Rainfall Measuring Mission</td>
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<tr>
<td>TSDIS</td>
<td>TRMM Science Data and Information System</td>
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<tr>
<td>USDA</td>
<td>United States Department of Agriculture</td>
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<tr>
<td>USGS</td>
<td>U.S. Geological Survey</td>
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<td>VHF</td>
<td>Very High Frequency</td>
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<td>VI</td>
<td>Vegetation Index</td>
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<tr>
<td>VIIRS</td>
<td>Visible Infrared Imager Radiometer Suite</td>
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<td>VIRS</td>
<td>Visible and Infrared Scanner</td>
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<tr>
<td>WF ABBA</td>
<td>Wildfire Automated Biomass Burning Algorithm</td>
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<tr>
<td>WI</td>
<td>Water Index</td>
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ABSTRACT

SATELLITE REMOTE SENSING OF FOREST DISTURBANCES CAUSED BY HURRICANES AND WILDLAND FIRES

Wanting Wang, Ph.D.
George Mason University, 2009
Dissertation Director: Dr. John J. Qu

The impact of forest disturbances, especially those caused by hurricanes and wildland fires, on forest ecosystems and forest carbon sequestration has become more pronounced in recent years. Remote sensing of these two natural hazards and their impacts received increasing attention among research communities for the carbon cycle study and forest management. The research presented in this dissertation is dedicated to promoting remote sensing of forest disturbances caused by hurricanes and wildland fires from space.

This study developed an algorithm for rapidly assessing post-hurricane forest damage using MODIS measurements, without relying on intensive ground inventory or sampling. The performance of five commonly used vegetation indices as post-hurricane forest damage indicators was investigated, among which the Normalized Difference Infrared Index (NDII) was found the optimal vegetation index. This new algorithm was validated by ground measurements. The validation
showed that the relative change of pre- and post-hurricane NDII was linearly related to the damage severity estimated in the ground inventory with a coefficient of determination of 0.79 and p value < 0.0001. This approach was applied to evaluate forest damage severity and the impacted forest region caused by Hurricane Katrina.

Based on the MODIS enhanced contextual algorithm and a smoke detection algorithm, an improved algorithm for monitoring low intensity fires in regional scale was developed. Sources of omission errors in the MODIS active fire product were diagnosed using a wildland fire database. This database was a collection of spectral signatures of low intensity fires, including fires missed by the MODIS enhanced contextual algorithm. This algorithm was applied and evaluated by case studies, which showed that this improved algorithm was more suitable for regional low intensity fire detection in the southeastern United States.

These algorithms and findings contribute to studies of the natural hazard detection, carbon cycle study and forest management. The rapid assessment algorithm can provide timely information on forest live fuel loading change, impacted regions and damage severity. The availability of change information on fuel loading will allow the quantitative study of hurricane impacts on forest fire danger. The improved fire detection algorithm can provide more accurate information on wildland fire events and decision support for firefighting activities and forest management.
CHAPTER 1
INTRODUCTION

1.1 REMOTE SENSING OF FOREST DISTURBANCES

Hurricanes and wildland fires are two of the major natural disturbances in forest ecosystems in the southeastern United States. The impact of hurricanes and wildland fires in US forest carbon sequestration has become more and more pronounced in recent years with the increased intensity and frequency of hurricanes and wildland fires (Goldenberg et al., 2001; Webster et al., 2005; Aber et al., 2001). Research into detecting these two natural phenomena and their impacts has attracted increasing attention from those communities for carbon cycle study, hazard relief, as well as forest management (Stanturf et al., 2007). In the past three decades, remote sensing has emerged as a unique technique to monitor forest status. Satellite remote sensing techniques are especially appropriate for monitoring forest status at regional and global scales because of high temporal and spatial resolution and extensive coverage comparing to the ground and aerial measurement. Using remotely sensed data partially eases the difficulties of low spatial coverage,
relatively large time span of ground measurements, and the observation in inaccessible regions.

From the perspective of fire management, the most immediate impact of hurricanes is that a massive amount of living forest biomass turns to dead fuel, and consequently increasing fuel bed depth (Miranda 1996) while decreasing dead fuel moisture (Gill et al. 1990, Loope et al. 1994). Hurricane-induced dead fuel and low humidity create ideal conditions for wildland fires, leading to an increase in the frequency and intensity of wildland fires in hurricane-impacted areas in the succeeding years after a landfall (e.g. Gardner et al. 1991, Myers and Lear 1998, Liu et al. 2003). Research on satellite remote sensing of hurricane-induced forest damage began in the late 1990’s. Sensors involved in this field included optical sensors (AVHRR, MODIS, SPOT, Landsat TM, ASTER and SLICER) and microwave sensors (ERS SAR, CARABAS-II SAR). The red, Near Infrared (NIR) and Shortwave Infrared (SWIR) channels were widely used in various change detection algorithms.

It has been more than 30 years since the satellite remote sensing techniques for wildland fire detection were first explored and developed (Croft 1973). Since then, several optical sensors onboard polar orbiting satellites and geostationary satellites have been used for active fire detection, including NOAA AVHRR, GOES Imager, DMSP-OLS, TRMM VIRS, Landsat TM, ETM and ETM+, Terra and Aqua MODIS, and Terra ASTER. Various fire detection algorithms based on optical remote
sensing can be divided in two categories: (1) Fixed threshold algorithms with single channel threshold or multi-channel thresholds, which were developed in the early stage; and (2) multi-channel contextual algorithms, used for most present active fire products.

1.2 RESEARCH MOTIVATIONS

Quantitative assessment of forest disturbances is important for fuel management, fire danger monitoring and carbon cycle study, since 26% to 33% of global carbon sink is sequestered in forest trees (Pacala et al. 2001). A single hurricane is capable of converting the equivalent of 10% of total annual US forest carbon deposits from living to dead biomass (McNulty 2002). Wildland fire statistics provided by the U.S. Fish & Wildlife Service showed that from 1995 to 2006 over 90 percent of wildland fires had burn areas of less than 1000 acres (405 hectares) in the United States.

Studies on remote sensing of hurricane-induced forest disturbances are still in the preliminary stages. Few operational and well validated algorithms have been developed for assessing hurricane-impacted forest regions and forest damage severity due to lack of efficient ways to measure abrupt fuel changes. Fuel loading is a key parameter in fire danger rating systems, which were not designed to assess increment of fire risk in hurricane-impacted forest regions. As a result, fixed fuel models in the National Fire Danger Rating System (NFDRS) (Schlobohm and Brain 2002) introduce uncertainties in fire risk estimation due to the high spatial and
temporal variability of hurricane-induced dead fuels. Therefore, fuel models should be able to account for such variability, which requires an efficient approach to measure abrupt fuel changes. Post-hazard relief activities (e.g. logging and fuel reduction) also require knowledge of the location and severity of forest damage to effectively carry out their missions (Stanturf et al. 2007).

Currently, most studies based on passive optical remote sensing use the change or standardized change of vegetation indices (VIs) as an indicator of post-hurricane forest damage without evaluating the quantitative relationship with forest damage, and without comparing performance of these vegetation indices. Few studies have been reported on assessing post-hurricane forest damage in the southeastern United States. Studies that directly detect structural changes of post-hurricane forests are even more preliminary.

Wildland fires are another primary natural disturbance of the forest ecosystem. On detecting wildland fires, most current algorithms were designed for global fire monitoring, and used thermal infrared (TIR) channels. The limitation is that false alarms are frequently generated over certain surface types during the day time, while low intensity fires are often missed using relatively high thresholds optimized for global fire detection (Martin and Boyce 1993, Stanturf et al. 2002, Wang et al. 2007, Wang et al. 2009). As the advanced fire detection algorithm at present stage, the MODIS contextual fire detection algorithm is designed for operational global fire monitoring. To reduce persistent false alarms over certain surface types during the day time, this global algorithm has to sacrifice the
sensitivity to relatively small fires (Justice et al. 2002b). Therefore, it has to be adjusted for regional fire detection in several aspects: fixed thresholds for identifying potential fire pixels; effects of reflected solar radiation; the impact of undetected fires in the valid background pixels; and problems caused by solar zenith angle and scan geometry. Therefore, when applied to regional active fire detection, low intensity fires are often missed due to flaws in the algorithm, special regional wildland fire patterns and environmental factors in the southeastern United States (Martin and Boyce 1993, Stanturf et al. 2002). The study by Wang et al. (2007, 2009) found a substantial number of low intensity fires were omitted by the MODIS enhanced contextual algorithm. Low intensity fires cannot be easily distinguished from non-fire background radiation using current remote sensing algorithms because of two reasons: (1) they do not emit sufficient radiation to penetrate dense canopies, and (2) the proportion of a burning area in a pixel may be small.

The goal of this study is to improve the understanding and methodology of detecting forest disturbances caused by hurricanes and wildland fires. The major objectives are:

(1) Identify a proper indicator among commonly used vegetation indices for assessing hurricane-impacted forest regions and forest damage severity;

(2) Develop an algorithm for rapidly assessing forest damage, and validate this algorithm;
(3) Construct a database of low intensity fires, which include fires omitted by the MODIS enhanced contextual algorithm;

(4) Diagnose sources of omission errors in the MODIS enhanced contextual algorithm, and develop an improved algorithm for detecting low intensity fires in regional scale.

1.3 DISSERTATION LAYOUT

This dissertation consisted of six chapters. Chapter 2 presented the background information on hurricane and wildland fire disturbances, various methods for remotely monitoring the forest damage and wildland fires, and challenges and limitations. Chapter 3-5 addressed research conducted for achieving the objectives of this dissertation. Chapter 6 summarized the dissertation and discusses future work.

Chapter 1 (this chapter) introduced the principles and current developmental state of satellite remote sensing of hurricane-induced forest damage and wildland fires. Various limitations and challenges were summarized, along with the objectives of this dissertation, and a list of the data sources used in this research. This chapter concluded with major findings and contributions of this dissertation.

Chapter 2 presented background information on hurricane-induced forest disturbances and wildland fires. The properties of post-hurricane forest damage and wildland fires were introduced, including descriptions and quantifications of forest damage, forest successions immediately following hurricane landfalls, and
characteristics of wildland fires. Satellite sensors, spectral channels and various approaches for detecting hurricane-induced forest damage and wildland fires were summarized. Challenges in this field were then outlined and discussed.

Chapter 3 investigated the performance of five commonly used vegetation indices for identifying forest damage caused by hurricanes. A new algorithm for assessing forest damage in regional scale was designed and validated. The first section of this chapter introduced physical principles of satellite remote sensing of post-hurricane forest damage, as well as the commonly used vegetation indices. The effects of Hurricane Katrina and its impact on the De Soto National Forest were then described in Section 3.2, along with ground data and remote sensing data used in this research. Section 3.3 discussed the methodology of this study, including a change detection method (univariate image differencing), and selection of an optimal forest damage indicator. The results of selecting a proper damage indicator for evaluating post-hurricane forest damage severity were presented in Section 3.4. In Section 3.5, a new rapid assessment algorithm for evaluating post-hurricane forest damage was constructed and demonstrated. Section 3.6 discusses the validation results, followed by concluding comments and discussions.

Chapter 4 analyzed the remote sensed characteristics of low intensity fires. Using statistical analysis of a collected database, this chapter identified the factors which affected the accuracy of the MODIS enhanced contextual algorithm when detecting low intensity fires. Several aspects were discussed and suggested for improving regional detection of low intensity fires. Following introduction in
Section 4.1, Section 4.2 briefly introduced physical principles of remote sensing wildland fires, the MODIS enhanced contextual algorithm, as well as challenges in detecting wildland fires in the southeastern United States. Section 4.3 introduced study areas and data sources, followed by Section 4.4, which described the methods adopted for this study. Section 4.5 presented the results of a statistical analysis of the spectral characteristics of low intensity fires. In Section 4.6, several aspects of improving the MODIS enhanced contextual algorithm were discussed, and a definition of low intensity fires was presented based on the above outlined analysis.

After Chapter 4 identified the factors most responsible for major omission errors produced by the MODIS enhanced contextual algorithm, Chapter 5 presented an improved algorithm for low intensity fire detection, using four TIR channels and seven solar reflectance channels. This approach was applied and evaluated using case studies from the southeastern United States, followed by a discussion section.

Chapter 6 summarized the entire dissertation, discussed its contributions and limitations, and recommended areas for future improvements.

1.4 SUMMARY OF DATASETS

The datasets used in this dissertation include the MODIS Nadir BRDF-Adjusted Reflectance (NBAR) Product (MOD43B4), MODIS Leaf Area Index (LAI) and Fractional Photosynthetically Active Radiation (Fpar) Product (MOD15A2), MODIS land cover product (MOD12Q1), post-Hurricane Katrina Forest health evaluation dataset, MODIS Level 1B Radiance product (MOD02/MYD02), MODIS
Level 1A geolocation product (MOD03 /MYD03) and MODIS thermal anomalies, fires and biomass burning product (MOD14/ MYD14). These datasets, summarized in Table 1.1, were used for:

(1) MODIS NBAR Products (MOD43B4)

The MODIS Nadir BRDF-Adjusted Reflectance (NBAR) Product (MOD43B4) contains visible and SWIR surface reflectance with a 1 km resolution at the mean solar zenith angle of each 16 day period and adjusted to nadir views (Schaaf et al. 2002). This product was used to derive the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) and Normalized Difference Infrared Index (NDII) time series in Chapter 3.

(2) MODIS LAI and Fpar Products (MOD15A2)

In Chapter 3, Leaf Area Index (LAI) and Fraction Photosynthetically Active Radiation (Fpar) in the MODIS LAI and Fpar products (MOD15A2) were adopted to estimate the change of LAI and Fpar before and after the hurricane.

(3) MODIS land cover products (MOD12Q1)

The IGBP land cover in the MODIS land cover product (MOD12Q1) was applied to identify areas covered by forests in Chapter 3.

(4) Forest health evaluation for forest damage caused by Hurricane Katrina

The USDA Forest Service conducted a forest health evaluation of Hurricane Katrina damage in the De Soto National Forest from October 3-7, 2005 (Meeker et al. 2006). A total of 54 plots (0.1 acre per plot) were examined within 18 separate stands, including average Diameter at Breast Height (DBH), average
height, average age and the percentage of damaged tree/basal area per acre. Hurricane damage was classified under four damage categories, including severe damage, moderate damage, light damage and no damage. The percentage of damaged trees in these four categories were calculated for each stand and used as ground truth data in Chapter 3.

(5) MODIS Level 1B Radiance products (MOD02/MYD02)

Seventy two MODIS Level 1B granules with substantive numbers of missed fire spots were selected. All these granules were observed from 2001 to 2004. The 1 km resolution datasets of this product were used to derive low intensity fires missed by the MODIS enhanced contextual algorithm (Chapter 4,5), and to derive fire masks using the MODIS enhanced contextual algorithm for the dates that the MODIS thermal anomalies, fires and biomass burning product was not available (Chapter 4, 5). The 250 m true color images of fire scenes were derived from the 250 m and 500 m resolution datasets of this product using the MODIS Direct Readout (DR) software package MODISNDVI_DB_V2.1. The 250 m true color images were used to evaluate the fire masks derived by the developed algorithm (Chapter 5).

(6) MODIS Level 1A geolocation products (MOD03/MYD03)

The MODIS L1A geolocation product was used in Chapter 4 and Chapter 5 to extract the land/sea masks and the geolocation of fire masks.

(7) MODIS thermal anomalies, fires, biomass burning products (MOD14/ MYD14)
### Table 1.1 Data used in this dissertation

<table>
<thead>
<tr>
<th>Data Products</th>
<th>Purposes</th>
<th>Section</th>
<th>Data Range</th>
<th>Data Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODIS NBAR Product (MOD43B4)</td>
<td>Derive NDVI, EVI and NDII time series</td>
<td>Chapter 3</td>
<td>2003-2006</td>
<td>USGS EOS Data Gateway</td>
</tr>
<tr>
<td>MODIS LAI and Fpar Product (MOD15A2)</td>
<td>Extract LAI and Fpar data</td>
<td>Chapter 3</td>
<td>08/2005 09/2005</td>
<td>USGS EOS Data Gateway</td>
</tr>
<tr>
<td>MODIS land cover product (MOD12Q1)</td>
<td>Extract IGBP land cover</td>
<td>Chapter 3</td>
<td>2004</td>
<td>USGS EOS Data Gateway</td>
</tr>
<tr>
<td>Forest health evaluation for forest damage caused by Hurricane Katrina</td>
<td>Evaluate the proposed algorithm as ground truth data for hurricane-induced forest damage</td>
<td>Chapter 3</td>
<td>10/2005</td>
<td>Forest Inventory and Analysis (FIA), USDA Forest Service</td>
</tr>
<tr>
<td>MODIS Level 1B Radiance product (MOD02/MYD02) 250m, 500m, 1km</td>
<td>Derive fire masks and true color images at 250m and 1km resolution</td>
<td>Chapter 4&amp;5</td>
<td>2001-2004</td>
<td>USGS EOS Data Gateway</td>
</tr>
<tr>
<td>MODIS Level 1A geolocation product (MOD03/MYD03)</td>
<td>Extract the geolocation of fire masks</td>
<td>Chapter 4&amp;5</td>
<td>2001-2004</td>
<td>USGS EOS Data Gateway</td>
</tr>
<tr>
<td>MODIS thermal anomalies, fires, biomass burning product (MOD14/ MYD14)</td>
<td>Extract fire masks derived by the MODIS enhanced contextual algorithm</td>
<td>Chapter 4&amp;5</td>
<td>2001-2004</td>
<td>USGS EOS Data Gateway</td>
</tr>
<tr>
<td>Database of low intensity fires</td>
<td>Analysis the characteristics of low intensity fires missed by the MODIS enhanced contextual algorithm</td>
<td>Chapter 4</td>
<td>2001-2004</td>
<td>EastFIRE Lab, George Mason University</td>
</tr>
</tbody>
</table>
This product was used in Chapter 4 and 5 to extract fire masks derived by the MODIS enhanced contextual algorithm.

(8) Database of low intensity fires

This study identified 6596 fire pixels in 72 granules, of which 3809 fire pixels were missed by the MODIS contextual algorithm. Their spectral properties, as well as geolocation and associated view angles, were stored in this database. This database was then used in Chapter 4 to analyze the characteristics of low intensity fires, and to identify reasons that affect the accuracy of the MODIS enhanced contextual algorithm for detecting low intensity fires.

1.5 RESULTS AND CONCLUSIONS OF THIS DISSERTATION

This dissertation studied satellite remote sensing of forest damage caused by hurricanes and wildland fires for developing and improving algorithms that can be applied in the southeastern United States.

A rapid assessment algorithm was developed for evaluating post-hurricane forest damage using Moderate Resolution Imaging Spectroradiometer (MODIS) measurements. The performance of five commonly used vegetation indices as post-hurricane forest damage indicators was investigated through statistical analysis. The Normalized Difference Infrared Index (NDII) was identified as the optimal damage indicator among these vegetation indices. An algorithm for assessing post-hurricane forest damage in regional scale, without mainly relying on ground inventory or sampling, was developed and validated. The validation showed that the
relative change of pre- and post-hurricane NDII was linearly related to damage severity estimated by the ground inventory with a coefficient of determination ($R^2$) of 0.79. This approach was applied to assess the impacted forest region and forest damage severity caused by Hurricane Katrina in 2005.

The MODIS enhanced contextual algorithm was also adjusted and improved based on the statistical analysis. A database was constructed to analyze the spectral properties of low intensity fires, including low intensity fires omitted by the MODIS enhanced contextual algorithm, and to diagnose sources of omission errors in the MODIS contextual algorithm for detecting low intensity fires. The findings included: (1) sensor view angles evidently affected the accuracy of the MODIS contextual algorithm for low intensity fire detection, especially for view angles of greater than 40 degrees; (2) the $R^2$ threshold 0.3 was still valid for detecting low intensity fires omitted by the MODIS enhanced contextual algorithm; (3) view angles did not substantially affect the validity of the $R^2$ threshold; (4) the threshold of test $T_{21} > 310$ K was too high for detecting low intensity fires, and $T_{21} > 293$ K should be adopted, and; (5) the $\Delta T$ threshold 10 K is too high. An improved algorithm was designed based on the MODIS enhanced contextual algorithm and a smoke detection algorithm. The performance of the improved algorithms was evaluated with a large number of fire events, which showed that the improved algorithm was more sensitive to low intensity fires, especially for observations at large scan angles.
1.6 SIGNIFICANCE OF THE STUDY

This study developed a new approach and improved the current algorithm for monitoring forest disturbances caused by hurricanes and wildland fires from space. The algorithms and findings produced by this study improved the understanding of monitoring post-hurricane forest damage and low intensity fire detection by providing elaborate statistical analysis based on a large volume of remote sensing data. This research contributes to communities for natural hazard detection, carbon cycle study and forest management.

This dissertation summarized and compared approaches and sensors adopted for detecting post-hurricane forest damage. A fast assessment algorithm without relying on intensive ground survey and sampling was for the first time developed to determine impacted forest regions and forest damage severity in regional scale. It was also innovative to (1) adopt MODIS NBAR data as a major data source for post-hurricane change detection; (2) integrate univariate image differencing and Fourier transform time series analysis for detecting forest modification; (3) quantitatively evaluate frequently used vegetation indices, and identify an optimal damage indicator; (4) quantitatively prove the validity of the optimal indicator on assessing forest damage by revealing the linear relationship between ∆NDII and forest damage observed through ground investigation.

An improved algorithm to detect low intensity fires in southeastern United Stated was developed based on the diagnosis of spectral properties of low intensity
fires. Major reasons that caused omission errors in the MODIS enhanced contextual algorithm was identified using the database of low intensity fires that was collected in this study. This study revealed several approaches to further improve the accuracy of detecting low intensity fires in the southeastern United States. Based on these findings, an improved algorithm was developed for detecting low intensity fires in regional scale. These results will contribute to future studies on improving active fire detection algorithms.

The rapid algorithm for assessing forest damage and the improved algorithm for wildland fire detection will be applicable to future missions of NPP (NPOESS Preparatory Project), NPOESS (National Polar-orbiting Operational Environmental Satellite System) and GOES-R (Geostationary Operational Environmental Satellites). VIIRS (Visible Infrared Imager Radiometer Suite), to be launched in NPP and NPOESS missions (in 2011 and 2014 respectively), possesses similar channels involved in these two algorithms, but with higher spatial resolutions than MODIS. The ABI (Advanced Baseline Imager), carried by the GOES-R satellite, also covers visible, NIR, SWIR and thermal bands with similar spatial resolution as MODIS, but with much higher temporal resolutions. The application of these two algorithms based on VIIRS and ABI sensors will be more effective for assessing post-hurricane forest damage and monitoring low intensity fires.
CHAPTER 2
FOREST DISTURBANCES AND REMOTE SENSING

Summary: This chapter presents a review of the use remote sensing techniques for detecting forest disturbances caused by hurricanes and wildland fires. It first introduces background information on the effects of hurricane and fire disturbances on forests, including forest damage and forest successions immediately following a hurricane, as well as the properties of wildland fires. Next, a review is presented of forest disturbances caused by hurricanes and wildland fires, and physical principles of satellite remote sensing to detect hurricane-induced forest damage and active wildland fires. A description of currently used satellite sensors, spectral channels and various approaches are summarized, and followed by a summary of their current status and challenges.

2.1 FOREST DISTURBANCES CAUSED BY HURRICANES

Hurricanes are major natural disturbances in forest ecosystems in the southeastern United States. Statistically, severe hurricanes (Saffir-Simpson scale 3 and above) make landfall along the western Atlantic and Gulf coastlines 2 out of every 3 years (Smith et al. 1994). This phenomenon has been more pronounced in
recent years, as ten hurricanes have made landfall along the southern coast in 2004, 2005 and 2008 (Jeanne, Ivan, Frances, and Charley in 2004, followed by Dennis, Katrina, Rita, and Wilma in 2005, Gustav and Ike in 2008).

Studies on hurricane-induced forest disturbances follow three general directions. The first direction involves qualitative description and quantitative measurement of forest damage, and efforts to find influencing factors and their relationships to hurricane-induced forest damage using field sampling and statistical analysis (e.g. Everham and Brokaw 1996, Foster 1998). This is a traditional school followed by most ecologists. The second direction, grounded in intensive ground inventories, involves projecting forest damage using weather models, topographic exposure models and/or ground observations (e.g. Boose et al. 1994, Kovacs et al. 2001, Jacobs 2007). The third research direction, satellite remote sensing techniques, has been gradually adopted since early 2000 by modeling studies (Ramsey et al. 2001, Kupfer et al. 2008, Wang and Xu 2008). Because traditional ground surveys face limited resources such as time, funds, man power, and range of spatial and temporal coverage, the remote sensing direction is being developed for the purpose of assessing forest disturbances with minimal need of ground survey data.

2.1.1 Forest Disturbances Caused by Hurricanes

Hurricanes can extensively influence the composition, structure and natural succession of forests (Foster 1988, Conner et al. 1989, Gresham et al. 1991, Boutet
Hurricane-induced forest damages include defoliation, branch loss, stem breakage, uprooting, overstory canopy removal, and mortality. Defoliation is the most common type of damage, followed by branch loss, snapping and uprooting. Severe hurricanes cause the mechanical destruction of forest structure (i.e. canopy height, vertical stratification and leaf area), and result in a massive transfer of biomass to the forest floor (Lodge and McDowell 1991). Brokaw and Walker (1991) found that even in less damaged forests there was a shift in the relative amount of foliage cover from upper to lower layers. Hurricanes can change horizontal structure of forest landscapes, creating heterogeneous damage patterns as a result of complex interactions among wind, rainfall, forest susceptibility, and physiographic factors (Foster and Boose 1992, Boose et al. 1994). Gaps created by hurricanes on forest landscape vary from smaller than 20-30 m² to more than 400 m² (Foster and Boose 1992, Webb 1986). The area of forest damage, in regional scale, rarely extends more than 100 km to either side of the storm track.

From the perspective of fire management, the most immediate impact of hurricanes is that a massive amount of living forest biomass turns to dead fuel, and the consequent increase of fuel bed depth and decrease of dead fuel moisture. McNulty (2002) estimated that a single hurricane could convert the equivalent of 10 % of total annual US forest carbon deposits from living to dead biomass, among which 90% of total downed wood is never salvaged, and becomes dead fuel for wildland fires in later years. For example, following hurricane Hugo, forest debris and litter was up to 3 m deep in many areas (Miranda 1996). It is found that post-


Quantitative assessment of forest damage in ground survey can be classified into five categories: (1) stem damage, (2) canopy damage, (3) volume or biomass changes, (4) mortality, and (5) classification categories (Everham 1998). The ground observation used in this dissertation falls into classification categories. The categorization may be based on estimation of stem damage (Gresham et al. 1991, Foster and Boose 1992, Imbert et al. 1996, Meeker et al. 2006), canopy damage (Jacobs and Eggen-McIntosh 1993, Kupfer et al. 2008), and/or subjective classification on case-specific experiences (Sheffield and Thompson 1992). In
various efforts, three to five categories are often adopted; however, their criteria are rarely same. In our case, forest damage is measured by total and percent basal area damage in five damage severity levels.

2.1.2 Successions Immediately after Hurricanes

Forest successions which occur immediately following a hurricane landfall include the sudden growth of underlying vegetation and the bloom of new leaves several weeks to several months later. It was reported that some tree species had new leaves within two weeks, and 70% of damaged trees produced new leaves within seven weeks after Hurricane Hugo (Walker 1991, Walker et al. 1992). Meléndez-Ackerman et al. (2003) found that forest recovery was evident within four weeks after Hurricane Georges.

2.2 WILDLAND FIRES

According to fire intensity and severity, forest fires can be categorized into three major types: crown fires, surface fires and ground fires (Aber and Melillo 2001). Crown fires burn the crowns of the dominant trees, as well as stems and the forest floor. The post-fire tree mortality rate is almost 100 percent. The soil organic layer is almost entirely burned, leaving bare soil. The released energy during a crown fire can reach 150,000 kWm$^{-1}$ (Barnes et al. 1998) and become much hotter than surface fires. Surface fires burn only along the forest floor and release up to 15,000 kWm$^{-1}$ of energy (Barnes et al. 1998). They are relatively cool and do not
change the major structure of the forest. In a light surface fire, canopy trees retain green leaves and generally do not die, although their stems often are scorched, and understory brush and herbaceous plants are dead. The soil organic layer within burned areas remained largely intact. In a severe surface fire, dominant tree mortality is extensive but canopy leaves are not consumed. Tree stems are scorched; brush and herbaceous plants are completely dead with organic matter on the top soil burned. Ground fires smolder down through the organic layer of the soil, and generally burn slowly over long periods of time. The energy released by ground fires is usually less than 10kWM⁻¹ (Barnes et al. 1998).

2.3 REMOTE SENSING OF FOREST DAMAGE AND WILDLAND FIRES

Over the past three decades, remote sensing has emerged as a unique technique to monitor forest status. Satellite remote sensing is especially appropriate for landscape-scale, regional-scale and global-scale study because of their high temporal and spatial resolution, and extensive coverage relative to ground and aerial measurements.

Ideally, studies on forest damage should include information on structure and function acquired pre- and post- hurricane. However, it is difficult to predict hurricane path and evolution accurately, therefore, collecting data prior to a storm is very difficult. Using remotely sensed data partially eases the difficulty because satellites revisit regularly over large areas, and so can provide information both before and after a hurricane. Satellite data can be used to estimate fuel type, fuel
moisture, vegetation structure, vegetation phenology, and the impact of natural
disturbances (e.g. wildland fires and hurricane impacts on biomass).

2.3.1 Detecting Hurricane-Induced Forest Damage

In this subsection, various methods of detecting hurricane-induced forest
damage are reviewed. Satellite sensors and spectral channels are introduced. Then,
the major change detection algorithms are summarized.

2.3.1.1 Approaches Adopted by Previous Studies

Most studies reported in peer-reviewed journals and governmental
publications (Table 2.1) can be classified into four categories based on physical
principles employed to detect forest damage: (1) detection based on the change of
et al. 2007, Lee et al. 2008), (2) detection based on the change of leaf water content
(Jin and Sader 2005, Aosier and Kaneko 2007), (3) detection based on the change of
nonphotosynthetic vegetation (Chambers et al. 2007), and (4) detection based on
structural changes of damaged forests (Dwyer et al. 1999, Wiesmann et al. 2001,

As demonstrated in Table 2.1, most studies used the change or standardized
change of NDVI as an indicator of post-hurricane forest damage. Ramsey et al. (1997)
analyzed the NDVI change derived from AVHRR multi-temporal images, and found
Table 2.1 Studies on post-storm forest damage assessment

<table>
<thead>
<tr>
<th>Name of Storm</th>
<th>Time</th>
<th>Sensors</th>
<th>Channels</th>
<th>Damage Indicator</th>
<th>Change Detection</th>
<th>Literature</th>
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<tbody>
<tr>
<td>Hurricane Georges</td>
<td>09/1998</td>
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<td>NDVI</td>
<td>univariate image differencing</td>
<td>Ayala-Silva &amp; Twumasi 2004</td>
</tr>
<tr>
<td>Typhoon Herb</td>
<td>07/30/1996</td>
<td>SPOT</td>
<td>Red, NIR</td>
<td>NDVI</td>
<td>univariate image differencing</td>
<td>Lee et al. 2008</td>
</tr>
<tr>
<td>Typhoon Songda</td>
<td>09/2004</td>
<td>ASTER</td>
<td>Red, NIR, SWIR</td>
<td>NDVI, NDII, LAI</td>
<td>univariate image differencing</td>
<td>Aosier &amp; Kaneko 2007</td>
</tr>
<tr>
<td>Ice Storm</td>
<td>1994</td>
<td>Landsat TM</td>
<td>Red, NIR</td>
<td>NDVI</td>
<td>univariate image differencing</td>
<td>Stueve et al. 2007</td>
</tr>
<tr>
<td>Ice Storm</td>
<td>01/1998</td>
<td>Landsat TM</td>
<td>Red, NIR</td>
<td>NDVI</td>
<td>univariate image differencing, Linear regression</td>
<td>Millward &amp; Kraft 2004</td>
</tr>
<tr>
<td>Hurricane Katrina</td>
<td>08/29/2005</td>
<td>Landsat TM/ MODIS</td>
<td>NIR, SWIR, Visible</td>
<td>Nonphotosynthetic vegetation</td>
<td>classification</td>
<td>Chambers et al. 2007</td>
</tr>
<tr>
<td>Hurricane Fran</td>
<td>09/06/1996</td>
<td>SLICER</td>
<td>NIR laser</td>
<td>Canopy height</td>
<td>-</td>
<td>Boutet &amp; Weishampel 2003</td>
</tr>
<tr>
<td>Hurricane Lothar</td>
<td>12/26/1999</td>
<td>ERS SAR</td>
<td>C-band (6 cm)</td>
<td>InSAR Coherence</td>
<td>classification</td>
<td>Dwyer et al. 1999, Wiesmann et al. 2001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CARABAS-II SAR</td>
<td>VHF-band (3.3-15 m)</td>
<td>Backscattering amplitude</td>
<td>linear regression</td>
<td>Fransson et al. 2002</td>
</tr>
</tbody>
</table>
that AVHRR could be used to detect abnormal growth in damaged forest within one to two months after Hurricane Andrew in the Atchafalaya Basin. The quantity of NDVI change is correlated to damage severity, i.e. the most heavily impacted sites sequentially had the highest decrease and increase in post-hurricane NDVIs. They inferred that post-hurricane NDVI variability was dependent not only on the severity of impact, but also on the type of damage. Later, they further estimated impact and recovery magnitudes for the damaged area (Ramsey et al. 1998). They reported that the spatial distribution of recovery followed the impact distribution; however, recovery and impact magnitudes were not necessarily covaried. These results suggested that damage extent and information on damage severity and type may be extracted from the temporal pattern of the NDVI change derived from the AVHRR images. Using the forest damage indentified by differencing the pre- and post-hurricane NDVI, Ramsey et al. (2001) also analyzed the relation of forest damage with the forest types and wind fields. They used multiple regression analysis based on forest damage, forest types and wind fields derived from AVHRR images, Landsat TM images and a hurricane-wind model, respectively. They found that the estimated impact based on the regression model was highly related to the duration and speed of extreme winds of Hurricane Andrew in 1992. The empirical model explained 73-87% of the forest damage. Ayala-Silva and Twumasi (2004) investigated the vegetation change caused by Hurricane Georges in Puerto Rico using the standardized change of NDVI (ΔNDVI) derived from AVHRR images. They found ΔNDVI linearly related to the distance of the hurricane track, which is the
relation found true in regional scale by numerous field studies and model studies. Millward and Kraft (2004) studied the canopy damage caused by a 1998 ice storm using a general linear model based on NDVI derived from Landsat images and in situ data. The general linear model achieved an accuracy of $R^2 = 0.83$ with $p<0.004$. Stueve et al. (2007) studied the topographic effect on the forest damage caused by 1994 ice storm in the Appalachian Mountains, and identified the forest damage by the change of NDVI derived from Landsat TM images. Lee et al. (2008) analyzed the relationship of forest type, topographic aspects, elevation and forest damage caused by Typhoon Herb in central Taiwan using NDVI derived from SPOT images. They confirmed that (1) the difference of NDVI pre- and post-typhoon is able to detect forest damage, and (2) forest damage caused by the elevation and the topographic aspect can be observed using NDVI.

Several studies detected post-hurricane forest damage using vegetation indices related to leaf water content. Aosier and Kaneko (2007) compared NDVI and adjusted NDII of health and damaged trees caused by Typhoon Songda 2004 using ASTER images. They found that the difference of NDVI for damaged trees is greater than the difference of adjusted NDII. This finding is inconsistent with prior findings that vegetation modification is better detected by the NIR-SWIR based vegetation indices than NIR-Red based vegetation indices (Ceccato et al. 2001, Bowyer and Danson 2004, Jin and Sader 2005, Sader et al. 2003, Wilson and Sader 2002). Tasseled Cap Wetness (TCW) is another vegetation index derived from multi-band images using tasseled cap transformation based on principle component analysis. It
has been reported to be sensitive to vegetation and soil moisture (Crist and Ciccone 1984). TCW has not been applied to detect post-hurricane forest damage. However, Jin and Sader (2005) compared tasseled cap wetness and NDII in detecting the forest disturbance caused by harvesting and partial harvesting. The forest damage caused by partial harvesting is similar to that caused by hurricanes. They reported that NDII and TCW were highly correlated ($R^2 > 0.98$) for four images they examined. For images with 1 and 2 years apart, errors of forest change detected by NDII were slightly lower than TCW.

Detection based on the change of nonphotosynthetic vegetation was reported by Chambers et al. (2007). They studied the forest damage caused by Hurricane Katrina using Landsat, MODIS, and field inventory data. Spectral mixture analysis was adopted to calculate the per-pixel fractional abundance of green vegetation (GV), nonphotosynthetic vegetation (NPV), soil, and shade. Using the difference of NPV ($\Delta$NPV) pre- and post-hurricane, seperately derived from Landsat images and field inventory data, the linear relationship between Landsat $\Delta$NPV and the field measured $\Delta$NPV ($R^2=0.88$, $p<0.0001$) was found. They developed a Monte Carlo model to estimate the forest damage in the MODIS scenes based on the Landsat images. Their model predicted 320 million large trees are dead or severely damaged with a total biomass loss of 105 Tg C. However, the validation results based on MODIS observations were not reported.

Studies based on structural changes of post-hurricane forests are more preliminary. SAR coherence data has been shown to be very effective at identifying
forest and non-forest areas (Floury et al. 1997). Dwyer et al. (1999) studied the coherence imagery and backscatter data derived from ERS for detecting the extent of forest damage caused by Storm Lothar in France. They used a supervised classification method to identify damaged areas, and found the classification was more successful where the damage severity was greater. The evaluation, conducted by comparing the results with the 1/50000 terrain map provided by the Swiss Federal Office of Topography, showed “excellent agreement of the forest/non-forest mapping by SAR”. Wiesmann et al. (2001) detected the forest damage caused by a storm using the classification method based on the InSAR coherence increase. The accuracy of the classification reached 89%. Fransson et al. (2002) investigated the use of airborne CARABAS-II VHF SAR imagery for detecting wind-thrown forests. They used the linear relationship between SAR backscattering amplitude and stem volume to estimate pre-storm backscattering amplitude. Using post-storm SAR image and the estimated pre-storm backscattering amplitude, they found that at a given stem volume the backscattering amplitude is considerably higher for wind-thrown forests than for unaffected forest. They concluded that VHF SAR has the potential to identify wind-damaged forests. Boutet and Weishampel (2003) studied post-hurricane canopy change using the Scanning Lidar Imager of Canopies by Echo Recovery (SLICER) sensor and field measurements at the local scale. They found that the autocorrelation of canopy heights disappeared after the hurricane, and the average fractal dimension of canopy heights rose from 1.71 to 1.94.
2.3.1.2 Summary of Sensors

The sensors used in the literature include AVHRR, MODIS, ASTER, Landsat TM, SPOT, Lidar and SAR (Table 2.2). The spatial resolutions of MODIS are 250 and 500 m for VIR and SWIR channels, and AVHRR’s resolution is 1.1 km. Their resolutions are not fine enough to detect the horizontal structural change of damaged forests, because the typical scale of forest gaps generated by hurricanes vary from 10 to 35 m (Foster and Boose 1992, Webb 1986). Though high resolution optical sensors, such as ASTER, Landsat TM and SPOT, have 10-30 m resolution (potentially able to identify major changes in horizontal forest structure with greater accuracy than moderate resolution sensors), however, the spatial coverage of high resolution sensors is narrower than moderate resolution sensors, ranging from 60 km to 185 km, whereas the typical scale of a hurricane impacted region is around 200 km. With regard to spatial coverage, moderate resolution sensors are more suitable for the regional study of hurricane impacted areas and severity. The spatial distributions of forest damage requires the combination of moderate and high resolutions sensors in order to conduct regional studies of forest damage with reasonable accuracy. The pioneering research by Champer et al. (2007) demonstrated an example of scaling up the observations obtained from a high resolution sensor (Landsat) and a moderate resolution sensor (MODIS).
<table>
<thead>
<tr>
<th>Satellite</th>
<th>Sensors</th>
<th>Channels (µm)</th>
<th>Resolution</th>
<th>Swath</th>
<th>Global Coverage</th>
<th>Data Range</th>
<th>Derived Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOAA series AVHRR</td>
<td>Red</td>
<td>0.58-0.68</td>
<td>1.1 km</td>
<td>2800 km</td>
<td>1 day</td>
<td>1998 - present</td>
<td>NDVI</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>0.73-1.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR</td>
<td>1.58-1.64</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terra Aqua MODIS</td>
<td>Red</td>
<td>0.62-0.67</td>
<td>250 m</td>
<td>2330 km</td>
<td>Twice per day</td>
<td>2000 - present</td>
<td>Nonphotosynthetic vegetation based on Landsat</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>0.84-0.88</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR-1</td>
<td>1.23-1.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR-2</td>
<td>1.63-1.65</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR-3</td>
<td>2.11-2.16</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terra ASTER</td>
<td>Red</td>
<td>0.63-0.69</td>
<td>15 m</td>
<td></td>
<td>16 days</td>
<td>2000 - present</td>
<td>NDVI, NDII, and LAI</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>0.78-0.86</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR-1</td>
<td>1.60-1.70</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR-2</td>
<td>2.15-2.19</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR-3</td>
<td>2.19-2.23</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landsat TM</td>
<td>Red</td>
<td>0.63-0.69</td>
<td>30 m</td>
<td>185 km</td>
<td>16 days</td>
<td>1982 - present</td>
<td>NDVI, NDII, TCW and nonphotosynthetic vegetation</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>0.76-0.90</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR-1</td>
<td>1.55-1.75</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR-2</td>
<td>2.08-2.35</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPOT 4/5 HRG</td>
<td>Red</td>
<td>0.61-0.68</td>
<td>10/20 m</td>
<td>60 km</td>
<td>26 days</td>
<td>1998 - present</td>
<td>NDVI</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>0.78-0.89</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SWIR</td>
<td>1.58-1.75</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Lidar</td>
<td>NIR laser</td>
<td>0.11 m vertical</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td>Canopy height</td>
</tr>
<tr>
<td>- CARABA S-II SAR</td>
<td>VHF &amp; HH (3.3-15 m)</td>
<td>2.5 m</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
2.3.1.3 Current Approaches for Change Detection and Drawbacks

The basic idea of change detection is that variations in vegetation will change reflectance values or local textures which are separable from signals caused by other factors (e.g. atmospheric conditions, view geometry and soil conditions). Lu et al. (2004) separated change detection methods into more than six categories, i.e. algebra, transformation, classification, Geographical Information System (GIS) approaches, visual analysis, and other approaches. Of all the methods in the algebra category, univariate differencing is most commonly used in practice (Coppin et al. 2004), as well as the preferred algorithm for detecting defoliation (Muchoney and Haack 1994). The univariate differencing approach is relatively simple, straightforward, and easy to implement and interpret. However, selecting suitable thresholds is difficult due to variations in atmospheric conditions, soil, view geometry, and vegetation phenology. Principle Component Analysis (PCA) and tasseled cap transformation are used most frequently in the transformation category for change/non-change detection. The tasseled cap transformation is more frequently used than the PCA approach when detecting vegetation modification. The drawbacks are the difficulty to select thresholds, interpret transformed images, and label the change information on the map. Classification approaches cannot quantitatively assess vegetation changes, so they are excluded from this research. With respect to detecting hurricane-induced forest damage, univariate differencing is the most highly used change detection method.
2.3.2 Detecting Wildland Fires

It has been over 30 years since the earliest techniques of active fire detection using satellite sensors were first explored and developed in the first half of the 1970s (Croft 1973). Since then, several meteorological satellite instruments have been used for this purpose even though they were not designed with any expectation for fire detection (Elvidge et al 1998). These instruments include the National Oceanic and Atmospheric Administration’s (NOAA) Advanced Very High Resolution Radiometer (AVHRR), the NOAA Geostationary Operational Environmental Satellite (GOES) Imager, the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS), and the Tropical Rainfall Measuring Mission (TRMM) Visible and Infrared Scanner (VIRS). As the development of Earth-Observing satellite missions, several other satellite instruments also have been used for detecting active fires, including the Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM) and Enhanced Thematic Mapper Plus (ETM+), the National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and the European Space Agency's (ESA) European remote sensing satellite Along Track Scanning Radiometer (ATSR) and Enhanced ATSR (Qu et al. 2008). The NASA National Polar-orbiting Operational Environmental Satellite System (NPOESS) Visible Infrared Imager Radiometer Suite (VIIRS), scheduled to launch after 2011,
and NOAA GOES-R, scheduled for 2014, will also be able to detect active fires. Several sensors that are most frequently applied toward identifying active fires, along with their algorithms and products, are summarized in Table 2.3. These sensors are AVHRR, GOES, TRMM and MODIS, from which active fire detection using AVHRR and MODIS is introduced in details.

Table 2.3 Sensor specifications for active fire detection

<table>
<thead>
<tr>
<th>Satellite /Sensors</th>
<th>Spatial Resolution</th>
<th>Temporal Resolution</th>
<th>Central Wavelength (µm)</th>
<th>Band</th>
<th>Saturation Temperature (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVHRR</td>
<td>1.1 km</td>
<td>2/day</td>
<td>3.75</td>
<td>3</td>
<td>325</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>10.8</td>
<td>4</td>
<td>325</td>
</tr>
<tr>
<td>GOES</td>
<td>4 km</td>
<td>4/hour</td>
<td>3.9</td>
<td>2</td>
<td>335</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>10.7</td>
<td>4</td>
<td>320</td>
</tr>
<tr>
<td>TRMM</td>
<td>2.2 or 2.4 km</td>
<td>2/day</td>
<td>3.75</td>
<td>3</td>
<td>322</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>10.8</td>
<td>4</td>
<td>325</td>
</tr>
<tr>
<td>MODIS</td>
<td>1 km</td>
<td>2/day</td>
<td>3.96</td>
<td>21</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3.96</td>
<td>22</td>
<td>331</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>11.03</td>
<td>31</td>
<td>400 (Terra) 340 (Aqua)</td>
</tr>
</tbody>
</table>

2.3.2.1 AVHRR

AVHRR (Kidwell 1998) is a pioneering sensor that was first used to investigate the ability to detect fires from space. It is on board the NOAA’s Polar Orbiting Environmental Satellites (POES). The first version of AVHRR had four channels (launched on October 1978), the second generation of AVHRR had five
channels (launched on June 1981), and the latest version is AVHRR/3, which had six channels (launched on May 1998), including visible, near infrared, shortwave infrared and three infrared channels. The central wavelengths of these channels related to active-fire detection remain unchanged in the last two versions of AVHRR (see Table 2.3).

AVHRR-based fire detection algorithms can be divided into two categories (Justice and Dowty 1994, Langaas 1995, Martin et al. 1999, Li et al. 2001): (1) Fixed threshold algorithms, using either a single channel at 3.75 µm, or multiple-channels, and; (2) multi-channel variable threshold algorithms, i.e. contextual algorithms. Most of the classical AVHRR fire detection algorithms developed in the earliest period (e.g. Flannigan and Vonder Haar 1986, Kaufman et al. 1990, Lee and Tag 1990, Setzer and Pereira 1991, Kennedy et al. 1994, Rauste et al. 1997, Arino and Melinotte 1998, Li et al. 2000) are based on fixed threshold tests derived by empirical analyses (Lasaponara et al. 2003). The major limitation of these algorithms is that fixed thresholds are applicable only in local to regional scales during a short fire season (Pu et al. 2004) due to the variations of the environmental temperature and the fire temperature. Multi-channel contextual algorithms were proposed to minimize false alarms caused by middle-infrared solar reflection, and to apply across regional and global scales (Lee and Tag 1990, Justice et al. 1996, Eva and Flasse 1996, Dwyer et al. 1998).

AVHRR single channel threshold algorithms use the mid-infrared channel 3 centered at 3.75 µm (Robinson 1991, Chuvieco and Martin 1994). However, the
channel 3 saturates at 325 K, which is a brightness temperature far below typical fire temperatures (ranging from 500 K for smoldering fires to 1000 K for flaming fires) and even lower than the temperatures of some non-fire pixels. Non-fire background pixels usually do not reach saturation temperature; but, solar reflectance from clouds and bright surfaces, such as bare soil and rock, can saturate channel 3 even in the absence of fires (Giglio et al. 1999). This is a major problem for detecting fires during daytime. Therefore, a single channel algorithm is only useful for environments with relatively low background reflectance and low background temperature, such as nighttime fire detection when the contribution of reflected solar irradiance is minimal (Malingreau 1990, Langaas 1992).

The AVHRR multispectral algorithm can overcome some limitations of single-spectral algorithms. Three major processes of these algorithms typically include (1) using channel 3 to identify potential fire pixels; (2) eliminating clouds by using thermal channel 4; and (3) identifying fires among potential fire pixels with warm background by inspecting the difference of brightness temperature at channel 3 and channel 4 (Li et al. 2001). But, the threshold values cannot be applied to global fire detection, and usually must be adjusted for environmental characteristics and fire conditions of particular regions. Additional tests may be used in multi-spectral algorithms to reject false alarms caused by high clouds (channel 4), low clouds and bright surfaces (Kennedy et al. 1994, Arino and Melinotte 1998), and thin cirrus clouds (Franca et al. 1995, Li et al. 1997). Other than the limitation caused by channel 3 saturation, another major error source is that the difference in brightness
temperature between channel 3 and channel 4 is not only dependant on fires, but also affected by atmospheric effects and solar reflection at channel 3. The last two factors contribute to omission errors and commission errors respectively, because the atmosphere attenuates the difference of these two channels, and solar reflection increases the difference. The saturation of channel 3 decreases the difference, which may introduce omission errors.

Contextual multispectral algorithms use dynamic pixel-specific thresholds, relying on the contrast between a potential fire pixel and its background pixels (Boles and Verbyla 2000), to identify fire pixels among potential fire pixels, where potential fire pixels are previously selected by a set of fixed thresholds based on the fixed threshold algorithms. These algorithms are more flexible and effective in variable surface conditions than fixed threshold approaches (Flasse and Ceccato 1996, Li et al. 2001). The pixel-specific threshold is derived from the threshold variables of the non-fire background pixels for a potential fire pixel. The concept of contextual algorithms was first introduced by Lee and Tag (1990), and then employed in various algorithms for regional and global fire detection (e.g. Justice et al. 1996, Eva and Flasse 1996, Flasse and Ceccato 1996, Giglio et al. 1999). The advantages of contextual algorithms are that they are based on the variety of background properties, and are less affected by heterogeneous background features and fire characteristics. Contextual algorithms are so far the most flexible and widely applied algorithm, and can achieve much better accuracy than fixed threshold algorithms.
2.3.2.2 MODIS

The launch of Terra in 1999 marked the beginning of a new era for detecting active fires from space. The Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Terra and Aqua has two channels centered at 3.96 µm (i.e. band 21 and 22), specifically designed for detecting active fires. Band 21 has the highest saturation brightness temperature (500 K) than any other similar bands (~ 4 µm) that have been designed for other sensors. MODIS is able to provide reliable active fire detection from regional to global scales. In addition, the fact that MODIS has 36 bands, spanning from 0.41 to 14.4 µm with 250 m, 500 m, and 1 km spatial resolutions, enable MODIS-based fire algorithms to use abundant information for excluding cloud and water pixels, and eliminating false alarms caused by mid-IR solar reflectance and clouds without using exterior ancillary data. The 3.75-µm channel used in AVHRR and TRMM was shifted to 3.96 µm to avoid the variable water vapor absorption and reduce reflected solar radiation (Li et al. 2001).

Most MODIS fire detection algorithms are a form of contextual algorithm based on heritage algorithms developed for AVHRR. Kaufman et al. (1998a, b, c) first proposed the MODIS fire detection algorithm, which selects potential fire pixels using fixed thresholds and confirm fire pixels by applying contextual tests. This algorithm was later refined (Justice et al. 2002a) by adjusting certain threshold values for selecting potential fires and contextual tests. The standard MODIS collection 3 fire products are based on this algorithm. In order to solve two
significant problems that limit the overall quality of collection 3 fire products, this algorithm was revised to eliminate (1) persistent false detections which occurred in some deserts and sparsely vegetated land surfaces, and (2) frequent omission errors caused by relatively small fires (Giglio et al. 2003). The major revisions include adjusting threshold values for selecting potential fire pixels and contextual tests, and additional contextual tests to reject false alarms caused by sun glint, desert boundary and coastal boundary. Based on the revised algorithm, the MODIS collection 3 fire products were upgraded to collection 4 fire products, which offer considerable improvement over previous versions. The standard MODIS fire products, distributed by the Earth Resources Observation Systems (EROS) Data Center (EDC) Distributed Active Archive Center (DAAC), include level 2 fire products, daytime and nighttime level 2G fire products, and daily and 8-day composited level 3 fire products (Justice et al. 2002a).

2.4 CHALLENGES IN DETECTION OF FOREST DISTURBANCES

2.4.1 Challenges in Detection of Post-Hurricane Forest Damage

2.4.1.1 Current Research Stage

Studies on remote sensing of hurricane/typhoon-induced forest damage are still in the preliminary stage. Few studies presented operational, stably performed, well tested and validated algorithm for rapidly assessing hurricane-impacted regions, as well as forest damage severity of defoliation, branch loss, stem loss and structure
changes. The majority of studies on passive optical remote sensing use the change or standardized change of vegetation indices as damage indicators without evaluating their quantitative relationship with forest damage, and without comparative analysis on the performance of these indicators. Studies for monitoring structural changes of forest canopy following a hurricane landfall are scant.

All reviewed optical sensors have Visible, NIR and SWIR channels, which can be used to derive NDVI, NDII, TCW, nonphotosynthetic vegetation, and detect damage severity. NDVI derived from MODIS, NDII and TCW derived from AVHRR, MODIS and SPOT have not been used for detecting hurricane-induced forest damage. The nonphotosynthetic vegetation data directly derived from AVHRR, MODIS, ASTER and SPOT have not been tested so far. Lidar has only been used for detecting the change of canopy height in local scale. SAR has been applied toward differentiating damaged versus non-damaged areas, but not for identifying damage severity.

Vegetation indices that have been adopted include NDVI, NDII, TCW and LAI. Most studies adopted vegetation indices as an indicator of post-storm forest damage. Although studies have shown that NIR_SWIR based vegetation indices are a superior indicator of vegetation modifications (Ceccato et al. 2001, Bowyer and Danson 2004, Jin and Sader 2005, Sader et al. 2003, Wilson and Sader 2002), little research has been conducted evaluating the accuracy of commonly used vegetation indices to detect hurricane-induced forest damage.

2.4.1.2 Error Sources
Eliminating or reducing errors caused by vegetation phenology is one of the primary challenges to developing a practical method for monitoring large-scale abrupt vegetation modification, because seasonal vegetation variations contribute to differences in canopy reflectance between two observations during growing seasons. Furthermore, variations caused by atmospheric effects, BRDF effect, soil reflectance, and radiometric noise interfere with vegetation modification detection.

2.4.2 Challenges of Fire Detection in the Southeastern U.S.

A small number of authors (Dozier 1981, Langaas 1993, Giglio et al. 1999, Lasaponara et al. 2003) have studied low intensity fire detection based on various methods such as theoretical analysis, fixed thresholds, or contextual algorithms using NOAA AVHRR multi-channel data. In the MODIS version 3 active fire detection algorithm (Kaufman et al. 1998a), sensitivity to relatively small fires was sacrificed in order to reduce persistent false alarms over certain surface types during daylight hours (Justice et al. 2002b). The MODIS enhanced contextual fire detection algorithm (Giglio et al. 2003) increased sensitivity to low intensity fires. This algorithm achieved significantly lower false alarm rates by using several solar reflectance channels to reject false alarms, and by adjusting the potential fire threshold and contextual thresholds in the earlier versions of the MODIS contextual algorithm.

The MODIS contextual fire detection algorithm is a widely recognized and frequently utilized algorithm for operational global fire monitoring. Because it is
designed for a global scale, however, it faces several challenges for detecting fires in the southeastern United States. Notable limitations include: fixed thresholds for identifying potential fire pixels; the assumption of a similar non-fire background nearby fire pixels; the effects of reflected solar radiation; the impact of undetected fires in the valid background pixels; problems caused by solar zenith angle and scan geometry; and the influence of atmospheric effects. When applied to regional active fire detection in the southeast, low intensity fires are frequently missed due to special regional wildland fire patterns and environmental factors (Martin and Boyce 1993, Stanturf et al. 2002). Additionally, low intensity fires exhibit different characteristics depending on biome, amount of fuel burning, time of day, fire-line, seasons, geographic region, and view geometry (Giglio et al. 1999). For above reasons, contextual algorithms were adjusted by changing the thresholds for identifying potential fire pixels, tuning the type of background pixels and the size of the background window. This suggests contextual algorithms are not self-adaptive enough for regional fire detection, and therefore regionally specified thresholds are necessary in order to develop effective regional fire detection algorithms (Lasaponara et al. 2003).

2.4.2.1 Wildland Fire Patterns in the Southeastern United States

Three broad physiographic regions were recognized for conducting wildland fire studies (Martin and Boyce 1993, Stanturf 2002): (1) the Coastal Plain (Atlantic and Gulf coasts, including peninsular Florida and the Lower Mississippi Alluvial
Valley); (2) the Piedmont/Southern Appalachians (including Appalachian plateaus and mountain ranges); (3) and the Interior Highlands (including the Interior Low Plateaus of Kentucky and Tennessee and the Ozark-Ouachita Highlands). Frequent light ground fires are the most common fire pattern in Coastal Plain ecosystems. Prescribed burning is most common in Coastal Plain pine forests and in the Piedmont region. It is used to a lesser extent in mountain forests. In the Piedmont region, shortleaf pines are more widespread than in the Coastal Plain. Fire patterns vary based on site and stand conditions, particularly the amount of pine versus hardwood in a stand. Shortleaf pine forests have an understory fire regime (Wade et al. 2000). In Mountains and Interior Highlands Regions, fire patterns depend more on the type of vegetation. Areas dominated by oak-hickory forests tend to have low intensity surface fire patterns, also called understory fires. Areas dominated by table mountain pines tend to have a mixed fire regime. Fire behavior is also less predictable because of highly variable topography.

Thus, understory fires tend to be the dominant fire pattern in the southeastern United States. Understory fires are usually smaller in size, cooler in temperature, and less intense than crown fires which are dominant in the western United States. As such, fires in the southeastern states are usually more difficult to detect.
2.4.2.2 Problems in Setting Fixed Thresholds

The MODIS contextual algorithm is composed of three basic steps: setting preliminary thresholds to identify potential fire pixels; conducting contextual tests to confirm fires among potential fire pixels (Martin et al. 1999), and; using contextual thresholds to reject false alarms. In the first step, selecting fixed preliminary thresholds is subtle. Too high a setting can risk omitting fire pixels (Li et al. 2001), whereas too low a setting can introduce numerous non-fire pixels to the matrix of potential fire pixels and increase the difficulty in rejecting false alarms in the third step. The MODIS enhanced contextual algorithm uses fixed thresholds to identify potential fire pixels. As a global application, the preliminary thresholds cannot be set low enough to detect most regional low intensity fires without introducing numerous false alarms. Therefore, it requires modification for regional fire monitoring and management.

The effectiveness of preliminary thresholds is also directly affected by scan geometry. The increase of scan angles diminishes fire signals for reasons: (1) the resolution of observation decreases with the increase of scan angle; (2) atmospheric effects intensify when the distance to the nadir increase.

Because fire severity varies with fuel type, fuel loading and weather conditions, potential fire thresholds should be contingent on these variables for regional applications (Li et al. 2001). Boles & Verbyla (2000) and Chuvieco & Martin (1994) demonstrated that fire detection accuracy was improved by using a fuel
model. Csiszar et al. (2003) also suggests that adjusting thresholds to local conditions is necessary to reach a reasonable compromise between omission and commission errors for regional fire detection. These studies indicate that potential fire thresholds should be based on regional variations or they should be set as a function of a vegetation index for regional fire detection (Chuvieco and Martin 1994, Martin et al. 1999).

2.4.2.3 Ambiguity in the Definition of Background Pixels

During the second step of the MODIS algorithm, it is critical to determine valid background pixels for each potential fire pixel, since the background pixels determine the background parameters for deriving the remaining dynamic thresholds. The separation of fire pixels and non-fire background pixels becomes ambiguous with increasing background temperature caused by the presence of undetected background fires, seasonal change and certain surface types. This can directly affect the performance of contextual algorithms. In addressing this problem, Giglio et al. (1999) excluded the eight pixels surrounding a potential fire pixel from the background window in order to screen out the fire contaminated pixels. This algorithm showed a higher sensitivity to low intensity fires compared with the algorithms of Justice et al. (1996b) and Flasse and Ceccato (1996).

2.4.2.4 Impacts of Reflection in 4-μm Channels

Reflected solar radiation around 4-μm channels causes high brightness temperatures of bare soil, exposed rock, senescent or sparse vegetation, desert,
tropical dry savanna and temperate grassland. It is also the cause of sun glint effect over small bodies of water surface, coastline, wet soil and cirrus clouds and misleadingly lower brightness temperature values on uneven forested areas (Giglio et al. 1999, Giglio et al. 2003, Lasaponara et al. 2003, Csiszar et al. 2003). One effect of this phenomenon is that reflected solar radiation reduces the contrast between fire pixels and non-fire background pixels. Although the commission errors caused by reflected solar radiance were reduced after the 3.75-μm channel (AVHRR) was shifted to the 3.96-μm channel in MODIS, the reflected solar radiation can only be reduced to the half of reflected sunlight at the 3.75 μm channel (Kaufman et al. 1998a).
CHAPTER 3

ASSESSMENT OF POST-HURRICANE FOREST DISTURBANCES

Summary: An algorithm was developed for rapidly assessing post-hurricane forest damage in regional scale, without relying on ground inventory or sampling. The performance of five commonly used vegetation indices (NDII, NDVI, EVI, LAI and Fpar) was investigated for assessing post-hurricane forest damage. The optimal damage indicator, NDII, was identified from among these vegetation indices. This algorithm was validated and applied toward assessing impacted forest regions and forest damage caused by Hurricane Katrina. A linear relationship between the optimal damage indicator and the ground observation was found with a coefficient of determination of 0.79.

The first section of this chapter introduces the physical principles of remote sensing on assessing the post-hurricane forest damage, as well as the commonly used vegetation indices. Hurricane Katrina and its impact on the De Soto National Forest are introduced in Section 3.2. Ground data and remote sensing data used in this research are also described in this section. Section 3.3 discusses the methodology of this research, including change detection methods and the approach on selecting a proper damage indicator. The results and discussions on identifying
the proper indicator are presented in Section 3.4. The new rapid assessment algorithm and post-Katrina damage severity analysis are discussed in Section 3.5. The validation method and results are presented in Section 3.6, followed by the conclusions in Section 3.7.

3.1 INTRODUCTION

Research on the global carbon cycle, an important aspect for climate change study, requires a knowledge of changes in the carbon sink caused by hurricane disturbances. This is because 26% to 33% of global carbon sink is sequestered in forest trees (Pacala et al. 2001), and a single hurricane has the potential to convert the equivalent of 10% of total annual U.S. forest carbon deposits from living to dead biomass (assuming on average value of 200 Tg C of forest across all US forests) (McNulty 2002). Hurricane Katrina, a category 3 hurricane when it landed on August 29, 2005, caused a total biomass loss of 105 Tg C (Chambers et al. 2007). Hurricanes are one of major natural disturbances to forest ecosystems in the southern United States. Statistically, severe hurricanes (Saffir-Simpson scale 3 and above) make landfall along the western Atlantic and Gulf coastlines 2 out of 3 years (Smith 1994). This phenomenon has been more pronounced in recent years, as ten hurricanes made landfall along the southeastern coast from 2004 to 2008, including Jeanne, Ivan, Frances and Charley in 2004, followed by Dennis, Katrina, Rita and Wilma in 2005, and Gustav and Ike in 2008.
The most immediate impact of hurricanes on forests is that a massive amount of living forest biomass turns into dead fuel. Because 90% of total downed wood is never salvaged (McNulty 2002), it can become dead fuel for wildland fires in later years. For example, in the wake of Hurricane Hugo forest debris and litter was piled up to 3-meter deep in many areas (Miranda 1996). Previous studies have indicated that occurrence and intensity of wildland fires substantially increase in hurricane-impacted areas in the years after landfall (Gardner et al. 1991, Hook et al. 1991, Wade et al. 1993, Myers and van Lear 1998, Liu et al. 2003). This can be attributed to such post-hurricane effects as large amounts of accumulating dead fuels accompanied by a decrease in dead fuel moisture in a microclimate of increased isolation and higher wind speeds (Gill et al. 1990, Loope et al. 1994). Therefore, fuel reduction in hurricane-impacted regions is necessary to reduce the risk and severity of future forest fires.

Fuel loading is one of the key input factors in fire danger rating systems and fire behavior models, which are decision support tools for fire management. Even state-of-the-art fire danger rating systems and fire spread models cannot quantitatively assess increments of fire risk and the change of fire behavior in the impacted region. One primary reason is the lack of an efficient way to measure abrupt fuel changes. As a result, the fuel components in the National Fire Danger Rating System (NFDRS) (Burgan et al. 1998, Schlobohm and Brain 2002) introduce uncertainties to predict changes of post-hurricane fire risk and fire behaviors due to the high spatial and temporal variability of fuels. Post-hazard relief activities (e.g. 
logging, fuel reduction) also require accurate data regarding the location and severity of forest damage.

Few algorithms that are primarily based on remote sensing have been developed to assess damage and severity to hurricane-impacted regions. The goals of this chapter are (1) to identify a proper indicator for assessing hurricane impacted regions and forest damage severity from among various commonly used vegetation indices, (2) to propose an algorithm for rapidly assessing forest damage, and (3) to validate said algorithm.

3.1.1 Physical Principles of Detecting Forest Damage

Leaf structure, associated pigment assemblages and leaf water content vary during different stages of the forest phenology and forest disturbances. The ability to remotely identify vegetation change is a result of wavelength-specific foliar reflectance, pigment absorptions, and foliar moisture absorptions (Lunetta et al. 2006). The spectral distribution of vegetation reflectance is significantly different with other objects, e.g. bare soil and water bodies, which are common backgrounds or adjacent objects of vegetation cover. Reflectance of green vegetation within NIR wavelengths is insensitive to leaf chlorophyll and water content, while in red bands (0.45 μm - 0.69 μm) reflectance is sensitive to leaf chlorophyll content, and in SWIR bands (1.0 μm - 2.5 μm) reflectance is sensitive to leaf water content. The absorption in red bands is the composite results of chlorophyll a, chlorophyll b and carotenoids absorption. Based on the above spectral properties of green vegetation,
various vegetation indices are designed to detect vegetation cover. The most commonly used vegetation indices are NIR-Red band based vegetation indices, such as NDVI, NIR-SWIR band based vegetation indices, e.g. NDII.

### 3.1.2 NDVI, EVI, NDII, LAI and Fpar

The NIR-Red spectra based vegetation index is the NDVI (Eq. 3.1) or its variations, e.g. EVI (Eq. 3.2):

\[
\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad (3.1)
\]

\[
\text{EVI} = G \times \frac{\text{NIR} - \text{Red}}{\text{NIR} + C_1 \times \text{Red} - C_2 \times \text{Blue} + L} \quad (3.2)
\]

where Red and NIR are the reflectance at 0.65 µm and 0.86 µm for MODIS, respectively, Blue is the reflectance at 0.47 µm for MODIS, and \( C_1 = 1, C_2 = 7.5, L = 1, G = 2.5 \).

The NDVI separates green vegetation from other surfaces because the chlorophyll in green vegetation absorbs red light for photosynthesis, and reflects the near-infrared (NIR) wavelengths due to scattering caused by the spongy mesophyll leaf structure (Tucker 1979). Thus, high NDVI values indicate high leafy biomass, canopy closure, leaf area (Jasinski 1990, Sellers 1985) and the amount of photosynthetically active green biomass. NDVI cannot differentiate very dense canopy and dense canopy cover due to the limited penetration capability of the reflected red spectrum, referred as the saturation problem; therefore, it is not sensitive to the change in forest structure for dense canopies.
The Enhanced Vegetation Index (EVI) is based on chlorophyll absorption with reduction of the effect of atmosphere and soil reflectance (Huete et al. 1999). It is more sensitive to the green vegetation in high biomass regions. In Eq. 3.2, the input reflectance of Red and NIR channels may be atmospherically-corrected or partially atmospherically-corrected for Rayleigh scattering and ozone absorption. The aerosol resistance term uses the blue band to correct for aerosol influences in the red band. By using the canopy background adjustment factor L, the EVI is insensitive to most canopy backgrounds except for snow.

Estimation of vegetation water content typically utilizes signals from liquid water absorption channels in the shortwave infrared (SWIR) spectra, as well as signals from liquid water insensitive channels in the near infrared (NIR) spectra. Several indices based on SWIR and NIR reflectance have been developed such as NDII (Eq. 3.3), Normalized Difference Infrared Index (1.65μm band and red band) (Hardisky et al. 1983):

\[
\text{NDII} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}}
\]  

(3.3)

where SWIR is the reflectance at 1.24 μm, 1.65 μm or 2.13 μm for MODIS. Studies have shown that SWIR-NIR based indices are related to the weight of water per unit area or the vegetation water content (Ceccato et al. 2001, Bowyer and Danson 2004). In this research, the 2.13-μm channel was adopted, due to a large volume of missing observations caused by serious stripping issues of MODIS/Aqua 1.65-μm channel (Wang et al. 2006).
Leaf area index (LAI) is another commonly used vegetation index. It is defined as the one-sided leaf area per unit ground surface area for broad leaf trees, or half the total needle area per unit ground surface area for coniferous trees (Pettorelli et al. 2005). It is a fundamental biophysical parameter that can connect remotely sensed reflectance of green vegetation with the leaf biomass presented in the canopy. The Fraction of Photosynthetically Active Radiation (Fpar) measures the proportion of available radiation in the photosynthetically active wavelengths (0.40 to 0.70 µm) that a canopy absorbs. LAI and Fpar can be remotely detected using MODIS and MISR (Knyazikhin et al. 1998 a, b). Fpar-Lo approach (Potter et al. 2005) was recently developed to detect ecosystem disturbances based on time series analysis, and has shown potential to detect forest damage.

3.2 DATA

3.2.1 Hurricane Katrina and Forest Damage

Hurricane Katrina made landfall as a category 3 hurricane with sustained wind speeds of 180-200 km h⁻¹ on August 29 2005 on the coast of Mississippi and southeast Louisiana. The strong wind caused widespread forest damage in Louisiana, Mississippi and Alabama. The USDA Forest Inventory and Analysis (FIA) reported approximately 8,300 km² National Forests were impacted in Mississippi. The potential timber losses amounted to roughly 4.2 billion cubic feet of timber within the 20234 km² of damaged forest land in Mississippi, Alabama and Louisiana
(FIA 2005). Chambers et al. (2007) estimated Hurricane Katrina caused mortality and severe structural damage for 320 million large trees with a total biomass loss of 105 Tg C.

3.2.2 De Soto National Forest

The De Soto National Forest (De Soto NF) is located in the southern Mississippi, and lies within the East Gulf Coastal Plain (Meeker et al. 2006). The De Soto NF encompasses 1,532 km² (378,538 acres) of upland forest and bottomland forest, and is managed by the USDA Forest Service. The tropical climate in the De Soto NF is characterized by mild, short winters and hot, humid summers (Kupfer et al. 2008); its high precipitation is evenly distributed throughout the year, and the topography consists largely of gently sloping uplands and floodplains.

The De Soto NF includes the Chickasawhay and De Soto Districts (Fig. 3.1). Both of these districts are dominated by longleaf pine forest, representing 44 percent of the forest cover (Windham 2005). Slash pine and hardwood covers 23% and 8%, respectively. A combination of loblolly, shortleaf and mixed yellow pine represents 14 percent. Pine and hardwood mixtures cover 10%. Bottomlands are dominated by hardwoods and sweetgum. Uplands are dominated by longleaf pine, loblolly pine, shortleaf pine and slash pine.
The De Soto NF suffered 2270 km² of forest damage after Hurricane Katrina. The eye of Hurricane Katrina passed within approximately 8 km of the western boundary of the De Soto National Forest (Bryant and Boykin 2007). The District experienced storm winds with maximum sustained wind speeds averaging 135-160 km h⁻¹ for several hours and peak gusts of 145-225 km h⁻¹ (Kupfer et al. 2008). The USDA Forest Service FIA conducted a forest health evaluation of post-hurricane forest damage in the De Soto National Forest during October 3-7, 2005. A total of 54 plots (0.1 acre per plot) within 18 separate stands were examined, including variables such as average DBH, average height, average age and the percentage of
damaged tree and basal area per acre (Meeker et al. 2006). These stands provided a representative range of hurricane damage from heavy to light levels. Hurricane damages were recorded as snapped trunk, windthrown, horizontally root-sprung (trunk >45° from vertical with major root exposure), vertically root-sprung (trunk at 25° – 45° from vertical with evident root exposure), slightly leaning (trunk < 20° from vertical), broken top, bent >30° from vertical, bent < 30° from vertical, severe branch breakage, moderate branch breakage, light branch breakage, twisted trunk, minor wounding and apparently undamaged. The forest damage was grouped into four damage categories based on the collected damage information, including severe, moderate, light and no damage. The percentage of damaged trees and basal areas in these four categories was calculated for each plot, and was used as ground truth data in this study. The location of these 18 stands (yellow dots) is marked in Fig. 3.2, overlaid with the MODIS IGBP 1 km land cover type map (2004).

The land pixels covered by evergreen needle leaf forest, evergreen broad leaf forest, deciduous broad leaf forest, mixed forests and woody savannas are studied in this research. Out of 54 plots, 20 plots are identified as evergreen needle leaf forest; 22 plots are covered by evergreen broad leaf forest; 1 plot is deciduous broad leaf forest; 9 plots are dominated by mixed forests; and 2 plots are woody savannas. In the ground inventory, the forest types for these plots are longleaf and shortleaf pines.
3.2.3 MODIS Products

The MODIS NBAR product (MOD43B4) contains visible and SWIR surface reflectance with 1 km resolution at the mean solar zenith angle of each 16 day period and adjusted to nadir views (Schaaf et al. 2002). This product provides the surface spectral reflectance as it would have been measured at ground level without atmospheric scattering or absorption. The correction scheme used for the NBAR product compensated for the effects of atmospheric gases, aerosols, and thin cirrus clouds. Since the BRDF and atmospheric effects have been removed from the MODIS NBAR product, the MODIS NBAR product is more stable and consistent than other
reflectance products. Therefore, it is an optimal choice for applications monitoring vegetation change on land surface at broad spatial scale (Coppin et al. 2004). In this study, the MODIS NBAR product is used to derive NDVI, EVI and NDII. LAI and Fpar measurements in the MODIS LAI and Fpar product (MOD/MYD15A2) are adopted to estimate the change of LAI and Fpar before and after the hurricane. The IGBP land cover in the MODIS land cover product (MOD12Q1) is applied to identify forest areas. MODIS products were obtained from the LP-DAAC, the EOS Data Gateway (EDG).

3.3 METHOD

A main impediment to developing practical methods for large-scale detection of abrupt vegetation modification is to eliminate or significantly reduce errors induced by vegetation phenology, because annual and seasonal vegetation variations contribute to the difference of canopy reflectance between two time scales of observations during growing seasons. Furthermore, variations caused by atmospheric effects, BRDF effect, soil reflectance and radiometric noise constitute noise for detecting vegetation modifications. By using the MODIS NBAR product, most noise caused by atmospheric effects, and the BRDF effect can be eliminated. Seasonal noise induced by vegetation phenology can be screened out by the discrete Fourier filtering method. To meet the Discrete Fourier Transform (DFT) precondition, i.e. that time series must be on a regular equidistantly spaced grid,
missing data were estimated using the CLEAN algorithm (Roberts et al. 1987, Baisch and Bokelmann 1999).

Vegetation indices that have been used for the detection of hurricane-induced forest damage include NDVI, NDII, TCW and LAI. Few studies have systematically compared the accuracy of these vegetation indices for detecting hurricane-induced forest damage. Therefore, the performance of NDVI, EVI, NDII, LAI and Fpar was analyzed in this research. An optimal indicator of forest damage was then identified. The TCW was not included in the comparison analysis because NDII and TCW are highly correlated ($R^2 > 0.98$) (Jin and Sader 2005). Based on the optimal indicator, a new algorithm was constructed to rapidly assess post-hurricane forest disturbances.

3.3.1 Univariate Image Differencing

Various approaches for change detection can be classified into two categories, i.e. time series analysis (temporal trajectory analysis) of variables that reflect vegetation properties, and bi-temporal change detection, which assumes overall phenological conditions are comparable on a two-point time scale or on a continuous timescale. Time series analysis uses continues observations of scenes at the region of change events. Bi-temporal change detection uses two-point timescale, i.e. change detection among times before the hurricane and after the hurricane. These two images usually are observed right before and immediately after the hurricane, or near anniversary dates (one year before and immediately after the
hurricane). Bi-temporal change detection is adopted by all the studies on hurricane impact based on vegetation indices. Univariate image differencing is a kind of bi-temporal change detection method, and is the most widely applied change detection algorithm for identifying vegetation modification. It involves subtracting an original or transformed (e.g. vegetation indices, albedo, etc.) imagery taken before a change event from the image taken after the change event. Two images have to be precisely registered (Banner and Lynham 1981, Nelson 1983, Hame 1986, Yasuoka 1988). With accurately georegistered data, this would result in a dataset in which positive and negative values represent areas of change and zero values represent no change. Lyon et al. (1998) monitored deforestation and loss of vegetation using NDVI differencing. They reported that NDVI differencing is the better change detection technique for vegetation modification. Nelson (1983) studied forest canopy changes due to gypsy moth defoliation in Pennsylvania. They found that vegetation index differencing is more accurate than any other single band difference or band ratioing.

 Appropriately selecting imagery acquisition dates is crucial for univariate image differencing. Anniversary dates of change events or anniversary windows are often used because they minimize reflectance noise caused by seasonal vegetation variation and sun angle differences. Hame (1988) concluded summer and winter are the best seasons because of their phenological stability. All studies on hurricane-induced forest damage choose anniversary dates/windows in summer. However, even at anniversary dates/windows in summer, inter-annual phenological disparities due to local precipitation and temperature variations are still major
sources of error. Univariate image differencing does not require large amounts of
time series data, therefore it is a feasible method for prompt and high spatial
resolution regional analysis of vegetation change.

Time series analysis has been proven appropriate for regional studies of
largely climate-driven land surface attribute changes (Lambin and Ehrlich 1997,
Kawabata et al. 2001) and phenological modifications (Myneni et al. 1997). One of
the advantages of time series analysis is that the influence of phenology on change
detection performance is resolved, because data are collected throughout the
growing season. Therefore, changes linked to seasonality can be separated from
other changes. The disadvantage is that at present only coarse moderate spatial-
resolution sensors (e.g. MODIS, AVHRR) provide the high temporal frequency of
observations necessary to establish time profiles. The limitation of spatial resolution
restricts the change categories that can be detected. Time series analysis requires
large volumes of time series data for all spatial points, which is computationally
expensive. The continuity of time series data is also an issue due to a significant
percentage of cloud coverage, especially in the southeastern United States.

In this study, time series analysis and univariate image differencing are both
adopted to separate vegetation phenological signals and noise induced by
observation geometry with change signals caused by hurricanes. The methods of
time series analysis involved in this research are: (1) CLEAN algorithm (Roberts et
al. 1987, Baisch and Bokelmann 1999), a nonlinear deconvolution approach based
on Fourier transform theory to fill in missing or low quality observations in the time
series of the optimal change indicator, and (2) Fourier transform to separate hurricane-caused change signal with change signal caused by annual and seasonal variations of vegetation.

3.3.2 Selection of a Proper Indicator

Various vegetation indices were designed to detect vegetation status based on their spectral properties. The most frequently used vegetation indices and variables are the NIR-Red and NIR-SWIR channel based vegetation indices, LAI and Fpar. First, I compared maps of relative reduction of vegetation indices (∆VIs) before and after hurricane landfall with the damage severity assessed by the USDA Forest Service, FIA (Clark et al. 2006). ∆VI is defined as the ratio of the difference in VI before and after hurricane landfall and the VI before hurricane landfall (Eq. 3.4):

$$\Delta VI = \frac{VI_{aug13} - VI_{sept14}}{VI_{aug13}}$$  \hspace{1cm} (3.4)

In this study, the MODIS NBAR product observed on August 13, 2005 and September 14, 2005 are chosen as the observations before and after Hurricane Katrina, respectively. Henceforth, these observations are referred as the observations before and after the hurricane. The ∆VIs derived from this period are referred to as ∆VIs2005 (including ∆NDVI2005, ∆EVI2005 and ∆NDII2005).

Thereafter, I analyzed the statistical distributions of ∆VIs2005 with the ∆VIs derived from the observations on August 13 and September 14, 2003 (∆VIs2003, including ∆NDVI2003, ∆EVI2003 and ∆NDII2003) and the same period in 2004 (∆VIs2004,
including $\Delta\text{NDVI}_{2004}$, $\Delta\text{EVI}_{2004}$ and $\Delta\text{NDII}_{2004}$) and 2006 ($\Delta\text{VIs}_{2006}$, including $\Delta\text{NDVI}_{2006}$, $\Delta\text{EVI}_{2006}$ and $\Delta\text{NDII}_{2006}$) for the forest area within the major impacted region (severely and moderately damaged region, assessed by Clark et al. (2006)). It was assumed that $\Delta\text{VIs}_{2005}$ shows the hurricane impact on moderately and severely damaged forest, while $\Delta\text{VIs}_{2003}$, $\Delta\text{VIs}_{2004}$, and $\Delta\text{VIs}_{2006}$ represent the status of $\Delta\text{VIs}$ without major natural disturbances, since no hurricane or other large-scale ecosystem disturbance occurred in this region during these three years. The mean of $\Delta\text{VIs}$ ($\overline{\Delta\text{VIs}}$), shift amplitude (the difference of $\overline{\Delta\text{VIs}}_{2005}$ and $\overline{\Delta\text{VIs}}_{2003}$), statistical dispersion (Interquartile of Range (IQR) of $\Delta\text{VIs}_{2005}$), and percentage of detected damaged tree pixels are calculated to present the sensitivity of a $\Delta\text{VI}$ as a post-hurricane damage indicator. The distribution of $\Delta\text{VIs}$ in 2003, 2004 and 2006, without major large-scale natural disturbances, will have near normal distribution, i.e. $\overline{\Delta\text{VIs}}$ equal to or approximately zero. Otherwise, a large discrepancy will be observed. Shift amplitude measures the sensitivity of an indicator to forest damages. The shift amplitude increases if an indicator is more sensitive to forest damages. The statistical dispersion is indicative of an indicator’s capability to distinguish forest damage severity. An indicator with large dispersion can differentiate damage severity levels better than other indicators. The percentage of detected damaged tree pixels also represents an indicator’s overall capability to detect forest damages.
3.4 POST-HURRICANE DAMAGE INDICATOR - ∆NDII

3.4.1 Direct Comparison

To visually compare the five damage indicators, the ∆NDII_{2005}, ∆NDVI_{2005}, ∆EVI_{2005}, ∆LAI_{2005} and ∆Fpar_{2005} are calculated and presented in Fig. 3.3 (b), (c), (d), (e), (f), respectively. The damage severity map reported by the USDA Forest Service (Clark et al. 2006) is presented in Fig. 3.3 (a), in which the area within the black box is defined as the major impacted region. The major impacted region is later used to derive the statistical variables presented in Fig. 3.4 and Table 3.1. The impacted region, used for deriving damage thresholds, is the area covered by the red box in Fig. 3.3 (a). On Panel (b) - (f), the pink line represents the hurricane track, and the red belt on the left is centered along the Mississippi River, where croplands constitute the major land cover type. This research focuses on detecting forest damage instead of crop damage. To facilitate comparison, the same scale is adopted by the color bars on Panels (b) - (f), where green and blue represent increases in vegetation indices caused by the hurricane, and yellow, orange and red indicate forest damage caused by the hurricane.

The most distinct feature of abrupt canopy modification detectable by optical remote sensing is the loss of green leaves, which should be directly represented by LAI decrease, and indirectly represented by a reduction of total chlorophyll and water content in the forest canopy. However, Fig. 3.3 (e) and (f) show that ∆LAI and ∆Fpar, derived from MODIS NBAR products, cannot detect most of the impacted
Fig. 3.3 Relative reduction of NDII, NDVI, EVI, LAI and Fpar pre- (August 13, 2005) and post (September 14, 2005) Hurricane Katrina. (a) Damage severity categories mapped by FIA, USDA Forest Service (Clark et al. 2006); (b) ΔNDII; (c) ΔNDVI; (d) ΔEVI; (e) ΔLAI; and (f) ΔFpar.
areas as shown in Panel (a). One of the reasons is that the MODIS Fpar product significantly underestimates the amplitude of ground Fpar change (Huemmrich et al. 2005). The hurricane impacts identified by ∆NDII (Fig. 3.3b) are more consistent with the damage severity assessed by the USDA Forest Service, Forest Inventory and Analysis (Clark et al. 2006) (Fig. 3.3a) than ∆NDVI (Fig. 3.3c) and ∆EVI (Fig. 3.3d). The impacted area (in yellow, orange and red) detected by ∆NDVI is smaller than ∆NDII, while ∆EVI significantly underestimates the impacted area and does not differentiate the damage level as well as ∆NDII. Based on the above analysis, it is found that ∆NDVI, ∆NDII and ∆EVI can detect the impact of hurricanes, while ∆LAI and ∆Fpar derived from MODIS NBAR product are unable to identify the impact of hurricane. Therefore, the statistic properties of ∆NDVI, ∆NDII and ∆EVI were further analyzed.

3.4.2 Statistical Analysis

The histograms (Fig. 3.4) of damage indicators (∆VIs, including ∆NDVI, ∆EVI and ∆NDII) within the major impacted region (black box in Fig.3.3a) demonstrate ∆VIs distributions with or without the hurricane impact. ∆NDVI and ∆EVI are sensitive to the change of canopy chlorophyll content. ∆NDII measures variations in canopy water content. The distributions of these indices are based on valid ∆VIs (13628 pixels) within the range [-0.4, 0.4], which present more than 99% of valid ∆VIs, except for ∆NDII_{2005} (96.8%). The histograms use lines instead of conventional bar charts to present the distribution of ∆VIs to facilitate the analysis. The relative
decreases of vegetation indices during the examined periods are presented by $\Delta \text{VI}s > 0$. The solid lines with filled marks are the histograms of $\Delta \text{VI}s_{2005}$, which illustrate the distribution of $\Delta \text{VI}s$ after the hurricane. The dotted lines with hollow marks

Fig. 3.4 Histogram of $\Delta \text{VI}s$ within the major impacted region, during August 13 and September 14, 2003 (dotted line) and the same period in 2005 (solid line).
show the distributions of $\Delta VIs$ in 2003, which represents the distributions of $\Delta VIs$ in a normal situation without the impact of large scale natural disturbances. The histograms of $\Delta VIs$ in 2004 and 2006 are similar with the ones in 2003, so for the sake of visual clarity only the results from 2003 and 2005 are contrasted. The filled and hollow marks show the number of pixels within the corresponding intervals of $\Delta VIs$, as they would be presented in a conventional histogram with bars. The mean of $\Delta VIs_{2003}$ and $\Delta VIs_{2005}$ ($\mu_{2003}$ and $\mu_{2005}$, respectively), the shift amplitude between $\Delta VI_{2003}$ and $\Delta VI_{2005}$ ($\mu_{2005} - \mu_{2003}$), the 25% and 75% quantiles of $\Delta VIs_{2005}$, the interquartile range (IQR) of $\Delta VIs_{2005}$, and the damage threshold are marked on Fig. 3.4 (b), (c) and (d). Fig. 3.4 (a) includes the distributions of $\Delta VIs_{2003}$ and $\Delta VIs_{2005}$ to ease the comparison among $\Delta NDII$, $\Delta NDVI$ and $\Delta EVI$. To analyze the distributions of same $\Delta VI$ in 2003 and 2005 with the information of statistic properties, $\Delta NDII_{2003, 2005}$, $\Delta NDVI_{2003, 2005}$ and $\Delta EVI_{2003, 2005}$ are separately presented in Panels (b), (c) and (d).

The histograms of $\Delta VIs_{2003}$ (Fig. 3.4 a) are approximately symmetric and bell-shaped, which have the mean ($\overline{\Delta VIs_{2003}}$) equal to approximately zero, as shown in Table 3.1. This pattern of $\Delta VIs_{2003}$ distribution is as expected because no large scale natural disturbance was observed during August 13 and September 14, 2003. However, distributions of $\Delta VIs$ in 2005 are shifted to the right, when compared with corresponding distributions of $\Delta VIs$ from the same period in 2003. This reflects the effects of Hurricane Katrina, the only major large-scale disturbance observed in this region within the same period in 2005.
Table 3.1 Statistics of ∆VIs from 2003 and 2005

<table>
<thead>
<tr>
<th>Statistical Variables</th>
<th>∆NDII</th>
<th>∆NDVI</th>
<th>∆EVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta VIS_{2003} ) (( \mu_{2003} ))</td>
<td>-0.03</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>( \Delta VIS_{2005} ) (( \mu_{2005} ))</td>
<td>0.14</td>
<td>0.06</td>
<td>0.04</td>
</tr>
<tr>
<td>Shift amplitude</td>
<td>0.17</td>
<td>0.06</td>
<td>0.04</td>
</tr>
<tr>
<td>IQR of ( \Delta VIS_{2003} )</td>
<td>0.101</td>
<td>0.056</td>
<td>0.090</td>
</tr>
<tr>
<td>IQR of ( \Delta VIS_{2005} )</td>
<td>0.243</td>
<td>0.063</td>
<td>0.096</td>
</tr>
<tr>
<td>( \Delta VIS_{2003} ) within [-0.4, 0.4] (%)</td>
<td>99.3</td>
<td>99.9</td>
<td>99.3</td>
</tr>
<tr>
<td>( \Delta VIS_{2005} ) within [-0.4, 0.4] (%)</td>
<td>96.8</td>
<td>99.9</td>
<td>99.4</td>
</tr>
<tr>
<td>Damage threshold</td>
<td>0.04</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>Damaged pixels (%)</td>
<td>86.2</td>
<td>81.8</td>
<td>55.8</td>
</tr>
</tbody>
</table>

Shift amplitude is directly related to the sensitivity of these indicators to hurricane impacts. The shift amplitude of \( \Delta NDII \) (0.17) is greater than \( \Delta NDVI \) and \( \Delta EVI \) as shown in Panels (b), (c), (d) and Table 3.1. The large shift amplitude of \( \Delta NDII \) means the amount of pixels with NDII decrease after the hurricane increased significantly, as shown in Panel (b). The shift amplitude of \( \Delta NDVI \) (0.06) is slightly greater than the one of \( \Delta EVI \) (0.04), but still insignificant when compared to the shift amplitude of \( \Delta NDII \).

The statistical dispersion (IQR) of \( \Delta VIS_{2005} \) (Table 3.1), indicates the sensitivity of an indicator to damage severity levels. The large IQR of \( \Delta NDII_{2005} \) (0.24) implies that the number of large \( \Delta NDII \) values towards two tails is more than what
\( \Delta \text{NDVI} \) and \( \Delta \text{EVI} \) can detect, so \( \Delta \text{NDII} \) is more sensitive to damage severity than other vegetation indices. The IQR of \( \Delta \text{NDII}_{2003} \) (0.101) is similar to that of \( \Delta \text{EVI}_{2003} \) (0.090), however, the IQR of \( \Delta \text{NDII}_{2005} \) (0.243) is much wider than that of \( \Delta \text{EVI}_{2005} \) (0.096). The IQR increase of \( \Delta \text{NDII} \) between 2003 and 2005 is 0.142, while the IQR increase of \( \Delta \text{NDVI} \) and \( \Delta \text{EVI} \) is relatively insignificant (0.007 and 0.006, respectively). Considering more than 99% of valid \( \Delta \text{VIs} \) within the range \([-0.4, 0.4]\), except for \( \Delta \text{NDII}_{2005} \), the 3% of valid \( \Delta \text{NDII}_{2005} \) values are larger than 0.4. This further supports the finding that the hurricane impact not only shifts, but also stretches the \( \Delta \text{NDII} \) distribution curve towards the positive direction more than it affects the other \( \Delta \text{VIs} \) distributions.

To present an overall estimation of the detecting capability of these vegetation indices, the percentage of detected damaged tree pixels is derived based on damage thresholds, which are calculated for each \( \Delta \text{VI} \). The damage thresholds are defined as \( \overline{\Delta \text{VI}} + \delta \), where \( \overline{\Delta \text{VI}} \) and \( \delta \) are the respective mean and mean absolute deviation of \( \Delta \text{NDII}, \Delta \text{NDVI} \) or \( \Delta \text{EVI} \) for undisturbed pixels within the impacted region (red box in Fig. 3.3 a) in 2003, 2004 and 2006. The undisturbed pixels are defined such that their \( \Delta \text{VI} \) are within the range of \( \overline{\Delta \text{VI}}_{\text{all}} \pm \delta_{\text{all}} \), where \( \overline{\Delta \text{VI}}_{\text{all}} \) and \( \delta_{\text{all}} \) are the respective mean and mean absolute deviation of \( \Delta \text{NDII}, \Delta \text{NDVI} \) or \( \Delta \text{EVI} \) for all pixels in the same region in 2003, 2004 and 2006. Mean Absolute Deviation (MAD) is adopted as the measure of dispersion rather than standard deviation because MAD is more resistant to outliers (Huber 1981). The damaged pixels identified by \( \Delta \text{NDII} \) were
86.2% of total tree pixels within the major impacted region. This ratio is higher than what ∆NDVI and ∆EVI detect (81.8% and 55.8%, respectively). Although ∆NDII and ∆NDVI can detect close ratios of damaged forest pixels, ∆NDII has more significant shift amplitude and much wider range of IQR.

The above statistical analysis indicates that ∆NDII is a better indicator than ∆LAI, ∆Fpar, ∆EVI and ∆NDVI for assessing the hurricane-induced forest damage, in terms of total impacted regions and severity levels. This finding is corroborated with the visual inspection of ∆VIs maps of the hurricane impacted region (Fig. 3.3), further confirming the previous finding that ∆NDII is a better indicator for detecting vegetation modifications (Ceccato et al. 2001, Bowyer and Danson 2004, Jin and Sader 2005, Sader et al. 2003, Wilson and Sader 2002).

3.5 RAPID POST-HURRICANE ASSESSMENT ALGORITHM

3.5.1 Construction of Rapid Assessment Algorithm

The rapid post-hurricane forest damage assessment algorithm includes seven steps (Fig. 3.5). In Step 1, the MODIS NBAR product that includes at least 3 years of observations is inspected to reject invalid or poor-quality observations using accessory quality flags. Then, the reflectance at 0.86-μm and 2.13-μm channels is extracted and used to derive original NDII time series (Eq. 3.3). In Step 2, the quality of the original NDII time series is checked to eliminate anomalous high and low values with the next observations immediately returning to near the previous values.
The CLEAN algorithm is then adopted to estimate the missing data, including abnormal high or low values, missing observations, and low quality observations. Fig. 3.6 shows an example of estimated missing NDII observations within a NDII time series. The missing data are filled in with the estimated values (solid dots), derived from the CLEAN algorithm. In Step 3, the Fourier transform technique is used to de-couple seasonal signals and post-hurricane 'noise-clean' change signals (clean NDII time series), followed by Step 4, NDII image differencing (Eq. 3.4). Fig. 3.7 shows an example of complete total NDII time series (solid line), its seasonal component (dash-dotted line) and the post-hurricane 'noise-clean' change signal (dotted line). The damage indicator $\Delta \text{NDII}_{2005}$ is defined as the difference of pre- and

Fig. 3.5 Workflow of the rapid assessment algorithm
post-hurricane clean NDII divided by the complete pre-hurricane NDII at the same location. The damage indicator $\Delta$NDII$_{2005}$ is then rescaled to $[0, 1]$ to construct damage severity in Step 5. The upper and lower limits for rescale are decided by the statistical analysis of $\Delta$NDII. For example, an upper boundary of 0.6 is selected, which covers 99.7% of valid $\Delta$NDII$_{2005}$ in the case of Hurricane Katrina effects. The 0.6 is then assigned to $\Delta$NDII$_{2005}$ greater than 0.6. The lower boundary is the damage threshold, decided by the distribution of $\Delta$NDII$_{2003, 2004, 2006}$, as elaborated in Section 3.3. Damage severity is then stratified in Step 6, using statistical analysis to identify impacted areas by damage levels. In Step 7, damage areas are identified based on the spatial density and continuity of individual damage levels.
Fig. 3.6 Estimated missing NDII observations (solid dots) within an incomplete NDII time series.
Fig. 3.7 Decoupling NDII time series. Complete total NDII time series (black solid line), its seasonal component (orange dash-dotted line) and the ‘noise-clean’ disturbance component (green dotted line).
3.5.2 Assessment of Post-Katrina Forest Damage

The results of this rapid assessment algorithm are presented in Fig. 3.8 and Fig. 3.9. The forest damage severity map (Fig. 3.8) is the product of Step 5. It illustrates the distribution of forest damage in a scale of [0, 1]. The pixels colored in light grey present no damage, while other pixels colored in gradual blue, green, yellow and red are impacted in degrees from light to most severe damage. Although
this map provide detailed damage information at the pixel level, which represents a
nominal area of 1 km², forest managers may need more general information to
manage the post-hurricane hazard relief activities.

A forest damage map (Fig. 3.9) can serve such purpose. Fig. 3.9a is the
distribution of forest damage levels estimated by the USDA Forest Service (Clark et
al. 2006), in which four severity levels were identified. Fig. 3.9c is the distribution of
forest damage levels at the pixel level, derived from Step 6 of the rapid assessment
algorithm. In the case of post-hurricane Katrina assessment, three levels were
initially selected, including the light (Level 1), moderate (Level 2) and severe (Level
3) damage, as shown in Fig. 3.9c. Pixels without damage or with land cover type
other than forest are masked in grey. The pixels in the same damage level are
mapped separately as shown in Fig. 3.9d (light damage, orange), Fig. 3.9e (moderate
damage, red) and Fig. 3.9f (severe damage, dark red). Based on the density and
continuity of individual damage level map, Fig. 3.9b, the map of damage area
distribution is generated. The light damage level shown in Fig. 3.9d is separated in
to two levels, including light damage (orange belt in Fig. 3.9b) and scattered light
damage (grey area with orange dots in Fig. 3.9b). Therefore, the damage area map
has four severity levels, i.e. scattered light, light, moderate and severe. Compared
with Fig. 3.9a, the area combining severely and moderately damaged areas in Fig.
3.9b is analogous to the severely damaged area estimated by the USDA Forest
Service (Fig. 3.9a). The rapid assessment algorithm addressed in this paper is able to
Fig. 3.9 Forest damage assessment after Hurricane Katrina.
(a) Damage levels mapped by FIA, USDA Forest Service (Clark et al. 2006); (b) Damage areas; (c) Damage severity levels; (d) Distribution of damage level 1; (e) Distribution of damage level 2; and (f) Distribution of damage level 3.
distinguish a new category of severity level that represents the most severely
damaged area. The area with light damage in Fig. 3.9b is similar to the area with
moderate damage in Fig. 3.9a. The area in Fig. 3.9b with scattered light damage is
comparable to the area combining the light and scattered light damage in Fig. 3.9a.

3.6 VALIDATION

The assessment that was produced by the rapid assessment algorithm was
validated with the ground truth data collected by the USDA Forest Service, FIA. The
ground damage estimated by the ground inventory for each plot is presented as the
percentage of basal area that suffered no, light, moderate and severe damage. For
comparison with ∆NDII estimated by the rapid assessment algorithm, the ground
damage data are converted to the total damage severity (DS) for each plot using Eq.
3.5:

\[
DS_i = \alpha_i \cdot \beta_i \left( \gamma_1 \cdot L_i + \gamma_2 \cdot M_i + \gamma_3 \cdot S_i + \gamma_4 \cdot N_i \right)
\]  

(3.5)

where DS_i stands for the ground estimated total damage severity for the ith plot.
The tree size factor \( \alpha_i \) for the ith plot is

\[
\alpha_i = \frac{\text{tree DBH at ith plot}}{\text{mean tree DBH of all plots}}
\]  

(3.6)
in which, DBH stands for the stem Diameter at Breast Height (DBH). The \( \beta_i \) presents
the effect of plot density for the ith plot:

\[
\beta_i = \frac{\text{tree density at ith plot}}{\text{maximum tree density among all plots}}
\]  

(3.7)
The constant \( \gamma_1, \gamma_2, \gamma_3, \) and \( \gamma_4, \) are weight factors which measure the relative
contribution of the four damage categories to the total damage severity. \( L_i, M_i, S_i \) and
$N_i$ are the percentage of basal area that suffered no, light, moderate and severe damage for the $i$th plot, respectively.

![Image](image_url)

**Fig. 3.10** Relationship of $\Delta$NDII and total damage severity.
The dark grey dotted line is 1:1 line.

Using Eq. 3.5-3.7, the total damage severity for 54 plots is derived. The $\Delta$NDII at these plots is retrieved using the nearest neighbor method. Despite the coarse damage categories used in the ground inventory, the scatter plot (Fig. 3.10) still shows a linear relationship between $\Delta$NDII and the total damage severity. This indicates that $\Delta$NDII can quantitatively present the damage severity of the
hurricane-impacted forest region based on a strong linear relationship. The linear fitting line is \( y = a + b \cdot x \), where \( a = -0.01 \), \( b = 1.06 \), \( R^2 = 0.79 \), SD (standard deviation) = 0.03, \( p < 0.0001 \).

3.7 SUMMARY

A new approach has been developed for identifying forest regions impacted by hurricanes and forest damage severity based on \( \Delta \text{NDII} \) time series derived from MODIS NBAR products. Using the MODIS NBAR product eliminated most uncertainties caused by BRDF effects and atmospheric effects when detecting vegetation modification. Missing data, excluded because of missing observations, and low quality or outliers, were estimated using the CLEAN algorithm during the data processing stage. Seasonal vegetation variations, a major error source for vegetation modification detection, were mostly removed using the Fourier filtering technique. Statistical analysis and comparison with the USDA estimated damage regions revealed that, out of all the commonly used vegetation indices (NDVI, EVI, NDII, LAI and Fpar), \( \Delta \text{NDII} \) is the optimal indicator for detecting hurricane-induced forest damage and its damage severity. A linear relationship was found between \( \Delta \text{NDII} \) and total damage severity based on ground measurements. This finding proved that \( \Delta \text{NDII} \) is able to quantitatively detect hurricane-induced vegetation damage and its damage severity. Maps of the hurricane-impacted region and its damage severity after Hurricane Katrina in 2005 were estimated using the proposed rapid assessment algorithm based on the optimal indicator \( \Delta \text{NDII} \).
The major contributions of this study include (1) combined univariate image differencing and time series analysis to study forest damage caused by hurricanes in regional scale, (2) evaluated the performance of commonly used vegetation indices on detecting forest damage, (3) found that ∆NDII is the optimal indicator, (4) designed the first algorithm for detecting hurricane-induced forest change, and (5) revealed the linear relationship between ∆NDII and observed forest damage from ground investigations.
CHAPTER 4
SPECTRAL PROPERTIES OF LOW INTENSITY FIRES

Summary: The characteristics of wildland fires were also studied, being a related natural disturbance common to the forest ecosystem in the southeastern United States, as well as one of the major contributors to the global carbon cycle. This chapter describes the remote sensed characteristics low intensity fires and provides a preliminary definition of the phenomenon. A database was collected including 6596 remote-sensed fire pixels in 72 MODIS granules. The statistical distributions of the sensor-observed fire reflectance and brightness temperatures at relevant spectral channels were analyzed. This chapter discusses and suggests several areas which could improve regional detection of low intensity fires.

The introductory Section 4.1 is followed by Section 4.2, which briefly introduces the physical principles involved in remote sensing active fires, the MODIS enhanced contextual algorithm, as well as various challenges in detecting low intensity fires in the southeastern United States. Section 4.3 describes the study area and data sources, followed by Section 4.4, which describes the algorithm adopted for this study. Section 4.5 presents the results of a statistical analysis of the spectral characteristics of low intensity fires. Section 4.6 discusses several aspects
related to improving the MODIS enhanced contextual algorithm, and presents a definition of low intensity fires.

4.1 INTRODUCTION

Wildland fire statistics provided by U.S. Fish & Wildlife Service show that from 1995 to 2006 over 90 percent of wildland fires in the United States had burn areas of less than 1000 acres (405 hectares). Wildland fires in the southeastern United States typically have small burn sizes and are less intense due to special regional wildland fire patterns (see Chapter 2), environmental factors, and frequent prescribed fires (Wade et al. 2000, Martin and Boyce 1993). Understory fires make up the dominant fire pattern in the southeast (Stanturf et al. 2002), and have smaller size and lower temperature than crown fires which are dominant in the West. The brightness temperature of these less intensive understory fire pixels around 4-µm channels is relatively low when observed with satellite sensors, therefore, this type of less intensive wildland fire is more difficult to detect using remote sensing techniques.

Previous study on low intensity fire detection by Wang et al. (2009) found a substantial number of low intensity fires in the southeastern United States are omitted by the MODIS contextual algorithm. Their algorithm provided a useful tool for identifying low intensity fires omitted by the MODIS contextual algorithm. The present study adjusted the MODIS contextual algorithm based on their results. This
study collected 6596 sample fire pixels from 72 granules for analyzing the performance of the MODIS contextual algorithm for detecting low intensity fires.

4.2 MODIS ENHANCED CONTEXTUAL ALGORITHM

This chapter analyzes several reasons that the MODIS enhanced contextual algorithm omits low intensity fires, and addresses several aspects on improving the accuracy of low intensity fire detection in the southeastern United States. This section outlines the physical principles of active fire detection, as well as the MODIS enhanced contextual algorithm.

The theory of active fire detection using remote sensing techniques was first developed by Dozier (1981) and Matson et al. (1981, 1984, and 1987). Based on the Wien displacement law (i.e. the wavelength of the maximum intensity of blackbody radiation is inversely proportional to the temperature), the theory reveals the fact that a high-temperature blackbody elevates the mid-IR (between 3 and 5 µm) brightness temperature while having little or no impact on thermal channels (between 8 and 12 µm) (Kennedy et al. 1994, Justice et al. 1996).

The MODIS enhanced contextual algorithm (Giglio et al. 2003) is based on heritage algorithms developed for AVHRR. When compared with the previous contextual algorithm developed for MODIS active fire detection, this algorithm is revised to eliminate persistent false detections in certain land types and frequent omission errors caused by relatively small fires. The MODIS enhanced contextual algorithm is composed of four phases, including data preprocessing, identifying
potential fire pixels using preliminary thresholds, selecting tentative fire pixels among the potential fire pixels using contextual tests, and rejecting false alarms using contextual tests.

4.2.1 Data Preprocessing

The MODIS Level 1B product is the primary input data for the MODIS enhanced contextual algorithm. Reflectance and radiance from several channels used in this algorithm include reflectance at 0.65-µm (R₁), 0.86-µm (R₂) and 2.1-µm (R₇) channels, and radiance at 3.96-µm (T₂₁), 11.03-µm (T₃₁) and 12.0-µm (T₃₂) channels. The quality of the L1B data at these channels was checked using accessory quality flags. Then cloud pixels were screened out by adopting cloud masking tests:

\[(R₁ + R₂ > 0.9) \text{ or } (T₃₂ < 265 \ K) \text{ or } (R₁ + R₂ > 0.7 \text{ and } T₃₂ < 285 \ K)\]

If daytime pixels satisfy above tests, they were flagged as clouds. For nighttime observations, pixels were flagged as clouds if \(T₃₂ < 265 \ K\) was satisfied. This cloud screening technique was used in the algorithm for the International Geosphere Biosphere Program (IGBP) AVHRR-derived Global Fire Product (Stroppiana et al. 2000). These criteria were able to detect larger, cooler clouds but consistently missed small clouds and cloud edges. But it has been reported that fire pixels have not been mistakenly flagged as clouds. The land/sea mask contained in the MODIS geolocation product is used to screen out water pixels.
4.2.2 Identification of Potential Fire Pixels

Pixels that satisfied $T_{22} > 360$ K (320 K at night) were identified as tentative fire pixels. Pixels which fail to pass this criterion have to be tested by several preliminary thresholds and contextual thresholds. They were flagged as non-fire, tentative fire or unknown.

A daytime potential fire pixel has to satisfy 3 criteria: (1) $T_{21} > 310$ K, (2) $\Delta T > 10$ K, and (3) $R_2 < 0.3$, where $\Delta T = T_{21} - T_{31}$. A nighttime fire pixel has to satisfy 2 criteria: (1) $T_{21} > 305$ K, and (2) $\Delta T > 10$ K.

4.2.3 Identification of Tentative Fire Pixels

In this phase, a series of contextual tests are applied to potential fire pixels to further identify tentative fire pixels. Potential fire pixels which do not satisfy these contextual tests are identified as non-fire pixels. Potential fire pixels which are lack of necessary parameters to construct contextual tests are flagged as unknown, indicating that the algorithm is not able to render a decision. Only those potential fire pixels that satisfy the contextual tests are labeled as tentative fire pixels.

To construct the contextual tests for each potential fire pixel, several background parameters have to be derived using valid neighboring pixels of each potential fire pixel. Valid neighboring pixels provide an estimation of background radiance of the potential fire pixel in the absence of fire. It is defined as those pixels that (1) are in a background window centered on the potential fire pixel, (2) are valid observations, (3) are identified as land pixels, (4) are not covered by cloud,
and (5) are not background fire pixels. Table 4.1 lists all parameters that are derived using pixels within the background window (Giglio et al. 2003).

The contextual tests are:

\[
\Delta T > \overline{\Delta T} + 3.5 \delta_{\Delta T} \\
\Delta T > \overline{\Delta T} + 6 \text{ K} \tag{4.2} \\
T_{21} > \overline{T}_{21} + 3 \delta_{21} \tag{4.3} \\
T_{31} > \overline{T}_{31} + \delta_{31} - 4 \text{ K} \tag{4.4} \\
\delta'_{21} > 5 \text{ K} \tag{4.5}
\]

---

Table 4.1 Parameters for constructing contextual tests (Giglio et al. 2003)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(N_v)</td>
<td>The number of valid neighboring pixels</td>
</tr>
<tr>
<td>(N_f)</td>
<td>The number of background fire pixels</td>
</tr>
<tr>
<td>(N_w)</td>
<td>The number of pixels flagged as water</td>
</tr>
<tr>
<td>(\overline{T}_{21})</td>
<td>The mean of (T_{21}) for valid neighboring pixels</td>
</tr>
<tr>
<td>(\delta_{21})</td>
<td>The mean absolute deviation of (T_{21}) for valid neighboring pixels</td>
</tr>
<tr>
<td>(\overline{T}_{31})</td>
<td>The mean of (T_{31}) for valid neighboring pixels</td>
</tr>
<tr>
<td>(\delta_{31})</td>
<td>The mean absolute deviation of (T_{31}) for valid neighboring pixels</td>
</tr>
<tr>
<td>(\overline{\Delta T})</td>
<td>The mean of (\Delta T) for valid neighboring pixels</td>
</tr>
<tr>
<td>(\delta_{\Delta T})</td>
<td>The mean absolute deviation of (\Delta T) for valid neighboring pixels</td>
</tr>
<tr>
<td>(\overline{T}_{21}')</td>
<td>The mean of (T_{21}) for background fire pixels</td>
</tr>
<tr>
<td>(\delta'_{21})</td>
<td>The mean absolute deviation of (T_{21}) for background fire pixels</td>
</tr>
</tbody>
</table>
A daytime potential fire pixel is a tentative fire pixel if \{test (4.1) – (4.3) are true and [test (4.4) or test (4.5) is true]\}. Otherwise this potential fire pixel is flagged as non-fire. A nighttime potential fire pixel is classified as a tentative fire if \{test (4.1) – (4.3) are true\}.

4.2.4 Rejection of False Alarms

Tentative fire pixels identified in subsection (4.1.2.2) and (4.1.2.3) might include false alarms because of sun glint, desert boundary or coastal boundary. Therefore, three sets of contextual tests are used for rejecting false alarms within the tentative fire pixels.

The contextual tests for rejecting sun glint pixels include:

\[
\theta_g < 2^\circ \quad (4.6)
\]

where \( \cos \theta_g = \cos \theta_v \cos \theta_s - \sin \theta_v \sin \theta_s \cos \phi \), \( \theta_v \) and \( \theta_s \) are view and solar zenith angles, respectively, and \( \phi \) is the relative azimuth angle,

\[
\theta_g < 8^\circ \text{ and } R_1 > 0.1 \text{ and } R_2 > 0.2 \text{ and } R_7 > 0.12 \quad (4.7)
\]

\[
\theta_g < 12^\circ \text{ and } (N_{aw} + N_w) > 0 \quad (4.8)
\]

where \( N_{aw} \) is the number of water pixels within the eight pixels surrounding the tentative fire pixel. If either of tests (4.6) – (4.7) are satisfied, the tentative fire pixel is rejected as sun glint and flagged as non-fire.
The contextual tests for desert boundary rejection are:

\[ N_f > 0.1 N_v \] \hspace{2cm} (4.9)

\[ N_f \geq 4 \] \hspace{2cm} (4.10)

\[ R_2 > 0.15 \] \hspace{2cm} (4.11)

\[ T'_{21} < 345 \text{ K} \] \hspace{2cm} (4.12)

\[ \delta'_{21} < 3 \text{ K} \] \hspace{2cm} (4.13)

\[ T_{21} < T'_{21} + 6 \delta'_{21} \] \hspace{2cm} (4.14)

The tentative fire pixels that passed the sun glint filter may be rejected as a hot desert boundary surface if tests (4.9) – (4.14) are satisfied.

The coastal false alarm rejection process includes two steps: (1) identify unmasked water pixels within the valid background pixels, (2) identify false alarms caused by unmasked water pixels. In the first step, the number of unmasked water pixels is counted, referring to \( N_{uw} \). It is defined as valid background pixels with \( R_2 < 0.15 \) and \( R_7 < 0.05 \) and NDVI < 0. If a tentative fire pixel that passed first two false alarm rejections does not satisfy \( T_{22} > 360 \text{ K} \) and its \( N_{uw} > 0 \), then this pixel is flagged as non-fire, otherwise it is a fire pixel.
4.2.5 Challenges in the MODIS Enhanced Contextual Algorithm

The MODIS version 4 contextual algorithm (Giglio et al. 2003) is an optimized algorithm for global fire detection. This algorithm, however, designed for operational global fire monitoring, has limitations for regional fire detection in the southeastern states that are dominated by the understory fire regime. These limitations include problems caused by large view angles, the over-high fixed threshold for identifying potential fire pixels, and the impact of undetected fire pixels that are falsely counted as valid background pixels.

The accuracy of low intensity fire detection decreases with the increase of view angles. Giglio et al. (1999) evaluated three global fire detection algorithms using simulated AVHRR infrared data, including a fixed threshold algorithm (Arino et. al 1993), and two contextual algorithms (Justice and Malingreau 1996, Flasse and Ceccato 1996). They found that the ability to detect low intensity fires decreases with increasing view angles. For scan angles up to ~45 degree this shift is gradual, but for larger scan angles the curve of difficulty increase rapidly. The brightness temperature $T_{21}$ and $T_{31}$ decrease as scan angles increase for low intensity fires ($\sim 100 \text{ m}^2$), where $T_{21}$ and $T_{31}$ represent brightness temperature at AVHRR 3.75-\text{$\mu$m} and 10.8-\text{$\mu$m} channels, respectively, or at MODIS 3.96-\text{$\mu$m} and 11.0-\text{$\mu$m} channels, respectively. However, $T_{21}$ decreases more rapidly than $T_{31}$. This results in a reduction in $\Delta T$, so that detection becomes less likely as scan angles increase.
These three issues in the MODIS enhanced contextual algorithm are interrelated. Preliminary thresholds \( (T_{21} > 310 \text{ K} \text{ and } \Delta T > 10\text{K}) \) which are too high, falsely excludes many low intensity fires with \( T_{21} \) lower than 310 K in the phase of selecting potential fire pixels. Of these fire pixels, some low intensity fires observed at large view angles are mistakenly marked as non-fire pixels due to their brightness temperature \( T_{21} \) and \( \Delta T \) being lower than they would be at the nadir. All these missed fire pixels, in turn, are mistakenly counted as non-fire background pixels, and increase the value of \( T_{21} \) and \( \Delta T \). This further falsely eliminates other fire pixels in the process of contextual tests. Therefore, when applied to regional active fire detection in the southeast, the MODIS enhanced contextual algorithm often misses low intensity fires.

### 4.3 STUDY AREA AND DATA SOURCES

MODIS granules with substantive numbers of missed fire spots were selected. All these granules, observed from 2001 to 2004, were downloaded from the EOS (EDG) LP-DAAC, including the MODIS Level 1B Radiance product (MOD02/MYD02), the geolocation product (MOD03/MYD03), and the thermal anomalies, fires, biomass burning product (MOD14/ MYD14). The MODIS Direct Readout (DR) software package MODISNDV1_DB_V2.1 was used to calculate atmospherically corrected solar reflectance at red, green, blue channels for generating true color
Fig. 4.1 Spatial distribution of collected fire pixels. (a) Fire pixels detected by both algorithms; (b) Fire pixels omitted by the MODIS contextual algorithm.
only had a small number or no fire spots, (2) were mostly covered by clouds, or (3) displayed no smoke plumes or other granules that could be used for comparative analysis.

6596 fire pixels were identified in these 72 granules, of which 3809 fire pixels were missed by the MODIS contextual algorithm. The spatial distribution of the 2787 fire pixels that were identified by both algorithms, and 3809 fire pixels missed by the MODIS contextual algorithm are displayed in Fig. 4.1 (a) and (b), respectively.

These fire pixels were broadly distributed in seven southeastern states, including South Carolina, Georgia, Florida, Alabama, Louisiana, Mississippi, and Arkansas. All fire samples were validated using the MODIS enhanced contextual algorithm (Giglio et al. 2003) and visual examination of MODIS 1 km resolution true color images, so that all identified fire spots were confirmed to be real fire pixels.

4.4 ALGORITHM ADOPTED FOR THIS STUDY

A challenge in studying remote-sensed characteristics of low intensity fires was to find an algorithm that can identify low intensity fires omitted by current algorithms. An adjusted algorithm (Wang et al. 2007) based on the MODIS version 4 contextual algorithm was recently developed to detect low intensity fires in the southeastern states. This algorithm is more sensitive to low intensity fires especially at large view angles because it attenuates the $T_{21}$ threshold ($T_{21} > 293$ K). This research utilized an adjusted MODIS contextual algorithm together with the results
of Wang et al. (2007). The adjusted algorithm changes the MODIS contextual algorithm in three aspects to allow more low intensity fires to be detected by relaxing the conditions of fire detection. Firstly, the preliminary test $T_{21} > 310 \text{ K}$ is substituted by the test $T_{21} > 293 \text{ K}$. Secondly, the contextual test (4.1) $\Delta T > \Delta T + 3.5 \delta_{\Delta T}$ is replaced by the test $\Delta T > \Delta T + 2.5 \delta_{\Delta T}$. Finally, the contextual test $T_{21} > T_{21} + 2.5 \delta_{T_{21}}$ is used instead of test (4.3) $T_{21} > T_{21} + 3 \delta_{T_{21}}$.

The results of the adjusted algorithm were evaluated by the MODIS contextual algorithm and visually examined with MODIS 1 km true color images. Fire events detected by both the MODIS contextual algorithm and the adjusted algorithm were considered true fires, since the MODIS contextual algorithm has been validated systematically and offers a significantly lower false alarm rate. The remaining fire pixels that can only be identified by the adjusted algorithm were visually inspected. If a detected ‘fire’ spot is accompanied by a smoke plume, it was considered as a real fire spot; otherwise comparative analysis was conducted between earlier and later observations at a given location. If a previous and/or later observation of this fire spot was also identified as a fire spot, said fire spot was believed to be a true fire spot; otherwise it was identified as an uncertain pixel and excluded from further analysis. The fire database, in which uncertain pixels were eliminated, included the information of reflectance, radiance and all parameters used in the tests for fire pixels.
Wildland fires are not static events, and will move from one pixel to another. Low intensity fires move slower than large fires. The low intensity fires studied in this research were so small that the MODIS contextual algorithm omitted them. In most cases, two MODIS observations used to do comparative analysis have a time difference of less than 12 hours. Within a span of several hours, it is very possible that a low intensity fire event could remain in the same pixel or adjacent pixels. This accounts for the vast majority of missed fire pixels in this study. If two observations spanned one day, which is in very limited circumstances, a fire pixel from a previous observation may have moved to the surrounded pixels, and the later surrounded fire pixels were considered as proof of the previous fire pixels. It is possible that two fire events spanning one day are two individual events, but because this circumstance is very rare, it will not affect the results of statistical analysis for over 6500 samples.

4.5 RESULTS

4.5.1 Fire Detection Using the Adjusted Algorithm

Examples of fire maps produced by the adjusted algorithm are displayed in Fig. 4.2. Fires in the left panels, marked in red with the background of MODIS 1 km true color image, were detected by the adjusted algorithm. The right panels show fires detected by the MODIS enhanced contextual algorithm. Panels (a) and (b) present a typical situation in which the sensor view angles were large. Panels (c)
Fig. 4.2 Low intensity fires detected by the adjusted algorithm (AA) and the MODIS enhanced contextual algorithm (MCA). Fires in left panels are detected by the adjusted algorithm, and fires in right panels are detected by the MODIS contextual algorithm.
and (d) are examples that the MODIS contextual algorithm systematically omits low intensity fires in sparsely vegetated areas, where the adjusted algorithm is able to detect more fire events. Panels (e) – (h) represent the capability of the adjusted algorithm to identify low intensity fires even when intermixed with low and high clouds.

The 6596 identified fire pixels could be divided into two groups. The first group MCA included fire pixels that can be detected by both algorithms, and was labeled as fire pixels identified by the MODIS contextual algorithm. The second group AA included fire pixels omitted by the MODIS contextual algorithm, and was referred to as fire pixels only detected by the adjusted algorithm. Three fixed thresholds to identify potential fire pixels in the MODIS contextual algorithm were analyzed based on these two groups.

**4.5.2 Test for 0.86-μm Reflectance (R₂)**

The histogram of R₂ for fire pixels (Fig. 4.3 Panel a) revealed that the fire pixels omitted by the MODIS contextual algorithm had similar distribution as the fire pixels detected by both algorithms. The density distribution of R₂ and view angles for all fire pixels (Fig. 4.3 Panel b) shows that the R₂ reflectance increased slightly with view angles greater than 40 degrees. The distribution of R₂ indicated that the test R₂ < 0.3 was still valid for detecting low intensity fires omitted by the MODIS enhanced contextual algorithm. The increase of view angles did not substantially affect the validity of this threshold.
4.5.3 Test for 3.96-µm Brightness Temperature (T21)

The histogram of T21 (Fig. 4.4 Panel a) shows a substantial number of fire pixels with T21 values lower than 310 K, none of which can be detected by the MODIS enhanced contextual algorithm. The combination of fire pixels from Group MCA and Group AA forms a nearly intact distribution of T21. The density distribution of fire pixels with the sensor view angle and T21 shows a decreasing trend with increasing sensor view angles. To show this trend more clearly, the maximum densities of fire pixels at every sensor view angle in Panel (b) are identified, and plotted in Panel (c), where the corresponding brightness temperature T21 converges to lower values (< 310 K) as the sensor view angle increases. This shows that the sensor view angle evidently affects the remote-sensed T21 values of fire pixels, and consequently influences the accuracy of the MODIS enhanced contextual algorithm.
because its fixed preliminary test threshold of $T_{21} > 310 \text{ K}$ is too high. One of the reasons that the adjusted algorithm can detect so many low intensity fires missed by the MODIS contextual algorithm is that the adjusted algorithm uses a more relaxed

Fig. 4.4 $T_{21}$ distribution for fire pixels. (a) Histogram of $T_{21}$. The distribution of the fire group MCA is in brown. Blue is for the fire group AA. (b) Density distribution of all fire pixels (Group AA and MCA) with $T_{21}$ and the sensor view angle. (c) Distribution of $T_{21}$ for maximum fire density at all sensor view angles. (d) Density distribution of all fire pixels with $R_2$ and $T_{21}$. 
preliminary test threshold, $T_{21} > 293$ K, thus avoiding the major effect of the sensor view angle on $T_{21}$. The fire density distribution with $R_2$ and $T_{21}$ (Panel d) shows that all fire pixels cluster to the area centered at $R_2$ equal to 0.19 and $T_{21}$ equal to 305 K with $R_2$ smaller than 0.3 and $T_{21}$ greater than 293 K. This further proves that (1) the $R_2$ threshold is still valid, (2) the test $T_{21} > 310$ K is too high for low intensity fire detection, and (3) 293 K is a more appropriate threshold for this test. Setting the $T_{21}$ threshold to 293 K allows the detection of most low intensity fires omitted by the MODIS contextual algorithm.

4.5.4 Test for $\Delta T$

Fig. 4.5 Panel (a) displays the histograms of $\Delta T$ for Group MCA (brown), Group AA (blue), and the combination of Groups MCA and AA (grey). The $\Delta T$ distribution for omitted fire pixels (Group AA) is not an intact distribution curve and is cut off at $\Delta T = 10$ K, which is the $\Delta T$ threshold used by both algorithms. While the skewed distribution for Group MCA is relatively intact. The distribution of $\Delta T$ for all fire pixels shows the same characteristics as the one of the omitted fire pixels (Group AA), and is not intact. Panel (a) implies that the threshold of the test $\Delta T > 10$ K is possibly too high to detect some low intensity fires, and both algorithms risk omitting low intensity fires because of the high threshold. Panel (b), which shows the density distribution of all fire pixels with $\Delta T$ and the sensor view angle, shows that as view angles increased, $\Delta T$ for fire pixels converged around lower values rapidly, and were likely to drop below 10 K. The maximum densities of fire pixels at
all sensor view angles in Panel (b) were identified and plotted in Panel (c), which also shows that the corresponding brightness temperature $\Delta T$ converged to 10 K rapidly as the sensor view angle increased. Because both algorithms used 10 K as the threshold, Panel (c) cannot display a real convergence point lower than 10 K.

Fig. 4.5 $\Delta T$ distribution for fire pixels. (a) Histogram of $\Delta T$. The distribution of fire pixels detected by the MODIS contextual algorithms (MCA) is in brown. Blue is for fire pixels that only can be detected by the adjusted algorithm (AA). All fire pixels from both groups are in grey. (b) Density distribution of all fire pixels with $\Delta T$ and the sensor view angle. (c) Distribution of $\Delta T$ for maximum fire density at all sensor view angles. (d) Density distribution of all fire pixels with $\Delta T$ and $T_{21}$. 
which is very possible. The density distribution of fire pixels with ΔT and $T_{21}$ (Panel d) shows an incomplete pattern. In the previous section it was found that a $T_{21}$ threshold of 293 K was valid, therefore the primary reason of this incomplete distribution was because the ΔT threshold of 10 K was too high. In the algorithm designed for low intensity fire detection, the ΔT threshold should be tuned to a value lower than 10 K.

4.5.5 Over-All Effect of View Angles

Fig. 4.6  Histogram of sensor view angles for fire pixels. The distribution of fire pixels detected by the MODIS Contextual Algorithms (MCA) is in brown. Blue is for fire pixels that only can be detected by the Adjusted Algorithm (AA).
The number of fire pixels detected by the MODIS contextual algorithm (Fig. 4.6, in brown) steadily decreased when view angles were larger than 40 degrees, because of the effect of sensor view angles as observed in Fig. 4.4 c and Fig. 4.5 c. Fig. 4.6 illustrates the trend of fire pixels missed by the MODIS contextual algorithm, i.e. the number of missed fire pixels (in blue) gradually increased with the view angle when it was less than 55 degrees. As analyzed in the previous subsections, the $T_{21}$ and $\Delta T$ of fire pixels decreased as the sensor view angle increased, which is a very important cause of omission errors in the MODIS contextual algorithm. In the adjusted algorithm, $T_{21}$ has been attenuated to a proper threshold so that it is not a major source of omission errors. Therefore, $\Delta T$ is possibly one of the reasons that the number of omitted fires decreased when the view angle was greater than 55 degrees.

4.6 SUMMARY AND DISCUSSIONS

In the southeastern United States, most wildland fires are of low intensity. A substantial number of these fires cannot be detected by the MODIS enhanced contextual algorithm. To improve the accuracy of fire detection for this region, the remote-sensed characteristics of these fires have to be systematically analyzed. Using an adjusted algorithm, a database was built collecting 6596 remote-sensed fire pixels in 72 MODIS granules, of which 3809 fire pixels were omitted by the MODIS enhanced contextual algorithm. This database contained all information of fire pixels, including locations, the reflectance of the 0.86-μm channel ($R_2$), the
brightness temperature of the 3.96-µm and 11.03-µm channels (T21 and T31), as well as all the parameters needed for constructing contextual tests.

4.6.1 The Improved Algorithm

This study analyzed the statistical distributions of the sensor-observed reflectance and brightness temperature at 0.86-µm, 3.96-µm and 11.03-µm channels for fire pixels. The study explained the reasons that the MODIS contextual algorithm omits significant low intensity fires. One of the major reasons was because of increase of view angles, especially view angles of greater than 40 degrees.

This study discussed and suggested several aspects which could improve regional detection of low intensity fires. The results indicated that the R2 threshold of 0.3 was still valid for detecting low intensity fires omitted by the MODIS contextual algorithm. The view angle did not substantially affect the validity of the R2 threshold. However, a decreasing trend of T21 was observed as the sensor view angle increased for fire pixels. This trend demonstrated that the sensor view angle evidently affected the accuracy of the MODIS contextual algorithm for detecting low intensity fires. The reason that the adjusted algorithm can detect many more low intensity fires is because the T21 threshold is attenuated to 293 K, which is inclusive of variations in T21 for fire pixels as a result of increased view angle. The study indicates the threshold of test T21 > 310 K is too high for low intensity fire detection, and T21 > 293 K should be adopted instead. A decreasing trend of ΔT which accompanies sensor view angle increase was also observed. As the view angle
increases, $\Delta T$ converges to a low value rapidly, and is highly probable to drop below 10 K, implying that the threshold 10 K is too high for detecting low intensity fires, and that both algorithms risk omitting low intensity fires.

In the design of a regional algorithm for low intensity fire detection, merely decreasing $T_{21}$ and $\Delta T$ thresholds will probably cause rapid increase of false alarms around the nadir region. Attenuating the threshold at 3.96 $\mu$m channels does reduce the accuracy of the algorithm given other tests unchanged. For this reason, false alarm thresholds should be further studied. An alternative option is to design $T_{21}$ and $\Delta T$ thresholds as functions of view angles. False alarm rejection tests also have to be studied with regard to increases in false alarms caused by lower $T_{21}$ and $\Delta T$ thresholds. This study's objective was to establish whether the preliminary fixed thresholds currently employed by the MODIS enhanced contextual algorithm are appropriate for low intensity fire detection. Future research will attempt to ascertain how to adjust contextual tests and false alarm tests to effectively eliminate false alarms caused by lowering preliminary thresholds.

4.6.2 Definition of Low Intensity Fires

As a less studied topic, clear and quantitative definition of low intensity fires has not been reported in past research. Many publications have used the terms “small, cool fires” or “low intensity fires” (Giglio et al. 1999, Dozier 1981, Langaas 1993, Li et al. 2001, Lasaponara et al. 2003), however few of them had described a
clear definition. Based on fire statistics of burn size and spectral characteristics, this subsection discussed a definition of low intensity fires.

4.6.2.1 Fire Size Categories Adopted by USDA Forest Service

![Fig. 4.7 Distribution of effective fire area and Fire Radiative Power (FRP) (Zhukov et al. 2005)](image)

In the Forest Fire Reports issued for 1982-1989, and 1992 (USDA Forest Service 1998), wildland fires were categorized into seven groups. They are: Size A 0.25 acre or less; Size B 0.26-9 acres; Size C 10-99 acres; Size D 100-299 acres; Size E 300-999 acres; Size F 1000-4999 acres, and; Size G 5000 acres or more. Data reported from Florida prescribed burns from 2002 indicated there were a total of 26,274 fire cases. Of this number, category Sizes A, B, F and G fires accounted for 0%, Size C accounted for 57%, Size D accounted for 27%, and Size E accounted for 13%.
4.6.2.2 Size of Low Intensity Fires

Zhukov et al. (2005) compared the fire detection and quantitative characterization detected by MODIS and BIRD. BIRD is the experimental Bi-spectral IR Detection (BIRD) mission, and has successfully demonstrated the capability to detect fires and conduct quantitative analysis in high resolution (370 m) (Zhukov et al. 2005). In their paper, three sites in Siberia, Portugal, and Australia were studied. They presented histograms of the effective fire area and the Fire Radiative Power (FRP) estimated from the entire MODIS and BIRD image swaths (Fig. 4.7). Fig. 4.7 shows that the accuracy of the MODIS contextual algorithm dropped sharply as the FRP decreased to less than approximately 10 MW and/or the effective fire areas were less than 1 Ha (2.5 acres), which is categorized as Size B (0.26-9 acres). This indicated that the MODIS contextual algorithm systematically omits fire pixels below this range. In the southeastern United States, the dominant scale of wildland fires (57%) were categorized as equal to or less than Size C. By combining the statistical analysis of burning area based on Forest Fire Report and the size comparison of detected burn areas as observed by MODIS and BIRD, a burn size of 100 acres is suggested as the upper limit in the definition of low intensity fires.

4.6.2.3 Brightness Temperature of Low Intensity Fires

The minimum fire temperature threshold used by the MODIS contextual algorithm for identifying potential fire pixels, $T_{21\text{min}}$, can be estimated from the brightness temperature of fire pixels with the FRP equal to or greater than 10 MW
(Eq. 4.15), because the minimal FRP of fire pixels that the MODIS contextual algorithm can indentify is around 10 MW. Fig. 4.7 Panel (b) implies the accuracy of the MODIS contextual algorithm rapidly decreases as the FRP falls to less than 10 MW. The FRP equation (Kaufman et al. 1998a)

\[ FRP = 4.34 \times 10^{-19} \left( T_{21}^{8} - \bar{T}_{21}^{8} \right) \quad (4.15) \]

was used to derive \( T_{21\text{min}} \), given \( \bar{T}_{21} = 300 \) K, \( FRP = 10 \) MW. The result is \( T_{21\text{min}} = 311.5 \) K, which is consistent with the preliminary threshold (\( T_{21} > 310 \) K) in the MODIS contextual algorithm.

Fig. 4.8 illustrates the relationship of \( T_{21} \), \( \bar{T}_{21} \), and FRP for fire pixels in Eq. 4.15, where the isolines represent the FRP of fire pixels, \( T_{21\text{background}} \) is the apparent background temperature, i.e. \( \bar{T}_{21} \), and two grey lines represent the threshold 310 K and 293 K adopted by the MODIS enhanced contextual algorithm and the adjusted algorithm, respectively. Fig. 4.8 elucidates that most fires with \( FRP \leq 10 \) MW would be omitted if the test is \( T_{21} > 310 \) K for any given \( \bar{T}_{21} < 310 \) K. On the other hand, if the test is \( T_{21} > 293 \) K, almost all fires with \( FRP < 10 \) MW would possibly be identified, given the \( \bar{T}_{21} > 285 \) K. The background brightness temperature \( \bar{T}_{21} \) can be lower than 300 K during winter, spring, and autumn due to low surface radiation, and attenuation caused by atmospheric effects and large scan angles. When the \( T_{21} \) threshold is set to 293K, the chance that \( \bar{T}_{21} \) is less than 285 K is greatly reduced.
According to the above analysis and Fig. 4.4 (b) and (d), the $T_{21}$ temperature value of low intensity fires is suggested to be less than 315 K. Therefore, this study suggests that low intensity fires are defined as wildland fires with a burn size less than 100 acres (0.4 km$^2$) and a brightness temperature of less than 320 K at the 3.96-μm channel.
CHAPTER 5

AN IMPROVED MODIS CONTEXTUAL ALGORITHM

Summary: Traditional fire detection algorithms have primarily relied on hot-spot detection using thermal infra-red (TIR) channels with fixed or contextual thresholds. Three solar reflectance channels (0.65 μm, 0.86 μm, and 2.1 μm) were adopted into the MODIS enhanced contextual algorithm to improve active fire detection. In the southeastern United States, where most wildland fires are small and relatively cool, the MODIS enhanced contextual algorithm can be adjusted and improved for more accurate regional fire detection. Based on the MODIS version 4 contextual algorithm and a smoke detection algorithm, an improved algorithm using four TIR channels and seven solar reflectance channels is described (Wang et al. 2007). The study reveals that the $T_{21}$ of most low intensity fires undetected by the MODIS version 4 contextual algorithm is lower than 310 K. The improved algorithm is much more sensitive to low intensity fires, especially those detected at large scan angles.

Section 5.1 provides an introduction to the current state of remote sensing fire detection techniques, and unique challenges this area poses in the southeastern United States. This is followed by description of the data and software involved in this research in Section 5.2. The improved algorithm is presented in Section 5.3,
including cloud and water masking, selection of potential fire area, identification of potential fire pixels, and contextual tests. In Section 5.4, the improved algorithm is evaluated with two case studies in the southeastern United States, followed by the discussions in Section 5.5.

5.1 INTRODUCTION

In the southeastern United States, wildland fires and prescribed fires are common (USDA Forest Service 1998). An estimated 3.2 million hectares of wildland are burned per year in the southeastern United States (Wade et al 2000). Most of the prescribed fires, and some of the wild land fires, can be classified as understory surface fires, characterized by their small burn area and relatively low temperatures (Stanturf et al. 2002).

It is difficult to detect low intensity fires using current remote sensing algorithms for two reasons: (1) dense canopies obscure the emitted radiation, and (2) the proportion of an observed pixel which is actually burning may be small. Therefore, these fires cannot be easily distinguished from non-fire background radiation. To date, most algorithms are designed for global fire detection, and rely on identifying hot spots using thermal infra-red (TIR) channels. The limitation of that technology is that false alarms are occasionally generated over certain surface types during the day time, and low intensity fires are frequently missed using relatively high thresholds optimized for global fire detection.
In this chapter, an improved algorithm is presented, developed to detect low intensity fires in the southeastern United States using MODIS daytime observations.

5.2 DATA AND SOFTWARE

Reflectance at the top of the atmosphere from MODIS solar reflective channels at a 1km resolution, were employed to derive smoke pixels. The 0.41 μm and 0.94 μm channels, denoted by $R_8$ and $R_{19}$, respectively, were used to reject vegetation pixels. The 2.13 μm and 0.44 μm channels, denoted by $R_7$ and $R_9$, respectively, were applied to reject bare soil pixels. The reflectance from the blue channel was denoted by $R_3$, and $R_8$ to reject water pixels.

Three thermal infrared channels and one solar reflective channel were applied to detect fire pixels. The brightness temperatures derived from the radiation of the 3.96-μm channels and the 11.03-μm channel were denoted by $T_{21}$ and $T_{31}$, respectively. The reflectance from the 0.86-μm channel at a 1km resolution was denoted by $R_2$. The reflectance from $R_2$ and the 0.65-μm channel, denoted by $R_1$ along with the brightness temperature derived for the radiance of the 12.02-μm channel ($T_{32}$) and the 7.32-μm channel ($T_{28}$) were used to flag cloud pixels and reject false alarms at the cloud edge.

All data were downloaded from the Earth Observing System Data Gateway, Land Processes Distributed Active Archive Center (DAAC) (Justice et al. 2002b), including MODIS Level 1B calibrated radiance products (MOD02/MYD02),
geolocation data sets (MOD03/MYD03), and thermal anomalies, fires and biomass burning products (MOD14/MYD14).

The MODIS Direct Readout (DR) software package MODISNDVI_DB_V2.1 was employed to calculate surface reflectance with atmospheric correction at three visible channels. The MODIS fire product at 18:50 GMT, December 20, 2004, not available at the DAAC, was generated by the DR software package MOD14-4. DR software was provided by the NASA Direct Readout Laboratory.

5.3 OVERVIEW OF THE IMPROVED ALGORITHM

![Fig. 5.1 Workflow of the improved algorithm.](image)
This regional fire detection algorithm (Fig. 5.1) was designed to reduce omission errors caused by fixed thresholds in the MODIS enhanced contextual algorithm for identifying potential fire pixels. A new method based on identifying smoke plumes (Xie et al. 2007) for obtaining potential fire areas was adopted to select potential fire pixels as the first stage of the algorithm. For the second part of the algorithm, the kernel of the enhanced contextual fire detection algorithm for MODIS (Giglio et al. 2003) was adopted and adjusted to identify low intensity fires. Difference between the improved algorithm and the MODIS enhanced contextual algorithm are marked in Fig. 5.1 with the grey background.

5.3.1 Cloud/ Water Masking, and Potential Fire Area

A water mask was obtained from the MODIS geolocation data set (Justice, 2002a). The cloud detection approach adopted the technique used in the MODIS contextual algorithm (Giglio et al. 2003). A pixel that satisfies the following condition is considered to be clouds:

\[(R_1+R_2 > 0.9) \text{ or } (T_{32} < 265 \text{K}) \text{ or } (R_1+R_2 > 0.7 \text{ and } T_{32} < 285 \text{K})\]  

(5.1)

The cardinal feature of the MODIS contextual algorithm lies in the contextual tests, which are based on the identification of potential fire pixels with several fixed thresholds. One of the primary tests is \(T_{21} > 310 \text{ K}\). This criterion assumes any pixel that fails to satisfy this test is a non-fire pixel, but studies based on the database of
fire events in the southeast shows $T_{21}$ values of missed low intensity fires are lower than 310K, especially for observations at large scan angles. The results in Chapter 4 show that the detected $T_{21}$ values for fire pixels were evidently affected by sensor view angles, which consequently influences the accuracy of the MODIS enhanced contextual algorithm due to its fixed preliminary test $T_{21} > 310$ K being too high. Therefore, the assumption that any potential fire pixels have $T_{21}$ greater than 310 K runs the high risk of omitting low intensity fires by omitting potential fire pixels, and including fire pixels into the valid background pixels.

The TIR radiance emitted by low intensity fires is partly blocked by high level canopies at the early stage of fire ignition or even the whole burning process. Most wildland fires and prescribed fires emit smoke due to the complex compositions of fuels and the percentage of fuel consumptions (Stanturf et al. 2002). Ward and Hardy (1991) indicated that emission factors for particles released from fires tend to increase inversely with combustion efficiency. In the southeast, fuel moisture is usually higher than the southwest, so the moisture released from fuels tends to absorb some of the heat energy from the fire. This limits combustion temperatures and fuel consumption percentages. Incomplete combustion usually produces more smoke emission; therefore, low intensity fires are more likely to have a longer smoldering combustion phases. The heat release rate from smoldering fires is usually not sufficient to lift the smoke into a well defined convective column. As a result, smoke plums from low intensity fires stay near the ground in high concentrations (McMahon 1983). The highly concentrated smoke facilitates the
remote detection of smoke plumes, however, reduces the radiative signals of fire spots that sensors receive from space.

The second step after filtering out cloud and water pixels was to identify smoke pixels from among all the cloudless and non-water pixels using a smoke mask technique adopted from a smoke detection algorithm (Xie et al. 2007). The potential fire area around smoke pixels was calculated. Then, the pixels in the potential fire areas were examined by the attenuated potential fire thresholds based on the MODIS version 4 contextual algorithm. Those pixels satisfying the above conditions were identified as potential fire pixels and further processed by the contextual tests.

The smoke detection algorithm developed by Xie et al. (2007) was adopted and modified for this study. One threshold was attenuated so that the method was very sensitive to small smoke plumes. The smoke detection accuracy on commission errors had to be sacrificed to some extent so that any possible smoke area could be identified. Any cloudless and non-water pixels were considered as candidate smoke pixels. Then four criteria were applied to exclude vegetation pixels, bare soil pixels, and water pixels. These tests are:

\[
0.5 \geq \frac{(R_8 - R_{19})}{(R_8 + R_{19})} \geq 0.15 \tag{5.2}
\]

\[
\frac{(R_9 - R_7)}{(R_9 + R_7)} \geq 0.30 \tag{5.3}
\]

\[
\frac{(R_8 - R_3)}{(R_8 + R_3)} \leq 0.09 \tag{5.4}
\]
Those candidate pixels satisfying tests (5.2) -- (5.5) were identified as smoke pixels. Smoke detection algorithms cannot separate smoke and low clouds with high accuracy. If a low cloud pixel is mistakenly classified as a smoke pixel, it won’t affect the accuracy of final fire detection result, because this pixel won’t satisfy the contextual tests and cloud false alarm rejection tests.

Fires are usually found at the origin of the plume. The wind direction, which drives the direction of smoke emission, can change depending on atmospheric conditions. Therefore, a fire could be at any spot within certain diameter centered on the smoke plume. The distance within which smoke plumes can penetrate dense canopies indicates the distance between the fire spot and the observed smoke plume, denoted by the radius of potential fire area $D$. The regional climate data and biomass structure provide the parameters to derive the average maximum distance $D_{max}$. These parameters are: minimum vertical wind speed $V_{min}$; average maximum surface wind speed $S_{max}$; and the maximum average height of the canopy layer $H_{max}$. Assuming the smoke plume disperses at a linear rate, $D_{max}$ is derived by the relation $D_{max} = H_{max} \times S_{max} / V_{min}$. Taking $S_{max}$ as 9.0 ms$^{-1}$ (Kaufman and Justice 1998b, Klink 1999, Archer and Jacobson 2003), $H_{max}$ as 10 m and $V_{min}$ as 0.013 ms$^{-1}$, $D_{max}$ is approximately 7 km. At the nadir view of MODIS, a 7 km radius’ area is covered by a 14×14 1km-pixel window. This area is defined as a potential fire area and is calculated for any smoke pixels to derive a potential fire area mask. The horizontal
wind profiles at the boundary layer are not distributed linearly, and the vertical wind shear and plume buoyancy generated by fire lines or background atmospheric flow usually increases the dispersion speed of smoke plumes. Taking these factors into account, the radius used for identifying potential fire area is generally smaller than $D_{\text{max}}$.

### 5.3.2 Identification of Potential Fire Pixels and Active Fire Pixels

Pixels within the potential fire area were considered as potential fire pixels if they satisfied the following tests: $(T_{21} > 293 \text{ K}, R_2 < 0.3, \text{ and } \Delta T > 10 \text{ K})$, where $\Delta T = T_{21} - T_{31}$. These tests were adopted from the MODIS enhanced contextual algorithm with a change in the $T_{21}$ threshold, which was attenuated in order to increase the sensitivity to low intensity fires. The $T_{21}$ threshold was selected based on the statistical analysis of over 6500 fire pixels in 72 granules that were broadly distributed across the southeast states over various seasons (see Chapter 4). Setting of $T_{21} > 293 \text{ K}$ was found to reduce the omission errors caused by the corresponding threshold, i.e. $T_{21} > 310 \text{ K}$, in the MODIS contextual algorithm, and decrease the number of fire pixels that are mistakenly included in the valid background pixels. The lower $T_{21}$ threshold also reduced omission errors due to large scan angles, since the radiance of the object decreases at large scan angles and the lower threshold allows low intensity fire pixels at large scan angles to be further processed.

Those potential fire pixels which passed the contextual tests were considered to be tentative fire pixels. Tentative fire pixels were screened using the tests to
reject false alarms caused by sun glint, desert boundary and coastal boundary. The contextual tests and false alarm rejection tests were adopted from the MODIS enhanced contextual algorithm.

5.4 APPLICATIONS AND EVALUATION

Two wildland fire cases detected by both MODIS/Terra and MODIS/Aqua in summer and winter were selected to evaluate the performance of the improved algorithm. One case was a fire event on December 20 - 21, 2004 at the border region between Georgia and Florida along the Atlantic coast, and the border region between Mississippi and Alabama along the Gulf coast. The second fire event occurred on September 29, 2003, located in the Red River Basin in Mississippi.

Each case was calculated using both the improved algorithm and the MODIS contextual algorithm. Fire events detected by the MODIS contextual algorithm were considered true fires, since the MODIS contextual algorithm had been validated systematically and offered a significantly lower false alarm rate. Comparative analysis was conducted between earlier and later observations of fire events which were undetectable using the MODIS contextual algorithm but which were detectable using the improved algorithm. If a previously undetected fire event was subsequently detected using the MODIS contextual algorithm and/or the improved algorithm, and the event was accompanied by obvious smoke plumes, this fire event is believed to be a true fire event which was previously omitted by the MODIS contextual algorithm. Those fire events which had been only detectable using the
improved algorithm at earlier time, but not detectable by both algorithms in subsequent observations, are considered uncertain spots. Uncertain spots were further inspected using MODIS 250 m true color images. For all investigated cases, MODIS true color images of the corresponding regions at 250m-resolution showed uncertain spots were accompanied by obvious smoke plumes. This supported the supposition that they were indeed fire spots.

From among the fire events in the Red River Basin (Fig. 5.2), eight fire spots undetected by the MODIS contextual algorithm are numbered in Panel (a) and (c). Taking fire spot 2 as an example, the improved algorithm detected this thermal anomaly at 17:15 GMT (Panel a), and both algorithms identified this spot as an active fire with an obvious smoke plume at 18:50 GMT (Panel c & d). In Table 5.1, both $T_{21}$ and $\Delta T$ for fire spot 2 increased by approximately 20 K during a period of 1.5 hours. This proves the fire at 17:15 GMT was an active fire. Fire spot 3 at 17:15 GMT and 18:50 GMT, and fire spot 5 at 17:15 GMT satisfy the threshold of $T_{21} > 310$ K (Table 5.1) as well as all contextual thresholds, but the MODIS contextual algorithm failed to identify them. This indicated the false alarm rejection thresholds in the MODIS contextual algorithm caused omission errors.
Fig. 5.2 Fire events on September 29, 2003. Fire spots were marked in red with the background of MODIS 1 km true color images. Fire spots in Panels (a) and (c) were detected by the improved algorithm, and fire spots in Panels (b) and (d) were identified by the MODIS contextual algorithm. Panels (a) and (b) were observed at 17:15 GMT by MODIS/Terra, and Panels (c) and (d) were observed by MODIS/Aqua at 18:50 GMT.
Table 5.1  Fire characteristics of fire events on September 29, 2003.

<table>
<thead>
<tr>
<th>Fire spots</th>
<th>Time (GMT)</th>
<th>(T_{21}) (K)</th>
<th>(\Delta T) (K)</th>
<th>(R_2)</th>
<th>Scan angle (degree)</th>
</tr>
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<tr>
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<td>16.2</td>
<td>0.171</td>
<td>19.5</td>
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<tr>
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<td>31.6</td>
<td>0.166</td>
<td>21.3</td>
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<td>10.6</td>
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</tbody>
</table>

The fire spots with “#” can only be detected by the improved algorithm. The fire spots without “#” can be detected by both algorithms.

In Fig. 5.3, fire spots 1 -- 12, marked in Panels (a), (c) and (e), were omitted by the MODIS contextual algorithm. Although fire spots 1, 5 and 6 were not accompanied by obvious smoke plumes in the 1 km resolution MODIS true color images, corresponding MODIS 250 m true color images showed that all of these three spots were indeed accompanied by smoke plumes. Spots 7 to 12 were fire spots because they were accompanied by obvious smoke plumes even in the 1 km images. Three spots in Panel (d) are detected as fire spots by the MODIS contextual
algorithm. The left and the right spots were not accompanied by smoke plumes even in the MODIS 250 m true color image. The spot in the middle was accompanied by ambiguous smoke in the MODIS 250 m true color image. This case presented a limitation of the improved algorithm and indicated fire spots lacking a detectable smoke plume in a 1 km resolution image could be omitted.

Table 5.2  Fire characteristics of fire events on December 20 and December 21, 2004.

<table>
<thead>
<tr>
<th>Fire spots</th>
<th>Time (GMT)</th>
<th>$T_{21}$ (K)</th>
<th>$\Delta T$ (K)</th>
<th>$R_2$</th>
<th>Scan angle (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>17.8</td>
<td>0.108</td>
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<td>0.123</td>
<td>23.1</td>
</tr>
<tr>
<td>3</td>
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<td>313.3</td>
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<td>0.141</td>
<td>51.4</td>
</tr>
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</tr>
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<td>11.7</td>
<td>0.118</td>
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</tr>
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<td>14.2</td>
<td>0.125</td>
<td>50.6</td>
</tr>
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<td>0.131</td>
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<td>315.2</td>
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<td>13.5</td>
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<tr>
<td>10</td>
<td>Dec.21, 16:20#</td>
<td>296.1</td>
<td>18.4</td>
<td>0.132</td>
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<tr>
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<td>Dec.21, 17:55#</td>
<td>298.9</td>
<td>11.7</td>
<td>0.120</td>
<td>51.2</td>
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</table>

The fire spots with “#” can only be detected by the improved algorithm. The fire spots without “#” can be detected by both algorithms.
Fig. 5.3 Fire events on December 20 and 21, 2004. Fire spots in left panels were detected by the improved algorithm, and fire spots in right panels were identified by the MODIS contextual algorithm. (a) and (b), (c) and (d), (e) and (f) were observations on
December 20, 18:50 GMT, December 21, 16:20 GMT, and December 21, 17:55 GMT, correspondingly.

Fig. 5.2 (c) and Fig. 5.3 (e) show that the improved algorithm is more sensitive to low intensity fires, especially for observations at large scan angles (Table 5.1 and 5.2). In the two fire events on September 29, 2003 and December 20-21, 2004, there were a total of 24 fire spots which were omitted by the MODIS contextual algorithm, but detected by the improved algorithm. The improved algorithm failed to detect low intensity fires lacking a visible smoke plume unless they are within the potential fire area of other fires.

The characteristics of low intensity fires undetected by the MODIS contextual algorithm were listed in the Table 5.1 and Table 5.2. The $T_{21}$ brightness temperatures of these low intensity fires are lower than 310 K, a critical threshold for identifying potential fire pixels in the MODIS contextual algorithm. The thresholds of $\Delta T$ and $R_2$ in the MODIS contextual algorithm were valid for low intensity fires undetected by the MODIS contextual algorithm. The fire characteristics of low intensity fires suggested that a threshold for $T_{21}$ greater than 310 K is too high to detect low intensity fires in the southeast, and the corresponding adjustment in the improved algorithm is reasonable. The improved algorithm was less sensitive to the negative effects caused by large view angles, mainly as a result of decreasing the $T_{21}$ threshold to 293 K.
5.5 DISCUSSIONS

The proposed algorithm in this chapter is complementary to the MODIS enhanced contextual algorithm for low intensity fire detection in regional scale. Large fires can be detected with the MODIS contextual algorithm directly without the process of smoke detection. Smoke detection was used as an ancillary approach to identify potential fire areas for detecting low intensity fires that may have been missed by the MODIS algorithm. From smoke detection, potential fire areas were estimated by setting a spatial window around the smoke pixels. The smoke detection may have missed some smoke pixels around the boundary of smoke plumes, but did would not likely miss all the smoke pixels from a fire event. Because of the use of spatial window, missing errors in smoke detection around the smoke plume boundary did not change the final result of active fire detection. Using the improved algorithm, the primary negative impact of commission errors of smoke detection is the increased computational workload. Reducing omission errors was the primary objective. The fraction of smoke plumes that can be detected in 1 km imagery depends on many factors, such as the density of smoke, the background land cover type and the horizontally projected area of smoke plumes. For smoke plumes that were very light due to no active fires, and plumes that did not have enough time to disperse (in very few cases), the smoke algorithm did not work. The improved algorithm produced omission errors in the cases of lack of smoke plumes.
The smoke detection method used in this algorithm should not be used for accurate smoke detection.

Not all low intensity fires could be detected by the improved algorithm due to the condition of smoke emissions and the spatial resolution of channels adopted. The detectability of smoke plume emitted by low intensity fires using MODIS 1 km data is a complex topic. Integration of collocated measurements from high spatial resolution sensors, such as ASTER, Landsat TM/ETM, is a promising approach to analyze MODIS detectability of smoke plumes, as well as low intensity fires. However, high spatial resolution sensors usually have narrow swath, thus cannot catch many of the fire events.
CHAPTER 6

CONCLUSIONS AND DISCUSSIONS

This dissertation utilized satellite remote sensing measurements to detect and assess forest disturbances caused by hurricanes and wildland fires in the southeastern United States. A new approach for detecting forest region impacted by hurricanes was developed. Comparing the predicted results based on this approach with ground measurements demonstrated good performance by this algorithm for rapidly assessing forest damage caused by hurricanes. Dead forest biomass which accumulates in the aftermath of a hurricane landing contributes to dramatically increased fuel loading in impacted regions, thereby increasing the likelihood of subsequent wildland fires. The current MODIS enhanced contextual algorithm frequently fails to recognize low intensity fires. So as to more accurately detect low intensity wildland fires, the sources of omission errors in the MODIS enhanced contextual algorithm were diagnosed by analyzing a database of low intensity fires. This database was established by collecting spectral signatures of low intensity fires missed by the MODIS enhanced contextual algorithm. An improved algorithm for detecting low intensity fires in regional scale was developed and validated. This
chapter discusses the main conclusions of this research, as well as its limitations and future directions.

6.1 CONCLUSIONS

The main achievement of this research included (1) finding that $\Delta$NDII is the optimal damage indicator among five commonly used vegetation indices; (2) developing a new approach for detecting forest region impacted by hurricanes and assessing forest damage severity; (3) constructing a database of low intensity fires, and analyzed error sources of omission errors in the MODIS enhanced contextual algorithm, and; (4) developing an improved algorithm for detecting low intensity fires in the southeastern United States.

6.1.1 Estimation of Forest Damage Caused by Hurricanes

The performance of NDVI, EVI, NDII, LAI and Fpar for assessing forest damage caused by hurricanes was analyzed for selecting an optimal indicator of hurricane-induced forest damage. Quantitative analysis led to the conclusion that $\Delta$NDII is an optimal indicator for detecting hurricane-induced vegetation modification among five commonly used vegetation indices. The damage indicators ($\Delta$VI), i.e. relative reduction of vegetation indices pre- and post-hurricane were derived from noise-cleaned NDVI, EVI, NDII, LAI and Fpar image differencing.
Among these indicators, ΔLAI and ΔFpar were found to hardly be able to identify most impacted areas. The impacted region identified by ΔNDII is more consistent with the damage severity of Hurricane Katrina assessed by the USDA Forest Service, FIA than ΔNDVI and ΔEVI. The histogram of ΔVIs from the same period of 2003, 2004, 2005 and 2006 within the major impacted forest region showed: (1) the \( \Delta VIs_{2003, 2004, 2006} \) manifest an approximately normal distribution with the \( \Delta VIs_{2003, 2004, 2006} \approx 0 \); (2) \( \Delta VIs_{2005} \) shifted in the positive direction, reflecting the impact of the hurricane. The shift amplitude, measured by the difference of \( \Delta VIs_{2005} \) and according \( \Delta VIs_{2003} \), represented the capacity of each index to detect the hurricane impact. The ΔNDII produced the most significant shift amplitude (0.17), greater than the shift of ΔNDVI\(_{2005}\) (0.06) and ΔEVI\(_{2005}\) (0.04). The statistical dispersion, represented by the Interquartile of Range (IQR) of ΔVIs\(_{2005}\), indicated the capability of an indicator to distinguish levels of damage severity. The large IQR of ΔNDII\(_{2005}\) (0.24) implied the ΔNDII was more sensitive to damage levels than ΔNDVI (0.06) and ΔEVI (0.10). To measure the overall capability of these indicators for detecting forest damage, the percentage of detected damaged tree pixels was derived. The ΔNDII\(_{2005}\) identified 86.2% of total tree pixels within the major impacted region as the damaged pixels, while ΔNDVI\(_{2005}\) found 81.8%, and ΔEVI\(_{2005}\) distinguished 55.8%.

A rapid assessment algorithm for post-hurricane forest damage was developed using the optimal indicator ΔNDII. This algorithm includes three steps: (1) data pre-processing, (2) Fourier filtering, and (3) univariate image differencing. In the data
pre-processing stage, the NDII time series derived directly from the MODIS NBAR product were filtered to eliminate poor-quality data, and anomalous high and low values. The eliminated data were estimated by using the CLEAN algorithm. In the Fourier filtering stage, change signals caused by hurricane-induced forest damage were decoupled with vegetation phenological signals. In the third stage, the univariate image differencing method was applied to noise-clean NDII time series to derive ∆NDII, the optimal indicator of hurricane-induced forest damage. Finally, the hurricane impacted forest region and the severity of forest damage was derived from ∆NDII.

This algorithm is validated using the ground truth data collected by the Forest Inventory Analysis group. The scatter plot of ∆NDII and ground-observed total damage severity showed a linear relationship with the $R^2 = 0.79$, and p value $< 0.0001$. This linear relationship indicated that ∆NDII can identify the hurricane-impacted region, and quantitatively represent the forest damage severity and levels.

6.1.2 Detection of Low Intensity Wildland Fires

Wildland fires in the southeastern United States are frequently low intensity fires, for the various reasons which were discussed in Chapter 4. A substantial number of low intensity fires in the southeastern United States have been found to be omitted by the MODIS enhanced contextual algorithm during the process of visual scanning MODIS true color images in the past years. The MODIS enhanced contextual fire detection algorithm was designed for operational global fire
monitoring. Therefore, when it was applied to regional active fire detection in the southeastern United States, low intensity fires are often missed. To diagnose reasons for omission errors in the MODIS active fire product, a database was established by collecting the spectral signatures of low intensity fires missed by the MODIS enhanced contextual algorithm. An improved algorithm for detecting low intensity fires in regional scale was then proposed and applied to case studies.

The analysis of the low intensity fire database showed that (1) sensor view angles evidently affected the MODIS contextual algorithm, especially when view angles were greater than 40 degrees; (2) sensor view angles did not substantially affect the validity of the $R_2$ threshold, and the $R_2$ threshold 0.3 was still valid for detecting low intensity fires omitted by the MODIS contextual algorithm; (3) the threshold of test $T_{21} > 310 \text{ K}$ was too high for monitoring low intensity fires; (4) the $\Delta T$ threshold 10 K was too high for detecting low intensity fires. Based on these findings, an adjusted algorithm, involving four TIR channels and seven solar reflectance channels, was designed based on the MODIS enhanced contextual algorithm and a smoke detection algorithm. This algorithm was applied and evaluated against case studies, which showed the adjusted algorithm to be more sensitive to low intensity fires, especially for observations at large scan angles. Thus, this improved algorithm was found to be more suitable for regional wildland fire detection in the southeastern states.
6.2 IMPLICATIONS OF THE RESEARCH

The studies presented in this dissertation were dedicated toward promoting satellite detection of forest disturbances caused by hurricanes and wildland fires. The algorithms developed and findings produced by this research will contribute to the communities of natural hazard detection, carbon cycle study and forest management.

The rapid assessment algorithm for estimating post-hurricane forest damage, presented in Chapter 3, can provide decision support for forest managers with timely information with better accuracy, higher resolution, broader spatial coverage and lower cost than that provided by traditional field surveys. The forest damage severity and associated accurate geolocation produced by the rapid assessment algorithm will support decision makers with scientific evidence for planning various hazard relief activities such as logging and fuel reduction. The evaluation of forest damage indicators has advanced our knowledge of the performance of commonly used vegetation indices for assessing forest damage.

This study contributes to assessing forest fuel change caused by hurricanes, which are large scale natural disturbances affecting global carbon sequestration. The amount of forest fuel change brought about by a major hurricane is a significant factor in the carbon cycle study and a topic for future research. The quantitative estimation of forest fuel change induced by hurricanes will improve forest fire danger risk estimation by providing high resolution dynamic fuel loading information.
Traditional fuel models used in fire danger risk models cannot reflect the massive forest fuel change introduced by major hurricanes. The availability of fuel loading change information will also allow us to quantitatively study impacts of hurricane landfalls on forest fire danger risk.

The improved algorithm presented in Chapter 5 is more sensitive to low intensity fires, which will benefit forest firefighting activities through early fire detection, and provide more accurate information on fire events for forest management. The statistical study of the sensor-detected spectral properties of low intensity fires, presented in Chapter 4, revealed several factors affecting the accuracy of the MODIS contextual algorithm. Thees results will contribute to future study on improving the active fire detection algorithm.

6.3 FUTURE DIRECTIONS

The rapid assessment algorithm for detecting post-hurricane forest damage was validated by the post Hurricane Katrina case, with less than 60 ground samples. More cases will be used to further validate this algorithm. The damage indicator ΔNDII is sensitive to the change of the canopy water content, however it is incapable of directly measuring changes in canopy chlorophyll content and canopy vertical structure. Lidar, SAR and InSAR sensors can directly detect vertical structural variations. Combining measurements from these sensors and optical sensors could provide more comprehensive information of forest disturbances caused by hurricanes.
The improved algorithm for low intensity fire detection improved on some of the factors that had caused omission errors in the MODIS contextual algorithm. Several other factors which also contribute to missing low intensity fires are still not considered in the improved algorithm. The $\Delta T$ threshold should be further investigated for a more appropriate value. A method for reducing or negating the effect of scan angles in the algorithm should also be explored. The attenuation of $T_{21}$ and $\Delta T$ thresholds increases commission errors in the algorithm, and is an area which has not been well studied. A contextual test for false alarm rejection should also be tested for the new thresholds of $T_{21}$ and $\Delta T$. 
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CURRICULUM VITAE

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