Measuring and Monitoring Long Term Disaster Recovery Using Remote Sensing: A Case Study of Post Katrina New Orleans

Reginald S. Archer, University of California Santa Barbara

ABSTRACT: This research focuses on measuring and monitoring long term recovery progress from the impacts of Hurricane Katrina on New Orleans, LA. Remote sensing has frequently been used for emergency response and damage assessment after natural disasters. However, techniques for analysis of long term disaster recovery using remote sensing have not been widely explored. With increased availability and lower costs, remote sensing offers an objective perspective, systematic and repeatable analysis, and provides a substitute to multiple site visits. In addition, remote sensing allows access to large geographical areas and areas where ground access may be disrupted, restricted or denied. Maximum likelihood classification, and change detection are applied to multi-temporal high resolution aerial images to quantitatively measure the progress of recovery. Images are classified to automatically identify disaster recovery indicators and exploit the indicators that are visible within each image. The advantage of this method is that it identifies which indicators are most suited to automation. By tracking the trajectory of individual indicators, the status of recovery progress can be determined for a given location at a given time. This approach is used to determine which particular indicators are more likely to have a strong impact on recovery assessment and progress detection. Furthermore, time to recovery can be predicted based on the temporal trajectory of specific indicators.

KEYWORDS: Change detection, classification, Katrina, New Orleans, remote sensing, disaster recovery

Introduction

Hurricane Katrina struck New Orleans and surrounding areas on August 29th 2005, and the impact of the devastation is still evident. Katrina was the costliest and one of the deadliest hurricanes to ever strike the United States and left more than 4,000 homes destroyed in the Lower Ninth Ward. The Greater New Orleans Community Data Center observed that by July 2008, population levels reached about 72% of pre Katrina population based on US postal service counts, and grew to 85% by the end of 2011 (Ortiz 2012). Although New Orleans has recovered much of its population and economic base, progress has not been able to keep pace with the growing challenges of the recovery of some of the hardest hit areas such as the Lower Ninth Ward. The question of how best to assess the status of recovery across sectors such as: housing, infrastructure, transportation, environment and community still remains. It is generally agreed that there is a lack of standards to measure, monitor and evaluate recovery processes. “On paper, the city's economy appears to be thriving, with relatively low unemployment, foreclosure and bankruptcy rates. But in post-Katrina New Orleans, residents' perceptions of their city's recovery tends to depend on where they live, their vantage point of it. Swaths of some neighborhoods are sparsely populated, even desolate, and federal rebuilding dollars have provided much of the economic resilience.” (Huffington Post 2009).

Remote sensing and Geographic information systems (GIS) have frequently been used for emergency response and damage assessment after natural disasters. However, techniques for spatiotemporal analysis of long term disaster recovery using remote sensing have not been widely explored. Limitations of indexes such as the "New Orleans Index," include an inability to adequately represent spatial metrics in a timely fashion. For initial emergency response and restoration, the literature shows that remote sensing is satisfactory. Following Katrina, various agencies made extensive use of remote sensing for assessment of the damage and management of the emergency situation (Robila 2006). However, using current technological advancements in remote sensing and change detection, aerial imagery can be used independent of other resources to monitor disaster reconstruction and recovery.

By and large, the recovery process is monitored with the use of qualitative and subjective information (Brown et al. 2008). In addition, recovery impacts the overall resilience of a community. The Community and Regional Research Initiative on Resilient Communities (CARRI) defines resilience as "a community or regions capability to prepare for, respond to, and recover from significant multi-hazard threats" (Colten et al. 2008). Remote sensing has enabled numerous advances in disaster management in terms of modeling, mapping, and understanding of hazard and risk assessment, disaster preparedness, rapid and adequate disaster relief and mitigation of natural disasters. However, techniques for analysis of long term disaster recovery using remote sensing have not been widely explored. Long term recovery (i.e., the reconstruction process) is characterized by attention to rebuilding and new construction, restoration of major urban services, and review of pre-disaster land uses, especially insofar as they include consideration of local hazards in the recovery plans for the affected area (Rubin and Barbee 1985). A recovery monitoring system based on remote sensing techniques could allow quantification of long term recovery tracking indicators. The proposed research focuses on evaluating long term recovery progress from the impacts of Hurricane Katrina on New Orleans, LA. Specifically, this research examines the reconstruction phase of recovery and investigates classification and change detection techniques that will allow adequate measuring and monitoring of long term disaster recovery indicators in the Lower Ninth Ward.

Kates et al. (2006) provides a comparative and historical perspective on the reconstruction of New Orleans and hurricane Katrina and also illustrate evidence of conflicting goals for reconstruction of rapid recovery, safety, betterment and equity. Their work describes the sequence and timing of reconstruction phases for post-Katrina New Orleans based on the Kates-Pijawka model of recovery activity (Haas et al. 1977) where reconstruction is part of a sequence of four identifiable post-disaster periods: emergency, restoration, reconstruction, and betterment or commemorative reconstruction. Based on the actual response time of six (6) weeks for New Orleans after Katrina, and historical experience for reconstruction, the sequence and timing of reconstruction projects a length of almost ten years before attaining pre-disaster levels of capital stock and activities. In New Orleans, the emergency period began immediately, during the disaster. Before the emergency phase ended, the restoration period began to repair essentials of urban life. Reconstruction tends to be the longest phase and begins during restoration. Reconstruction provides infrastructure, housing, and jobs and attempts to rebuild the post-disaster population to pre-disaster levels. Following reconstruction is the

commemorative or betterment reconstruction phase. Kates et al. (2006) takes a close look at behaviors and factors that arise in recovery efforts and how they may lead to different trajectories of recovery for each phase. Using past disasters as a guide, Kates et al. (2006) gauges the progress of recovery to better assess the length of time required for reconstruction based on a calendar of historical experience. Their research points out that although the recovery process can be uneven, different social groups, even within the same community, experience the sequence quite differently. Figure 1. shows a plot of the reconstruction experience for the year following Katrina and projects future activity based on historical experience. Kates et al. (2006) also found that after one year, a unified recovery process had not yet begun; some neighborhoods had begun their own individual planning process. Figure 1. Also identifies sample indicators of recovery; however, it is important to investigate the temporal trajectories of individual indicators in order to determine which indicators of recovery provide the best measure of progress detection.

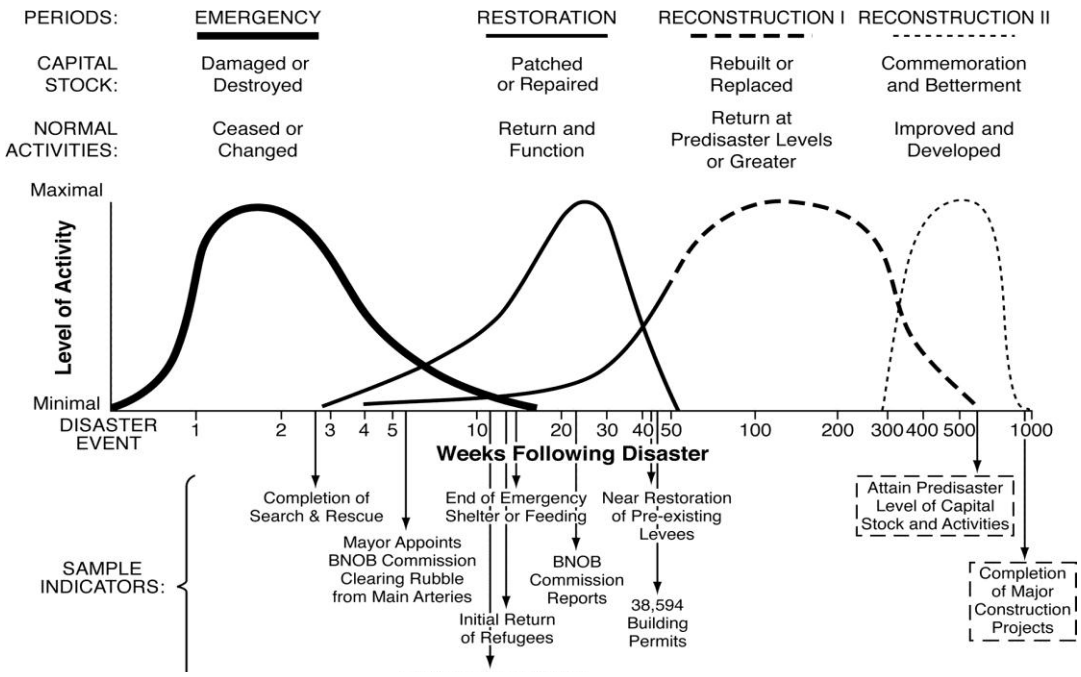

Figure 1. The sequence and timing of reconstruction after Katrina in New Orleans with actual experience (solid lines) and sample indicators for the first year along a logarithmic time line of weeks after the disaster. Kates R W et al. PNAS 2006;103:14653-14660

In general, speed and quality are the measures of a successful recovery process. Speed is important to keep businesses alive, rebuild infrastructure, and provide temporary and permanent housing (Olshansky et al. 2006). Although previously existing plans can help to improve both speed and quality of post disaster decisions, a remote sensing long term recovery monitoring system could advance coordination and decision making by quantitatively indicating the status of recovery for a given time and place. Remote sensing as a whole for disaster recovery has been steadily gaining interest over recent years. Recovery has more recently been conceptualized as a dynamic, endless process

where security is often an issue and data is hard to obtain (Brown et al. 2008). Therefore remote sensing data, which is rapid, independent and reliable, is especially valuable in the dynamic long term disaster recovery conditions,

Although remote sensing is used widely in combination with GIS, ground surveys and other methods to measure and monitor recovery, aerial images can be used independently to assess recovery. With increased availability and lower costs, remote sensing offers an objective perspective, systematic and repeatable analysis, and provides a substitute to multiple site visits. In addition, remote sensing allows access to large geographical areas and areas where ground access may be disrupted, restricted or denied. In this case study, aerial images are classified using maximum likelihood classification (MLC) to automatically identify disaster recovery indicators. Post classification change detection is then applied to datasets from 2006-2007 to quantitatively analyze recovery indicators. This approach explores the disaster recovery experiences in the Lower Ninth Ward in an effort to determine whether neighborhood characteristics impact recovery. Previous research has identified twenty four indicators that are visible in remote sensing imagery. Certain indicators are more likely to have a stronger impact on recovery assessment in the Lower Ninth Ward. Individual indicators will be measured to determine their impact on progress detection.

Data and Methods

True color aerial images for Orleans County were obtained from the Regional Planning Commission (RPC) for Jefferson, Orleans, Plaquemines, St. Bernard and St. Tammany Parishes (see Figure 2 below). The 2006 imagery was produced through a cooperative agreement entered into with the State of Louisiana, Governor's Office of Homeland Security and Emergency Preparedness (OEP), the United States Army Corps of Engineers, the United States Geological Survey (USGS), the National Geospatial-Intelligence Agency (NGA), the Plaquemines Parish Emergency Planning Committee, and the RPC. The true color aerial photography was flown between February and May 2006 by 3001, Inc using the Z/I imaging DMC digital camera. The photography is projected to UTM NAD83 with a unit of measure of meters. The spatial resolution is approximately a 6" pixel. The 2007 imagery was captured between February 8-10, 2007 by AirPhoto USA and acquired by Digital Globe. The imagery is projected to Stateplane NAD83; the unit of measure is feet, and the spatial resolution is a 1 foot pixel.

Data Pre-processing

One of the important issues in the change detection is to ensure that the changes detected are not confused with errors. These sources include data acquisition, processing, analysis, and conversion. Any of the error sources that affect the accuracy of single image analysis will contribute to the change detection accuracy (Dai and Khorram 1998). Therefore, before any direct comparison between the images can be performed, the images need to be pre-processed to ensure accurate geometric registration of the two images. Both images had to be in the same spatial reference system and have the same pixel size. In addition, the images co-registered in order to minimize errors due to misregistration. Of the various pre-processing steps for change detection, multidate image registration is one

of the most important (Deng et al. 2009). We first address the issues of spatial reference and cell size. The 2007 image is re-projected from Stateplane NAD83-feet to UTM

(a) (b)

Figure 2. (a) shows a subset of the 2006 true color aerial image; (b) shows a subset of the same area in 2007.

NAD83-meters. The 2006 image was resampled using nearest neighbor, to 0.304 meters ~ 1ft.

A geometric rectification was established by selecting ground control points (GCP) interactively between the two images. The GCPs were selected within ENVI's registration tool for image to image registration. The images were co-registered using a 4th degree polynomial with thirty eight (38) GCPs and a total RMS error of 0.8625. The images were then clipped to subset the Lower 9th Ward area. One of the problems with the use of multi-temporal images acquired from different sensors is that the data is usually collected under different sun angles and other atmospheric conditions that affect the performance of the image classification. Radiometric normalization was not performed on the data for this study.

Image Classification

The next step was to classify the pre-processed images by developing training classes or regions of interest (ROI). The ROIs, or change classes, represent sample areas for each of the desired output classes which are based on the designated indicators of recovery that are visible in the images. For this study, seven indicator ROIs were identified: blue tarps, FEMA trailers, houses, red roof tops, pavement, green vegetation, and other

buildings. Other indicators of recovery were also visible such as dumpsters, construction equipment, and debris; but because aerial images lack multispectral information, the classification methods being used cannot necessarily distinguish between debris and other ROIs, or construction equipment and anything yellow for example.

ROIs were selected for each of the images separately and a supervised classification was performed on each dataset individually. Some of the change classes were not very discernible from each other. For example, houses, classified by the roof tops, vary in shape and color and the spectral signatures were similar to roads, shadows, dark pavement or other buildings (see Figure 3 below). In order to distinguish roads from other features, the roads were masked out during classification.

Figure 3. Example of different color rooftops, and similarities between colors of features.

A set of validation ROIs was also designated to be used in the post classification accuracy assessment. The training ROIs and validation ROIs were adjusted experimentally until acceptable classifications were produced, based on the post classification confusion error matrix. The classification results for the two images are shown in Tables 1 and 2, below.

Classification Results

The confusion matrix provides a summary of the overall accuracy, user and producer accuracies as well as the omission and commission errors. The overall accuracy of the images were 84.536% with a Kappa coefficient = .8042 for 2006, and 80.3758% with a Kappa coefficient = 0.7508 for 2007. The low overall accuracy seems to be cause by the confusion between the building class and the FEMA class, pavement class and housing class. Some of the building rooftops are white which may explain the confusion between the FEMA trailer class and the building class. The white or light colored rooftops can

also be seen in Figure 3. Although the user accuracy for FEMA class in 2006 was 33.29% and the user accuracy for the pavement class 64.28%, the housing class had a user and producer accuracy around 80%. The 2007 classification had some of the same errors associated with the different classes. The user accuracy for the FEMA class was 32.23%, pavement: 54.96% and housing was 66.78%. The producer accuracy for the building was around 69% for both classification images. The total accuracy of both classification results improved significantly with the building class omitted from the set of ROIs. The blue tarp class performed very well in terms of user and producer accuracy.

Table 1. Confusion error matrix for 2006 maximum likelihood classification.

				2006								
Overall Accuracy= (256505/303427) 84.536%												
Kappa Coefficient = 0.8042												
	Ground Truth (Percent)											
Class	GreenVeg-Valid	BlueTarp-Valid	FEMA-Valid	House-Valid	RedRoof-Valid	Pavement-Valid	Building-Valid	Total	Commission (Percent)	Omission (Percent)	Prod. Acc. (Percent)	User Acc. (Percent)
Unclassified	0	0	0	0	0	0	0	0				
GreenVeg	**98.05**	0	0.18	4.42	5.89	0.36	2.73	29.75	6.64	1.95	98.05	93.36
BlueTarp	0	**99.99**	0	0	0	0	0	4.71	0.01	0.01	99.99	99.99
FEMA	0.03	0	**88.15**	0.01	0	0	4.13	1.92	66.71	11.85	88.15	33.29
House	0.86	0	0.86	**80.89**	3.2	2.07	7.89	15.66	20.26	19.11	80.89	79.74
RedRoof	0.49	0	0	1.19	**90.16**	1.07	0.66	6.81	9.8	9.84	90.16	90.2
Pavement	0.34	0	0.54	9.22	0.44	**88.16**	15.88	18.06	35.72	11.84	88.16	64.28
Building	0.23	0.01	10.26	4.27	0.31	8.33	**68.71**	23.1	8.3	31.29	68.71	91.7
Total	100	100	100	100	100	100	100	100				

Table 1. Confusion error matrix for 2007 maximum likelihood classification.

				2007								
Overall Accuracy = (191419/238155) 80.3758%												
Kappa Coefficient = 0.7508												
	Ground Truth (Percent)											
Class	BlueTarp-Valid	GreenVeg-Valid	FEMA-Valid	House-Valid	RedRoof-Valid	Pavement-Valid	Building-Valid	Total	Commission (Percent)	Omission (Percent)	Prod. Acc. (Percent)	User Acc. (Percent)
Unclassified	0	0	0	0	0	0	0	0				
BlueTarp	**99.81**	0	0	0.03	0	0	0	4.04	0.18	0.19	99.81	99.82
GreenVeg	0	**91.8**	0	2.24	0.5	0	0.12	22.13	2.19	8.2	91.8	97.81
FEMA	0	0	**90.75**	0.03	0	0	7.97	4.4	67.77	9.25	90.75	32.23
House	0.01	6.35	0.05	**75**	1.03	5.97	12.69	20.71	33.22	25	75	66.78
RedRoof	0	0.8	0	0.97	**94.37**	0.07	0.16	5.3	8.23	5.63	94.37	91.77
Pavement	0	1.04	1.18	17.05	4.1	**90.12**	10.3	16.39	45.54	9.88	90.12	54.46
Building	0.18	0	8.02	4.67	0	3.84	**68.76**	27.04	5.09	31.24	68.76	94.91
Total	100	100	100	100	100	100	100	100				

Classes for the study were defined according to which indicators of recovery can be seen in the imagery. The entire Lower 9th ward study area was used to select training and validation regions. While the training ROIs are representative of the land cover, there is not enough spectral information available to do a simple supervised classification. With subtle differences between some of the training regions, many pixels are misclassified. Figure 4 and 5 show how white rooftops can be classified as FEMA trailers, paved roads can be classified as housing, and asphalt pavement can be classified as a building. However, blue tarps are classified extremely accurately based on the accuracy assessment error matrix. It may be better to use other types of classification tools and techniques to distinguish between change features in the images. Filters were not used in this classification to eliminate some of the noise. With limited spectral information, incorporating other methods should improve the overall accuracy of the image classification.

Figure 4. Pre-processed 2006 image depicting white rooftops, different color pavement, blue tarps, white paved areas as well as the similarities between rooftops and pavement.

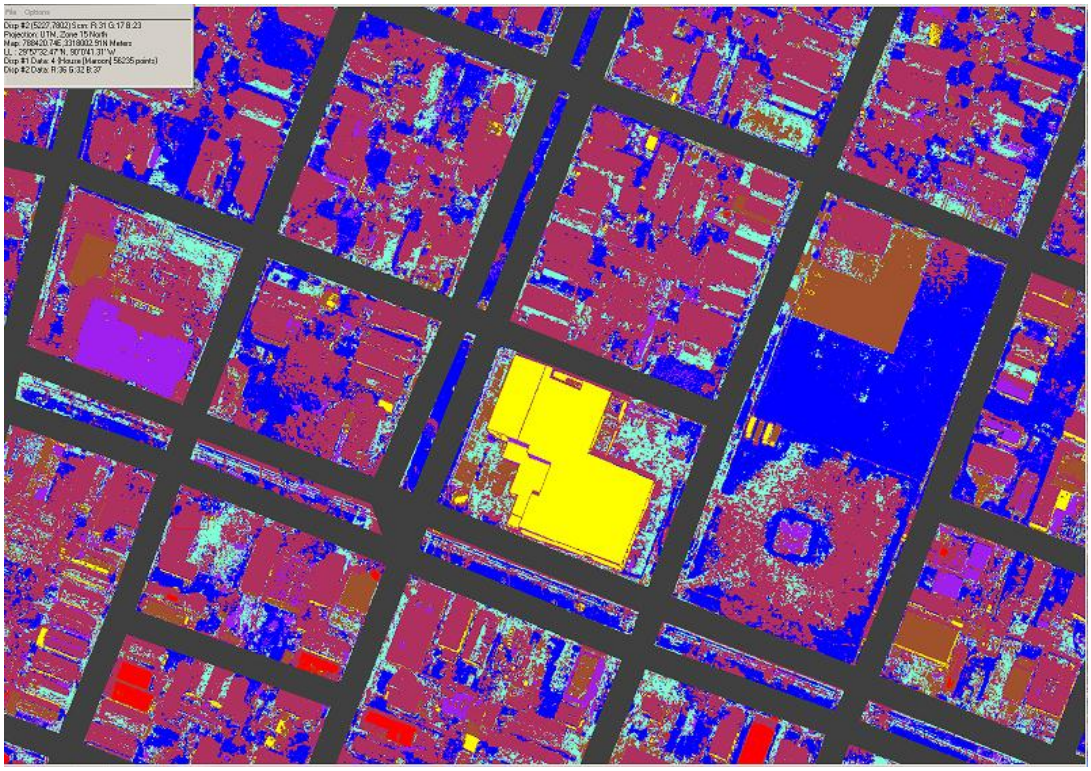

Figure 5. 2006 Classification results. Yellow represents FEMA Class, Blue -GreenVeg, Brown -Building, and Maroon is housing.

While the overall accuracy is decent, the individual errors (or accuracy) explain that the MLC detects almost all of the blue tarps on roofs. The MLC detects most of the FEMA trailers and vegetation as well. The MLC does not perform as well distinguishing between paved road surfaces and grey rooftops. In addition, red rooftops tend to be confused with sandy areas or dirt paths. The pavement class and building rooftops also introduce some confusion to the algorithm. In the 2007 classification, houses and other buildings were indistinguishable in many cases.

Change Detection

To detect recovery progress and changes in the study region, true aerial images for two different time periods were classified using a simple maximum likelihood method. Once the accuracy assessment was performed and the classification results were sufficient for both datasets, the new classified image maps can be compared directly to detect changes on the ground. The classified images were compared using post-classification change detection statistics. This was possible because the images were co-registered prior to the individual classification. The two classification maps are compared using a change detection matrix to illustrate class occurrence from 2006 to 2007.

Results

Classification and change detection were performed on images between 2006 and 2007 to identify changes in disaster recovery indicators on the ground. The change classes selected for this study represent land cover features that can be identified in the remotely sensed images and used to monitor disaster recovery in the Lower 9th Ward. The maximum likelihood classification algorithm was trained on ROIs selected from the 2006 and 2007 true color aerial images. The overall classification accuracy for the images was approximately 85% for 2006 and 80% for 2007 (table 1 & 2). Experimenting with different ROIs and carefully selecting training features for both datasets brought the overall accuracy up to a value sufficient enough to calculate the change statistics.

It was expected that as recovery efforts increased, the number of FEMA trailers would increase as well. In addition, once a roof top covered with blue tarp was repaired then that house should be detected in the housing class for the 2007 classification instead of the initial blue tarp class. The following tables illustrate the results of the changes that occurred in the Lower 9th ward between 2006 and 2007.

Table 3. Class changes in terms of percentage.

		Initial State 2006										
	Percentages	Masked Pixels	BlueTarp 16359	GreenVeg 280572	FEMA 2555	House 56235	RedRoof 19055	Pavement 30312	Building 82771	Unclassified	Row Total	Class Total
Final State 2007	Unclassified	0	0	0	0	0	0	0	0	0	0	0
	BlueTarp [Red] 11643 points	0	24.349	0.057	0.295	0.348	0.163	0.144	0.482	0	100	100
	GreenVeg [Blue] 217878 points	0.024	3.583	53.703	10.36	16.913	24.853	19.182	16.208	0	100	100
	FEMA [Yellow] 5431 points	0	1.25	0.541	35.053	1.095	1.035	1.335	6.036	0	100	100
	House [Maroon] 60076 points	1.388	50.376	17.182	12.935	52.947	19.222	20.785	18.24	0	100	100
	RedRoof [Purple] 22430 points	0.006	5.17	5.739	1.988	3.462	25.516	4.069	3.119	0	100	100
	Pavement/Dirt [Aquamarine] 38137	0.008	9.281	21.538	19.301	20.843	26.731	49.026	37.329	0	100	100
	Building [Sienna] 184336 points	0.001	5.869	0.898	19.977	4.232	2.11	5.038	17.999	0	100	100
	Masked Pixels	98.571	0.123	0.342	0.091	0.161	0.37	0.42	0.586	0	100	100
	Class Total	100	100	100	100	100	100	100	100	0	0	0
	Class Changes	1.429	**75.651**	**46.297**	**64.947**	**47.053**	**74.484**	**50.974**	**82.001**	0	0	0
	Image Difference	-1.015	**-52.607**	**-17.042**	**30.905**	**-15.116**	**29.928**	**153.718**	**-45.298**	0	0	0

Table 4. Class changes in terms of Area.

		Initial State 2006										
	Area (Square Meters)	Masked Pixels	BlueTarp 16359	GreenVeg 280572	FEMA 2555	House 56235	RedRoof 19055	Pavement 30312	Building 82771	Unclassified	Row Total	Class Total
Final State 2007	Unclassified	0	0	0	0	0	0	0	0	0	0	0
	BlueTarp [Red] 11643 points	12.54	9852.65	909.24	168.9	5727.38	280.01	612.97	1613.26	0	19176.95	19176.95
	GreenVeg [Blue] 217878 points	734.12	1449.66	853996.7	5924.98	278471.8	42715.24	81681.1	54252.87	0	1319226	1319226
	FEMA [Yellow] 5431 points	7.15	505.76	8602.36	20047.36	18036.38	1778.81	5683.81	20204.27	0	74865.91	74865.91
	House [Maroon] 60076 points	42224.52	20383.76	273226.54	7397.4	871748.3	33036.32	88506.03	61054.21	0	1397577	1397577
	RedRoof [Purple] 22430 points	195.1	2091.8	91269.62	1136.85	56994.06	43854.6	17327.44	10439.89	0	223309.4	223309.4
	Pavement/Dirt [Aquamarine] 38137	247.4	3755.33	342503.59	11038.18	343169.3	45943.71	208760.19	124946.9	0	1080365	1080365
	Building [Sienna] 184336 points	24.34	2374.69	14276.97	11425.12	69671.06	3625.82	21454.38	60246.97	0	183099.4	183099.4
	Masked Pixels	2997630	49.8	5442.26	52.21	2643.56	636.76	1787.92	1961.46	0	3010204	3010205
	Class Total	3041075	40463.45	1590227.3	57191.02	1646462	171871.3	425813.84	334719.8	0	0	0
	Class Changes	43445.18	**30610.81**	**736230.58**	**37143.66**	**774713.5**	**128016.7**	**217053.65**	**274472.8**	0	0	0
	Image Difference	-30870.6	**-21286.5**	**-271000.9**	**17674.9**	**-248885**	**51438.09**	**654550.78**	**-151620**	0	0	0

Table 3 shows that about 50% of the total pixels for green veg, housing, and pavement had no change from the initial state to the final state, however, blue tarps had only 25% of total pixels with no change. The majority of the blue tarp class seems to have changed from blue tarp to housing class. The blue tarp class also had the highest percentage decrease in the number of equivalently classed pixels. Around 20% of all the pixels in the green veg class, FEMA, housing and red roof classes were classified as pavement in the final state. A large percentage of pixels went from the housing class to green veg or pavement class. According to the image difference, the pavement class increased the total number of pixels by over 150%.

Spatially, the change detection statistics allow an examination of areal change from initial state of each class to the final state of each class. According to Table 4, the total area classified as housing decreased by -248,884.74 square meters. The total area of blue tarps and green vegetation also decreased. But the total area of pavement class and, FEMA class, and red roof class each increased. The total area of the pavement class increased by 654,550.78 square meters, while the building class area decreased by a total of -151,620.46 square meters. Despite the overall accuracy of the individual classifications, the change detection statistics describe some of the expected changes on the ground.

Discussion and Conclusions

It is evident based on the above tables that recovery is taking place in terms of changes on the ground. As was the assumption, the total number of pixels classified as FEMA trailers increased. As recover progressed in the early stages and as people returned home to Lower 9th Ward, the number of FEMA trailers increased in New Orleans and the surrounding areas. By 2007, the debris had been removed from many of the areas devastated by flooding and a number of destroyed houses had also been demolished. This may explain why there was a decrease in the total area for the housing class, and an increase in total area for pavement class. Many houses were demolished leaving only the house foundation which may be classified as pavement. And with less rooftops, the total percentage of pixels identified as housing also decreased. According to Table 3, 50% of pixels classified as blue tarps in 2006 represent rooftops that have been repaired and were then classified as houses in 2007.

It is clear that the classification and change detection performance would be enhanced if different tools and methods were included in the training datasets for the classification. The quality and quantity of training data are crucial to produce satisfactory change detection results. Employing spatial pattern (texture) analysis to extract texture features may distinguish between rooftops and pavement, or trees and debris. In addition, principal components analysis can be applied to further exploit the variation between pixels.

This study demonstrates that it is possible to use aerial images and classification methods to detect change and measure and monitor long term recovery progress. Maximum likelihood classification, and change detection were applied to multi-temporal high resolution aerial images to quantitatively measure change within the seven classes. The indicators of recovery identified for this study were FEMA trailers, housing (identified by rooftops), green vegetation, blue tarps, red rooftops, buildings and pavement. This approach identified blue tarps and FEMA trailers as strong indicators which are more likely to have a strong impact on recovery assessment and progress detection then housing and buildings. However, with enhanced classification and change detection methods, such as texture analysis and principal components analysis, other indicators can be exploited as well. Although the methods employed in this study provided sufficient results, future efforts will include more imagery, and increase the number of recovery indicators.

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