Remote Sensing in Natural Resources Mapping: Land Cover Change Analysis of Nairobi, Urbanization and Rising Frequency of Flooding

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ABSTRACT

More frequent flooding is becoming a serious problem in Nairobi, causing millions of dollars in damages and in some case, loss of life. With the increased likelihood of heavy rainfall events due to climate change, understanding the causes of flooding are key to mitigation and prevention. This report uses remotely sensed Landsat satellite imagery to determine the land cover change to urban from 1986 to 2016. During this time period, urban land cover increased 13 percent, resulting in the loss of rangeland and vegetation/agriculture land cover. Action must be taken to alleviate the causes of flooding as soon as possible, and in the future more thoughtful urban planning is needed as the city continues to expand.

BACKGROUND

Nairobi is located in southern Kenya (Figure 1) and is not only the capital of Kenya, but also the largest city in the country. The city's population has grown rapidly since the 1970s (Figure 2) with over 3.1 million residents as of the 2009 census. Nairobi started off as a railway depot, connecting Mombasa and Uganda. The land turned to mud during the wet season, and drainage became a serious problem left unaddressed until the 1948 master plan. The plan set aside open spaces and riparian areas to help absorb the excess rainwater. Increased urbanization has reduced the amount of space available to absorption, leading to increased frequency and severity of flooding.

Figure 1. Location of Nairobi in Kenya.

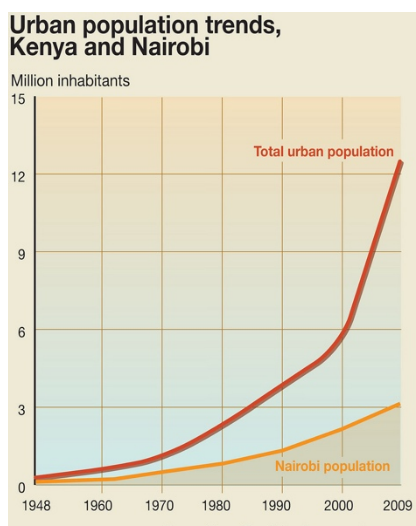


Figure 2. Population growth of Nairobi.

Flooding and mudslides following periods of heavy rainfall cause damage to infrastructure, contaminate the city's drinking water supply, wash out food crops and livestock, and can lead to loss of life. In 2016, two major flooding events occurred within one month of each other. Building and perimeter wall collapses led to 25 deaths between the two floods, as well as two additional deaths due to drowning.

Although there are several factors contributing to the increased frequency and severity of flooding and mudslides in Nairobi, this report will focus on increased urbanization. Land cover change from 1986 to 2016 will be determined using the post classification approach to estimate the increase of urban land cover. The study area includes the county of Nairobi.

SATELLITE DATA USED

Landsat data were used because of ease of access, affordability and historic archives of imagery. Two Level-1 Landsat multispectral satellite images (WRS2 Path 168, Row 61; Coordinate System WGS 1984 UTM Zone 37N) were obtained through United States Geological Survey Earth Explorer with a spatial resolution of 30 meters. The two selected images (Figure 3 and Figure 4) were acquired on 5 January 1986 (Landsat 5 TM) and 24 January 2016 (Landsat 8 OLI).

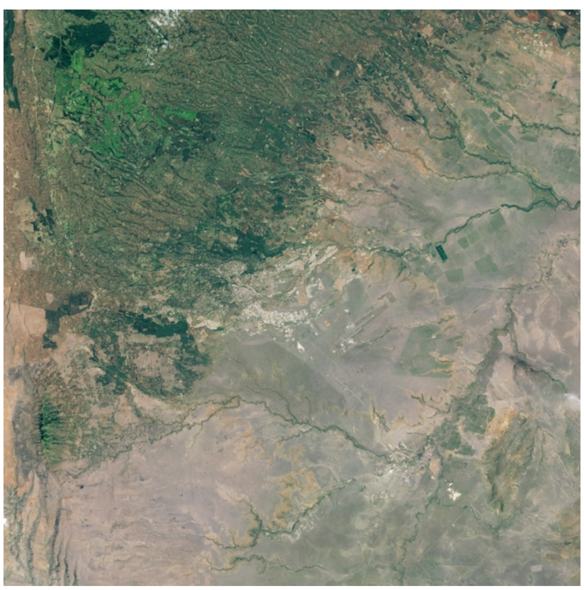


Figure 3. Landsat 5 TM image
from 5 January 1986.

Figure 4. Landsat 8 OLI image
from 26 January 2016.

IMAGE PREPARATION

Bands 1 – 5 were used for the 1986 image, and bands 2 – 6 were used for the 2016 image. Both images were subset in ArcGIS using the boundaries for Nairobi County (see Figure 5 for year 2016). Histogram matching was performed in ERDAS Imagine with the 1986 image matched to the 2016 image using all bands (Figure 6). This was done not only to aid in change detection, but also because reference data was not available for 1986, and knowledge gained from the 2016 classification and accuracy assessment was used for the1986 classification and accuracy assessment. Greener vegetation is present in the 2016 image due to a rainy El Niño cycle (NASA 2016).

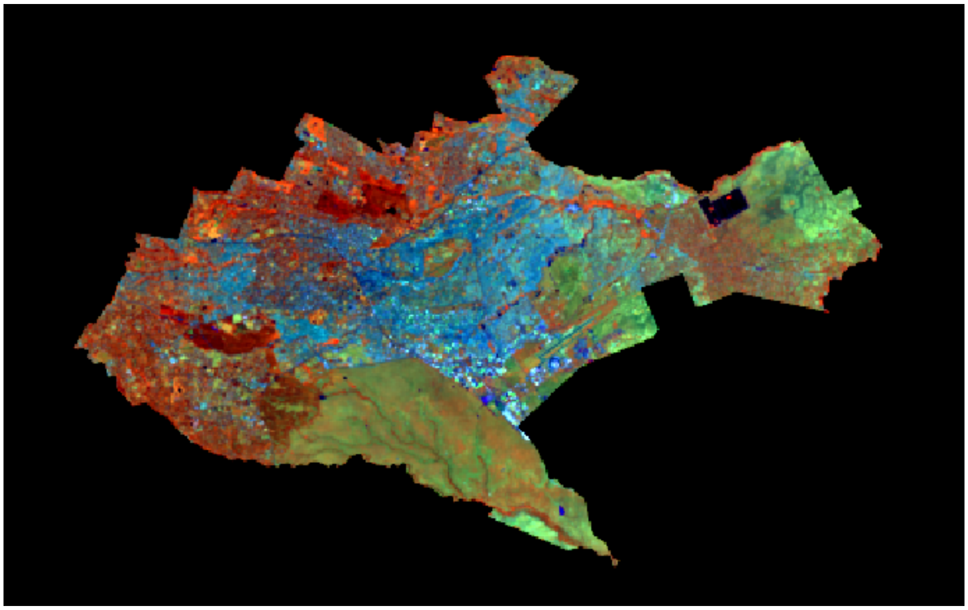


Figure 5. False color (5, 6, 4 in R, G, B) of study area (year 2016).

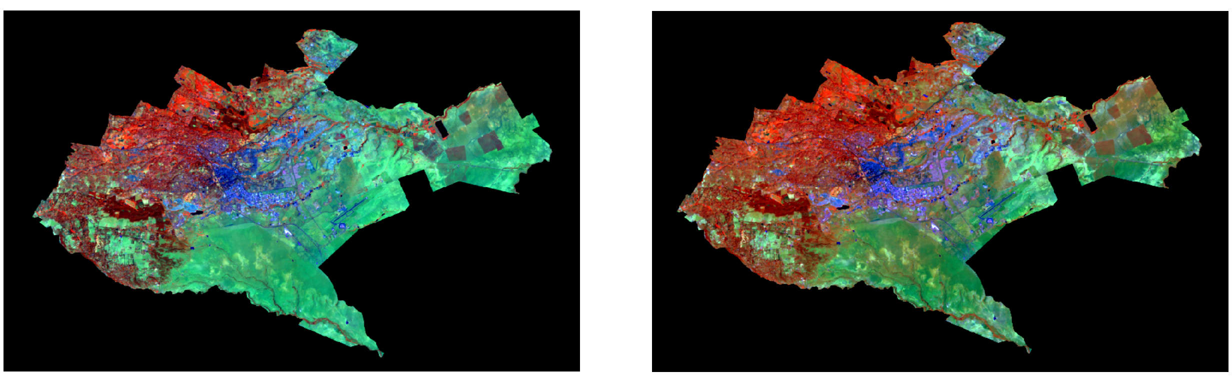


Figure 6. False color (4, 5, 3 in R, G, B) of study area before (left) and after (right) histogram matching (year 1986).

CLASSIFICATION AND CHANGE ANALYSIS

The unsupervised classification was performed using the ISODATA algorithm in ERDAS Imagine. This algorithm uses the spectral distance and iteratively classifies the pixels, redefining and reclassifying the pixels with each iteration, until spectral patterns emerge. For this process 100 classes were produced using 50 iterations and a convergence threshold of 0.99. From the 100 classes, five separate land cover classes were selected for the project: forest, vegetation and agriculture, urban, rangeland and water. A limited number of classes were selected because the focus of this project was urbanization.

The supervised classification was carried out in ERDAS Imagine using the maximum likelihood classifier. Supervised classification was first performed on the 2016 image, and training signatures were selected using Google Earth as a reference. A total of 15 signatures were selected for the 2016 image in order, with multiple signatures for all classes except urban, to achieve the most accurate classification. Fifteen signatures were also selected for the 1986 image, with multiple signatures for all classes. After the classification was performed, classes for the same land cover were recoded and merged into one class. Signature separability reports can be seen in Table 1 (year 1986) and Table 2 (year 2016). Results of the supervised classification can be seen in Figure 7 (year1986) and Figure 8 (year 2016).

Table 1. Best average separability for 1986 image training signatures (R – Rangeland, F – Forest, W – Water, V/A – Vegetation/Agriculture, U – Urban; number indicates multiple signatures for class).

	F	R2	R3	W1	V/A1	V/A2	R4	R5	R6	V/A3	U1	U2	U3	W2
R1	4868	2682	858	10834	1977	7264	2701	1402	2200	6961	4912	3992	4059	10109
F		7327	4083	8649	3382	5716	5857	5215	4591	6175	7888	6646	6094	8984
R2			3394	12812	4111	8631	4093	2200	4133	8080	3702	3378	4574	11449
R3				10150	1504	6997	2737	1668	1875	6810	5041	4161	3787	9504
W1					10688	14301	9253	11421	8937	14803	12460	13050	9026	4179
V/A1						5532	4224	2025	3119	5384	5364	3810	4655	10110
V/A2							9662	6972	8491	1068	9428	6935	9766	14225
R4								3685	1750	9486	5883	6089	3606	8649
R5									2986	6607	3747	2694	3772	10290
R6										8411	5430	5139	3053	8188
V/A3											9044	6470	9671	14577
U1												2991	3570	10130
U2													4841	11292
U3														7009

Table 2. Best average separability for 2016 image training signatures (R – Rangeland, F – Forest, W – Water, V/A – Vegetation/Agriculture, U – Urban; number indicates multiple signatures for class).

	F2	U	R1	R2	R3	W1	V/A1	V/A2	W3	W3	R4	W4	W5	W6
F1	1100	7017	3928	3883	2977	9536	10522	6799	9145	7864	5470	5972	8432	9694
F2		7688	3985	4396	3690	10522	9466	5765	10132	8807	5599	6942	9163	10690
U			5164	4118	4225	10628	14434	11038	10223	9485	4837	8697	7633	9360
R1				1773	2456	12077	9889	6418	11671	10579	1648	8850	9972	11723
R2					1300	10693	11595	8041	10302	9350	2248	7641	9124	10346
R3						9652	11765	8087	9246	8202	3417	6545	8034	9309
W1							19873	16193	474	2049	12922	3701	7000	2686
V/A1								3758	19470	18031	10644	16348	16961	19800
V/A2									15786	14370	7453	12676	13516	16114
W3										1625	12529	3385	6580	2434
W3											11568	2517	5602	2807
R4												9880	10834	12460
W4													6680	4803
W5														4939

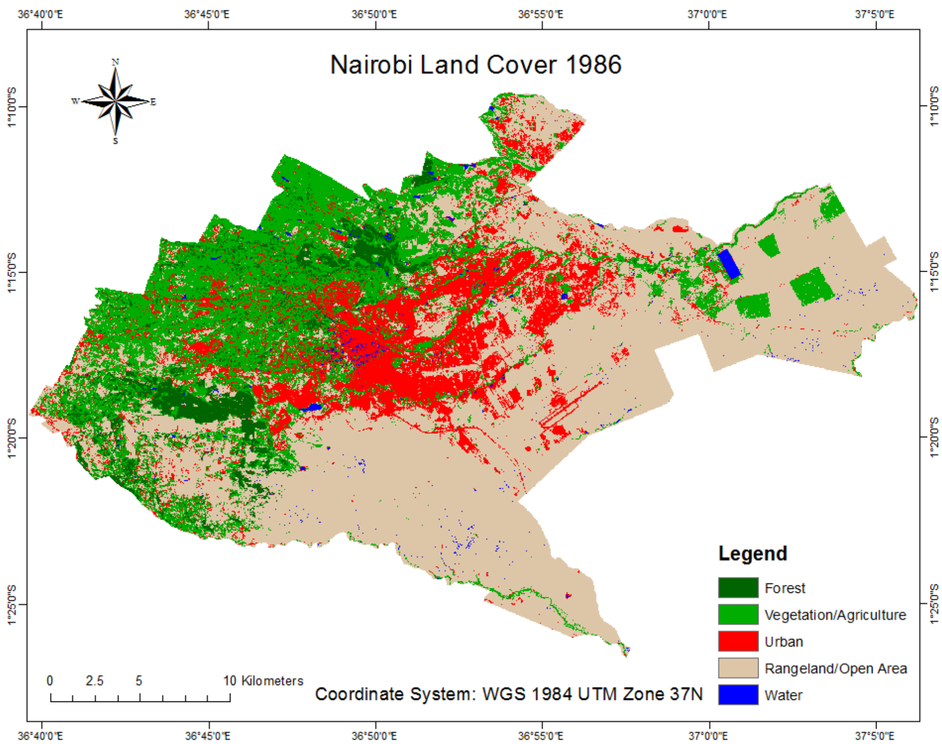


Figure 7. Supervised classification of 1986 image.

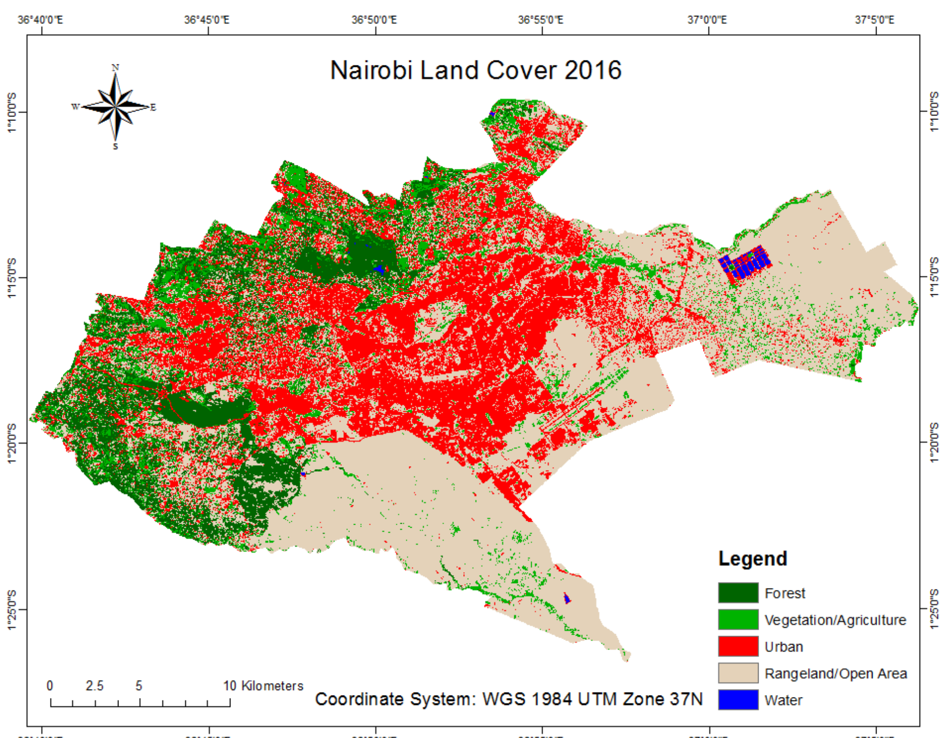


Figure 8. Supervised classification of 2016 image.

After the recoding of the classes, an accuracy assessment was performed using 50 random points for each class (equalized random). Google Earth was used to verify the reference points for the 2016 image (Figure 9), and the knowledge gained of the class and its associated pixel colors was used to verify the 1986 image reference points.

Figure 9. Image Nairobi from Google Earth.

The overall accuracy for the 1986 classification was 83.6 percent, and 78.4 percent for the 2016 classification. The overall kappa coefficient for the 1986 classification was 0.7950, and 0.7303 for the 2016 classification. The results of the accuracy assessments can be seen in Table 3 (year 1986) and Table 5 (year 2016), as well as the kappa coefficients in Table 4 (year 1986) and Table 6 (year 2016). Because of the presence of greener vegetation in the 2016 image, the accuracy of the rangeland classification was low due to the signature overlap between rangeland and vegetation/agriculture (Figure 10).

Table 3. Accuracy assessment results for 1986 image.

	Forest	Veg/Ag	Urban	Rangeland	Water	Total
Forest	39	6	3	1	1	50
Veg/Ag	7	40	1	2	0	50
Urban	5	4	40	1	0	50
Rangeland	1	1	1	47	0	50
Water	0	0	6	1	43	50
Total	52	51	51	52	44	250

Table 4. Kappa coefficients for 1986 accuracy assessment.

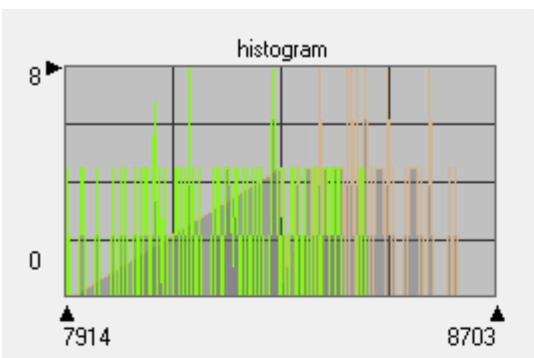
1986	Kappa
Forest	0.7222
Veg/Ag	0.7487
Urban	0.7487
Rangeland	0.9242
Water	0.8301
Overall	0.7950

Table 5. Accuracy assessment results for 2016 image.

	Forest	Veg/Ag	Urban	Rangeland	Water	Total
Forest	34	13	2	1	0	50
Veg/Ag	5	41	0	4	0	50
Urban	1	0	42	4	2	49
Rangeland	0	15	6	29	0	50
Water	0	0	0	0	50	50
Total	40	69	50	38	52	249

Table 6. Kappa coefficients for 2016 accuracy assessment.

	Kappa
Forest	0.6190
Veg/Ag	0.7514
Urban	0.8000
Rangeland	0.5047
Water	1.0000
Overall	0.7303



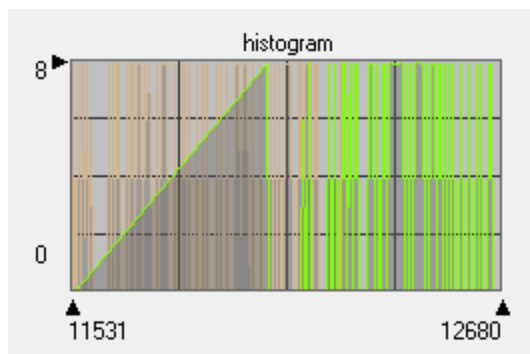


Figure 10. Histograms of rangeland and vegetation/agriculture signatures
for green band (left) and shortwave infrared (right).

Post-classification change detection was performed using the cross tabulation technique. This technique was chosen because it gives the size of the changed areas as well as the percentages of land cover classes that changed in each individual land cover class.

RESULTS

The statistical results from the land cover change cross tabulation can be seen in Table 7. In 1986 only 16 percent of the land cover was urban, compared to 29 percent in 2016. Although some portion of each land cover was converted to urban from 1986 to 2016, rangeland changed the most. Out of the 12,862 hectares converted to urban, 7,661 of those is rangeland. Vegetation/Agriculture is the second most affected land cover with 4,561 hectares converted to urban. A land cover change map was generated using the matrix union function in ERDAS Imagine to visualize the land cover change (Figure 11).

Table 7. Cross tabulation analysis results of land cover change from 1986 to 2016, in percentage of land cover change and hectares changed (horizontal axis – 1986 classes, vertical axis – 2016 classes).

Percent Change

	Forest	Veg Ag	Urban	Rangeland	Water
Forest	72.20%	25.26%	2.67%	4.33%	6.60%
Veg Ag	8.08%	28.96%	3.16%	6.87%	9.87%
Urban	11.42%	27.15%	71.87%	19.97%	42.33%
Rangeland	7.83%	28.55%	22.27%	68.52%	30.63%
Water	0.46%	0.08%	0.03%	0.31%	10.58%

Hectares Change

	Forest	Veg Ag	Urban	Rangeland	Water
Forest	2656	4243	293	1662	34
Veg Ag	297	3184	347	2636	51
Urban	420	4561	7887	7661	220
Rangeland	288	4796	2444	26288	159
Water	17	14	3	120	55

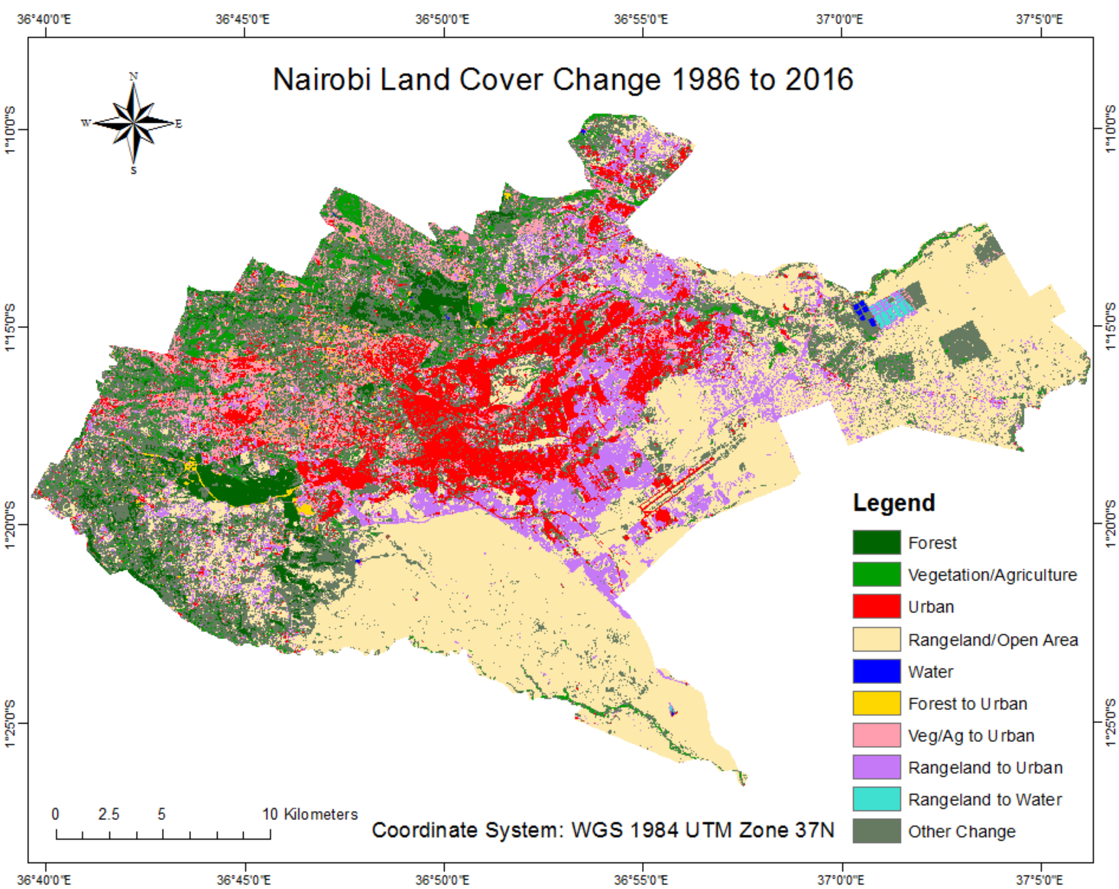


Figure 11. Land cover change from 1986 to 2016.

CONCLUSIONS

This study shows that land cover maps derived from remotely sensed satellite images are effective for detecting land cover changes. The increase of urban areas increases impervious surfaces and decreases water absorption areas. With a 13 percent increase in urban areas, not only is flooding more likely to occur, but it is more likely to affect the residents of Nairobi, as many residents are located near sources of flooding. Proper drainage in the urban areas, removing river flow obstructions, and relocation of slums along the riverbanks are possible solutions to the current flooding problem. Future work on hydrological studies, and watershed and run-off models could be done to aid decision makers and planners to mitigate or prevent heavy flooding in the city.

REFERENCES

NASA – National Aeronautics and Space Administration, Earth Observatory. (2016) "Nairobi Swells with Urban Growth." www.earthobservatory.nasa.gov/IOTD/view.php?id=88822. Accessed 19 April 2017.