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REMOTE SENSING OF POTENTIAL MOSQUITO BREEDING SITES

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Abstract:

Human-induced changes in hydrology (e.g., creation of stagnant water) are pervasive and are inextricably linked to processes that affect national health and disease control in myriad ways. The causal relationships between mosquitoes, stagnant water and malaria are well appreciated among scientists, however the contribution of neglected swimming pools to the stock of stagnant water is largely unknown in Harare. Although Harare is not a malaria risk area, one of the major fears associated with climate change is the emergence of deadly tropical vector borne diseases (e.g., malaria) to areas previously free from those diseases. In this work we used a combination of field-based survey techniques and object-based image analysis (OBIA) of GeoEye-1 imagery to identify neglected swimming pools in Harare. Our object-based image classification algorithm achieved a very high accuracy (overall accuracy 92% and overall Kappa Coefficient 70%) in extracting neglected swimming pools and showed that thirty-seven percent of swimming pools in Harare are neglected. The average age of the neglect is 9.6 ± 4.2 years. We hypothesize that in the event of climate change-induced emergence of malaria in previously malaria-free areas, malaria vectors (e.g., Anopheles gambiae mosquitoes) may use neglected swimming pools as opportunist stages for oviposition. Our results upgrade the database for potential breeding grounds for mosquitoes, support malaria control efforts and highlights the utility of geo-information and remote sensing science to disease control.

Keywords: Remote sensing science, changes in hydrology.

1.0 INTRODUCTION

Mosquitoes are vectors which are responsible for spreading the protozoan parasites which cause some of the most devastating diseases to humans in tropical regions (Beck-Johnson, 2013). Those diseases include malaria (Snow, 2001), dengue fever (Hemingway, 2009), chikungunya (Weaver, 2015), zika virus (Hayes, 2009), yellow fever and filariasis (Beck, 2000). Mosquito-transmitted diseases affect millions of people throughout the world, for example half the world's population is at risk of malaria (WHO, 2016). In 2015 alone, human mortalities associated with malaria were estimated at ~429 000 and malarial cases were roughly 212 million. However global mortalities resulting from malaria have been going down in the past 10 years due to increased prevention and control measures. Despite the reduction in malarial cases and deaths, Sub-Saharan Africa continues to carry a disproportionately high share of the global malaria burden. It recorded 90% of malarial cases and 92 % of malarial deaths in 2015 (GHO, 2017). In many countries in sub-Saharan Africa, malaria is the third of illness and mortality (Mabaso, 2005).

The mosquito species that transmit the deadly protozoan parasite which causes malaria breed under specific environmental conditions including in lotic aquatic conditions (Morse, 2001). In those aquatic conditions, oviposition, hatching and larva success is influenced by a myriad of factors including sun exposure, temperature, nutrient load, and pH (Kling, 2007). Thus, mosquito breeding grounds types are categorized into open habitats (water bodies exposed to open air and light) and closed habits (water in closed and dark environments for example pit latrines, soakage tanks and septic tanks) (Fillinger, 2008). For example, drains and ditches when blocked by litter may hold back stagnant water which provide breeding grounds for mosquito (Patz, 2000). Additionally, puddles and vehicle tyre tracks depressions which hold water serve as potential mosquito breeding sites (Mutuku, 2006) as well as containers for ornamental plants and flowers and drinking pans for animals (Barrera, 1995). According to (Reisen, 2008) neglected or unmaintained swimming pools are also potential mosquito breeding sites in urban areas.

Understanding the mosquito breeding sites in any human habitat is important for the control of mosquito transmitted diseases (Stephens, 1995). A variety of prevention mechanisms including draining of water ponds are used to limit mosquito breeding potential (Schweigmann, 2010). In swimming pools, mosquito breeding is controlled by the application of chemicals such as chlorine as well as filtration of the water to remove mosquito eggs as well as the physical removal of allotchthonous and autochthonous nutrient sources (Govender, 2007). For various reasons, many of them economic, swimming pools are often neglected so become potential habitat for mosquito to survive and reproduce (De Silva, 2012). It is estimated that tens of thousands of adult mosquitoes could emerge from a single pool every night (McFeeters, 2013). Many urban suburbia have thousands of swimming pools, but the location and condition of those swimming pools remain unknown.

Many studies have integrated Remote Sensing and Geographic Information System technologies in an effort to detect neglected and maintained swimming pools in urban areas (McFeeters, 2013) In recent years remote sensing of water using very high spatial resolution satellite imagery has become available with pixel sizes similar to those of aerial photographs (Minho, 2011). Thus, it is possible to detect and isolate swimming pools from other features on a satellite image (McFeeters, 2013). Additionally, it is possible to go a step further and distinguish between properly maintained versus neglected swimming pools using algorithms designed for the remote sensing of water (Wolf, 2012).

There are many algorithms designed for the remote sensing of water. For example, the Normalized Difference Water Index (NDWI) (Gao, 1996) which provides good detection of open sources of water, Modified Normalized Difference Water Index (MNDWI) (Han-Qui, 2005) which produces better results, as it reveals subtle features of water more efficiently than NDWI or other visible spectral bands do, due largely to its wider dynamic data range, (Supervised SVM) which detects water from the classification of Aerial RGB Images (Zebedin, 2006), Principal Component Analysis (PCA) (Wold, 1987), which is a technique used for production of uncorrelated output bands, segregation of noise components and reduction of dimensionality of data set. The detection of swimming pools has been achieved with Spectral Angle Mapper (SAM) (Govender, 2007), using a multi-spectral satellite image but it requires an accurate training site to work properly. More recently, the Normalized Difference Swimming Pool Index and Dumpster Shafer Theory (Rodríguez-Cuenca, 2014) have been formulated to identify swimming pools by differentiating them from all other features in a satellite imagery.

All the methods and algorithms mentioned above utilize multiband-high spatial resolution images which are difficult to impossible to get for developing countries. As such, there is need to invent new methods that depend on satellite image data which can easily be available at the appropriate resolution for developing countries. Such data includes 50 cm-1m resolution RGB-only imagery provided 'freely' on the Open Map Layers platform. However native remote sensing operations using those data are not straight forward. This study focuses on designing an algorithm that differentiates maintained and neglected swimming pools from Open Map Layers RGB-only imagery using Harare as a case study. Swimming pools have been recognized as potential breeding grounds for mosquitoes by the public health authorities and research in different countries (Schweigmann, 2010; McFeeters, 2013). The number of neglected swimming pools increase during times of financial crisis and economic hardships. Many studies have integrated GIS and Remote Sensing technologies in an effort to detect neglected and maintained swimming pools in urban areas (Minho, 2011). In recent years, remote sensing very high spatial resolution satellite (VHSR) imagery have become available with pixel sizes similar to those aerial photographs. Several studies have explored swimming pools extraction from aerial photographs and very high spatial resolution imagery and achieved satisfactory results. However, the use of such imagery in developing countries is limited by the cost constraint. As such there is need to find cheaper and appropriate technologies for detecting swimming neglected swimming pools for mosquito abatement programmes in developing countries.

Finding an economic way of detecting neglected swimming pools will generate information that will improve the monitoring and eliminating the potential mosquito breeding sites. Such information will help public agencies, insurance companies, private companies, fire brigade and banks can benefit greatly from the identification of properties that contain swimming pools. The main objective of this study is to detect and map neglected swimming pools in from RGB-only imagery provided on the Open Map Layers platform

2.0 STUDY AREA

The study was conducted in the Harare Metropolitan City which lies on the high veld region of Zimbabwe at an altitude of 1449m with humid subtropical (Ndamba, 2004). Harare lies between latitude 17^0 49^I and longitude 31^0 04^I. During the winter season the temperature ranges between 16^{0}C and 23^{0}C (Kutsaga, 2017) with the coldest month in July with an average temperature of 13^{0}C. November is the hottest month with an average daily temperature of 22^0 C (Kutsaga, 2017). Precipitation which is largely in the form of rainfall is received from November to April with a long-term annual average of 986mm, two thirds of that being received in January and February (Mabasa, 2014). The cool dry season starts in May and ends in October (Kutsaga, 2017). Several perennial streams flow through Harare Metropolitan including Gwebi, Marimba and Mukuvisi and drain into Cleveland, Hunyani and Price Edward and Chibero lakes (Musemwa, 2010)

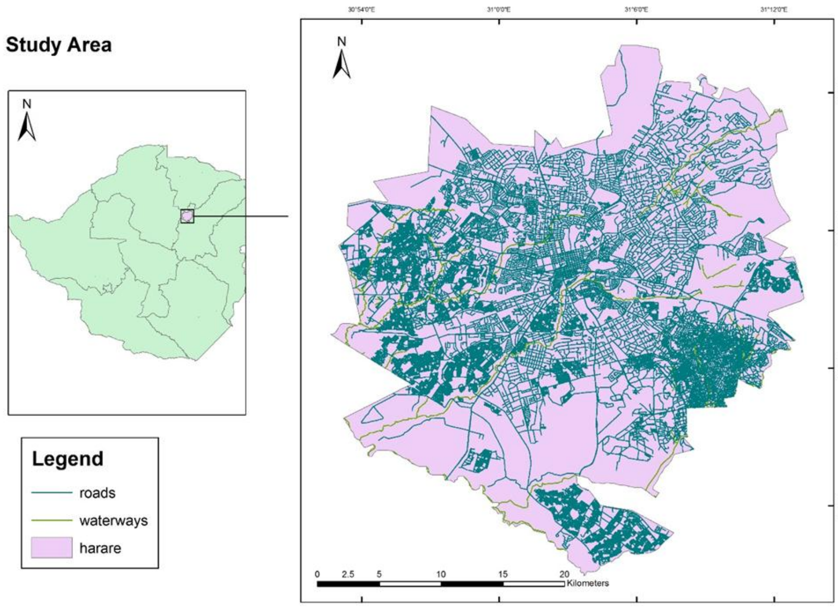


Fig. 1: The Study Area, Harare, Zimbabwe

The population of the city was estimated at 2.2 million in 2012 (Zimstat, 2012), and it is the fastest growing city in Zimbabwe. The country has recently experienced a financial crisis that has caused closures of industries and companies with Harare having the most population engaged in informal economic activities (Chipunza, 2016). The last survey conducted four years ago by Zimstat, pegged unemployment rate at 11% and has been criticized as a gross underestimate of the problem. This figure is based on the belief that the number of people in informal sector, mainly vendors, are considered employed (Kwaramba, 2016). As a result, recent economic downturn cause difficulties for residents with swimming pools to maintain their swimming pools. The cost of living became expensive for them to install liquid chemical feeders, salt chlorinators, pool heating equipment and purchase pool testing kits (Mathew, 2017). All these factors in turn increase the possibility of neglected swimming pools to be suitable potential mosquito breeding sites. Urban water crisis also lead to abandonment of swimming pools as the supply of water continues to decline (Musemwa, 2010). Due to economic hardships some people are negligible to maintain the acquired properties hence result in neglected swimming pools (Muchemwa, 2013). Considering the magnitude of the abandoned swimming pool problem, we selected the Harare northern medium and low residential suburbs for this research where almost 95% of the residential houses owns a swimming pool. Our study area contained a mixture of water bodies, natural environment as well as residential and industrial buildings. The urban classes of our satellite images consist of metal roofs, dark-toned concrete/ asbestos roofs, roads, swimming pools, ponds, trees, shadow, bare ground and grass. Figure 1 below shows the map of the study area.

3.0 METHODOLOGY

3.1 DATA SETS USED IN THE STUDY

GeoEye (RGB only) satellite imagery acquired on 27 October 2016 from Earth Explorer 1.65m spatial resolution, RGB-only imagery available on the Open Layers platform was used for this study. We used the QGIS functionality to download the image in 500-m2 tiles and merged the files before processing. Figure 2 shows GeoEye-1 satellite imagery used in this study.

Figure 2: Geoeye-1 image used for detection of maintained and neglected swimming pools.

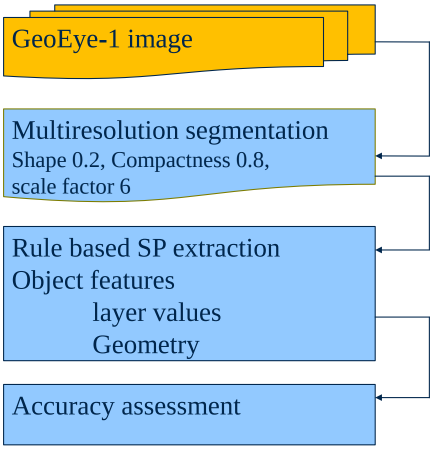
3.2 DIGITAL IMAGE CLASSIFICATION

According to (Weih, 2015) Digital Image Classification refers to grouping pixels or extracting information to form classes from a multiband raster image to represent land cover features. The resulting raster from image classification can be used to create thematic maps. Land cover could be forested areas, urban settlements, agricultural and other types of features in space. Common techniques of classification include supervised, unsupervised and Geographic Object Based Image Classification (GEOBIA) (Wang, 2004).

3.3 CHOICE OF IMAGE CLASSIFICATION METHODS

A study from the University of Arkansas compared object-based vs pixel-based classification (www.gisgeography.com, 2017) using colour infrared high spatial resolution aerial imagery and medium-spatial resolution satellite imagery. Overall, geographic object-based classification out-performed both unsupervised and supervised pixel-based classification methods in that study. The higher accuracy was attributed to the fact that geographic object-based image classification took advantage of both spectral and contextual information in the remotely sensed imagery (Weih, 2015). Thus, in this study GEOBIA was used because of its accuracy in classification.

3.4 GEOBIA IMAGE CLASSIFICATION



We used eCognition software to detect the neglected swimming pools using GEOBIA, an image segmentation approach. Geographic object-based image classification generates objects of different shapes and scale. GEOBIA steps are to perform multi-resolution segmentation, define statistics and classification (gisgeography.com, 2017). Multi-resolution segmentation produces homogeneous image objects by grouping pixels. Objects were generated with different scales in an image simultaneously. We classified these objects based on texture, context, shape and scale. Object-based image analysis supports the use of RGB-only images for segmentation and classification. The statistics to classify image objects were defined. After defining statistics eCognition then classifies objects based on statistics defined. For this study we used the following procedure.

3.5 IMAGE SEGMENTATION

In this study, GEOBIA was adopted to extract swimming pools from GeoEye-1 satellite imagery. We utilized the number of pixels within an image object to estimate the physical area of each segment by applying Trimble eCognition® Developer (version 8) for segmenting and deriving relevant spectral and spatial attributes of each image object. The most important part of GEOBIA is segmentation and we used multiresolution segmentation as an algorithm. Image objects were created whereby pixels are grouped in numerous iterative steps, smaller image objects were merged into larger ones until a given threshold was reached. On one hand, applying a low segmentation scale will create too many small image objects, which is termed over-segmentation (Blaschke, 2010). On the other hand, very high segmentation scale produces a few large image objects representing different land-cover classes, which is termed under-segmentation. A low segmentation scale was used to preserve the feature boundary. Multiresolution segmentation parameters used were shape 0.2, scale parameter 40, compactness 0.8, and scale factor 6. Figure 4 below shows multi-resolution segmented image.

Figure 4: Multiresolution segmentation algorithm used to differentiate landcover classes.

The RGB-only imagery plays an important role in separating a targeted feature from background or non-targeted features. However, our initial analysis showed that the spectral reflectance of swimming pools especially neglected pools was close to that of the other landscape features such as building rooftops and roads as shown in Figure 2

We also utilized the spectral signatures of both maintained and neglected swimming pools. Open water surfaces (oceans, rivers, lakes, for example.) have a characteristic of spectral signature. The highest reflectance of water surfaces in the electromagnetic spectrum occurs in the blue wavelengths (0.45 to 0.47 μm) and the greatest absorption in the infrared wavelengths (0.7 to 300 μm). Figure 5 shows the spectral signatures of maintained and neglected swimming pools. For maintained swimming pools the highest reflectance is obtained in the wavelengths corresponding to blue. Neglected swimming pools have lower reflectance occurring at the wavelengths corresponding to the R wavelengths. It was observed that neglected swimming pools could be resolved in the blue and red bands.

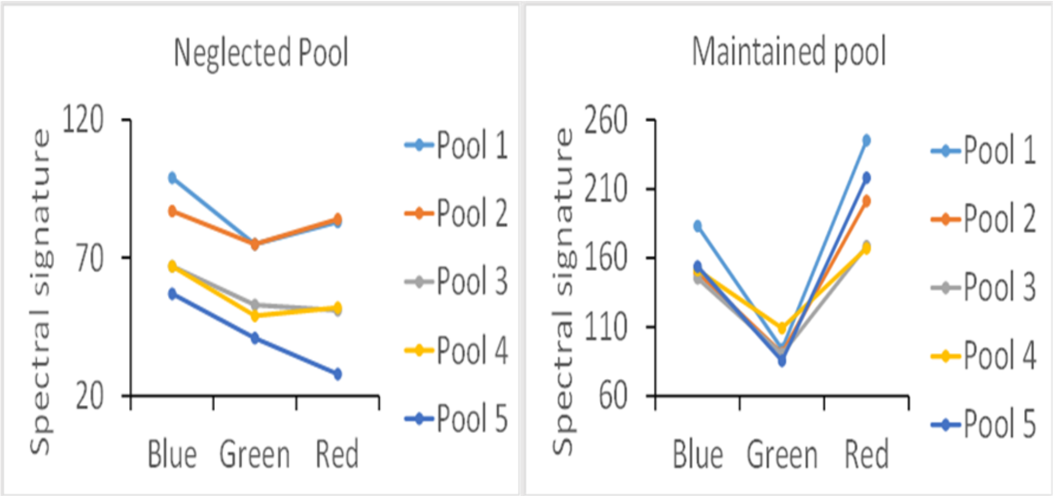


Figure 5: Spectral signatures for both maintained and neglected swimming pools.

4.0 RULE BASED CLASSIFICATION

Rule-based classification is an advanced feature extraction method by partitioning image data into land-cover classes on the basis of defined rule sets (Shafri, 2015). A rule set can be defined using one or more conditions and a combination of spatial, spectral, textural features, and indices can be considered in a rule set. We used our knowledge and reasoning in rule building to extract swimming pools. After extracted image objects from the specified segmentation parameters, we used object features to determine appropriate threshold condition which provides values of each feature across all the image. By using feature view in combination with image object information we determined appropriate threshold for separating water features from other features from the image scene. Setting the threshold condition and updating the range of water in feature view, we extracted object features which meet our criteria as shown below in Figure 6.

Figure 6: Threshold setting for feature extraction by partitioning image data into land-cover classes on the basis of defined rule sets.

Figure 6 above shows object features including shadows cast from buildings and trees also classified as water features. This is because of their spectral characteristics which are similar to those of water features but their geometry characteristics is different.

We used the area geometry to filter out shadows from the classification procedure as shown in figure 7.

Figure 7: Filtering out shadows from the classification procedure using area geometry.

Knowing that typical residential swimming pools are gular in shape and ranges from 100m2m to 200m2 in area, we filtered out narrow long rectangular objects as shown in Figure 7.

Figure 8: Growing feature objects by specifying the area geometry.

Thus, we remained with meaningful size range of objects which are close to those of average swimming pools. We then grow water feature objects specifying the area geometry to greater than <200m2. We then extracted swimming pools as shown in Figure 8.

5. ACCURACY ASSESSMENT

Accuracy assessment of the classification outputs was accomplished by the use of a standard confusion matrix which determines how well the study was able to isolate maintained swimming pools from neglected swimming pools. The overall, users and producer's accuracy and coefficient (κ) measures of the swimming pool detection method were derived from the confusion matrix by comparing the classification results with the ground truth data. Ground truth data was used as reference data for accuracy assessment. A field visit was also conducted to acquire the reference information.

6. RESULTS

Our effort detected neglected swimming pools with very high accuracy as measured with the Confusion Matrix. We obtained producers and users of over 90% for both pool and non-pool classes. The classified image achieved 91.6% overall accuracy and 0.82 Kappa. We correctly identified 451 neglected pools with an accuracy of 93%. However, some image segments were incorrectly classified as swimming pools which resulted in lower user's accuracy of 90.6% than the producer's accuracy for pools as shown in Table 1.

Table 1: Accuracy assessment of classification results for both maintained and neglected swimming pools.

Classification	Pool	Non-Pool	User's accuracy
Pool	451	47	90.6%
Non-pool	34	428	92.6
Producer's accuracy	93.0%	90.1%	

Overall accuracy = 91.6, Overall Kappa coefficient = 0.82

Figure 9 shows the object classified as neglected swimming pools using OBIA with the RGB-only image. The boundary of each classified swimming pool is delineated in red colour and a missed swimming pool at the bottom of the image missed swimming pools are not showing here. All the extracted maintained and neglected swimming pools can be located in a GIS spatial database which will expedite ground truthing.

Figure 9: Final result of swimming pool classification. Solid red represents correctly detected neglected swimming pool ovel red represent missed neglected swimming pool

7. DISCUSSION

This study is an initial step to building a spatial database for swimming pools in Harare, Zimbabwe. Our research revealed that combining GEOBIA and GeoEye-1 RGB-only imagery could be utilized to detect and map neglected swimming pools with high accuracy. In particular, GEOBIA was found to be the cost-effective method of identifying neglected swimming pools which is vital for mosquito or malaria control. GEOBIA was adopted to detect maintained and neglected swimming pools from GeoEye-1 imagery for the purpose of identifying potential mosquito breeding sites to facilitate mosquito abatement procedures and programs. The high level of accuracy may be attributed to the fact that inclusion of the spectral signature and rule-based classification yield better results. Also specifying the threshold condition in GEOBIA, pixels other than non-water features were eliminated resulting in few errors of commission and omission.

The analysis of the data correctly identified 451 residential houses that have swimming pools as having detectable surface water out of 485. The analysis failed to identify 34 residential houses that actually have swimming pools resulting in error of omission. Examination of the image data using ground trothing revealed that there was enough vegetation in the backyards of the houses to prevent the determination as to whether there was even a swimming pool present. Also, some swimming pools were covered with nets and pool blankets for safety as a result satellite missed those pools. Recent advances in sensor technology have expanded the number of spectral wavelengths regions with increased spatial and spectral resolutions which aid in acquiring information about environmental risk factors for human diseases (DigitalGlobe, 2010). For example, World View 3 is a high-resolution satellite imagery which identifies objects as small as one foot (30 cm) (Woollaston, 2014).

Our final GEOBIA classification demonstrated that shadows inherent from buildings and tress were confused with swimming pools. (Zhou, 2009) regarding the shadow issue, used an additional data set, i.e., light detection and ranging data (lidar) data, to differentiate shadows from non-shadows with high-resolution digital aerial imagery. From our research taking the size range of swimming pools into consideration facilitate the separation of pools from non-pool water bodies that are larger than pools. Besides having the spatial database of neglected and maintained swimming pools, it is crucial to continue educating residents about personal protection against mosquito bites and encourage residents to report neglected pools to vector control officers which will aid in controlling those potential mosquito breeding sites.

8. CONCLUSION

Our research established that GEOBIA could be used for accurate GIS spatial databases for detecting of both maintained and neglected swimming pools. The spectral signatures of maintained and neglected swimming pools played a crucial role in reducing classification confusion between swimming pools and non-pool features. The GIS swimming pool database is expected to assist in eliminating the mosquito breeding sites and assist in mosquito control programs. Also, public agencies, insurance companies, private companies, fire brigade and banks can benefit greatly from the identification of properties that contain swimming pools (Digital Globe, 2016). It is important to note that combining GEOBIA and multispectral high-resolution imagery may be acquired by mosquito abatement districts and analyzed by GIS technicians in those districts. The same procedures could be applied by local authorities in any urban area to save costs in identification to eliminate potential mosquito breeding sites.

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