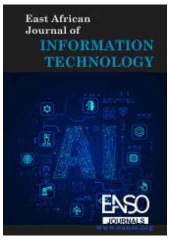


East African Journal of Information Technology
eajit.eanso.org
Volume 8, Issue 1, 2025
Print ISSN: 2707-5346 | Online ISSN: 2707-5354
Title DOI: https://doi.org/10.37284/2707-5354

EAST AFRICAN NATURE & SCIENCE ORGANIZATION

Original Article

Analysis of Urban Green Spaces Using Support Vector Machine in Urban West Region of Zanzibar

Asha Hamad[1], Yahya Hamad Sheikh, PhD[1] & Abubakar Diwani Bakari, PhD[1]*

[1] The State University of Zanzibar, P. O. Box 146, Zanzibar, Tanzania.
* Author's ORCID ID: https://orcid.org/0009-0001-7404-7480; Email: ashasharfiy@gmail.com

Article DOI: https://doi.org/10.37284/eajit.8.1.2740

Date Published:

04 March 2025

Keywords:

Machine Learning, Support Vector Machine, Urban Green Space, Remote Sensing, Classification.

ABSTRACT

Integrating remote sensing techniques with Machine learning-based methods is crucial for analyzing land spatial structures. This study employs the Support Vector Machine to analyze Urban Green Space in the Urban West Region of Zanzibar. The analysis focused on evaluating Support Vector Machine performance in remote sensing imagery classification, assessing green landscape connectivity, and examining geospatial green change trends over 10 10-year periods. The findings revealed that the accuracies of the Support Vector Machine classification exceeded 0.9, making it suitable for further analysis. Thematic maps generated from the study visualize low green connectivity with poor spatial patterns of green patches in the west of the Urban West Region, primarily due to the higher density of buildup areas. The analysis also indicates the absence of green corridors to enhance connectivity between the patches. Additionally, approximately 0.019% of green area coverage was lost between 2009 and 2018, attributed to shoreline damage along the coastal zone of the eastern side of the Urban West Region. The transition of green spaces, such as trees, shrubs, and grass, into low-density buildup areas and, subsequently, into high-density buildup areas was significant. This transformation poses potential challenges, including increased air pollution and mental health concerns. To address the green challenge issues, the Urban Municipalities of Zanzibar must implement robust strategic plans to preserve and enhance Urban Green Space; such initiatives are essential for promoting sustainable urban development in Zanzibar and mitigating the adverse effects of urbanization on green spaces and overall environmental quality.

APA CITATION

Hamad, A., Sheikh, Y. H. & Bakari, A. D. (2025). Analysis of Urban Green Spaces Using Support Vector Machine in Urban West Region of Zanzibar. *East African Journal of Information Technology*, *8*(1), 13-21. https://doi.org/10.37284/eajit.8.1.2740

CHICAGO CITATION

Hamad, Asha, Yahya Hamad Sheikh and Abubakar Diwani Bakari. 2025. "Analysis of Urban Green Spaces Using Support Vector Machine in Urban West Region of Zanzibar". *East African Journal of Information Technology* 8 (1), 13-21. https://doi.org/10.37284/eajit.8.1.2740.

Article DOI: https://doi.org/10.37284/eajit.8.1.2740

HARVARD CITATION

Hamad, A., Sheikh, Y. H. & Bakari, A. D. (2025) “Analysis of Urban Green Spaces Using Support Vector Machine in Urban West Region of Zanzibar”, *East African Journal of Information Technology*, 8(1), pp. 13-21. doi: 10.37284/eajit.8.1.2740.

IEEE CITATION

A., Hamad, Y. H., Sheikh & A. D., Bakari “Analysis of Urban Green Spaces Using Support Vector Machine in Urban West Region of Zanzibar.”, *EAJIT*, vol. 8, no. 1, pp. 13-21, Mar. 2025.

MLA CITATION

Hamad, Asha, Yahya Hamad Sheikh & Abubakar Diwani Bakari “Analysis of Urban Green Spaces Using Support Vector Machine in Urban West Region of Zanzibar”. *East African Journal of Information Technology*, Vol. 8, no. 1, Mar. 2025, pp. 13-21, doi:10.37284/eajit.8.1.2740.

INTRODUCTION

Urban Green Space (UGS) is an essential component of urban design that provides cultural, economic, social, and psychological services for the well-being of urban dwellers Azwar & Ghani (2014). UGS balances ecology in urban areas for a complementary good standard of life by maintaining and protecting the environment and distributing air pollution. People use UGS for different purposes, including rest, restitution, and socializing. However, in most cases, they use the UGS for socializing (Peschardt, 2012).

Due to the decrease of natural areas such as green areas, particularly in urban areas, green space has become essential for sustainable development. Greenspace is applicable in various disciplines, including urban design and planning, health and medical sciences, ecology, and other social sciences, each on its own terms and depending on the objectives (Taylor & Hochuli, 2017). From the health and well-being perspective, green space is land covered with vegetation that stimulates various health activities (Lee et al., 2015). Public Health England expands the scope of green space to incorporate all vegetated lands, including both private and public spaces such as gardens, parks, playing fields, woods, children’s play areas, and other natural areas, cemeteries and allotments, disused railway lines, river and canals, green corridors, derelict, and contaminated land which has the potential to transformed (PHE, 2014).

UGS significantly improves public health by promoting health behaviours, improving social contact, giving people a sense of familiarity and belonging, supporting development and skill capabilities, and mediating potential harm (Lee & Maheswaran, 2011). Sustainable UGS needs some implementation measures to maintain and improve its quality, such as having a strategic plan for its creation and improvement. Worldwide, rapid urban population growth impacts the UGS due to increased demand for the UGS, which often contradicts an increase in residential and economic establishments. Urbanization causes degradation and fragmentation of UGS that may result in many effects such as air pollution, congested cities, and others (Mensah, 2014; Bhaskar, 2012). However, more creative and innovative urban development projects may help improve the quality and quantity of the UGS, ultimately reducing the impact of fragmentation and degradation of UGS, which usually leads to disruption of biodiversity and urban ecosystem, worsening the quality of life.

In the context of Zanzibar, rapid urbanization, particularly in the Urban West Region, presents significant challenges for urban green spaces (UGS). As the population grows, the demand for land increases, putting pressure on existing green spaces and urban planning systems. This study aims to emphasize the importance of sustainable UGS development in Zanzibar. It utilizes a Support Vector Machine (SVM) to analyze changes in green cover patterns in the Urban West region, with the objective of evaluating SVM performance in remote sensing imagery classification, assessing green landscape connectivity, and examining geospatial trends in green space changes over a 10-year period.

MATERIALS AND METHODS

The research was conducted in the Urban West region, one of the five regions in Zanzibar,

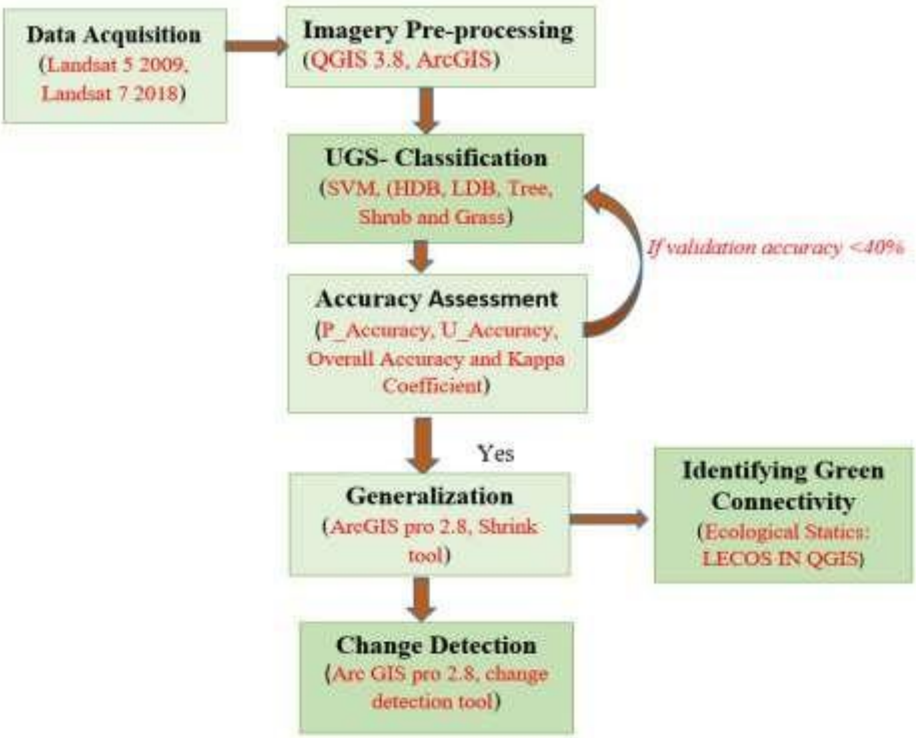
Article DOI: https://doi.org/10.37284/eajit.8.1.2740

Tanzania. The two Islands along with several small islets located 35 km off the east coast of Mainland Tanzania. Covering 2,462 sq.km (951sq.miles), Zanzibar is divided into five regions; Urban West, Unguja North, Unguja South on Unguja Island and Pemba South and Pemba North on Pemba Island. The Urban West Regions, the focus of this study, is the government and commercial hub of Zanzibar, characterized by rapid urbanization and a dense population of approximately 465,242 (47.7% of Zanzibar's population) based on the 2022 census. With an area of just 230 sq.km, the region has a population density of 2,581 people per sq. km and a growth rate of 4.2%, intensifying pressure on green spaces.

Two sets of remote sensing data were utilized, as shown in the conceptual framework (Figure 1). These are Landsat 5, which captures seven spectral bands with a 30m resolution thermal band, and Landsat 7, which offers similar features with enhanced capabilities.

Figure 1: Conceptual Framework for Data Collection and Processing

The study adopted the six-phase approach by



integrating geospatial research frameworks; these are data acquisition by obtaining Satellite imagery, data pre-processing to prepare images for analysis, segmentation, and classification where Urban green space was classified using Machine Learning methods, assessment of machine learning classification accuracy, Green Connectivity analysis by assessment of the connectivity between green patches, and identifying change detection trends of green space change over 10 years.

Classification and Map Generation

Remote Sensing Image Collection

Multispectral satellite imagery of the TM and ETM+ sensors had some related characteristics, as presented in the table downloaded from the Earth Explorer website for assessing the UGS. Many land cover studies used Landsat images, including UGS assessment and classification (Abbas & Jaber, 2020). For the UGS assessment of the Urban West Region, researchers used Landsat 5 2009 and Landsat 7 2018, and they

Article DOI: https://doi.org/10.37284/eajit.8.1.2740

downloaded satellite images that had cloud coverage, stripes of the sensors, and uncombined bands that each held specific information about t he satellite imagery. Data pre- processing was pe rformed using QGIS and ArcGIS software for band combination and selection. Different band combinations between band 1-5 and band 7 of Landsat satellite imagery with 30m spatial were used as green space cover. The composite band tool in ArcGIS was u sed by combining bands 1-5 and band 7 to get the visible satellite images. The RGB composite renderer was implemented for viewing images, and Band1, Band2, and Band3 were applied as R BG composite, respectively. The satellite images contain scan line error strips caused by Landsat ETM+ sensor malfunction for Landsat 7 2018. The scan line error strips were removed by loading the satellite image and corrected with its mask layers to remove them using raster analysis tools in QGIS3.

All data were projected to universal transverse M ercator zone 37N using 30m spatial resolution in QGIS. Then, the imagery was clipped to get an urban area by masking it with the Unguja shape file of the Zanzibar Urban West region in QGIS using a raster analysis tool.

UGS Segmentation and Classification

In this study, an object-based supervised classification workflow from ESRI was adopted. The reason for implementing object-based supervised classification was to utilize the value of the pixel and geographical inf ormation, including colour and shape, for better results as claimed by (Omar & Cabral, 2020) and Khati & Acharya, (2021). After the segmentation of images into objects, objects were assigned to f ive classes using the training manager in ArcGIS. The training schema as training samples were created. The raster images were classified into high-density build-up (HDB), low-density build-up (LDB), tree, shrub, and grass.

The classification was performed by an SVM classifier in ArcGIS. SVM decreases the empirical classification error and increases the geometric margin as suggested by Wasel et al., (2018). For this study, SVMuse and RBF were used for the UGS classification of the Zanzibar Urban West region. This is because the two approaches perform well when applied in remote sensing images due to higher dimensionality and fewer numerical problems. The results of the satellite images were validated using the accuracy assessment method in ArcGIS. This study considered the original imagery before classification as reference data for ground truth value as suggested. The compute Confusion Matrix tool was applied to produce the performance of SVM in the error matrix table.

Green landscape connectivity is the degree to which the green space facilitates movement among green patches. It is essential for the conservation of the urban environment in terms of ecosystem and biodiversity.

In this study, the structural connectivity of a UGS was assessed usi ng the LECOS plugin with QGIS and the landscape metrics by Hyseni et al. (2021) and Jung (2013). A post-classification comparison was implemented in ArcGIS using a spatial analysis tool with an image analysis extension. ArcGIS used the change detection wizard for categorical change pixels from 2009 to 2018 with a smoothing neighbourhood tool 3X3 of 3-pixel rows by 3-pixel columns.

RESULTS

SVM Validation

The SVM validation was performed after the accuracy assessment process of SVM, where 100 points were generated, which resulted in producer accuracy (P_Accuracy), user accuracy (U_Accuracy) and Kappa Coefficient. According to the result as presented in Table 1, all accuracies performance reach above 96% which is in the range of 81-100% which is classified as almost perfect, Landis and Koch (1977) assert the performance scale for Kappa coefficient that shows < 0% is poor, 0-20% slight, 21% - 40% is fair, 41%-60% is moderate, 61%-80% is substantial and 81%-100% almost perfect. Also,

Article DOI: https://doi.org/10.37284/eajit.8.1.2740

the ESRI community proclaims that all accuracies range from 1% to 100% (low to high). With this result, it was concluded that SVM demonstrated good performance and thus, the results of classification had been used for further analysis.

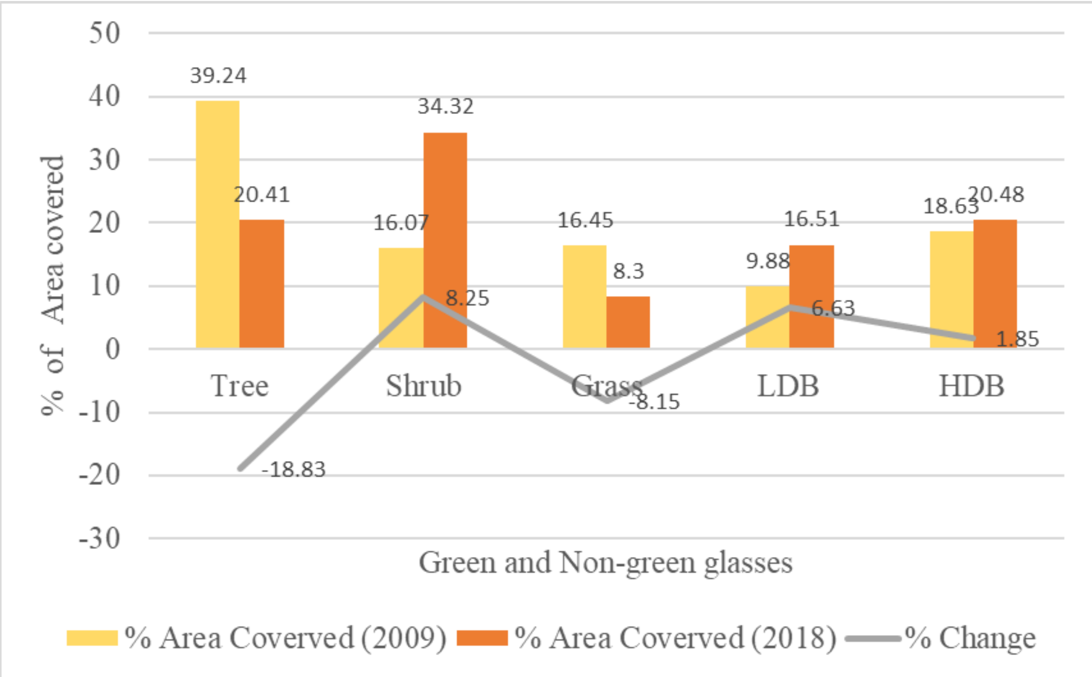
Table 1: Kappa Coefficient, Overall Accuracy, User and Producer Accuracies of SVM in Landsat 5 2009 and Landsat 7 2018.

Data	*P_Accuracy (%)*	*U_Accuracy (%)*	*Overall Accuracy (%)*	*Kappa Coefficient (%)*
Landsat 5 2009	97.38	96.43	97	96.19
Landsat 7 2018	98.82	99.1	99	98.68

Classification Results

Green classes (Tree, Shrub and Grass) and build-up classes (HDB and LDB) distribution are visualized in Figure 2; the land cover classification of UGS in Zanzibar was implemented using SVM that was credited in its performance for both Landsat images 2009 and 2018. The attribute tables for both imageries show approximately 22989.6 ha and 22980.87 ha are the total areas of the Urban West region for 2009 and 2018 respectively. Approximately 0.019% of the covered area decreased from 2009 to 2018 due to the damage to the shoreline in the coastal zone of the Urban West region of its east side which is surrounded by the Indian Ocean. Shoreline change is caused by many factors including erosion, sedimentation and movement of water waves from the ocean (Yadav & Donamanj, 2019).

Figure 2: Percentage of Area Covered for 2009 and 2018 with % Changing.



Change Detection

The overall changes in urban green cover, as shown in Figure 3, were observed over a 10-year period from 2009 to 2018. Table 2 indicates that approximately 79.57% of the tree cover remained in the same class, while 4.15%, 3.16%, 2.1%, and 10.6% were converted to shrubs, grass, high-density buildings (HDB), and low-density buildings (LDB), respectively. This suggests that large areas of tree cover were converted to low-density built-up areas, with only a small portion shifting to higher-density areas.

Article DOI: https://doi.org/10.37284/eajit.8.1.2740

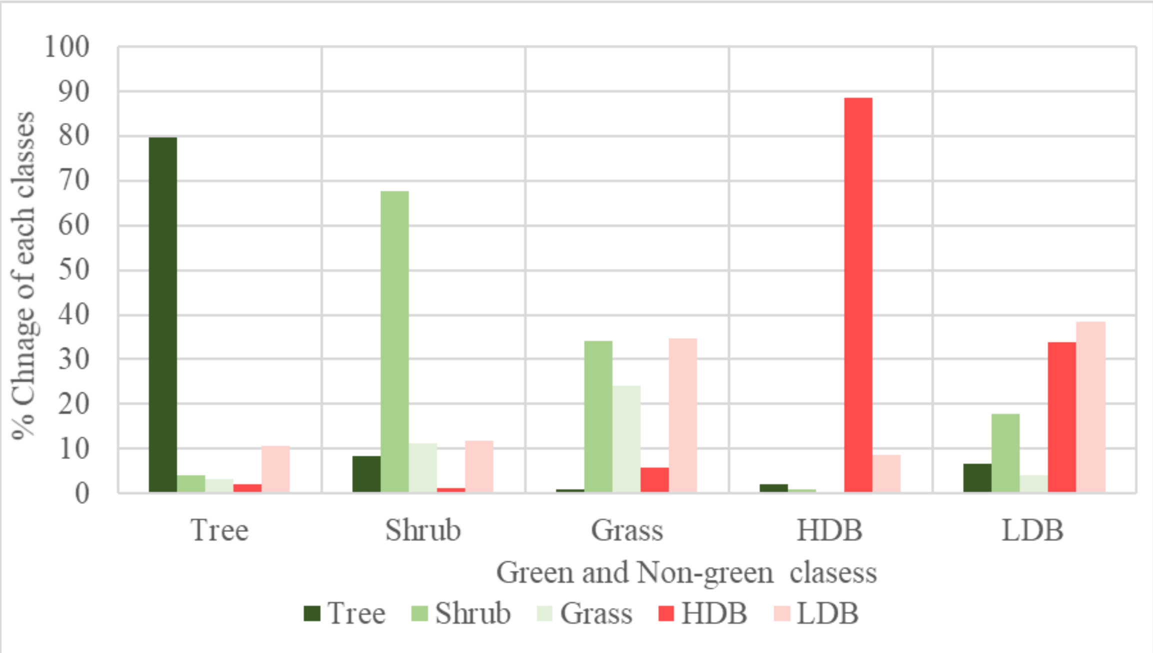
Table 2: Percentage Change of Classes from 2009 to 2018

Class Value (%)	Tree (0)	Shrub (1)	Grass (2)	HDB (3)	LDB (4)	Total changing
Tree (0)	79.57	4.15	3.16	2.1	10.60	20.43
Shrub (1)	8.31	67.75	11.08	1.13	11.9	32.25
Grass (2)	0.92	34.0	24.49	5.83	34.75	75.51
HDB (3)	1.96	0.77	0.14	88.6	8.52	11.4
LDB (4)	6.71	17.73	3.9	33.85	38.3	61.7

Moreover, approximately 67.75% of shrubs rema ined in the same class, and approximately 8.31%, 11.08%, 1.13%, and 11.9% changed to tree, grass, HDB, and LDB, respectively, where a large portion of shrubs changed to the low, dense realm and the small area changed to the high dense realm. A 24.49% of grass remained in the same class, but 0.92%, 34.0 %, 5.83%, and 34.75% of grass changed to tree, shrub, HDB, and LDB, respectively; the percentage change of LDB appeared higher and lower for HDB. Also, approximately 88.6% of HDB remain in the same class, and 1.96%, 0.77%, 0.14%, and 8.52% change to tree, shrub, and grass. The change of LDB was higher and the area covered by grass was low. Furthermore, 38.3% of the LDB remains in the same state while 6.7%, 17.7%, 3.9% and 33.3% were for change in tree, shrub, grass, and HDB respectively.

Changing to HDB was large and low for the areas covered with grass. According to this data, we can conclude that all classes were changed highly to low-dense buildup area, while low-dense area changed highly to HDB. Moreover, low changes appeared in HDB in trees and shrubs. The grass changed low to a tree, while HDB and LDB seemed lower in the grass.

Figure 3: Classes Changes from 2009 to 2018.



Article DOI: https://doi.org/10.37284/eajit.8.1.2740

Green Connectedness

Green connectedness involves the structural connectivity of a green space. The landscape ecological statistics of satellite imagery used in this study show the number of patches (NP) of shrubs, grass, and trees were extensively decreased, about 97.55%, 93.45% and 78.92%, respectively. The distribution of patches for tree class is fragmented and disconnected in both imageries but was highly disconnected in 2018. It also decreased at the south fringes of the Urban West region.

Patches of shrubs were complex in shape in 2018 and were disconnected in 2009, and most of the patches are highly concentrated at the south fringes of the Urban West Region. Likewise, grass has the lowest value of other green classes; its patches have decreased significantly in 2018 and are more disconnected than in 2009. Mean Patch Area (MPA) slightly increased for all green classes from 2009 to 2018, while the trees had a higher mean patch area due to decreasing patches. Also, there are increases in the Large Patch Index (LPI) and Effective Mesh Size (EMS) for shrubs while there were decreases in trees and grass due to the increasing human activities including economic and social a ctivities. Hence, there is a slight increase in green spatial distribution in shrubs and a slight decrease in trees and grass. According to the thematic maps obtained, the green connectivity is low, with a poor spatial pattern of green patches at the west of the Urban West Region due to the higher density of the buildup area. Also, no green corridors have been observed that can increase green connectedness b etween the patches.

DISCUSSIONS

Based on the findings presented in the previous section, the discussion is based on three main areas: applicability of the SVM for satellite image classification, quality of UGS (quantitatively and qualitatively), and green space change.

Applicability of the SVM for Satellite Images Classification

Results show SVM performs well, as it is not affected by data dimensionality and limited sample and is in line with the findings by Wessel et al. (2018). SVM has been credited for its performance compared to other machine learning methods in image classification. For example, a study that maps and classifies UGS using four machine learning methods, including ANN, NB, RF, and SVM, performs better than another language, especially when working on data from varied intensity (Abbas & Jaber, 2020; Yadav & Dodaman, 2019; Rudranapal & Subhedar, 2015). This study proves the same, as the data used for analysis was not huge, and the classification results were good.

Green Space Change

Generally, green cover influences the city's urban morphology, topography, and structural character istics (Kranjčić et al., 2019; Cetin, 2015). The increasing urban population and spatial change in green space affect the urban silhouette. Research by Mattsson and Möllerström (2014) investigated the impact of urbanization in Zanzibar City and found that the urban expansion rate is slightly low compared to the increasing rate of the urban population. The impact of this urbanization results in many land cover changes. For instance, based on findings, there is a significant change in trees, grass, and shrubs to a low-density buildup area that eventually will become a higher-density build-up area.

CONCLUSIONS

Broadly, the amount of green space is large compared to the build-up area, but the area is unevenly distributed, with building-up areas very connected, so there are no integrated green spaces. Thus, the urban planning council and urban municipalities should take some strategies to improve the existing green spaces and create new spaces for the sustainable development of urban areas in Zanzibar. Also, more studies about UGS are needed to improve urban areas. The authorities should take measures to improve the quality of

Article DOI: https://doi.org/10.37284/eajit.8.1.2740

urban green space in the Urban West region due to unstructured green space.

Awareness campaign and active community involvement in green space maintenance: The urban planning council should influence a policy in maintaining green space development by upholding the accessibility rule of green space from people's houses, which means linking the residential area with the green space area. The council should also provide guidance to urban communities on urban development with respect to green nature preservation (Haaland & Bosch, 2015).

REFERENCE

Abbas, Z., & Jaber, H. S. (2020). Accuracy assessment of supervised classification methods for extraction of land use maps using remote sensing and GIS techniques. *IOP Conference Series: Materials Science and Engineering, 745*(1), 012166. https://doi.org/10.1088/1757-899X/745/1/012166

Azwar, D. H., & Ghani, I. (2014). The importance of green space: Towards a quality living environment in urban areas. *Journal of Architectural Research, ArchNet-IJAR, 3*(1), 267. https://doi.org/10.26687/archnet-ijar.v3i1.267

Cetin, M. (2015). Using GIS analysis to assess urban green space in terms of accessibility: A case study in Kutahya. *International Journal of Sustainable Development and World Ecology*, 1– 5. https://doi.org/10.1080/13504509.2015.1061066

Haaland, H., & van den Bosch, C. K. (2015). Challenges and strategies for urban green-space planning in cities undergoing densification: A review. *Urban Forestry & Urban Greening, 14*(4), 760–771. https://doi.org/10.1016/j.ufug.2015.07.009

Hyseni, C., Heino, J., Bini, L. M., Bjelke, U., & Johansson, F. (2021). The importance of blue and green landscape connectivity for biodiversity in urban ponds. *Basic and Applied Ecology, 57*, 129–145. https://doi.org/10.1016/j.baae.2021.10.004

Jung, M. (2013). LecoS-A QGIS plugin to conduct landscape ecology statistics. *PeerJ Preprints*. https://doi.org/10.7287/peerj.preprints.116v2

Khati, R., & Acharya, T. (2021). Deep learning in land cover classification. *International Journal of Engineering Research, 4*, 32–38.

Kranjčić, N., Medak, D., Župan, R., & Rezo, M. (2019). Machine learning methods for classification of green infrastructure in city areas. *ISPRS International Journal of Geo-Information, 8*(10), 463. https://doi.org/10.3390/ijgi8100463

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics, 33*(1), 159–174. https://doi.org/10.2307/2529310

Lee, A. K., Jordan, H., & Horsley, J. (2015). Value of urban green spaces in promoting healthy living and wellbeing: Prospects for planning. *Risk Management and Healthcare Policy, 8*, 131– 137. https://doi.org/10.2147/RMHP.S61654

Lee, A. K., & Maheswaran, R. (2011). The health benefits of urban green spaces: A review of the evidence. *Journal of Public Health (Bangkok), 33*(2), 212–222. https://doi.org/10.1093/pubmed/fdq068

Mattsson, A., & Möllerström, M. (2014). Urbanization and density in Zanzibar. *Bachelor Thesis, The State University of Zanzibar*.

Mensah, C. A. (2014). Destruction of urban green spaces: A problem beyond urbanization in Kumasi City (Ghana). *American Journal of Environmental Protection, 3*(1). https://doi.org/10.11648/j.ajep.20140301.11

Omar, H., & Cabral, P. (2020). Ecological risk assessment based on land cover changes: A case of Zanzibar (Tanzania). *Remote Sensing,*

Article DOI: https://doi.org/10.37284/eajit.8.1.2740

12(19), 3114. https://doi.org/10.3390/RS12193114

Peschardt, K. (2012). Use of small public urban green spaces. *Urban Forestry & Urban Greening, 11*(3), 235–244.

Public Health England (PHE). (2014). Improving access to green spaces. *Health Equity Brief, 8*(September).

Rudrapal, D., & Subhedar, M. (2015). Land cover classification using support vector machine. *International Journal of Engineering Research, 4*(9). https://doi.org/10.17577/IJERTV4IS090611

Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning, 158*, 25– 38. https://doi.org/10.1016/j.landurbplan.2016.09.024

Wessel, M., Brandmeier, M., & Tiede, D. (2018). Evaluation of different machine learning algorithms for scalable classification of tree types and tree species based on Sentinel-2 data. *Remote Sensing, 10*(9), 1419. https://doi.org/10.3390/rs10091419

Yadav, A., & Dodamani, B. M. (2019). Shoreline change: A review. *March*, 2019.

