



## URBAN VEGETATION 3D-INFORMATION EXTRACTION TECHNIQUE FROM AIRBORNE BASED LiDAR POINT CLOUD AND MULTISPECTRAL DIGITAL IMAGE DATASETS

Mohammed AdamuDogonYaro\* Alhajihussaini\*\* KabiruShehu\*\*\*

\*Department of Surveying and Geo informatics, Abubakar Tafawa Balewa University, Bauchi, Bauchi State, Nigeria.

\*\*Department of Geography, AminuSaleh College of Education Azare, Bauchi State, Nigeria.

\*\*\*Department of Geography, AminuSaleh College of Education Azare, Bauchi State, Nigeria.

### Abstract

Urban vegetation mapping plays an important role in modern urban spatial data management, as many benefits could be derived from this detailed up-to-date data sources. Timely and accurate acquisition of information on the condition of urban vegetation serves as a tool for decision makers to better appreciate urban ecosystems and their numerous values which are critical to building up strategies for sustainable development. The conventional techniques used for extracting information about urban vegetation include ground surveying and interpretation of the aerial photography. However, these techniques are associated with some constraints, such as labour-intensive field work and a lot of financial requirements, which can be overcome by means of integrated processing of airborne LiDAR point cloud and multispectral digital image datasets. Compared to predominant studies on vegetation extraction mainly in purely forested areas, this study concentrates on urban areas, which have a high structural complexity with a multitude of different objects, presented a workflow about semi-automated approach for extracting 3D information about urban vegetation from integrated processing of airborne based LiDAR point cloud and multispectral digital image datasets, over Istanbul city of Turkey. The paper reveals that, the integrated datasets is a suitable technology and viable source of information for urban vegetation management. Also, it provides a snapshot about location, composition, status and extent of vegetation in the Istanbul. This is considered useful to city planners and other stakeholders, in order to understand how much canopy cover exists, identify new planting, removal or reforestation opportunities and what locations have the greatest need or potential to maximize benefits of return on investment. It can also help track trends/changes to urban vegetation over time and inform future management decisions.

**Key Words:** Urban Vegetation, 3D-Information, Airborne Lidar and Multispectral Digital Image.

### Introduction

Urban vegetation have many advantages such as preserving energy, improving water quality, minimizing greenhouse gasses and many other environmental pollutants, as well as connecting urban dwellers with nature (McPherson, 2006 and Nowak and Crane, 2007). To exploit these benefits, information about location, composition, status and extent of urban vegetation is often needed for planning and management purposes. This information can be employed for a different type of analysis, like vegetation growth tracking or monitoring and appraisal of trees condition. Conventionally, this information is obtained through field surveying methods which are highly expensive, laborious (tedious), time-consuming and usually cannot be carry out over large areas. In spite of efforts and capital spent on the conservation of ecosystem, especially vegetation, many cities around the world often do not have an all-inclusive information on their conditions (Yang, 2012), which is a major limitation for actualizing their benefits (Zhang, and Qiu, 2012). In order to realize numerous economic, environmental and sustainable decision-making processes, accurate, up-to-date and in-depth information on spatial distributions, extents and health conditions of urban ecosystem is necessary.

Advancements in remote sensing tools have introduced laser technology which bridges the gap of remote sensing imagery inability to pass through the vegetation cover and/or trees canopy. The technology accords distinctive advantages for management of urban natural resources. Light Detection and Ranging (LiDAR) as a remote sensing technology, is a preference tool, which presents a promising potentiality for mapping and studying natural resources such as urban forests (Plowright, 2015). LiDAR is an evolving technology which has the ability to generate an accurate, intense, cost effective and a well-defined 3D representation of features on and above ground surface especially, over wide spatial scales (Carter, et al., 2012 and Reitberger, et al., 2009). The capability of LiDAR to pass through vegetation has attracted remarkable concern from the field of natural resources management (Hudak, et al., 2009; Coops, et al., 2007; Patenaude, et al., 2004; Seielstad and Queen, 2003; Vierling, et al, 2008; Woods, et al., 2008; Holmgren and Persson, 2004 and Zhang, 2010). Even though considerable research has been carried out regarding LiDAR applications in forestry (Brolly, et al., 2013; Lang, et al., 2006; Hyypa, et al., 2008 and Hyypa, et al., 2009), its usage in the study of urban vegetation has been limited. As LiDAR applications in urban forestry mapping expand, therefore, automated approach for vegetation detection technique is most likely to increase (Heinzel, et al., 2008).

Whilst LiDAR systems have no band which makes it insufficient for vegetation classification, especially in urban forests with diverse species and high spatial heterogeneity, Digital multispectral imagine, usually possesses many distinct bands, therefore, exhibit a great potential in identifying and mapping vegetation feature with their rich spectral contents. Airborne



LiDAR data and digital imagery are highly complementary (Caldwell, 2005), the images can validate the filtration accuracy (Jawak, et al., 2013) while the elevation information from LiDAR can be used to ortho-rectify images datasets (Flood, 2002 and Savopol, et al., 2004). Highly dense LiDAR data with multiple returns per square meter would be overwhelming for tree crown depiction and for determination of crown shape while image spectral properties can be used to differentiate vegetation objects (Holmgren, et al., 2008 and MacFaden, et al., 2012). Therefore, data products which are highly information-rich can be created. It is assumed that both data sources concurrently will be more successful for vegetation detection in contrast with any of them alone (Chen, et al., 2005 and Zhang, 2010).

The objectives of this paper includes extraction of shadow free vegetation features from the digital images using shadow index and Normalized Difference Vegetation Index (NDVI) techniques and automated extraction of 3D information about vegetation features from the integrated processing of shadow free vegetation features image and LiDAR point cloud datasets. The remaining part of this paper describes, the study area and datasets used in section 2, the extraction technique in section 3, the results and discussion in section 4 and finally, the conclusion in section 5.

### Study Area and Datasets Used

#### Study Area

The study area is located in Besiktas district, the city center of Istanbul, north-western Turkey with a total area of 5,343 km<sup>2</sup> (Ba ar, et al., 2011). Istanbul is among the most special cities in the world with its position as a bridge between Europe and Asia. It is positioned between 28° 01' and 29° 55' eastern longitudes and 41° 33' and 40° 28' latitudes. Bosphorus strait (Fig. 1) which connects the Sea of Marmara at the north and the Black Sea to its south divides the city into an Asian city closest to Europe and the closest European city to Asia (Gregory, 2010 and Efe, et al., 2011). Istanbul is a typical urban area with complex spatial assemblages of vegetation, buildings, roads, and other man-made features.



Figure 1: Location of the study area.



### **Datasets Used**

The datasets used in this study include airborne multispectral digital image with Red, Green, Blue and Near Infrared bands and LiDAR point cloud.

### **Airborne Multispectral Digital Image**

The multispectral images provide more details on spatial geometry and spectral information about the study area useful for detection and extraction of vegetation features. These include Red, Green and Blue (RGB) bands (Fig. 2) and Near Infrared (NIR) bands (Fig. 3) band images at 0.1m and 0.5m spatial resolution respectively.



Figure 2: RGB Bands Image

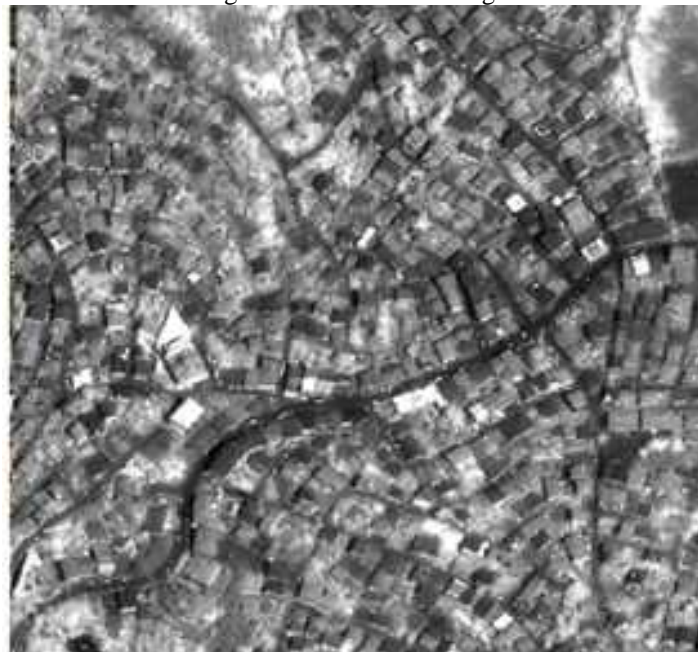


Figure 3: NIR Band Image



### Airborne LiDAR Point Cloud

The LiDAR (Fig. 4) data provides an accurate, georeferenced, intense and highly effective 3D spatial information about the shape and surface characteristics of the study area through x,



Figure 4: Airborne Lidar Point Cloud.

y and z points commonly referred as point cloud. It provides accurate height information which is missing in the digital images and also supporting information about crown shape (Hyypä, et al., 2008).

### Extraction Technique

The extraction techniques and steps adapted (Fig. 5) were focused toward achieving shadow free vegetation features extraction from digital images, using shadow index and Normalized Difference Vegetation Index (NDVI) techniques and automated extraction of 3D information about vegetation features from the integrated processing of shadow free vegetation features image and LiDAR point cloud datasets.

### Image Geo-Rectification

The NIR image does not have the same pixel depth and spatial resolution with the multispectral image. Consequently, the NIR image which has 0.5m spatial resolution and 16bit pixel depth has been geo-rectified in order to have the same spatial reference system with the RGB image which has 0.1m spatial resolution and 8bit pixel depth.

### Shadow Index

Shadow index is an indicator which describes presence of shadow objects in a digital image. The presence of shadows of vegetation is a major problem during classification as shadow of trees may wrongly classify as vegetation objects. Therefore, in order to get rid of the confusing spectral problem between reflected spectra of specific kind of trees and the reflected spectra of the shadow of trees, the shadow values of the multispectral digital images have been determined using Equation 1 below:

$$SI = (256 - Red) (256 - NIR) (1) \dots \dots \dots (Mustafa, et al., 2015).$$

Where; NIR and Red are the Near Infrared and the Red bands respectively.

Furthermore, the shadow index image which provides precise shadows information was threshold to detect absolute shadow information on the digital image. The threshold value for

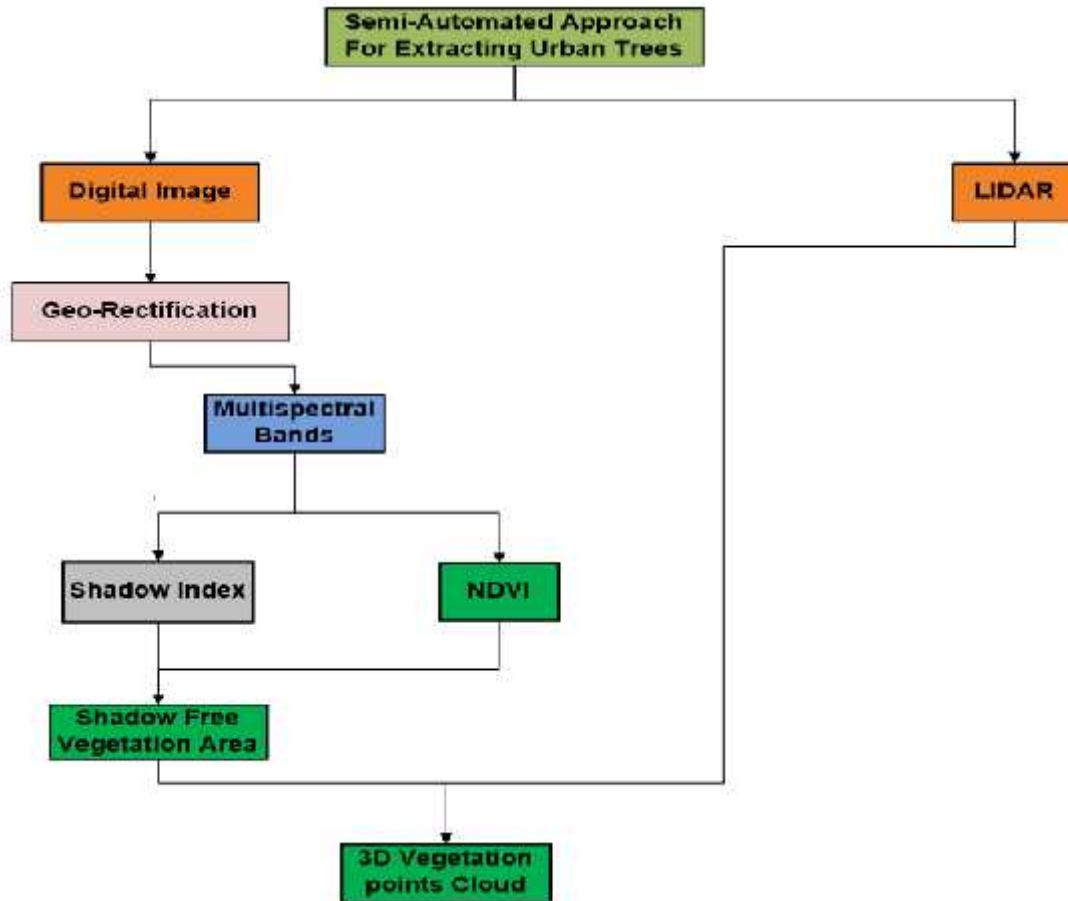


Figure 5: Shadow Free Vegetation Features Extraction Techniques

Shadow image was estimated empirically, as 180. By utilizing this threshold value, a binary image was obtained with a value of 0 indicating presence of non-shadow objects and a value of 1 indicating presence of shadow objects.

**Normalized Difference Vegetation Index (NDVI)**

NDVI is an index of plant “greenness” or photosynthetic activity (Blanco, et al.,2008 andMróz, et al., 2004). It is based on the observation that different surfaces reflect different types of light differently. Photosynthetically active vegetation, in particular, absorbs most of the Red light that hits it while reflecting much of the Near Infrared light. Vegetation that is dead or stressed reflects more Red lights and less Near Infrared light. Likewise, non-vegetated surfaces have a much more even reflectance across the light spectrum. By taking the ratio of Red and Near Infrared bands from a remotely-sensed image, an index of vegetation “greenness” which ranges from -1 to +1 can be defined. Consequently, the NDVI values of the digital image were determined on a per-pixel basis using Equation 2 below:

$$NDVI = (NIR - Red) / (NIR + Red) \dots\dots\dots (2) \text{ (Mustafa, et al., 2015).}$$

Where; NIR and Red are the Near Infrared and the Red bands respectively.

Furthermore, the NDVI image which provides precise information about vegetation features was thresholded to detect absolute information about the vegetation objects present in the study area. The threshold value for NDVI image was estimated empirically, as 0.6. By utilizing this threshold value, a binary image was obtained with a value of 0 indicating presence of non-vegetation features and a value of 1 indicating presence of vegetation features.

**Shadow Free Vegetation Features Image**

The image showing shadow free vegetation features was determined by masking out every shadow objects from the NDVI binary image. Hence, a binary image was created with a value of 0 indicating presence of non-vegetation objects and a value of 1 indicating presence of shadow free vegetation objects.



### Extracting 3D Information about Vegetation Features

In order to achieve this task, the shadows free vegetation features image and the LiDAR point cloud datasets were integrated in order to extract 3D information about the vegetation features. This task has been completely processed in an automated fashion using the Python programming tool.

### Results and Discussion

#### Shadow Index

It has been evidently proved that the presence of shadows poses a great challenge during vegetation objects extraction from the digital image (Mustafa, et al., 2015). This is due to the fact that NDVI normally fails to distinguish between the spectral reflectance of vegetation objects and that of their shadows. Based on this reasons, therefore, all areas identified as shadows have been removed from the digital image. This has been achieved by applying Equation 1 to calculate shadow values of the digital image. The result of shadow index is a new image file (Fig. 6) with shadow values ranging from 1 to 239. The white pixels which have high shadow values represent shadow objects, while the black or dark grey pixels which have low shadow values represent objects without shadow.

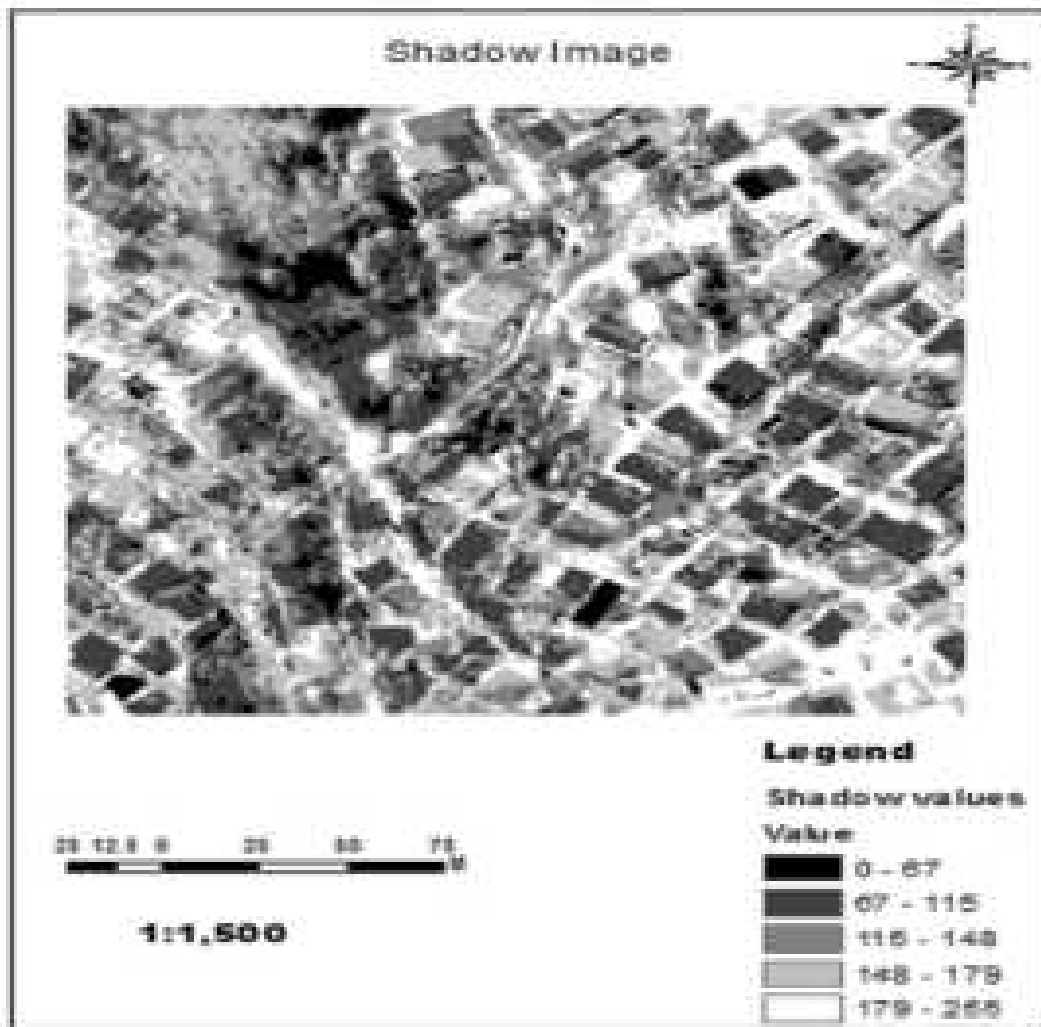


Figure 6: Shadow Index Image

After applying an absolute threshold value to the shadow index image, a binary image (Fig. 7) was determined with a value of 0 representing non-shadow objects (i.e. black colour pixels) and a value of 1 representing the shadow objects (i.e. white colour pixels). The threshold value for shadow index image was estimated empirically, as 180.

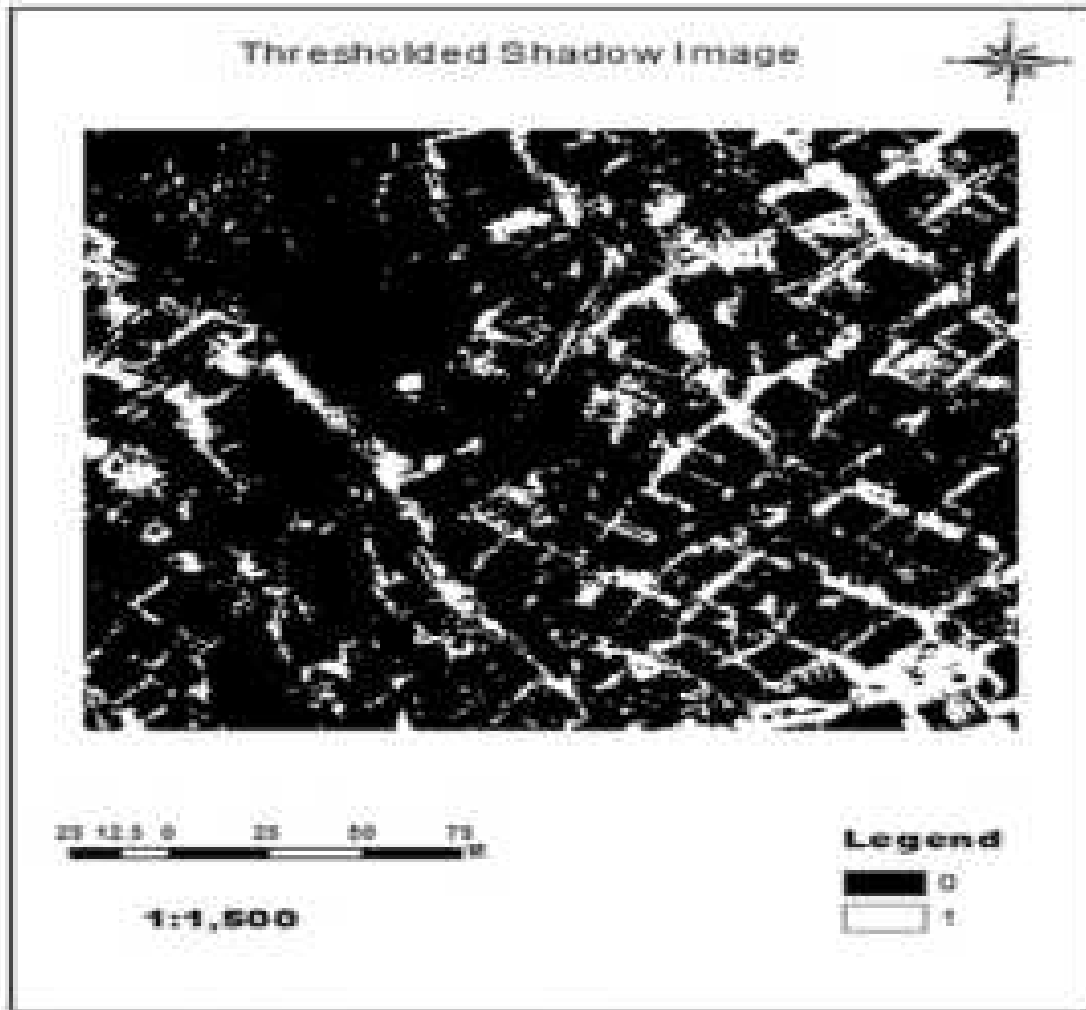


Figure 7: Shadow Index Image After Applying A Threshold

### TheNDVI Output

The NDVI which is an index of plant greenness or photosynthetic activity has been used to calculate NDVI values of the digital image on a per-pixel basis by applying Equation 2 given in section 3. This helps to distinguished pixels which belong to vegetation features from pixels which belong to non-vegetation features on the digital image (Geerken, et al., 2005, Moleele, et al., 2001). The output of this operation is a new image file (Fig. 8) with values ranging from -1.0 to +0.98. The white pixels which have high NDVI values represent the vegetation objects while the black or dark grey pixels which have low NDVI values represent the non-vegetation objects.

After applying an absolute threshold value to the NDVI image, a binary image (Fig. 9) was created with a value of 0 indicating the non-vegetation features (i.e. black colour pixels) and a value of 1 indicating the vegetation features (i.e. white colour pixels). The threshold value for NDVI image was estimated empirically, as 0.6.

### Shadow Free Vegetation Image

This has been achieved by removing shadow objects from the NDVI binary image. Thus, a binary image was created with a value of 0 indicating non-vegetation objects (i.e. black colour pixels) and a value of 1 indicating shadow free vegetation objects (i.e. white colour pixels). After the shaded areas have been removed, the final output (Fig. 10) was then turned into an image which has only vegetation features without shadow objects. In this way, it became possible to get rid of the confusing spectral problem between reflected spectra of vegetation and their shadows.

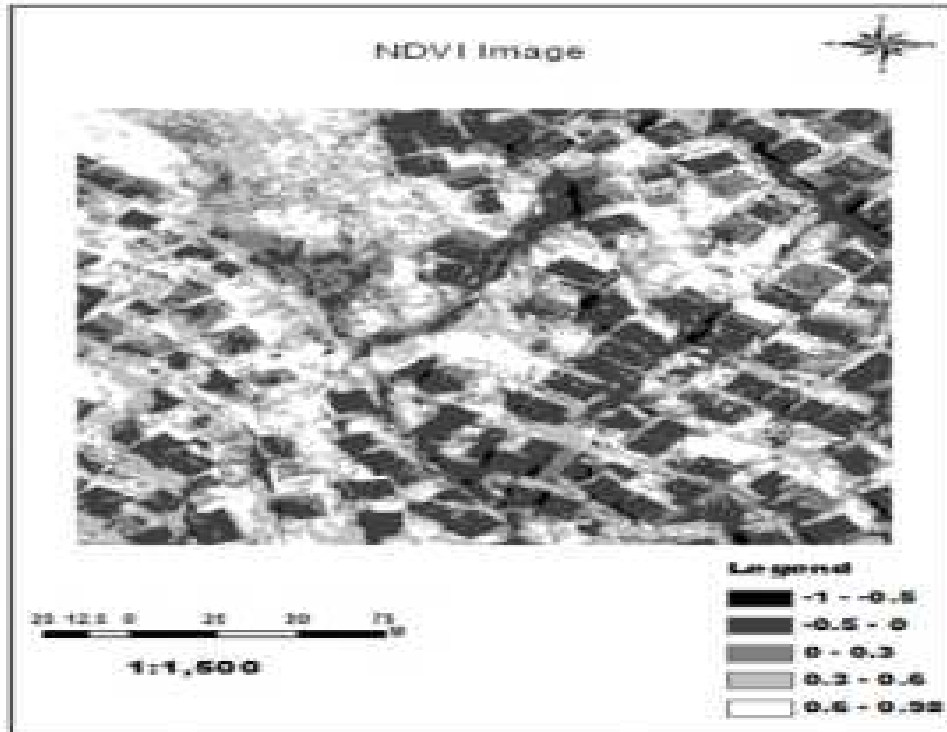


Figure 8: NDVI image

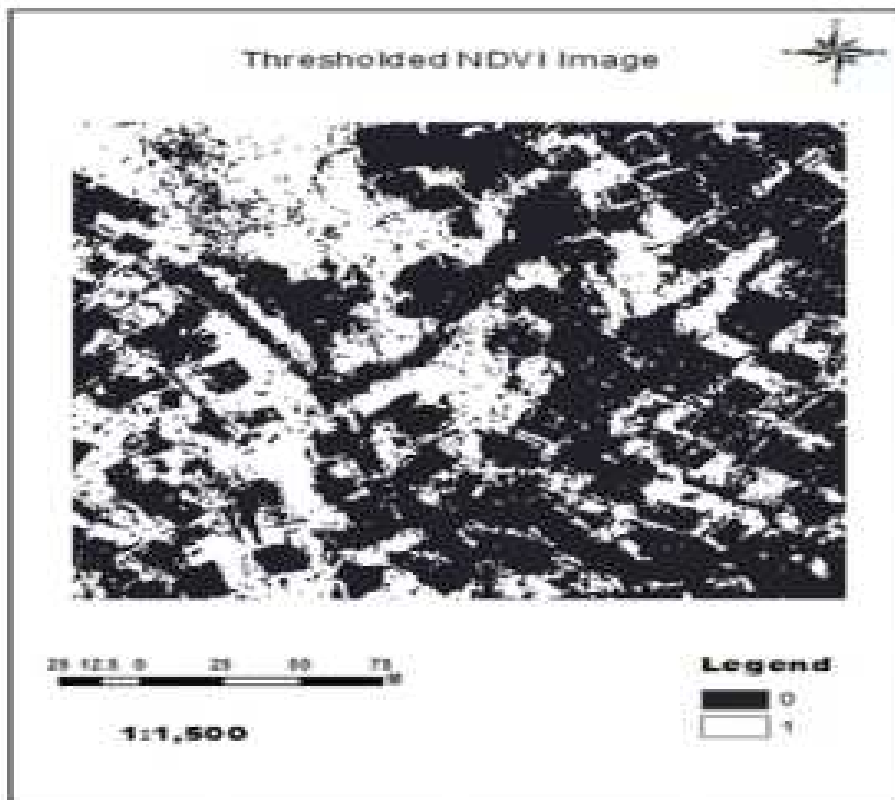


Figure 9: NDVI Image After Applying A Threshold.



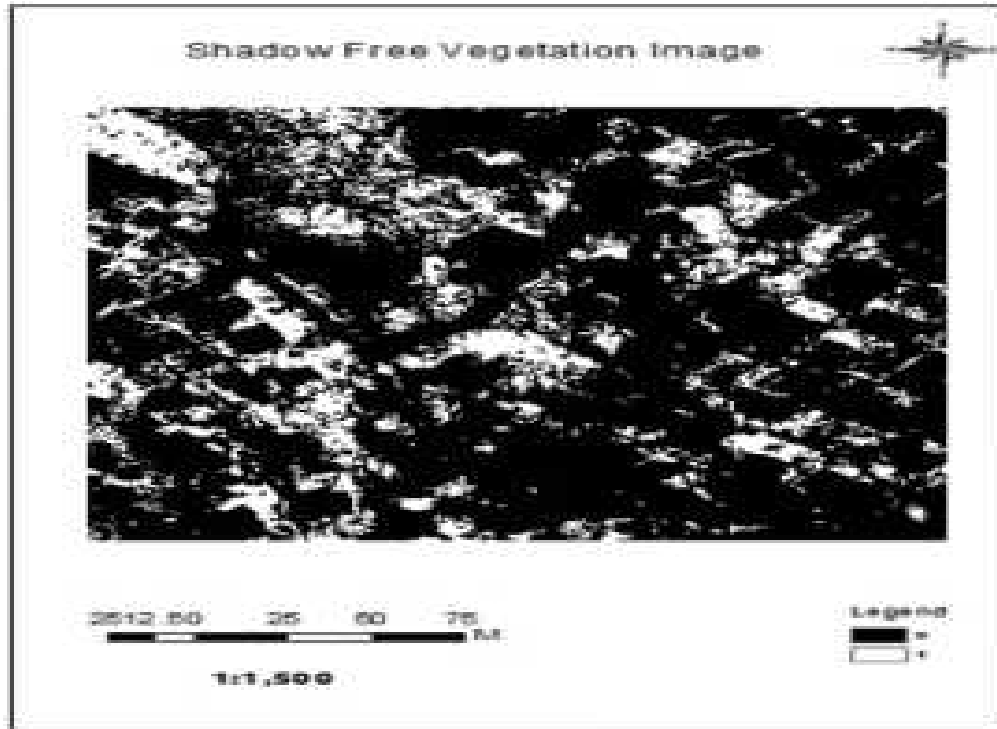


Figure 10: Shadow Free Vegetation Image.

#### Extracting 3D Information about Vegetation Features

3D information about vegetation features (Fig. 11) has been obtained in a fully automated fashion by extracting LiDAR points which belong to vegetation features from integrated processing of shadow free vegetation image and LiDAR points cloud datasets.



Figure 11: 3D Vegetation Features



The modus operandi (filtration techniques) of the developed algorithm used in processing the above task includes the following steps:

1. Accessing (data input) the shadows free vegetation image file.
2. Reading the shadows free vegetation image file.
3. Detecting contour polygons of the vegetation features.
4. Determining boundaries of each contour polygon of the vegetation features.
5. Accessing (data input) the LiDAR text file (.txt).
6. Reading the LiDAR text file (.txt).
7. Integrating the shadows free vegetation image and the LiDAR data files.
8. Extracting LiDAR points falling inside each polygon of the vegetation features.
9. Saving the extracted LiDAR points (data output) into a new text file (.txt).

The mode of operation (filtration techniques) of this task has also been represented using pseudo code flow chart (Fig. 12).

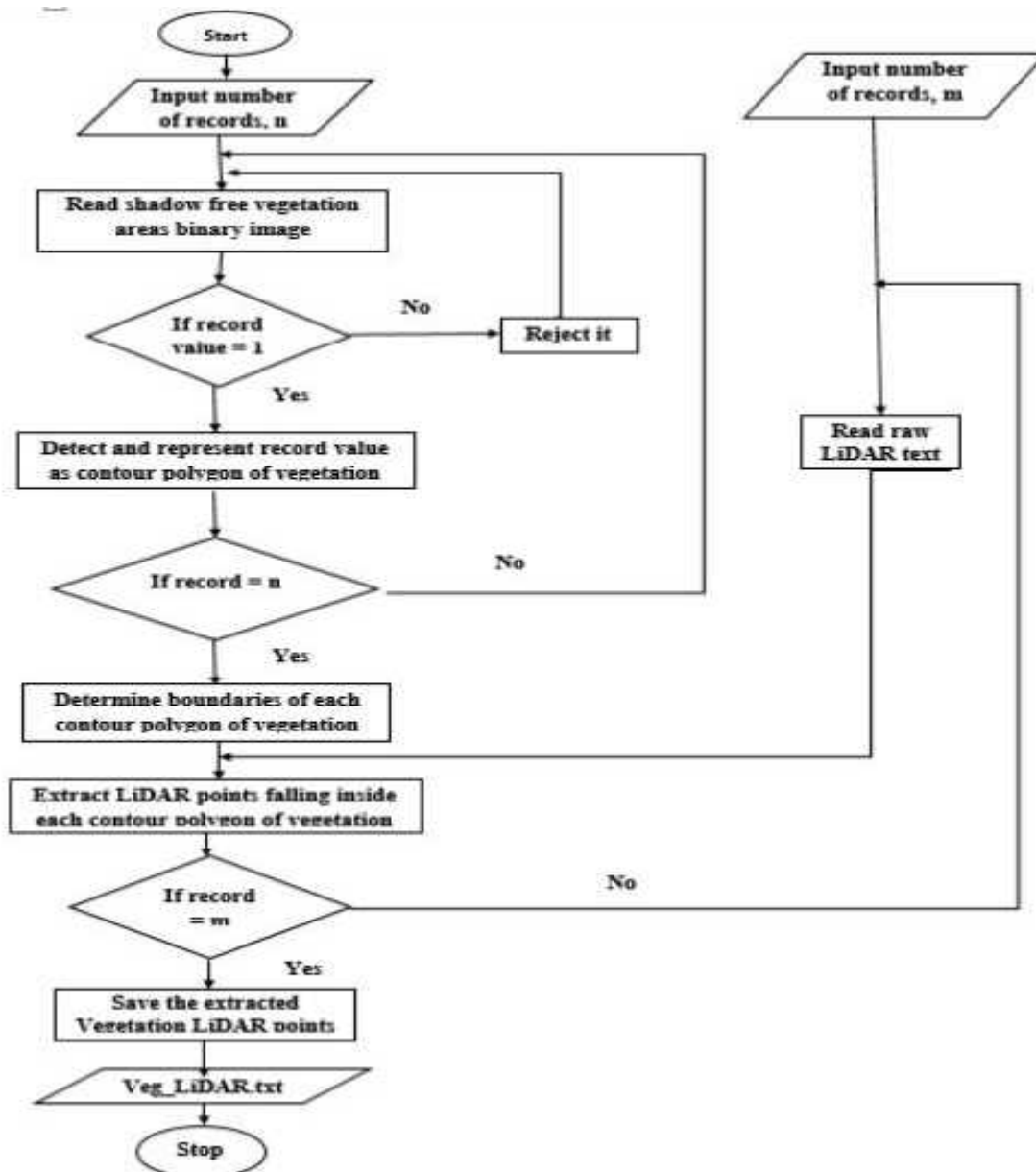


Figure 12: Pseudo Code Flow Chart For Extracting 3D Information About Vegetation Features.



## Conclusion

This paper presented a workflow about semi-automated approach for extracting 3D information of urban vegetation from integrated processing of airborne based LIDAR point cloud and multispectral digital image datasets. The paper proved that the integrated datasets are suitable technology and viable source of information for city managers to analyze, evaluate and enhance urban landscape patterns in order to gain a better understanding of the current compositions, spatial distribution and status of vegetation features in urban settings. Furthermore, the extracted information provides a snapshot of current location, compositions, status and extent of vegetation features in the study area which will be useful to city planners and other urban natural resources managers or stakeholders to get a better understanding of how much canopy cover exists, identify new planting, removal, or reforestation opportunities and what locations have the greatest need or potential to maximize benefits of return on investment. It can also help track trends or changes to the urban vegetation over time and inform better future management decisions.

Finally, critical analysis of the extracted LiDAR data (i.e. 3D information about vegetation features) reveals that the extracted data is made up of various forms of vegetation objects such as trees, grassland, shrubs, etc. Therefore, future work should concentrate on developing an approach or techniques which can be used to classify the extracted LiDAR points of vegetation features into let say trees, shrubs and/or grasslands. In addition, the designed algorithms have so far only been tested over the Istanbul urban area. Further research is needed in other urban areas with different species, forest compositions and structural complexity in order to examine the robustness and extensibility of the extraction techniques.

## References

1. Ba ar.A., Çatay, B. and Ünlüyurt, T. (2011).A Multi-period Double Coverage Approach For Locating the Emergency Medical Service Stations in Istanbul. *Journal of the Operational Research Society*, 62(4), pp.627-637.
2. Blanco, L.J., Aguilera, M.O., Paruelo, J.M., and Biurrun, F.N. (2008).Grazing Effect on NDVI Acrossan Aridity Gradient in Argentina. *Journal of Arid Environments* 72(5):764-776.
3. Brolly, G., Király, G., &Czimer, K. (2013).Mapping Forest Regeneration from Terrestrial Laser Scans.*ActaSilvicaetLignariaHungarica*, 9(1), 135-146.
4. Caldwell, J. (2005). Merging Technologies – LIDAR Complements Multispectral Imagery. *Earth Imaging Journal*.
5. Carter, J., Schmid, K., Waters, K., Betzhold, L., Hadley, B., Mataosky, R. and Halleran, J. (2012). LiDAR 101: An Introduction to LiDARTechnology, Data and Applications, National Oceanic and Atmospheric Administration (NOAA) Coastal Services Center. Charleston, SC.
6. Chen, L., Chiang, T., and Teo, T. (2005).Fusion of LiDARData and High Resolution Images forForest Canopy Modelling.In Proc. 26th Asian Conf. on Remote Sensing.
7. Coops, N.C., Hilker, T., Wulder, M.A., St-Onge, B., Newnham, G., Siggins, A. and Trofymow, J.T. (2007). Estimating Canopy Structure of Douglas-fir Forest Stands from Discrete-return LiDAR. *Trees*, 21(3), pp. 295-310.
8. Efe, R. and Cürebal, I. (2011).Impacts of the “Marmaray” Project (Bosphorus Tube Crossing, Tunnels, and Stations) on Transportation and Urban Environment in Istanbul.In *Engineering Earth* (pp. 715-733).Springer Netherlands.
9. Flood, M. (2002). Product Definitions and Guidelines for Use in Specifying LiDAR Deliverables.*Photogrammetric Engineering and Remote Sensing*, 68, pp. 1230–1234.
10. Geerken, R., Zaitchik, B., and Evans.J.P. (2005).Classifying Rangeland Vegetation Type and Coverage from NDVI Time Series using Fourier Filtered Cycle Similarity. *International Journal of Remote Sensing* 26(24, pp. 5535-5554.
11. Gregory, T.E. (2010). A history of Byzantium, (Vol. 19).John Wiley & Sons.
12. Heinzl, J.N., Weinacker, H. and Koch, B. (2008).Full Automatic Detection of Tree Species Based on Delineated Single Tree Crowns – A Data Fusion Approach for Airborne Laser Scanning Data and Aerial Photographs. *Proceedings of SilviLaser*, 2008, p. 8.
13. Holmgren, J. and Persson, Å. (2004).Identifying Species of Individual Trees using Airborne Laser Scanner. *Remote Sensing of Environment*, 90(4), pp. 415-423.
14. Holmgren, J., Persson, A and Soderman, U. (2008).Species Identification of Individual Tree byCombining High Resolution LiDARData with Multispectral Image. *International Journal of Remote Sensing*, 29 (5), pp. 1537-1552.
15. Hudak, A.T., Evans, J.S. and Stuart, S.A.M. (2009).LiDARUtility for Natural Resource Managers. *Remote Sensing*, 1(4), pp. 934-951.
16. Hyypä, J., Hyypä, H., Leckie, D., Gougeon, F., Yu, X., and Maltamo, M. (2008).Review of Methods of Small-footprint Airborne Laser Scanning for Extracting Forest Inventory Data in Boreal Forests.*International Journal of Remote Sensing*, 29(5), pp. 1339-1366.
17. Hyypä, J.U.H.A., Hyypä, H., Yu, X., Kaartinen, H.A.R.R.I., Kukko, A.N.T.E.R.O. and Holopainen, M. (2009).Forest Inventory using Small-footprint Airborne LiDAR. *Topographic Laser Ranging and Scanning: principles and processing*, pp. 335-370.



18. Jawak, S.D., Panditrao, S.N., and Luis, A.J. (2013). Validation of High-Density Airborne LiDAR-Based Feature Extraction Using Very High Resolution Optical Remote Sensing Data, *Advances in Remote Sensing*, 2013.
19. Lang, S., Tiede, D., Maier, B. and Blaschke, T. (2006). 3D Forest Structure Analysis from Optical and LIDAR Data, *RevistaAmbiência, Guarapuava, v.2 Edição Especial, Vol. 1, No. 1*, pp. 95-110.
20. MacFaden, S. W., O'Neil-Dunne, J. P., Royar, A. R., Lu, J. W., and Rundle, A. G. (2012). High-resolution Tree Canopy Mapping for New York City using LIDAR and Object-based Image Analysis. *Journal of Applied Remote Sensing*, 6(1), 56-71.
21. McPherson, E.G.(2006). Urban Forestry in North America, *Renewable Resources Journal*, 24, pp. 8–12.
22. Moleele, N., Ringrose, S., Arnberg, W., Lunden, B., and Vanderpost, C.(2001). Assessment of Vegetation Indexes Useful for Browse (forage) Production in Semi-arid Rangelands. *International Journal of Remote Sensing* 22(5) pp. 741-756.
23. Mróz, M. and Sobieraj, A. (2004). Comparison of Several Vegetation Indices Calculated on the Basis of a Seasonal SPOT XS Time Series and their Suitability for Land Cover and Agricultural Crop Identification. *Tech. Sci*, 7, pp. 39-66.
24. Mustafaa, Y. T., Habeebb, H. N., Steinc, A. and Sulaimanb, F. Y. (2015). Identification and Mapping of Tree Species in Urban Areas Using WORLDVIEW-2 Imagery. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, pp. 1, 175-181.
25. Nowak, D.J. and Crane, D.E.(2007). Carbon Storage and Sequestration by Urban Trees in the USA. *Environmental pollution*, 116(3), pp. 381-389.
26. Patenaude, G., Hill, R.A., Milne, R., Gaveau, D.L.A., Briggs B.B. J. and Dawson T.P. (2004). Quantifying Forest above Ground Carbon Content Using LiDAR Remote Sensing, *Remote Sensing of Environment*, Vol. 93, No. 3, pp. 368-380.
27. Plowright, A. (2015). Extracting Trees in an Urban Environment using Airborne LiDAR. GSS cIRcle Open Scholar Award (UBCV Non-Thesis Graduate Work).
28. Reitberger, J., Krzystek, P. and Stilla, U.(2009). Benefit of Airborne Full Waveform LiDAR for 3D Segmentation and Classification of Single Trees, *ASPRS-2009 Annual Conference* pp. 1-9.
29. Savopol, F. and Armenakis, C. (2004). Assessment of LiDAR and Digital Camera Data in the Context of Rapid Change Detection Methodologies. *ISPRS, Commission IV, WG IV/7*.
30. Seielstad, C.A. and Queen, L.P.(2003). Using Airborne Laser Altimetry to Determine Fuel Models for Estimating Fire Behavior. *Journal of Forestry*, 101(4), pp. 10-15.
31. Vierling, K.T., Vierling, L.A., Gould, W.A., Martinuzzi, S. and Clawges, R.M. (2008).
32. LiDAR: Shedding New Light on Habitat Characterization and Modelling. *Frontiers in Ecology and the Environment*, 6(2), pp. 90–98. doi:10.1890/070001.
33. Woods, M., Lim, K., and Treitz, P. (2008). Predicting Forest Stand Variables from LiDAR Data in the Great Lakes – St. Lawrence Forest of Ontario. *The Forestry Chronicle*, 84(6), pp. 827–839. doi:10.5558/tfc84827-6.
34. Yang, J.(2012). Urban Forestry in Challenging Environments. *Urban Forestry & Urban Greening*, 11(2), pp. 103-104.
35. Zhang, C., (2010). Urban Forest Inventory using Airborne LiDAR Data and Hyperspectral Imagery (Vol. 74, No. 01).
36. Zhang, C., and Qiu, F. (2012). Mapping Individual Tree Species in an Urban Forest using Airborne LiDAR Data and Hyperspectral Imagery. *Photogrammetric Engineering and Remote Sensing*, 78(10), pp. 1079-1087.