Machine learning approach to extract building footprint from high-resolution images: the case study of Makkah, Saudi Arabia

Kamil Faisal¹, Ayman Imam², Abdulrahman Majrashi³ and Ibrahim Hegazy², ₄, *

¹ Department of Geomatics, Faculty of Architecture and Planning, King Abdulaziz University, P.O.Box 80200, Jeddah, Saudi Arabia; ² Department of Urban and Regional Planning, Faculty of Architecture and Planning, King Abdulaziz University, P.O.Box 80200, Jeddah, Saudi Arabia; ³ Department of Islamic Architecture, Faculty of Engineering and Islamic Architecture, Umm Al-Qura University, P.O.Box 715, Makkah, Saudi Arabia; ⁴ Department of Architecture, Faculty of Engineering, Mansoura University, P.O.Box 35516, Mansoura, Egypt

Abstract

Extracting and identifying building boundaries from high-resolution images have been a hot topic in the field of remote sensing for years. Various methods including geometric, radiometric, object based and edge detection were previously deliberated and implemented in different studies in the context of building extraction. Nevertheless, the reliability of extraction process is mainly subject to user intervention. The current study proposes a new automatic morphology-based approach for extracting buildings using high-resolution satellite images of Al-Hudaybiyah region in the city of Makkah as a case study. The proposed technique integrates the support vector machine for extracting buildings that have bright and dark roofs. The appropriateness of this method has been examined by means of various indicators for example completeness, correctness and quality. Preliminary findings will illustrate the precision and accuracy of the used machine learning algorithm. Research results can provide a generic indicator to assist the planning authorities in achieving better urban planning processes taking into account all potential environmental, social and urban demands and requirements.

Keywords: machine learning; extract building footprint; high-resolution images; Makkah

*Corresponding author. ibmrizk@yahoo.com

Received 9 November 2020; revised 10 December 2020; editorial decision 16 December 2020; accepted 16 December 2020

1. INTRODUCTION

Worldwide, there are many illegal constructions, particularly in the major cities, and private transactions. Because of the limits of policy and conventional technological methods, the illegitimate construction may lead not only to the rigid building obstacle in the empirical decision-making related to urban economic and social growth but also may hinder the planning processes of urban real estate development, business control and resident population management services. In this context, a segregation of economic, social, administrative and legal parameters results in unplanned development and creating a substantial number of illegal constructions.

There are a large number of illegal constructions in the Kingdom of Saudi Arabia, particularly in major cities, and procedures in the private sector are at present a matter of face. As a result of the limitations of conventional technical strategies and procedures, the illegal underground market not only impedes severe construction in the scientific decision-making for urban economic and social development but also restricts the planning
processes for urban real estate market, building regulations and local population management services.

In Makkah, most informal buildings do not look like dense slums on the outskirts of big cities. Such type of buildings can be commonly found in the periphery of Makkah, fundamentally due to the growth of the population in the main urban centers, the new developments in the road and rail networks that have reduced mobility times, in addition to the great demands for urban lands in regions with well environmental circumstances. The local government of Makkah has imposed high fines in case of detection of any informal buildings, but this did not only effectively deal with the problem. Technically, one of the commonest reason for the management incompetence to regulate the unplanned developments is the difficulty of locating the under construction informal buildings in a cost-effective and quickly way and prevent the construction processes at its start or enforce penalties within a short period of its completion.

Based on the statistics, the area of Makkah construction land is about 1200 km², and the area of prohibited constructions reaches up to 16% of the total built up areas [1]. The number of the illegal constructions is increasing dramatically, they are widely distributed and their impact on the social and economic development became more evident. Both the objective and the methods of monitoring share the similarities and dissimilarities with other cities. To examine urban and suburban environment for identifying illegal constructions, intensive periodical measures have to be made, spread over large areas of interest. The application of contemporary methods can considerably increase the productivity and decrease the detection cost.

In this context, the efficient buildings footprint detection technique could offer supportive data to obviate the impacts of other terrain objects, and accordingly develop the extraction of building boundaries. Approaches, for example the machine learning-based classification and traditional hierarchical stripping classification, were promoted to reveal building footprints [2–4]. Previously, researches have applied the machine learning approach, for example support vector machine (SVM) [5,6], artificial neural networks [7,8], random forests [9] and AdaBoost [10], to extract buildings footprint. The machine learning approach can develop a model that can detect buildings footprint by automatically examining the classification rules using training data [11].

The key objectives of this study are to (1) examine the ability to use geographic information system (GIS) and remote sensing techniques to detect the buildings footprint in the city of Makkah as a case study; (2) to evaluate the new machine learning techniques to derive the illegal construction in the city of Makkah. Remote sensing data will be first obtained for the case study at less than 1 m² spatial resolution in 2016 and 2018. ‘SVM machine learning approach’ will be applied to extract all buildings footprints as polygon shapes. Based on the satellite images time series, the outputs will detect the change occurred during 2016 and 2018. Assessment of binary classifiers approach will be applied to assess the outcomes of building footprints based on several performances that measure data interpretation.

2. SIGNIFICANCE OF RESEARCH TO SAUDI ARABIA

Each year, millions of Muslims from all over the world visit Saudi Arabia to perform the Umrah and Hajj, and this number has seen a rising trend each year. In tandem with the Kingdom Vision 2030 reform plan, the Saudi government seeks to increase this number, principally those of the Umrah pilgrims numbers, up to 30 million. According to the Ministry of Hajj and Umrah, this includes providing pilgrims with outstanding services, experience and accommodation conditions. Therefore, besides providing hospitality services of international standards, the authority responsible for the Hajj and Umrah pilgrim affairs and Ministries of Hajj and Umrah aspire to ensure the Hajj and Umrah companies provide and enrich the pilgrims’ experience by raising the quality of the services and housing. Hence, monitoring the urban expansion and illegal construction is the top priority to ensure the safety and quality of housing for all residents and pilgrim. One of the challenges would be how to manage and enhance monitoring urban expansion and illegal constructions, which is considered the key point of this research. In order to address this issue, it is proposed that the use of new technologies of remote sensing and machine learning algorithm can assist achieving this aim. These technologies offer services and products based on geomatics information for observation and analysis this valuable information with the ultimate visual technology experiences. The research outcomes can be used to support the planning authorities for better city planning processes, taking into account all likely environmental, social and urban concerns or constraints.

3. LITERATURE REVIEW

The traditional techniques of monitoring the illegal constructions mostly depend on the public report and regular survey, which is time cost and low effectiveness. With urban growth, illegal infringements are more challenging to find, the classic techniques are difficult to achieve the monitoring needs [12]. The contribution of contemporary methods and tools is essential for designing an automated and objective method for detecting informal expansion [13]. Such measures are already examined in some countries, e.g., monitoring constructions activity using high-resolution satellite imaging [14–16], artificial intelligence and special multimedia mapping to develop an information system able to provide an up-to-date maps and reports [17].

Optical satellite data, such as SkySat, have been widely used to detect illegal constructions. SkySat is characterized by the ability to revisit any place on Earth at 72 cm resolution with higher frequencies than any other commercial high-resolution images supplier. Leveraging machine learning in cooperation with SkySat cloud-based images library helped in the implementation and development to create quickly accurate constructions footprints [18]. By fusing both sources of Earth Observation information and modern machine learning techniques, scholars can provide
actionable insights for observation, analysis and monitoring business processes for example urban planning, supply chain management and industrial asset monitoring that include real estate, insurance, energy and location-based services [19–22].

The literature provides a great deal of implementations from satellite imagery to extract an advantage. A lot of studies’ effort has gone into developing algorithms for the extraction of buildings footprint. A various range of automatic and semi-automatic methods has been suggested to extract buildings in various studies. In the discussion below, the efforts made in these related studies are highlighted.

In 1999, a comprehensive survey was carried out on aerial image-based buildings extraction methods. A comparative evaluation of several methods was completed based on specific criteria for example, assessment and complexity, data and its complexity. Moreover, taking into account the advantages and limitations of different methods, an object extraction model from aerial images was developed. The developed model deals with the major concerns in the extraction of objects, for example, contexts and scales, in addition to 3D structures. In 2004, a monitoring clustering and edge detection-based method was proposed. It was used in the large buildings extraction from high-resolution satellite panchromatic images, which have shadow evidence. However, this model has been unsuccessful in extracting small buildings that have little or no shadow.

In 2010, an SVM classification procedure was used for extracting rectangular and circular building forms using high-resolution satellite pan sharpened and pan-chromatic images. The results were verified on identified residential and industrial regions in the imagery using parameters, for example, building detection percentage and quality percentage. In order to enhance classification accuracy, an SVM was proposed to enable techniques, such as C-voting, and P-fusion, which integrates structural, semantic and spectral features for classifying high-resolution satellite images. The proposed approach has been examined in both object and pixel levels and informed that object-based P-fusion and C-voting techniques enhance overall accuracy by 0.3%–2.0% when comparing with their pixel-based versions.

4. CASE STUDY OVERVIEW AND IMPORTANCE

The Al-Hudaybiyah region was named with this name in relation to the Al-Hudaybiyah well near the tree under which the Prophet Muhammad, may God’s prayers and peace be upon him, pledged what was known in history as the Bai‘at Al-Radwan, and there is a narration that re-names the Humpa tree that was in that location and is now known as the Shumaisi area, located to the west of Makkah and on the boundaries of Al-Haram (see Figure 1).

The area follows today to the province of Bahra in the area of Makkah, which is located between the cities of Makkah and Jeddah, and has a population of about 70 thousand people, and occupies historical importance due to the fact that it is the center of caravans of pilgrims in the past, as it is one of the most important tourist centers in the Kingdom of Saudi Arabia today due to the presence of the most important religious and historical monuments, where millions of Muslim tourists flock to it annually from all parts of the world.

Today, Al-Hudaybiyah region is considered a suburb of Makkah Al-Mukarramah, and it was inhabited by a large number of well-known tribes, then they migrated to Makkah and Jeddah in search of a livelihood, and in recent years life has revived again in the suburb of Al-Hudaybiyah and witnessed a massive population encroachment in light of the development projects taking place in Makkah. Several neighborhoods were formed on the right and the left of the city next to Makkah.

5. METHODOLOGY

Figure 2 identifies the overall methodology for the case study adopted in this research, the City of Makkah, which can summarize the following steps. Two Worldview-3 satellite images of Al-Hudaybiyah region were firstly obtained from King Abdulaziz City for Science and Technology to conduct research. The Worldview-3 images were imported into ENVI V5.3, and then clipped and projected into the Universal Transverse Mercator UTM coordinate system. The absolute atmospheric correction model, Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH), built-in ENVI V5.3 software was used to correct all the images. FLAASH was first used to carry out radiometric calibration [23] and eliminate the changes occurred to the spectral features of the land topographies. Sensor parameters, comprising sensor mode, pixel size, the date of the acquisition, sun elevation and zenith, have been acquired as well as weather conditions to assist in conducting the subsequent atmospheric corrections. Moreover, the calibration parameters for the Worldview-3 sensor (gains and offsets) have been encompassed into the atmospheric corrections. After performing the atmospheric correction, the corrected images were then used for classification using SVMs to extract the urban footprint from the images (see Figure 3). Subsequently, a change detecting approach was implemented to locate all the urban within the two images. The last step of the work is to validate the research outcome and assess the used method in this research.

6. SUPPORT VECTOR MACHINE

SVM is a theoretically superior machine learning methodology that introduced for solving pattern recognition problems [24,25]. Several scholars showed that SVM can generate significant results in pattern recognition, particularly for supervised classification of high-dimensional datasets. Previously, SVM was investigated for only pixel-based image classification. In recent years, scholars studied SVM in the discipline of object-based image analysis with an integration of high-level and low-level computer vision systems [26]. Computer vision methods have been utilized for
remote sensing images for example segmentation, knowledge-based and object-oriented methods to classify high-resolution imagery. Researchers showed that SVM has great advantages for remote sensing data, especially for high-resolution multispectral data [27,28]. In recent studies, SVM shows better robustness and accuracy with respect to other classification techniques, for instance neural networks, nearest neighbour, decision tree and maximum likelihood classifiers for remote sensing imagery. Therefore, SVM was utilized in this research work [26]. The SVM method aims to achieve the optimum hyperplane separation between classes by concentrating on the training cases positioned at the edge of the class descriptors. Those training cases are called vectors of support. Several publications explain a complete formulation of SVM [24,25,29]. In this section, the principles of SVM is discussed and evaluated for urban footprint classification.

Let us consider a training data are represented by \( \{x_i, y_i\}_{k=1}^n \) where \( y_i \in \{-1, +1\} \), \( n \) is the number of training samples, \( y_i = +1 \) for class \( \omega_1 \) (Building) and \( y_i = -1 \) for class \( \omega_2 \) (no building). This denotes that it is likely to identify at least one hyperplane determined by a vector \( w \) with a bias \( w_0 \), which can break up the classes without error [30]:

\[
    f(x) = w \cdot x + w_0 = 0
\]

To identify the hyperplane, \( w \) and \( w_0 \) should be assessed in a way that \( y_i(w \cdot x + w_0) \geq +1 \) for \( y_i = +1 \) (class \( \omega_1 \)) and \( y_i(w \cdot x + w_0) \leq -1 \) for \( y_i = -1 \) for (class \( \omega_2 \)).

The main objective is to explore the hyperplane that omits the maximum margin between classes. To be capable of getting the optimal hyperplane, the support vectors have to be realized. The support vectors placed on two hyperplanes that are parallel to the ideal and are given by [30]:

\[
    w \cdot x + w_0 = \pm 1
\]

If a simple rescaling of the hyperplane parameters \( w \) and \( w_0 \) take place, the margin can be stated as \( \frac{2}{\|w\|} \). The ideal hyperplane can be identified by solving the following optimization problem [30]:

\[
    \text{Minimize } \frac{1}{2} \|w\|^2
\]

Subject to \( y_i(w \cdot x + w_0) - 1 \geq 0 \) \( i = 0, 1, \ldots n \)

Using a Lagrangian formulation, the ideal hyperplane discriminant function becomes [30]:

\[
    f(x) = \sum \lambda_i y_i (x_i x) + w_0
\]

where \( \lambda_i \) is the Lagrange multiplier and \( S \) is a subset of training samples which correspond to non-zero Lagrange multipliers. These training samples are called support vectors.
7. GEOGRAPHIC INFORMATION SYSTEM OVERLAY

GIS overlay is a multi-criteria application, which utilizes data layers for particular location [31]. Remote sensing data were represented as digital data in raster format. Nevertheless, the extracted building footprint was presented in the GIS vector format. In this study, the GIS overlay integration technique has been utilized in the combination of the derived building footprints in the year 2016 and 2018 to assist in change detection. After conducting the image classification using SVM algorithm from the Worldview-3 images, all the building footprint derived from the satellite image can be overlaid to look for change in the building footprint within the 2 years (2016 and 2018). Let $C_1$ be the GIS overlay for the building footprint within 2016 and 2018, as shown in Figure 3. The process begins by first identifying those ‘no change’ building footprint collected at time $t$; that is, $C_1$ within area $L$. Once all the $C_1$ and $C_2$ are determined for the temporal period, $t \in \{1\ldots T\}$, they are spatially overlaid to estimate the new building footprint and the removed building footprint within the 2 years. The overlay function can be generated using the following equation:

$$C_t = C_1 \cap C_2$$ (5)

Where $C_t$ is the overlay layer that contains the building footprint during 2016 and 2018, $C_1$ is the building footprint in 2016 (in red color), $\cap$ stands for the intersect operator, $C_2$ is the building footprint in 2018 (in blue color) (see Figure 4). Figure 5 shows the change detection occurred between 2016 and 2018 using the GIS overlay. It is noted that the majority of changes occurred in the East and South parts of the case study.

8. ACCURACY ASSESSMENT

A number of studies have made a lot of effort to evaluate the accuracy of the urban footprint with various approaches, including comparing urban boundaries to population densities reported on census maps [32]. The subnational statistics approach was also
used to validate urban footprint using urban populations [33] and examine several urban areas that presented in both composite DMSP images (the stable lights and radiance-calibrated images) and Landsat imagery for the same time periods [34]. Regardless of the data availability, the methods mentioned above require overheads data collection and hectic efforts. Moreover, the thresholds based on the constant lights are more questionable, specifically with comparing across cities at different levels of development. As there is a scarcity of ground truth to validate the results, it is proposed to apply human settlement areas manually digitized from high-resolution images provided by Google Earth to assess the urban footprint results. The assessment of the binary classifiers technique [35,36] has been implemented to evaluate the urban footprint depending on the performance measurement through data interpretation: precision and accuracy. Precision (P) is a measurement that approximates that a positive outcome is correct using the following equation:

$$P = \frac{|TP|}{|TP| + |FP|}$$

(6)

Accuracy (Acc) assesses the efficiency of the classifier by its percentage of true forecasts using the following equation:

$$Acc = \frac{|TN| + |TP|}{|FN| + |FP| + |TN| + |TP|}$$

(7)

Where TP indicates the 'True Positive' that represents the polygon from the suggested algorithm physically located in the reference layer. TN indicates the 'True Negative' depicting the polygons that are not identified in the suggested algorithm and layer of reference. FP indicates the 'False Positive' meaning that the polygon of the proposed algorithm does not exist in the reference layer. With the proposed reference layer, which was manually digitized from the Google Earth image, the urban footprint layer from the results of the suggested procedure for data sets was assessed.
9. RESULTS AND DISCUSSION

Figures 6 shows the changes occurred in the case study between 2016 and 2018 using the GIS overlay. According to the GIS overlay approach, it is concluded that the total number of buildings have been increased by more than 220 buildings with an area about 10,200 square meters from 2016 and 2018. It is detected that there are 465 buildings with an area about 112,435 square meters have been built between 2016 and 2018. Although 4424 buildings with an area about 800,000 square meters have no changes and are still exist with the same conditions, there are 204 buildings with an area more than 15,500 square meters demolished and removed (Figure 7).

10. CONCLUSION

We evolved an approach for extracting buildings boundaries using SVM and GIS overlay. Two types of strategies are designed. The first applies SVM for image classification for extracting boundary features, which is consequently inserted to the GIS overlay. The second sets detecting buildings footprint with SVM classification, and thereafter clusters the footprints to get subsets of candidate buildings, from which the buffer of each building is built. The benefit of our method is extracting buildings alike to the ground surfaces, which are overlooked in the other approaches.

The outcomes revealed that the precision was 95% for the GIS overlay technique. Thus GIS overlay is one of the successful approaches for incorporating different datasets from different data sources. GIS overlay proposes an intelligent platform for developing a comprehensive database to detect buildings footprint. In the current research, GIS overlay represents accurate results respecting the binary classifiers technique, which advocates that GIS overlay could be a preferable technique in terms of the multi-parameter integration.

There are a few proposals for similar future studies: (1) more recent GIS and remote sensing data are needed to promote the outcomes; (2) census socioeconomic data usually relates to administrative units and could be modified in a short period of time, which may make it hard to be available all over the world; (3) incorporation among GIS, remote sensing and socioeconomic data requires alteration between data, for example from vector to raster or from raster to vector, a step that may result in a certain loss of spatial information.

In conclusion, GIS and remote sensing techniques could offer effective information for detecting buildings footprints. However, other urban and environmental parameters should be considered to develop a more universal technique to detect the buildings footprint. Consequently, future research is in its way to investigate...
different approaches to limit the variety of parameters, in addition to identifying a new approach to be implemented in different Saudi Arabian cities.

ACKNOWLEDGEMENTS

The authors would like to thank Deanship of Scientific Research and Prince Khalid Al-Faisal Chair for Developing Makkah Al-Mukarramah and the Holy Places at Umm Al-Qura University (Project No. DSRUQU.PKC-41-2) for the financial support. The authors also would like to thank the National Center for Remote Sensing Technology in King Abdul Aziz City for Science and Technology for the data and information that they provided to support this research work.

REFERENCES

[1] Al-Gendy M, Al-Anwar O, Al-Said M. The social and economic impact of slums projects on the dwellers in Makkah and Jeddah of Saudi Arabia. J Al-Azhar Univ Eng Sector 2017;12:489–500.

[2] Dai Y, Gong J, Li Y, Feng Q. Building segmentation and outline extraction from UAV image-derived point clouds by a line growing algorithm. Int J Digit Earth 2017;10:1077–97.

[3] Rottensteiner F, Sohn G, Gerke M et al. Results of the ISPRS benchmark on urban object detection and 3D building reconstruction. ISPRS J Photogramm Remote Sens 2014;93:256–71.

[4] Mongus D, Lukac N, Zalik B. Ground and building extraction from LiDAR data based on differential morphological profiles and locally fitted surfaces. ISPRS J Photogramm Remote Sens 2014;93:145–56.

[5] Vapnik VN. An overview of statistical learning theory. IEEE Trans Neural Netw 1999;10:988–99.

[6] Turker M, Koc-San D. Building extraction from high-resolution optical spaceborne images using the integration of support vector machine (SVM) classification, Hough transformation and perceptual grouping. Int J Appl Earth Observ Geoinform 2015;34:58–69.

[7] Fukushima K, Miyake S, Ito T. Neocognitron: A neural network model for a mechanism of visual pattern recognition. IEEE Trans Syst Man Cybern 1983;SMC-13:826–34.

[8] Lari Z, Ebadi H. 2007. Automatic extraction of building features from high resolution satellite images using artificial neural networks. In Proceedings of the ISPRS Conference on Information Extraction from SAR and Optical Data, with Emphasis on Developing Countries. Istanbul, Turkey, 16–18 May.

[9] Ho TK. The random subspace method for constructing decision forests. IEEE Trans Pattern Anal Mach Intell 1998;20:832–44.

[10] Freund Y, Schapire RE. A decision-theoretic generalization of on-line learning and an application to boosting. J Comput Syst Sci 1997;55:119–39.

[11] Guo B, Huang X, Zhang F, Sohn G. Classification of airborne laser scanning data using JointBoost. ISPRS J Photogramm Remote Sens 2015;100:71–83.

[12] Uzun B, Çete M, Palancıoğlu HM. Legalizing and upgrading illegal settlements in Turkey. Habitat Int 2010;34:204–9.

[13] Ioannidis C, Psaltis C, Potsiou C. Towards a strategy for control of suburban informal buildings through automatic change detection. Comput Environ Urban Syst 2009;33:64–74.

[14] Li D, Wang M, Hu F. Utilizing Chinese high-resolution satellite images for inspection of unauthorized constructions in Beijing. Chinese Sci Bull 2009;54:2524–34.
Machine learning approach to extract building footprint from high-resolution images

[15] Bayburt S, Büyüksalih G, Baz I et al. Detection of changes in Istanbul area with medium and high resolution space images. *Int Arch Photogramm Remote Sens Spatial Inf Sci* 2008;37:1607–12.

[16] Bouziani M, Goïta K, He DC. Automatic change detection of buildings in urban environment from very high spatial resolution images using existing geodatabase and prior knowledge. *ISPRS J Photogramm Remote Sens* 2010;65:143–53.

[17] Li X, Lao C, Liu Y et al. Early warning of illegal development for protected areas by integrating cellular automata with neural networks. *J Environ Manag* 2013;130:106–16.

[18] Dyer JM, McClelland J. 2017. Paradigm change in earth observation-skybox imaging and SkySat-1. In *Proceedings of the 12th Reinventing Space Conference*. Cham: Springer. 69–89.

[19] Pesaresi M, Syrris V, Julea A. A new method for earth observation data analytics based on symbolic machine learning. *Remote Sens* 2016;8:399.

[20] Deng C, Wu C. The use of single-date MODIS imagery for estimating large-scale urban impervious surface fraction with spectral mixture analysis and machine learning techniques. *ISPRS J Photogramm Remote Sens* 2013;68:100–10.

[21] Darabi H, Choubin B, Rahmati O et al. Urban flood risk mapping using the GARP and QUEST models: A comparative study of machine learning techniques. *J Hydrol* 2019;569:142–54.

[22] Jing W, Yang Y, Yue X, Zhao X. Mapping urban areas with integration of DMSP/OLS nighttime light and MODIS data using machine learning techniques. *Remote Sens* 2015;7:12419–39.

[23] Flaash USG. 2009. *Atmospheric Correction Module: QUAC and Flaash User Guide v. 4.7*. Boulder, CO, USA: ITT Visual Information Solutions Inc.

[24] Vapnik V. 2013. *The Nature of Statistical Learning Theory*. Springer Science & Business Media.

[25] Vapnik V. 1998. The support vector method of function estimation. In *Nonlinear Modeling*. Boston, MA: Springer. 55–85.

[26] Tzotsos A, Argialas D. 2008. Support vector machine classification for object-based image analysis. In *Object-Based Image Analysis*. Berlin, Heidelberg: Springer. 663–77.

[27] Dixon B, Candade N. Multispectral landuse classification using neural networks and support vector machines: One or the other, or both? *Int J Remote Sens* 2008;29:1185–206.

[28] Ustuner M, Sanli FB, Dixon B. Application of support vector machines for landuse classification using high-resolution rapideye images: A sensitivity analysis. *Eur J Remote Sens* 2015;48:403–22.

[29] Cortes C, Vapnik V. Support-vector networks. *Mach Learn* 1995;20:273–97.

[30] Tzotsos A, Argialas D. 2008. Support vector machine classification for object-based image analysis. In *Object-Based Image Analysis*. Berlin, Heidelberg: Springer. 663–77.

[31] Greene R, Devillers R, Luther JE, Eddy BG. GIS-based multiple-criteria decision analysis. *Geogr Compass* 2011;5:412–32.

[32] Lawrence WT. A technique for using composite DMSP/OLS city lights’ satellite data to accurately map urban areas. *Remote Sens Environ* 1997;61:361–70.

[33] Sutton P, Roberts D, Elvidge C, Baugh K. Census from heaven: An estimate of the global human population using night-time satellite imagery. *Int J Remote Sens* 2001;22:3061–76.

[34] Henderson M, Yeh ET, Gong P et al. Validation of urban boundaries derived from global night-time satellite imagery. *Int J Remote Sens* 2003;24:595–609.

[35] Faisal K, Shaker A. An investigation of GIS overlay and PCA techniques for urban environmental quality assessment: A case study in Toronto, Ontario, Canada. *Sustainability* 2017;9:380.

[36] Faisal K, Shaker A. Improving the accuracy of urban environmental quality assessment using geographically-weighted regression techniques. *Sensors* 2017;17:528.