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Building Classification from Lidar Data for Spatio-temporal Assessment of 3D Urban Developments

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Abstract

Three dimensional calculations of elements of urban form such as buildings and vegetation volumes are necessary for assessment of trends in spatio-temporal sustainable 3D urban form because the volume of vegetation and buildings affect the level of energy consumption and reduction of air pollution. For such studies, the first step is to acquire 3D point clouds of urban form such as by airborne lidar sensors. There is a technical question in respect of pixel and object based building classification approaches on time series lidar data as to which approach is more appropriate for comparing volumetric indicators of 3D urban development sustainability over time. This paper aims to answer this question by comparing the results of building classification of bi-temporal airborne lidar datasets using Support Vector Machines (SVM) algorithm and an object-based classification tool in ERDAS software. The results show that the omission errors for classified building points are not similar for the same buildings in the bi-temporal lidar data sets. This inconsistency affects the measurement of volumetric descriptors of 3D urban form over time. Therefore, two change detection methods of image differencing and SVM are also evaluated. While the level of noise in the SVM change detection results is lower than occurring in results derived by image differencing, the magnitude of change cannot be determined using SVM. Therefore, we conclude that a combination of change detection methods is preferred for spatio-temporal urban analyses.

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Keywords: Airborne Lidar; Machine Learning; 3D Urban Form; GLCM; Sustainability

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1. Introduction

Remote sensing data has been used so far for monitoring urban areas, measuring urban green space characteristics [1, 2] urban developments and land use change [3]. In these studies, remote sensing data is used mostly over large urban areas at a metropolitan scale. In addition, urban form has been seen as a two dimensional phenomenon. Therefore, the third dimension of cities, that is the height value of ground and urban objects, and also the local scale of urban form analysis have been neglected in studies of urban form.

To monitor 3D urban form developments, advanced remote sensing 3D data such as airborne lidar is required so that it provides necessary local information. Airborne lidar equipment is mounted on aircraft and the 3D point clouds are acquired based on scanning laser beam normal to the flight direction and measured distances from the aircraft to the terrain surface. The equipment determines positions and elevations of the terrain surface at densities on several points per m^2, together with the intensity of the return beam. The emitted laser pulses are reflected from features such as buildings and returned to the lidar equipment. The first returned pulse is mostly reflected from the highest objects such as the tops of vegetation while the last return may or may not be reflected from ground surface. Trinder [4] reports lidar as a suitable source of remote sensing data for deriving environmental factors of sustainability. While the demand for airborne lidar data over urban areas is increasing and airborne lidar data is becoming more readily available for use for spatio-temporal assessment of sustainability of 3D urban developments, the usability of such data for extracting volumetric indicators of urban sustainability at local scale has not been tested.

Filtering buildings to determine their heights above the ground surface in time series lidar data is crucial for spatio-temporal assessment and monitoring trends of changes in vegetation and building volume information required for sustainability studies. As an example, mapping the volume of buildings is required for deriving density maps of buildings for sustainability assessment of residential developments in urban areas [5]. Building analysis for urban energy planning [6] is another example in which 3D modelling of buildings is necessary. For calculation of the volume of buildings from airborne lidar data, the first step is to classify buildings and determine their above ground surface heights by interpolating ground elevation values corresponding to the classified building points. The final product of this process that includes buildings points with height values above the ground surface is referred to as Digital Building Model (DBM) in this study.

Now, the first question is, among methods of building classification from time series lidar datasets, which approach is more appropriate for assessing spatio-temporal patterns of volumetric changes of buildings as indicators of sustainability? As will be discussed in this paper, while there are classification algorithms for filtering buildings points from airborne lidar data, the question remains on the evaluation of the performance of the two approaches of pixel and object based building classification algorithms for the purpose of assessing urban form development in terms of sustainability.

Pixel-based building classification methods include such methods as Support Vector Machines (SVM), Self-Organizing Map (SOM), Classification Trees (CT) and Maximum Likelihood (ML). In this paper, among these methods, SVM is chosen based on its proved good performance compared with other mentioned classification methods, as described by: 1) Gualtieri and Cromp [7], Chapelle et al [8], Lodha et al [9] 2) Rafiee and Saradjian [10] who reported a problem of 'class overlap' for ML that is not the case for SVM; and 3) Trinder and Salah [11] who found a higher overall classification accuracy and lower levels of omission and commission errors from SVM compared to SOM and CT. Axelsson [12] reported that pixel-based methods of lidar classification are less accurate than point-based classification because information contained in the 3D points is lost by interpolating a 2.5 D image. This means that depending on the pixel size and the method used to assign values to pixels, the interpolated 2.5D surface may become smooth or exaggerated. For example, assigning extreme values of a pixel such as maximum or minimum may exaggerate the interpolated surface while assigning mean pixel values may cause the surface to be smoothed. Therefore, in this research, the performance of an object-based building classification tool in ERDAS is also evaluated for which thresholds for the parameters of buildings as objects of interest were determined by careful inspection and tests for the study extent.

Tóvári, and Vögtle [13] propose an object-based approach for distinguishing between buildings, vegetation and ground, in which it is required to define the thresholds of textural characteristics of the objects present in the dataset.

These textural characteristics include shape and size, height texture, gradients at segment borders and laser pulse intensities. In another study, Brunn and Weidner [14] investigated a "roughness" indicator that "measured by differential geometric quantities, such as gradients or curvatures" using the "height of step edges and the variance of surface normal" for creating edges and then distinguishing between buildings and vegetation.

In addition to its application for building classification, SVM is also evaluated for change detection in this paper and its performance is compared with the method of image differencing. Recently, the application of SVM for change detection studies has gained more interest. In the case of urban areas, Griffiths et al. [15] used SVM for mapping horizontal urban growth. However, SVM has rarely been applied for detection of changes over urban areas using only elevation values from airborne lidar data (i.e. DSMs).

The originality of this paper lies in: 1) the addition of Local Spatial Statistics (LSS) as defined below, to the attributes required for classification of buildings from airborne lidar data, 2) comparisons of the two different approaches of pixel and point-based building classification using only airborne lidar data, 3) application of SVM for change detection using only time series airborne lidar data 4) comparison of the results of building classification of time series airborne lidar data and change detection methods for deriving volumetric indicators for assessing spatio-temporal sustainability of urban form.

2. Building classification and change detection methods

Support vector machines are non-parametric learning algorithms for image classification in which there are no assumptions about parameters and the model in the dataset. A model is generated based on a training dataset where the parameters are identified and this model is used for prediction of classes in the entire dataset. Separation between two classes is maximized with respect to a chosen hyper plane. Two applications of SVM in remote sensing are classification and change detection. In the remote sensing arena, SVM has become popular for image classification because it operates adequately with less training data than Artificial Neural Networks and Maximum Likelihood classification [16].The power of SVM comes from the kernel used. There are four well-known kernels used in SVMs, namely, Linear kernel, Polynomial, Sigmoid and Radial Basis Function (RBF) kernels. Among these kernels, RBF is reported as a superior kernel for multiclass SVM problems. For example, Trinder and Salah [11] reported that the RBF kernel results in the best performance compared with Sigmoid, Linear and Polynomial kernels for solving multi-classification problem of buildings, ground, vegetation and roads using airborne lidar and aerial images. In this research, SVM is applied on the classification of Digital Surface Models (DSMs). In addition, to extract more information, textural maps are generated by determining Grey Level Co-occurrence Matrix (GLCM) [17] measures on elevation values and then SVM (RBF kernel) is applied on the extracted textural maps. To do so, the textural maps derived for the lidar data DSM are generated and stacked. Training areas showing buildings, vegetation and ground classes are created as Regions Of Interest (ROI) in the stacked layers. Here, SVM functions are applied as a multiclass classifier by a pairwise classification strategy, in which one binary SVM is generated to separate each pair of classes *a* and *b*. The SVM classifier then is applied using the textural maps and ROIs and three classes of building, vegetation and ground are determined.

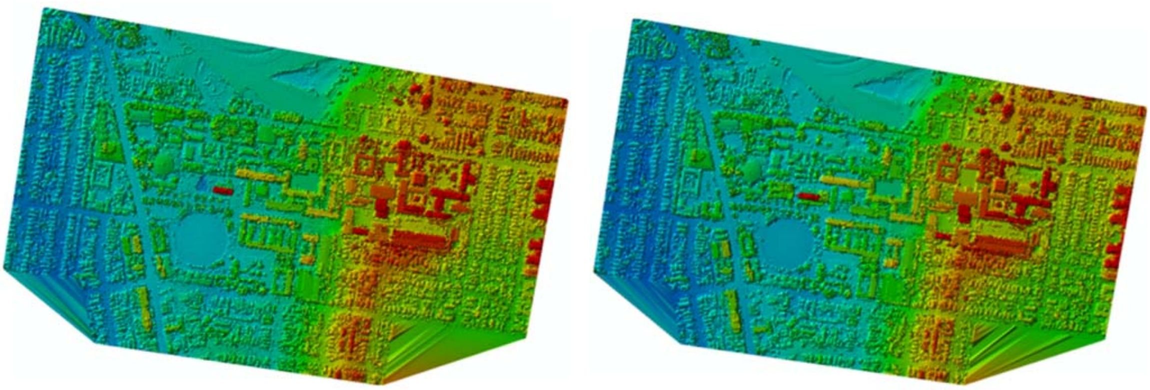
Volpi et al [18] uses GLCM measures in a SVM classification to detect changes in Very High Resolution (VHR) images and Salah et al [19] apply textural features derived from DSM, NDSM (Normalised Digital Surface Model, which is the difference between the DSM and the digital elevation model or terrain surface) and lidar intensity in conjunction with NDVI derived from aerial image to classify buildings. For SVM method, using textural features such as those derived by the GLCM can improve the classification results as they provide more information about the texture of objects within a predefined neighbourhood. Trinder and Salah [11] fused lidar derived products (i.e. DSM, NDSM and lidar intensity map) and aerial imagery for generation of GLCM layers for the application of SVM. In this study, Local Spatial Statistics (LSS) [20] based on Local Moran's I, G_i^* and Geary C in the DSMs, NDSMs and intensity maps are also generated to add to the textural attributes. Su et al. [21] and Seng et al. [22] report improvement of classification results using Local Moran's I for satellite imagery. For Local Spatial Statistics, Rook's rule [23] for considering neighbouring pixels is selected.

In this research, SVM is also applied on temporal GLCM products of DSMs, intensity and NDSMs for change detection. To do so, the textural maps for each epoch of lidar data DSM are generated and stacked. Training areas showing *increased*, *decreased* and *unchanged* classes are created as Regions Of Interest (ROI) on the stacked layers. The SVM classifier then is applied to determine three classes of *increased*, *decreased* and *unchanged* [24] based on the training areas of changed classes.

For the image differencing method, DSMs with the same pixel sizes derived from the first return lidar data from the two datasets are co-registered and the DSMs and subtracted. One of the difficulties in applying this method is the selection of the appropriate thresholds for the *unchanged* class. This problem was also reported by Hussain et al. [25]. Lu et al. [26] proposed thresholds to be $[m - \gamma\sigma , m + \gamma\sigma]$, where m and σ are the mean and the standard deviation of the distribution in the histogram of the resultant difference image. In Lu et al. [26], values of γ are selected between 2.5 m and 3.5 m. In doing so, *unchanged* values should be grouped around zero [26].

3. Methodology

In this study, bi-temporal airborne lidar datasets collected in 2005 and 2008 over the University of New South Wales Campus and nearby residential areas with 1 point/m^2 density are available as shown in Figure 1. The data comprise first and last returns of the signal from ground features emitted by the lidar sensor. The terrain on the Campus contains plain, sloping and complex urban scenes.



(a) (b)

Fig. 1. Temporal lidar datasets: UNSW DSM 2005 (a), UNSW DSM 2008 (b)

The methodology for applying SVM is displayed in Figure 2 which consists of three parts. In part 1, the products of DSM, NDSM and intensity map are derived directly from the airborne lidar datasets. NDSM is extracted from the classified non-ground points using enhanced autocorrelation based algorithms [27]. These products are used in Part 2 for extracting GLCM features (i.e. mean, second moment, variance, homogeneity, entropy, dissimilarity, correlation and contrast) and layers of LSS (i.e. Local Moran's I, G_i^* and Geary C). The results of GLCM measures are dependent on window size and in the case of these studies, a 3 by 3 pixel window is used. The size of pixels for all DSMs is 1 m. All the GLCM features and LSS are stacked in Part 3 to be used as input for SVM method for either building classification or change detection.

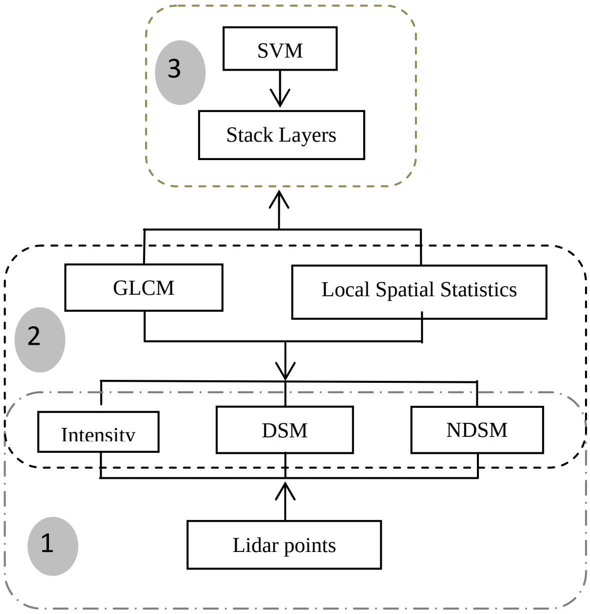


Fig. 2. The method of applying SVM for building classification and change detection using airborne lidar data

Three preparation tasks for the datasets are required before applying change detection algorithms that are: 1) Equalising the sizes of the study areas for both datasets, 2) Removing outliers from datasets and 3) Defining the same datum and projection systems for both datasets as GDA_1994 and MGA_Zone_56.

To generate DSM, first and last returns were initially separated and the elevation values of all unclassified first lidar data pulse returns are interpolated using Inverse Distance Weighting (IDW) algorithm. To prepare NDSM for application in GLCM, the DEM and NDSM are extracted using autocorrelation statistics [23]. Firstly, the points are classified into ground and non-ground. Then the heights above ground are extracted for determining the NDSM for the building classification by the SVM method based on procedures in ArcGIS, ENVI and ERDAS software to set the ground elevations of the NDSM to 0 so that all the height values above ground are preserved. The extracted non-ground points are used as input in the process of building point extraction. For the object-based classification tool in ERDAS, the thresholds of min area, plane offset, min slope, min height, max area and roughness are required to be assigned [28].

4. Results

4.1. Building classification results

Among LSS results, the result derived from the application of Geary C is poor; therefore, it is not used in the remainder of building classification procedures. A number of the GLCM measures contribute little to the extraction of buildings from the airborne lidar data; namely, variance, contrast and correlation. Therefore, these features are also not included for the application of SVM. In Salah et al. [19] all these GLCM measures were used as GLCM features, while Clausi [29] suggested the use of a combination of contrast, correlation and entropy or a selection among one of contrast, dissimilarity or homogeneity features. Two acceptable GLCM measures for building classification are mean and entropy.

The SVM building classification result for 2005 dataset is demonstrated in Figure 3, where there are significant misclassifications between roads and buildings in sloping terrain. The point-based classification tool in ERDAS is also tested for comparison with the SVM and thus a conclusion was made on the best method for building classification.

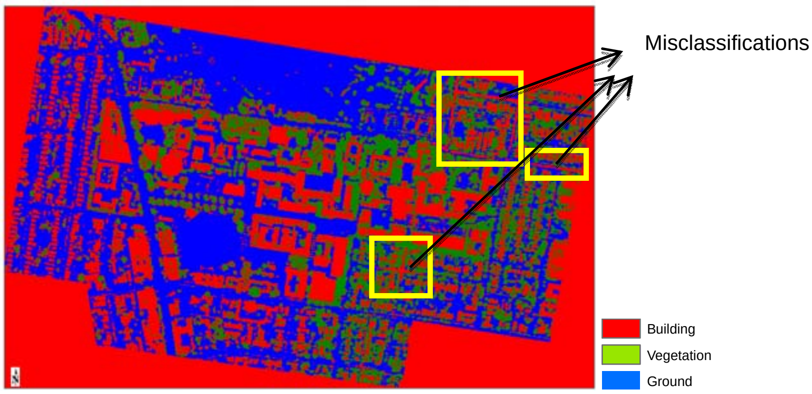
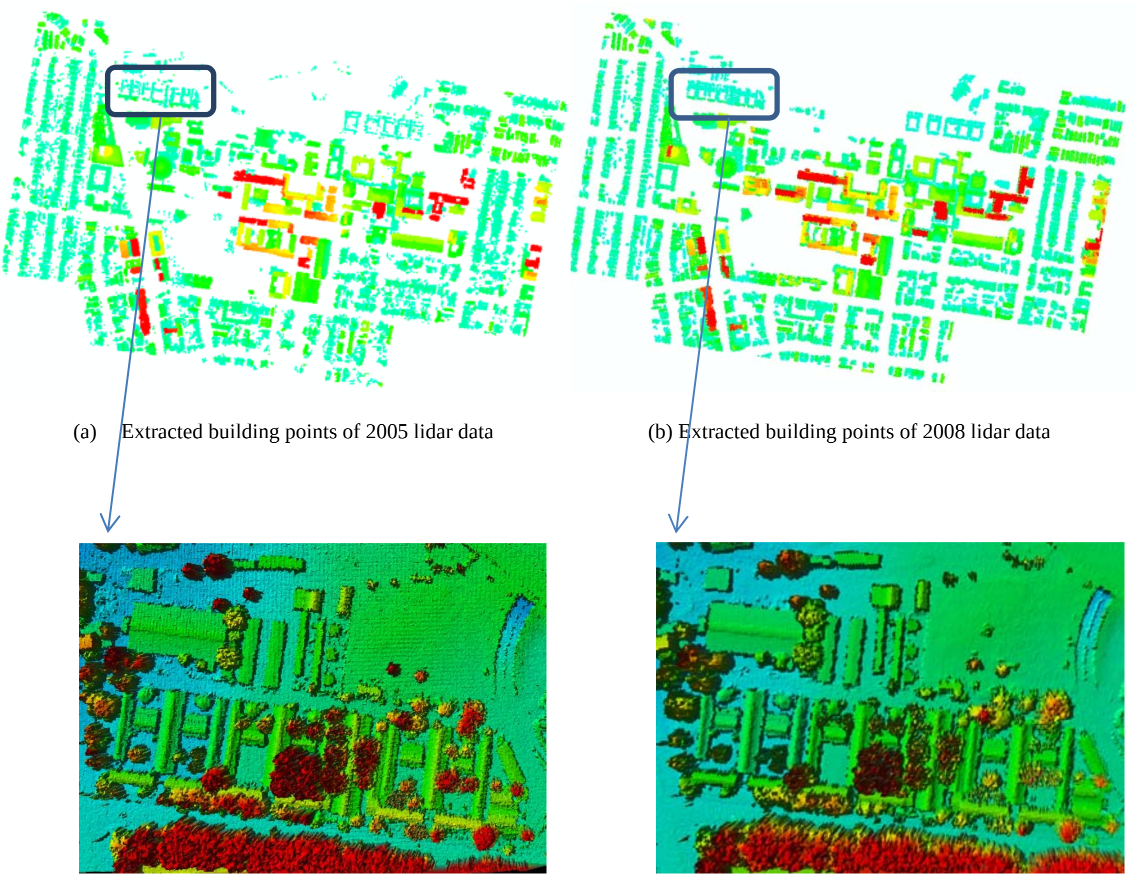


Fig. 3. The problem of misclassification between roads and buildings in sloping terrain of UNSW dataset using SVM method

The examined thresholds for the parameters of the object-based classification tool in ERDAS show that values of 30 degree, 100 m^2, 1m, 0 m, 10,000 m^2 and 0.3m for the parameters of min slope, min area, plane offset, min height, max area and roughness, respectively, result in more acceptable outcomes compared to other tests, and also those based on SVM, because most of the buildings are classified correctly and also there is no problem of misclassification between roads and buildings in sloping terrain.

4.2. The problem of building classification for spatio-temporal analyses of urban form using lidar data

Therefore, classifications of buildings in the UNSW bi-temporal datasets were based on the abovementioned thresholds. However, the results for the extraction of *unchanged* building points in these bi-temporal lidar point clouds are not similar. Omission errors in UNSW 2005 dataset are higher than in UNSW 2008 dataset. This can be seen in the rounded rectangles in Figures 4 (a) and (b) where based on the DSM representations in Figure 4 (c), there is no change in building class in this area from 2005 to 2008. This inconsistency affects the determination of volumetric descriptors based on such data as well as the results of pixel-based spatio-temporal building volume change calculation over a time interval. Therefore, this is an important issue for spatio-temporal analysis of changes in volumetric characteristics of urban form over time and has motivated the application of other change detection algorithms.



(a) Extracted building points of 2005 lidar data

(b) Extracted building points of 2008 lidar data

(c) DSMs of same part in 2005 and 2008 lidar datasets

Fig. 4. Inconsistent results of building classifications for 2005 and 2008 datasets (a and b), the DSMs (c) of the corresponding areas from careful visual inspection for existence of any building change between 2005 and 2008 datasets.

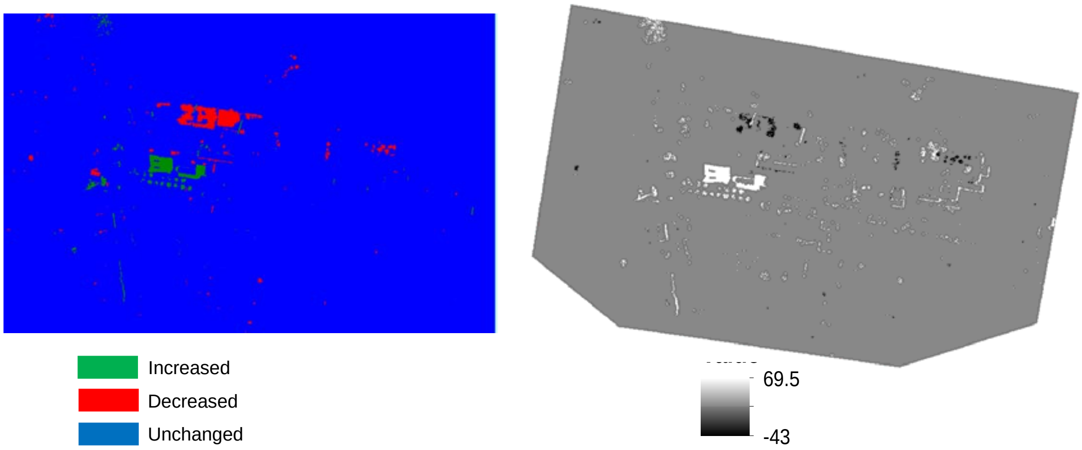
4.3. Change detection results

DSMs and NDSMs are used for the image differencing method. The results for first pulse DSM differencing and NDSM differencing show a ‘salt and pepper effect’ and errors in building boundaries for NDSM difference product are less than for the DSM differencing. However, in all change detection methods that use NDSMs, there is a level of uncertainty which is caused by the ground/non-ground point separation process and NDSM extraction.

As mentioned before, for the image differencing method, consideration of a threshold for no change is required [30]. Three thresholds for γ of 2, 3 and 4, are tested. Lu et al. [26] proposed assigning values of γ between 2.5 and 3.5 and finding the threshold for assignment of the *unchanged* class by trial and error. In this study, a low value (e.g. 2) results in a greater salt and pepper effect, while a higher value (e.g. 4) removes many pixels in the *increased* and *decreased* classes, especially in the *decreased* class. Missing data is also one source of error that affects the results of DSM and NDSM differencing.

There is a level of uncertainty in the NDSM generation and also the intensity map derived from lidar data is a poor image since the terrain surface is not completely sampled. Therefore, the results of SVM based on temporal NDSMs and intensity maps and any textural maps derived from these products are ignored for the remainder of this study. In addition, a combination of all GLCM features in these algorithms was tested and it is found that the salt and pepper effect is high as it contains uncertainties of NDSM derived features and also poor intensity derived textural maps. Therefore, as a result of these problems in NDSM extraction and also the sampling of the intensity, SVM is applied only on the bi-temporal first pulse DSM products for all GLCM or LSS features (e.g. SVM on temporal correlation maps).

As can be seen in Figure 5(a), the magnitude of change cannot be achieved using the SVM method, whereas the magnitudes of change are determined by the DSM differencing method, as demonstrated in Figure 5(b). The DSM differencing reveals a high level of salt and pepper effect that can be eliminated by choosing a higher value of 4 for γ which impacts on the density of the pixels in the *decreased* class.



(a) (b)

Fig. 5. Change detection results: SVM (a), DSM differencing with γ =4 (b)

5. Discussion

The results of the application of textural features on first pulse DSMs show that Geary C, and GLCM contrast, correlation and variance produce poor images for both building classification and change detection. GLCM dissimilarity, entropy, homogeneity and second moment produce good images for distinguishing building boundaries and elevation levels; however, they produce poor images for determination of the changes in terrain surface. The research also reveals that that while the results produced by the application of Mean, G_i^* and LMI on the first pulse DSMs are clear and appropriate for change detection, they are not suitable for building classification.

It is observed that the misclassification between roads and buildings using SVM mostly occurs in either hilly or vegetated areas for the case study. Such areas are considered as complex scenes for classification [31]. Our results are in line with the findings of previous studies such as Rottensteiner et al. [32] who found that building classification of lidar data using a pixel based method is challenging in dense urban areas since it leads to misclassifications between building boundaries and vegetation. The problem of misclassification between the boundaries of buildings and trees is common for both Trinder and Salah [11] and our studies in the same area.

For the problem of inconsistency of the classified buildings points in time series airborne lidar datasets, two change detection methods are also evaluated and it is found that a combination of SVM and image differencing should be suggested for future studies to overcome both problems of noise from image differencing and lack of magnitude of changes in SVM method.

6. Conclusion

In this paper, two approaches of pixel and object based building classification are compared for time series airborne lidar datasets to find a preferred approach for spatio-temporal 3D urban development analysis in sustainability studies. Considering the problem of inconsistency of the same buildings in the time series lidar data, change detection methods of SVM and image differencing are also evaluated. We found that an integration of image differencing and SVM is required to obtain the magnitude of change and reduce the noise in the results in the form of a salt and pepper effect. In addition, we suggest the object-based lidar classification tool in ERDAS software as a more appropriate method for building classification in a snap shot of a city.

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