The Separation of the Unpaved Roads and Prioritization of Paving These Roads Using UAV Images

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ABSTRACT: Prioritization of pathways to perform asphalt pavement operations has always been one of the most important concerns for municipalities, for which, currently there is no specific planning and pattern. In the present study, using (Unmanned Aerial Vehicle) UAV images, a land cover map of the case study was prepared. For this purpose, the accuracy of various object-based classification methods including the Bayes method, the Support Vector Machine (SVM), the K nearest neighbor (KNN), the Decision tree (DT), and the Random tree (RT) was investigated. Findings of the study showed that by increasing heterogeneity in the composition of the studied phenomenon in the image, different classification algorithms offer results different from each other. The obtained results of the accuracy evaluation of classification methods indicate that the SVM method with 80% kappa coefficient and 89% overall accuracy had the best performance compared to other methods. As a result, built-up land covers, bare land, vegetation cover, and paved roads were separated using this method. Then, the exact boundary of pathways was prepared using Google Earth images, and then, using the land-use map prepared from the case study, the roads were divided into two categories: paved and unpaved. To determine the prioritization of unpaved roads for applying asphalt, the proportion of built-up lands (BUL) to bare (non-built-up) lands (BL) was used in each path. Based on the obtained results, 1% of the roads in the case study was placed on a very high level of asphalt, and then 9%, 3%, 49%, 38%, were placed on a high priority to low priority, respectively.

KEYWORDS: Road classification, unpaved road, pavement prioritize, UVA images

Introduction

The road is one of the most important infrastructures of the transportation system (Timor-Leste-Strategic-Plan, 2030-2011). For most people, roads are just a layer of asphalt or concrete, which is built on the soil, creating a smooth surface to make vehicle movement possible (Schnebele et al., 2015). Roads are generally classified into two categories, namely paved and unpaved. The subsurface layer is different from the road type and has a major role in road performance (Huang, 2004). Unpaved roads are usually a mixture of gravel placed and compacted on finer-grained soil such as clay or silt. This layer of fine-grained soil forms the structure of the road and is referred to as the subsurface layer (Lay, 2009). The thickness, grading, and type of gravel available on the bed surface are highly dependent on the presence of materials available near the construction site as well as the type of subsurface layer (Giroud & Noiray, 1981; Schnebele et al., 2015).

Unpaved roads receive less attention and funding than paved roads due to the low volume of traffic. Nevertheless, they play an important role in connecting residents to their homes in relatively less developed areas (Dobson et al., 2013). Poor infrastructure, especially in the transport sector, is recognized as a major obstacle to economic progress (Pereira et al., 2018). Monitoring the conditions of roads, especially on unpaved roads, is a very important step in the framework of the road construction process. A desirable road monitoring system will reduce the time and cost required by obtaining sufficient information, so the results can be more effective. On the other hand, human visual monitoring is still the main form of road condition assessment methods, which is a time-consuming and costly method, and in addition, the results are highly influenced by human mentality and experience. Moreover, it is not easy to carry out such a method (Pereira et al., 2018).

The importance of combining remote sensing with civil engineering and geological techniques has been recognized by the National Research Council of the United States (Council, 2006; Piri et al., 2019). Nowadays many US departments use remote sensing techniques in combination with their standard methods to manage and assess the road asphalt conditions (Schnebele et al., 2015). In addition, the integration of geographic tools and techniques in transportation management is a growing research agenda (Olsen, chen, et al., 2013). Remote sensing as one of the mapping methods that has no direct and physical contact with the surface or subsurface of roads, if used properly, can quickly survey and monitor large areas with a variety of coarse or fine surface textures (Wang, 2011). Remote sensing is also a good way to study the damage to infrastructures and buildings after natural disasters (Ardakani et al., 2022; Olsen, Raugust, et al., 2013) because it is able to quickly collect information from a wide area of data. However, the use of remote sensing in the study and analysis of road structure or post-crisis access is a new research approach (Schnebele et al., 2015).

Remote sensing as an appropriate alternative to traditional road assessment methods using much faster instruments with temporal and spatial resolution, such as (Unmanned Aerial Vehicle) UAVs, airplanes, satellites, and electromagnetic sensors, has made the use of these methods more appropriate than traditional methods such as questionnaires and field visit. Remote sensing has become one of the most important, economical, and useful approaches for exploration at regional levels. Moreover, the use of remote sensing has no limits in terms of weather conditions and the range of services to identify and analyze road asphalt conditions. Nowadays, there are many methods, including the use of airborne and aerospace data to identify the state of infrastructure on a regional scale. Currently, the use of multi-source and multispectral data leads to more advanced identifications of the state of infrastructure (Schnebele et al., 2015). Research has shown that UAV is a low-cost option to provide surveillance images (Malamiri et al., 2021). In this regard, many studies using remote sensing have examined the condition of unpaved roads. In a study using visible to near-infrared multispectral data of the Digital Globe Quick Bird with a spatial resolution of 60 cm, Brooks et al. (2007) drew the map types of surface roads including the unpaved roads. In this study, they extracted maps of a variety of roads with an accuracy of 86%. Zhang (2008) showed the ability and application of UAV images to describe the condition of unpaved roads. This study also showed that 2-dimensional analysis of road images is appropriate in extracting much of the information needed to monitor the condition of unpaved roads. Dobson et al. (2013) collected and analyzed UAV data to identify road distress. Using SFM algorithm and data with a spatial accuracy of a few centimeters, their study investigates the condition of unpaved roads and proves the application of the obtained information in the study of vital transportation resources of larger areas as well as villages with low-to-zero tree cover, which improves the performance of UAV in the road section. Schnebele et al. (2015) aimed at simplifying the assessment of the condition of the asphalt road via creating a link between remote sensing and traditional methods; hence, they compared remote sensing methods such as visible method, ground-penetrating radar (GPR), infrared thermography, Lidar, and ground laser, and hyperspectral data. This study has proven the role of remote sensing in facilitating the review and evaluation of road conditions and significant reduction of field data and introduced visible methods more tangible and cheaper than methods such as radar and terrestrial scanning. Brooks et al. (2017) distinguished paved roads from unpaved ones in a regional road network using remote sensing and four-lane UAV images and object-based classification. The results of this study proved the relationship between the number of bands and the accuracy of separation, classification, and segmentation of paved and unpaved roads. While tree shadows and spectral similarity of roads were introduced as a challenging factor for road classification in this study, the accuracies of 82% to 94% indicate the optimal performance of this algorithm in classification.

The mentioned studies, using different methods, examined the condition and separation of paved and unpaved roads, but the proposed strategy to change the condition of the roads to a more favorable condition is relatively rare. Therefore, according to the model of land-use change in A small (332 ha) area of Yazd city, the capital of Yazd province, Iran in order to build houses and thus increase the unpaved roads containing residential houses, the present study intends to classify a part of inner-city roads in the case study using UAV image and while identifying the roads, classify and separate the paved roads from the unpaved and present the strategy of prioritizing the change of the condition of these roads to the desired condition (paved) according to the needs of citizens.

Materials and methods

Study area

The case study is a part of Yazd city, with an area of 332 ha. is located in Yazd province, Iran. This area is located in the western part of Yazd city, between 54° to 18° of east longitude and 31° to 51° of north latitude (Figure 1). Yazd city, as a world city and the 15th metropolis of Iran, is located in the central part of Iran on an arid and semi-arid belt in the northern hemisphere (Dehghan, 2011). This city, as the center of the province, has an area of 110 km² and has an altitude of 1,228 m.

Data and methodology

Data used

In this study, to classify four types of land cover including built-up land (BUL), paved roads (PR), bare lands (unpaved) (BL), and vegetation cover (VC), UAV images were used with a spatial accuracy of 15 cm including three bands of red, green and blue (RGB). For image classification, five object-based classification methods were evaluated, and finally, the method with the highest accuracy was used for classification. To collect training data to train the classification algorithm, more than 500 training data were introduced into the algorithm for each class. In the next stage, unpaved roads and paved roads were separated from each other, and then unpaved roads were prioritized based on the ratio criteria of the number of built-up to non-built-up lands for asphalt operations. A flowchart of the research implementation steps is shown in Figure 2.

Methodology

Image classification

In general, there are two object-based and pixel-based approaches to preparing a classification map of satellite images (Wang et al., 2004). Pixel-based methods are based on the DN value of pixels, in which phenomena with the same DN value are placed in the same class (Paola & Schowengerdt, 1995;
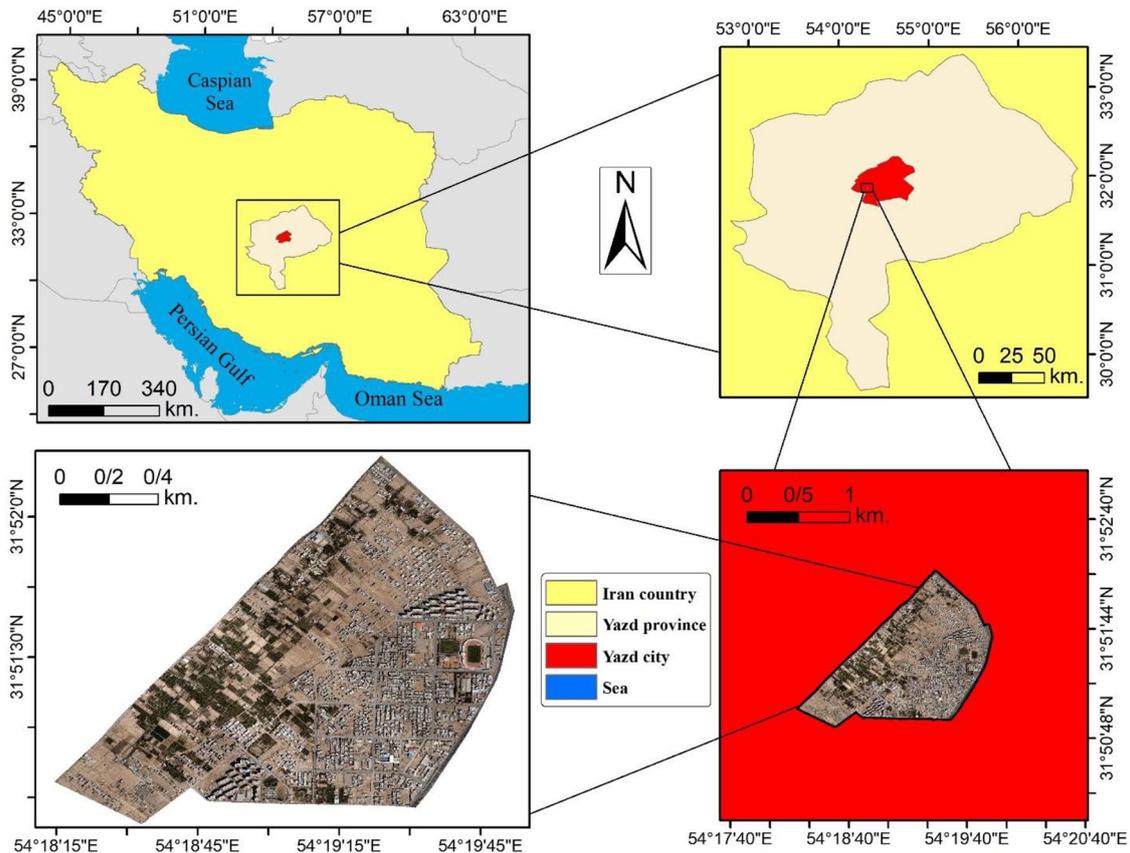
Figure 1. The RGB UAV image of the study area is part of the city of Yazd and its location map on Iran, Yazd province, and Yazd city.

Yuan et al., 2005), while object-based methods classify adjacent pixels with the same information value (spatially and spectrally) as a separate unit that is informed of a segment or fragment, and include both segmentation and classification processes (Yan, 2003). In this study, in order to classify and extract image information in four types of land cover, including BUL, PR, BL, and VC, different types of object-based classification methods such as Support Vector Machine (SVM), Bayes, K Nearest Neighborhood (KNN), Decision tree (DT), and Random Tree (RT) were evaluated in terms of accuracy and performance on the image of the case study.

Support machine vector method

This 2-dimensional classification method was developed by Vapnik (1995) based on statistical learning. This method produces a hyperplane for each individual floor, where the distance to the relevant floor is to be the maximum. To measure the distance of the hyperplane to the corresponding class, the point data closer to the hyperplane are used, which are called the support vectors. The model of the SVM method consists of two parts; training and testing. The evaluation of the generalizability of the trained model has been carried out at the end of the training phase through experimental data (Vapnik, 1995).

According to this model, if $D = \{(x_i, y_i)\}_{i=1}^{l}$ is a data set containing l sample x_i with tags $y_i \in \{-1, 1\}$ from two separate classes, there will be an infinite number of hyperplanes to linearly separate the two floors, and the most optimal page to split with the least error is the page that creates the most margins between the two floors. By defining margin as the sum of the distance of the nearest point from both floors to the separating plane, the balance between the error of erroneously classified samples and the margin can be controlled by a positive value of C. In this case, the decision function will be in accordance with equation (1).

$$f(x) = sign\left[\sum_{i=1}^{l} \lambda_i y_i x^t x_i + b\right] \quad (1)$$

Where λ_i is the Lagrange coefficients. The support vectors that are located on the boundary between two classes are data in which these coefficients are below zero. Since nonlinear data classification with linear classifiers will reduce the data efficiency, transferring data to a feature space with a higher dimensional allows the use of nonlinear classifiers (equation (2)).

$$x \in R^d \rightarrow z(x) \equiv (\phi_1(x), ..., \phi_n(x)) \in R^n \quad (2)$$

where in this new space, the linear decision function is converted into equation (3).

$$f(x) = sign\left[\sum_{i=1}^{l} \lambda_i y_i z^t(x)_z(x_i) + b\right] \quad (3)$$
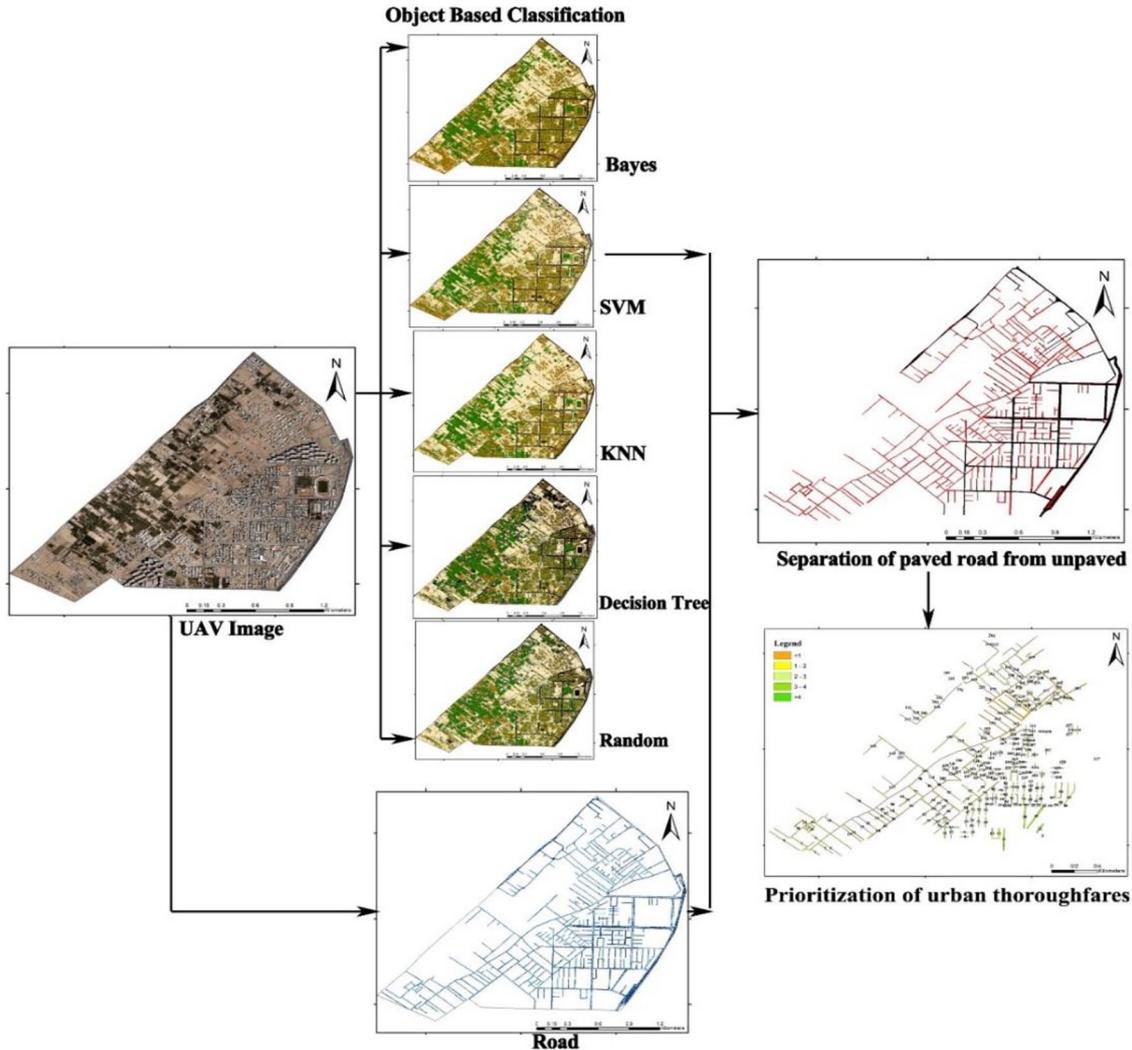
Figure 2. The flowchart and processing steps of the paper.

The key part of calculating the SVM decision functions is $z^t(x)_z(x_i)$, for which a variety of K-kernel functions including linear, polynomial, RBF, and convolution functions are used to train the model (Cristianini & Shawe-Taylor, 2000; Osuna, 1998).

Bayes method

Bayes is a method which is applied based on Bayesian theory to integrate classifiers with single-value output (Schölkopf et al., 2002). If $P(S_j)$ is the probability that the classifier D_i classifies data x into class D_i, then the final support for class w_k will be according to equation (4).

$$p(s / w_k) = p(s_1, s_2, ..., s_1 / w_k) = \Pi_{i=1}^l p(s_i / w_k) \quad (4)$$

In the practical design of the Bayes method for real data sets, each D_i *the* classifier will have a $C \times C$ confusion matrix called CM_i, which is obtained using training data. The number of elements of the data whose real class is w_k (while assigned to the class w_s by the classifier) also (k, s) is the most important member of this matrix $CM_{k,s}^i$. N_s is the total number of instances of Z that belongs to the class w_s. If $CM_{k,s}^i \mid N_k$ is an estimation of the latter probability and $N_k \mid N$ is an estimation of the previous probability for class k, the final degree of support by each class k for data $\times$ would be equal to equation (5).

$$\mu_k(x)\alpha \frac{1}{N_k^{l-1}} \Pi_{i=1}^l cm_{k,s_i}^i \quad (5)$$

K-Nearest Neighborhood method

The KNN algorithm performs labeling at the corresponding geographical point based on the relationship between two datasets of land sample information and the digital values of satellite images in the form of the data matrix. So each pixel of the image has a land measurement label and each land sample has a corresponding spectral information label. K-Nearest Neighborhood algorithm predicts and estimates the desired

properties for other non-sample pixels (target sets) by creating this connection in the form of a database for the case study. In this algorithm, the number of K is determined from the nearest training samples to the target point (pixels without land sample) (Souza et al., 2014).

Decision tree method

Unlike one-step classification methods which make only one decision for each pixel and assign the pixel to a specific class, in the DT method, which is one of the most common multi-stage classification methods, a set of decisions is made to classify the desired pixel correctly. The DT method uses interrelated classifiers which perform each part of the classification process and do not operate alone. The DT is a representation of branches and nodes, with each node leading to a set of possible answers (Lennon, 2002). In this method, the optimal branch structure with the lowest error rate and the minimum number of nodes should be specified, and the class sharing and the number of used branches and layers should be considered. The accuracy and efficiency of the classification in this method are highly dependent on the selection of branches (Rounds, 1980).

Random tree method

The RT is a supervised classifier and a group learning algorithm that generates a large number of individual learners. This algorithm uses the idea of a suitcase to generate a random set of data to build a DT. In a standard tree, each node is divided among all variables using the best segmentation. In a random forest, each node, using the best segmentation, is divided into a subset of defaults in which the node is randomly selected. The RT algorithm was introduced by Leo Breiman and Adele Cutler. This algorithm can be suitable for solving both classification and regression issues. The RT algorithm is a set (group) of tree predictors called the forest. The function of this classification is as follows. The RT classification receives the input feature vector and classifies it with each forest tree. Then its output is to create the label for the class that receives a majority of votes (Kalmegh, 2015).

Evaluating the accuracy of classification methods

To evaluate the accuracy of different classifiers, for each class, more than 500 random scattered points were collected by land visit, visual interpretation, and user experience as confidence points and introduced to the algorithm. Kappa method and overall accuracy were used to evaluate the classification accuracy. Kappa coefficient and overall accuracy (Sexton et al., 2013) were then calculated for each of the classification methods. The non-parametric kappa coefficient test is used to determine the degree of compatibility between the actual values and the values assigned by the user (Ishtiaque et al., 2017). Kappa is commonly used as an indicator to evaluate the measurement

quality of binary specifications. When the compatibility is complete, the kappa output will be one (100%), meaning that the classification is in any context in accordance with reality. A value of zero (zero) kappa indicates that the compatibility of the data is not even better than a random value. The negative value of kappa also indicates that due to the marginal distribution, the compatibility of the data is even less than a random value. The kappa coefficient not only is dependent on the sensitivity and unique quality of the two classification classes but also depends on the correct distribution of the characteristics of the statistical population (Thompson & Walter, 1988).

Overall accuracy is the quotient of dividing all correctly classified pixels by all available pixels in the N error matrix (equation (6)) (Story & Congalton, 1986).

$$P_j = \frac{\sum_{i=1}^{k} x_{ii}}{N} \tag{6}$$

The separation of the paved roads from unpaved

To separate the unpaved roads, first, the land cover map of the case study in four floors of bare lands, build-up lands, vegetation cover, and the paved road was prepared and the exact boundary of these roads was prepared using UAV images. By placing this border on the land cover map, roads were classified into two groups; paved and unpaved. In this way, the passages that were located on the barren ground floor were included in the group of unpaved roads. However, the road that was located on the bare ground floor was included in the group of unpaved roads.

Prioritization of roads for asphalting

To determine the priority of unpaved roads for asphalt application, the ratio of built-up land (BUL) to bare (non-built-up) lands (BL) was used in each road. For this purpose, first, the build-up land ratio created for each road was calculated from equation (7) (Source: Author).

$$BUR = \frac{BUA}{BL} \tag{7}$$

where BUL is the number of build-up lands and BL is the number of bare lands (non-built-up). Accordingly, roads that had a higher ratio, were placed on a higher priority.

Results

Evaluating the accuracy of classification methods

To prepare a map of land cover in the four floors under study, including build-up lands, bare lands, paved roads, and vegetation cover, the accuracy of different object-based methods was first examined. The results showed that the object-based classifiers evaluated in this study (SVM, Bayes, K-Nearest Neighborhood, DT, and RT) showed different results based on
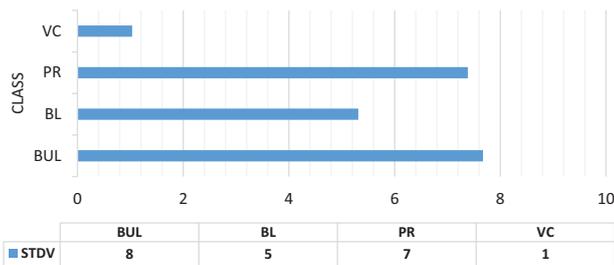
Figure 3. Standard deviation of different land cover (Vegetation Cover (VC), Paved Road (PR), Bare Land (BL), and Built-up Land (BUL)) areas by the classifiers tested in the research.

Figure 4. Comparison of the land cover area (Vegetation Cover (VC), Paved Road (PR), Bare Land (BL), and Built-up Land (BUL)) in the algorithms tested in the research.

the area of each cover. This difference is the highest in the area of build-up lands with a standard deviation of eight and is the lowest in the vegetation cover class with one (Figure 3). This difference indicates the great diversity of built-up areas and the uniformity of vegetation cover as compared to other classes in the UAV image of the case study.

Thus, the output of the build-up land floor area in the mentioned classification algorithms has been different from 62 ha. in the RT algorithm to 134 ha. in the Bayes algorithm. However, to cover bare lands, the area of this floor has been different from 103 ha. in the Bayes algorithm to 148 ha. in the SVM algorithm. Also, the area of paved roads had been different from 16 ha. In the Bayes algorithm to 77 ha. in the DT algorithm. These results have been recorded for the vegetation cover floor area from 72 ha. In the KNN algorithm to 82 ha. In the RT algorithm (Figures 4 and 5).

The results of evaluating the accuracy of the classification methods indicate that the SVM method with 80% kappa coefficient and 89% overall accuracy had the best performance compared to other methods. On the other hand, the Bayes method with the lowest kappa coefficient (60%) and the RT method with the lowest overall accuracy (72.6%) showed the lowest accuracy among the classification methods (Table 1).

Image classification

After determining the SVM method as the most accurate classification method for the case study, the output of this method was used to classify and separate unpaved roads from bare lands. As a result of this separation, out of a total of 148 ha. of bare lands (45% of the total classification area), 19.6 ha. were identified as unpaved passages. Thus, in total, 19.6 ha. of unpaved roads and 128.4 ha. of bare lands were identified (Figure 6).

Prioritization of roads for paving

To prioritize roads for paving, the ratio between the number of built-up lands to bare (unpaved) lands was used in each road. These ratios were classified into five categories; smaller than one (very low priority), 1 to 2 (low priority), 2 to 3 (medium priority), 3 to 4 (high priority), and greater than four (very high
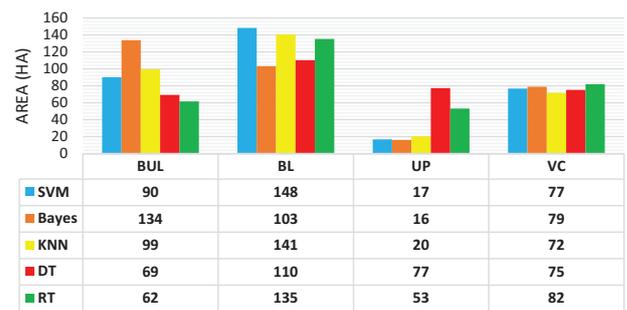
priority). Thus, the higher ratio assigned to each passage (based on ID) indicates the higher priority of that road for paving (Table 2).

According to the obtained results, 38% of the total roads (91 roads) were placed on a very low priority, 49% of the total roads (119 roads) were placed on a low priority, 3% of the total roads (8 roads) were placed on a medium priority, 9% of the total road (21 passages) were placed on a high priority and 1% of the total roads (2 passages) were placed on a high priority (Figure 7).

Discussion

This study aimed to evaluate different classified methods in separating unpaved lands from other land covers (especially bare lands) and then prioritize these lands based on the ratio of proximity to residential areas. Because object-based methods are accurate when correct object characteristics and segmentation levels are used (Salehi et al., 2012), classification algorithms based on this method were used to evaluate the classification accuracy. Based on the results of this study, the SVM method with kappa coefficient and overall accuracy of 80% to 89% (respectively) has achieved the highest accuracy in the separation of four land cover classes including built-up lands, bare lands, urban paved roads. KNN, DT, RT, and Bees with 70%, 70%, 70%, 60%, 83.4%, 74.3%, 72.6%, 74.7% of kappa coefficient and overall accuracy respectively are in the next levels of accuracy. The results of the evaluation of the accuracy of the classification algorithm, are compatible with the previous researches that mentioned the SVM as the relatively more accurate algorithm, in the classification of high-resolution images (Melgani & Bruzzone, 2004; Wang et al., 2016). Also, the highest and lowest differences in the classification results were related to the classes of built-up lands (8σ) and vegetation (1σ), respectively, which is probably due to the greater diversity of phenomena in the built-up lands and greater uniformity in vegetation cover. Thus, based on the results obtained from the SVM classifier, 19.6 ha. of unpaved roads and 128.4 ha. of barren lands were classified and separated on the UAV image. Statistics and visual comparisons (Figure 7) of the separation between paved and unpaved roads
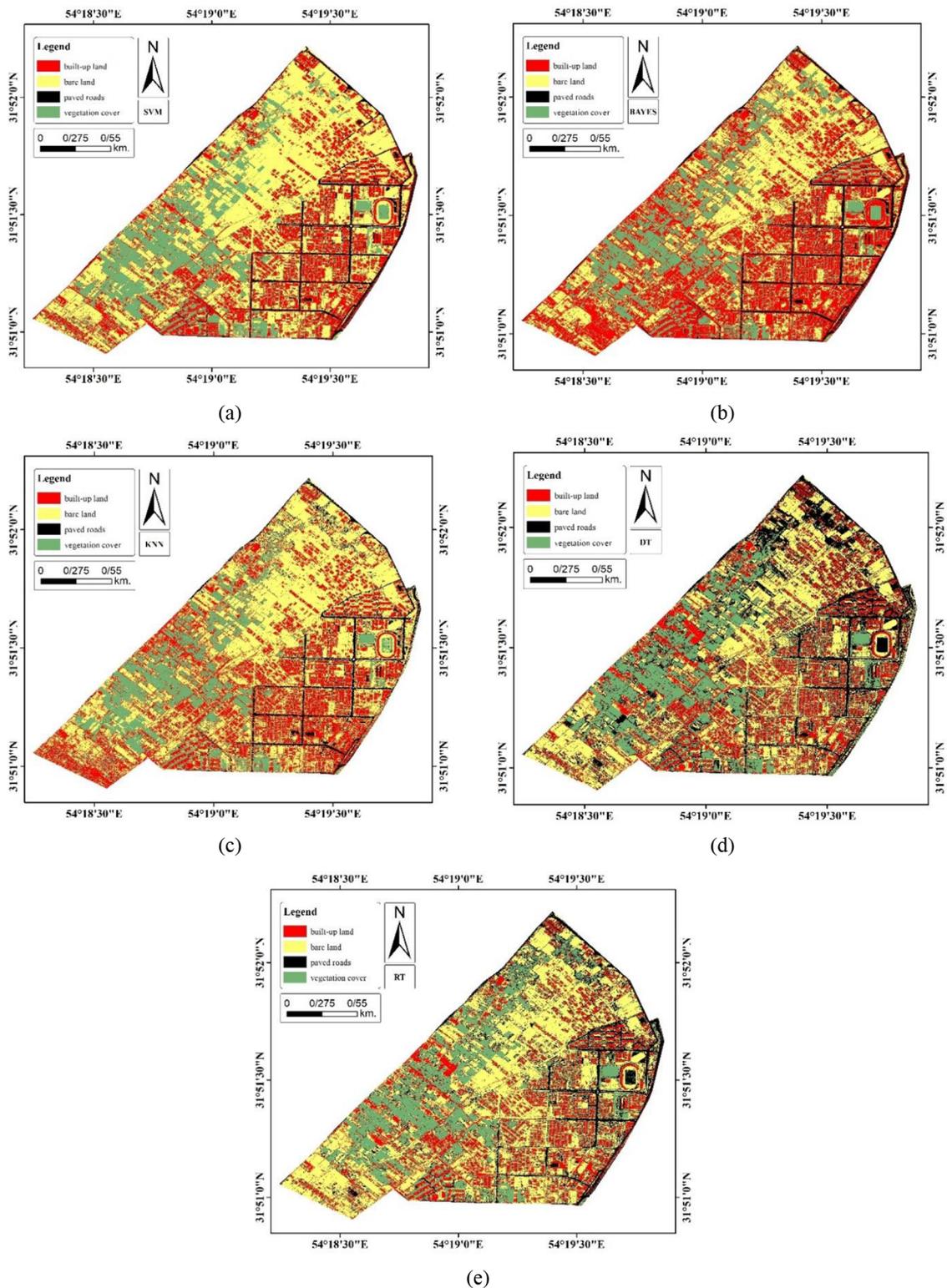
Figure 5. Land cover map of the case study using algorithms (a) Bayes, (b) KNN, (c) SVM, (d) DT, and (e) RT.

indicate that most of the roads in the case study are not paved and this section probably includes lower grade and more informal roads. In fact, the roads which are more important and more regular in terms of the transportation network have been paved. This makes it more necessary to pay attention to unpaved roads for the well-being of residents. However, since it is not possible to pave all these roads at once, it is better for these roads to be prioritized based on the ratio of built-up to non-built-up lands (bare lands) and to be nominated for asphalt. Then, the unpaved road was prioritized for asphalting in four floors: very low, low, medium, high, and very high, based on their importance due to their proximity to residential areas.

Table 1. Comparison of accuracy of classification methods (Support Vector Machine (SVM), Bayes, K Nearest Neighborhood (KNN), Decision tree (DT), and Random Tree (RT)) Used in Research.

INDEX (%)	SVM	KNN	DT	RT	BEES
Kappa	80	70	70	70	60
Overal accuracy	89	83/4	74/3	72/6	74/7

(a)   (b)
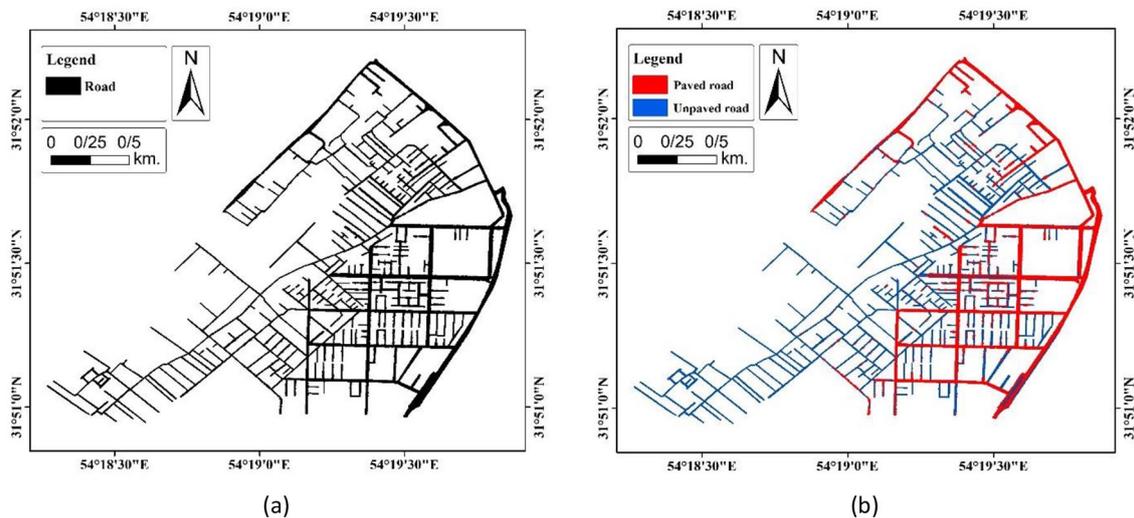
Figure 6. (a) Roads map and (b) classification map of paved and unpaved roads.

Table 2. Prioritization of roads for paving based on the ratio of build-up land to bare land.

RATIO	ROAD ID
<1	27, 160, 170, 173, 182, 24, 146, 148, 151, 167, 171, 189, 18, 19, 20, 46, 61, 75, 79, 102, 103, 118, 119, 131, 135, 150, 156, 158, 159, 161, 165, 177, 180, 181, 184, 185, 186, 190, 194, 218, 225, 229, 230, 231, 232, 235, 25, 44, 96, 145, 178, 166, 168, 174, 179, 195, 233, 39, 40, 45, 56, 58, 63, 105, 123, 143, 153, 176, 193, 211, 234, 31, 38, 59, 77, 116, 132, 137, 224, 32, 93, 95, 122, 200, 213, 238, 74, 83, 120, 191, 212
1–2	1, 2, 5, 8, 17, 22, 26, 30, 43, 47, 51, 52, 55, 62, 64, 65, 66, 72, 76, 82, 85, 86, 88, 89, 90, 91, 94, 97, 98, 99, 101, 106, 107, 108, 109, 110, 111, 112, 114, 115, 117, 121, 124, 125, 126, 127, 129, 130, 133, 134, 136, 139, 140, 141, 144, 152, 154, 155, 157, 162, 163, 164, 169, 172, 183, 187, 196, 197, 199, 201, 202, 203, 204, 206, 207, 208, 209, 210, 214, 215, 216, 217, 219, 221, 226, 227, 228, 237, 239, 240, 42, 78, 198, 28, 35, 104, 188, 192, 36, 60, 128, 147, 175, 205, 220, 222, 149, 6, 11, 12, 23, 41, 53, 81, 84, 113, 223, 92, 4
2–3	80, 9, 14, 33, 34, 71, 87, 100
3–4	37, 0, 3, 7, 10, 13, 15, 21, 29, 48, 49, 50, 57, 67, 68, 69, 70, 73, 138, 142, 236
>4	54, 16

Accordingly, 38% of the total unpaved roads were in very low priority, 49% of the roads were in low priority, 3% in medium priority, 9% in high priority, and 1% of the total unpaved roads were in very high priority. Thus, 23 high-priority and very high-priority thoroughfares close to residential areas were identified and displayed on the map.

Conclusion

The obtained results in this study indicate that different object-based classification methods evaluated in this study, including SVM, Bayes, K nearest neighbor, DT, and RT show different results from the area of different land cover classes. This difference decreased with increasing and decreasing the land cover diversity (in build-up lands with a standard deviation of 8), and the obtained area Figures from different algorithms get closer to each other (in vegetation cover areas with standard deviation 1). Among the mentioned methods, the SVM method outperformed others with an overall accuracy of 80% and a kappa coefficient of 89%; relatively high and acceptable accuracy was shown in the classification of four classes of built-up lands,
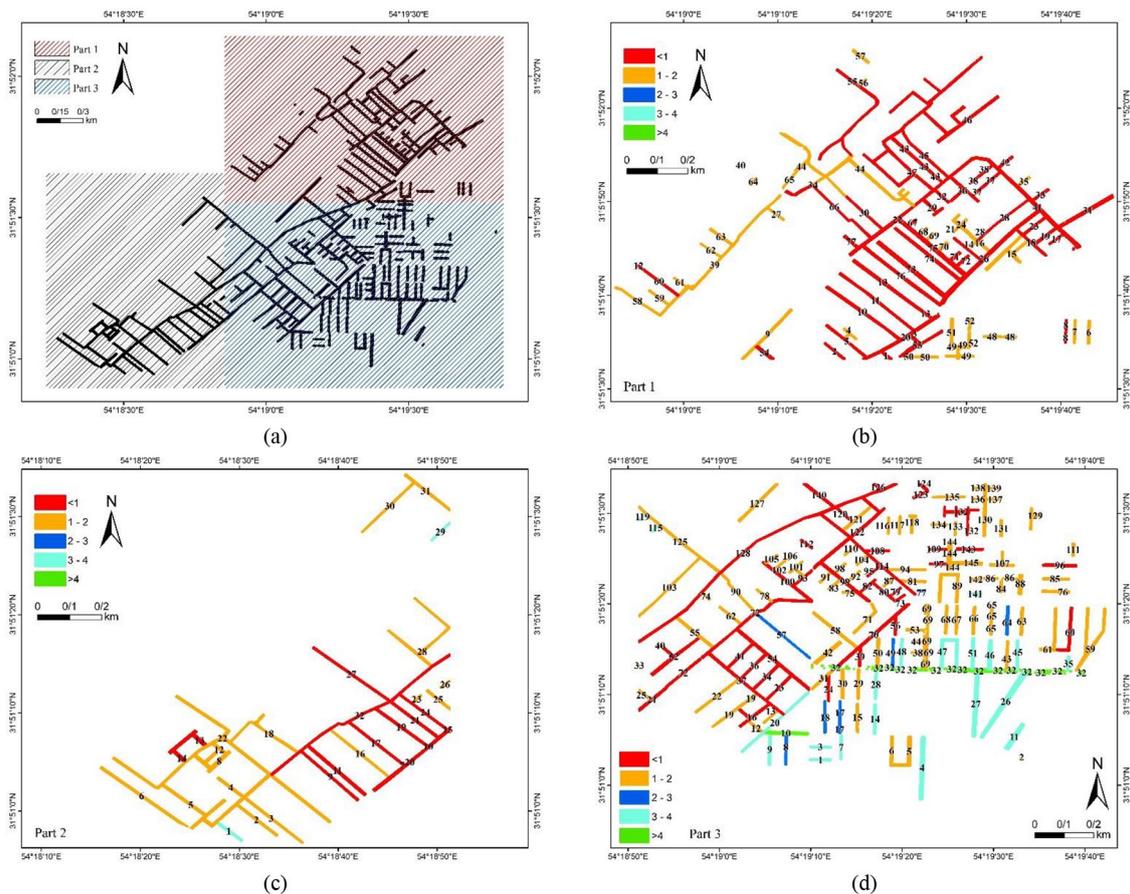
Figure 7. (a) Prioritization map of roads for paving based on the ratio of build-up land to bare land (divided into three parts to facilitate map display) and (b) Part-1 (c) Part-2 (d) Part-3.

bare lands (including bare lands and unpaved roads), paved roads and vegetation cover. Therefore, this method was used to classify roads. The results showed that 90 ha. of build-up land, 128.4 ha. of bare land, 17 ha. of paved roads, 19.6 ha. of unpaved land, and 77 ha. of vegetation cover were identified in the area. This study then prioritized the roads paving based on the ratio of built-up to bare (non-built-up) land, according to which 1% of roads were placed on a very high priority for paving. Then 9%, 3%, 49%, 38% are placed in a high priority and low priority for paving, respectively. These results also indicate that the majority (87%) of the existing roads have a medium to low priority, so there are fewer build-up lands in them. On the other hand, 13% of the roads have a medium to high priority and the asphalt of these roads should be given more priority to ensure the well-being of its relatively more inhabitants.

Declaration of conflicting interests

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